Can Educational Outreach Improve Experts' Decision Making? Evidence from a National Opioid Academic Detailing Program

Jonathan Zhang*

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Abstract

Healthcare providers often deviate from guidelines, leading to worse outcomes. I study the impact of academic detailing (also known as educational outreach) to primary care teams on safer pain management, risk evaluation, harm reduction, and opioid use disorder treatment. Using data from over 5 million patients, I find detailing improves provider behavior: it increases naloxone prescribing, prescription drug monitoring queries, and reduces opioid prescriptions for three years. Patients have fewer emergency visits and hospitalizations for overdoses, suicides, and accidents, especially heavy opioid users. Importantly, pain scores remain stable despite reduced opioid use, highlighting detailing's role in fostering safer, effective care.

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*Sanford School of Public Policy, Duke University, National Bureau of Economic Research, and VA Office of Mental Health and Suicide Prevention, jonathan.zhang@duke.edu. The views expressed herein are those of the authors and do not necessarily reflect those of the United States Department of Veterans Affairs or the Veterans Health Administration. This research has benefited greatly from discussions and comments from Abby Alpert, Mark Bounthavong, Benjamin Cowan, Sarah Eichmeyer, Boriana Miloucheva, Elizabeth Oliva, Adrienne Sabety, Joe Sabia, Dan Sacks, Molly Schnell, David Silver, Jodie Trafton, and participants at the Economics of Risky Behavior Workshop 2022, University of Waterloo, and VA HERC Cyberseminar. I am especially grateful to Mark Bounthavong, Melissa Christopher, Marcos Lau, Michael Harvey, and the VA Academic Detailing team for invaluable insights and help in navigating institutional details.

1. Introduction

Across many settings, experts often make systematically different decisions when facing the same circumstances. For example, judges make different sentencing rulings, teachers have different teaching styles, and physicians have prescribing tendencies. These differences can lead to varying, and thus worse, outcomes (Dobbie et al., 2018; Jackson, 2018; Cuddy and Currie, 2020). Changing guidelines and standards can complicate the decision-making process over time and necessitate continuing professional education.

In medicine, innovations and medical best-practices change rapidly, but clinicians receive the vast majority of their training at the start of their careers. Evolving medical practices call for updating medical training. While many countries have continuing education requirements, these programs are piecemeal and do not systematically target engrained practices which may no longer be consistent with the newest clinical evidence and guidelines.

The opioid crisis is a salient, ongoing example of rapidly evolving practices, guidelines, and technologies for pain and dependence treatment (Volkow and Blanco, 2021; Cutler and Glaeser, 2021). Physician practices in opioid prescribing and pain treatment vary widely and research have found that these differences have caused adverse outcomes including overdoses and deaths (Barnett et al., 2017; Eichmeyer and Zhang, 2022). Furthermore, more liberal opioid prescribers are less likely to stay up-to-date on and follow opioid-related guidelines (Eichmeyer and Zhang, 2023).

In the past decade, policies that have attempted to reduce dangerous prescribing and its negative impacts have generally been blunt (e.g., laws on prescribing limits and prescription drug monitoring programs) and often ineffective (Meara et al., 2016; Maclean et al., 2020). This is in direct contrast with the clear effectiveness of promotion and detailing by pharmaceutical companies such as Purdue Pharma in increasing prescribing of opioids (Alpert et al., 2022; Arteaga and Barone, 2022). This has led many policymakers and researchers to wonder what supply-side policies can curtail the opioid crisis, and the role of physician education (Schnell and Currie, 2018; Dowell et al., 2019; Currie and Schwandt, 2021; Humphreys et al., 2022).

In this paper, I study the largest opioid-related education program in the United States. Academic detailing (also called educational outreach) is a form of continuing education where a trained healthcare professional visits individual clinicians to provide practical, evidence-based information such as systematic reviews, recommended guidelines, patient education materials and resources. The educating provider (detailer) utilizes data (e.g., records of physician prescriptions) to provide feedback to highlight discrepancies between individual clinicians practice and clinical guidelines. The detailed clinician is also provided population management tools with which they can review to see whether and where their treatment practices were not concordant with guidelines.

In 2015, following a White House mandate, the US Department of Veterans Affairs (VA) implemented a national academic detailing campaign where they developed opioid-related educational materials based on VA/DOD and CDC guidelines to train clinicians—the majority of whom were primary care providers (PCPs). With the goal to reduce opioid overdose mortality, the VA promoted evidence-based recommendations and guidelines around four areas: i) appropriate pain management (e.g., alternate non-opioid pain treatment, appropriate doses of opioids); ii) substance use monitoring (e.g., use of prescription drug monitoring programs and urine drug screens to evaluate opioid risk); iii) opioid use disorder (OUD) treatment (e.g., how to identify and treat OUD); and iv) harm reduction methods (e.g., naloxone distribution). Over the next five years, VA clinical pharmacists began to visit thousands of clinicians on these topics via largely face-to-face visits, typically lasting 40 minutes.[1]

The VA and its academic detailing campaign is attractive to study for four reasons. First, the implementation of the academic detailing was staggered across the nation, giving way to a staggered treatment ("difference-in-differences") design to study detailed (treated) PCPs and their patients (Callaway and Sant'Anna, 2021). Second, the treatment is at the PCP

[1]While academic detailing is not new (Avorn and Soumerai, 1983; Soumerai and Avorn, 1990), the VA campaign is the largest nationally implemented academic detailing. Pharmaceutical promotion uses similar techniques along with financial incentives to promote their products, typically with sales representatives. Prior work have found pharmaceutical promotion to impact prescribing (Agha and Zeltzer, 2022; Carey et al., 2021; Grennan et al., 2021; Shapiro, 2018), but the impacts of *academic* detailing on prescribing and clinical practice more generally are mixed (see Hoof et al. (2015) for a meta-analysis and O'Brien and Harvey (2007) for the Cochrane review). In both cases, its impact on downstream patient outcomes is unknown.

team-level[2] and is well-powered, allowing me to precisely observe a wide range of physicians' actions, including prescribing, referrals, prescription drug monitoring program checks, among others. Of the over 6,000 primary care teams in the VA, a little over half received detailing, and as a result 2.75 million primary care patients had their PCP treated.

Next, rich electronic health records at the VA allow me to directly observe provider responses and patient outcomes. I construct a detailed analytic sample on physician prescribing and patient outcomes by linking rich administrative data on detailing visits with data on the prescribing history of each provider—salaried employees who typically only work in the VA—with the universe of electronic health records for all five million primary care patients. This linked microdata allow me to study how provider education impacts outcomes that prior studies focusing on supply-side opioid policies have typically been underpowered to study, such as serious adverse events.

Finally, the VA and the veteran population are a particularly relevant and important group for studying the impacts of opioid policies. Because VA eligibility criteria enrich for patients with high rates of chronic pain (Clancy, 2015), opioid prescribing rates at the VA were historically higher than the rest of the country (Hadlandsmyth et al., 2018); and veterans using VA healthcare have higher rates of substance abuse and mental health related risk factors (Seal et al., 2009), other risky health behaviors (Cesur et al., 2016), and in turn are at higher risk of opioid overdoses (Bohnert et al., 2011). From a policy standpoint, the veterans in the VA health system closely resemble the at-risk population who may benefit the most from having their PCPs detailed on opioid-related topics. However, it is important to keep in mind that there may be features unique to the VHA that foster physician education and its impacts—I discuss this in more detail towards the end of the paper.

I find that academic detailing had a large and persistent impact on PCPs' medical practice. An academic detailing visit increased take-home naloxone[3] prescribing by roughly one per 1,000 patients, per quarter, a 200% increase, with the effects lasting for at least three years.

[2]Primary care in the VA is delivered in team-based models where a team consists of a PCP (physician or nurse practitioner), two medical support staff, and an administrative clerk. Throughout this paper, I will use the term PCP and team interchangeably to refer to the team, which is the unit of analysis. I explain this in more detail in the following section.

[3]Take-home naloxone—sometimes referred to by the brand name Narcan—is a medication used to reverse overdoses, and is prescribed to ensure at-risk patients have a supply on hand in case of an emergency.

This resulted in 33,528 additional naloxone prescriptions between October 2015 and December 2019, equivalent to 24.5% of all naloxone prescribed from primary care in the VA. Opioid prescribing decreased by 6% (16.6 fewer prescriptions per 1,000 patients, per quarter). A fraction of the reduction in opioid prescribing is offset by an increase in referrals to alternate non-opioid therapy (e.g., pain clinics, acupuncture, and physical therapy). Reductions in opioid prescribing were largest for higher dose prior opioid users. The academic detailing campaign was responsible for 732,000 fewer opioid prescriptions or 18.2% of the total reduction in opioid prescribing in VA primary care over the study period. Queries for prescription drug monitoring programs increased by 9%. Measures of risky opioid practice decline: the largest prescribing reductions are in higher dose opioids, fewer patients are on opioid and benzodiazepine combinations (which can increase risk of overdose and dependence), and there is a decline in a composite overdose risk index based on medication usage and medical morbidities.

Did changes in PCPs' behaviors impact patient outcomes? Despite a significant reduction in opioid prescribing, self-reported pain is unchanged, even for patients on higher prior dose of opioids or with chronic pain. Using data on millions of pain scores (a "fifth vital sign" in the VA and measured at the time of the clinic visit), I find a statistically insignificant effect of -0.006 on a mean pain score of 2.5 (on a 0 to 10 scale, with 10 being most pain). The effect is precisely estimated: 95% confidence intervals rule out increases in pain of more than a quarter of a percent, and the distribution of pain scores is also precisely constant. This suggests that either the pain relief benefits of opioids are very small for the average patient who experienced a reduction in opioids and/or PCPs are using their expert judgment to reduce opioid prescribing for exactly the patients for whom opioids have no effect on pain.[4]

Furthermore, PCPs alter their opioid-related practices in ways and to patients that may have resulted in modest improvements to downstream outcomes. I find that detailing leads to 0.10 fewer (a 2.1% reduction; significant at the 10% level) emergency department (ED) visits and hospitalizations for overdose poisonings, suicide attempts, and accidents ("serious adverse events") per 1,000 patients, per quarter. This effect is concentrated among higher

[4]Small-scale RCTs have found that opioids have limited effects on pain reduction relative to non-opioid pain therapy in specific settings (Krebs et al., 2018); I build on this work by providing large-scale quasi-experimental estimates of the impacts of physician-induced opioid reductions on pain.

dose prior opioid users.[5] Among this group, there is a 10% reduction in serious adverse events. From the ED/hospitalizations alone, the program resulted in over $51 million in cost savings for the VA. Turning to mortality, the coefficient is negative (an effect size of 1.1% reduction in mortality), but imprecisely estimated.

This paper speaks to the literature on supply-side opioid policies. Prior research study laws at the state-[6] (e.g., prescription drug monitoring program (PDMP) laws, prescribing limits, "pill mills", etc.) or national-[7] (e.g., OxyContin reformulation) level. Unlike laws that mandate prescriber practice, the VA's academic detailing program targets individual providers, allowing me to study their actions and their patient outcomes directly. Ahomäki et al. (2020); Doctor et al. (2018) show that "light touch" informational nudges to physicians may influence opioid prescribing, but it is unclear whether the effect is persistent and its impact on patient outcomes. This paper finds that formal detailing can have immediate and persistent impacts on physician practice, with downstream effects on patient outcomes.

Prior studies on academic detailing suggests that it may alter provider behaviors. Outside of the VA, Saffore et al. (2020) study an opioid academic detailing program in Chicago and find that clinicians who self-reported an intention to prescribe fewer opioids (after a detailing visit) go on to prescribe fewer opioids. The VA's academic detailing team has conducted early clinical evaluations as well. Bounthavong et al. (2019) investigated naloxone distribution and discovered that stations with a higher proportion of detailed clinicians also had a higher

[5]Higher dose prior opioid user is defined as greater than average 20 milligrams of morphine equivalents per day in the prior year.

[6]The research on supply-side laws have generally arrived at mixed results. The evidence on PDMPs is mixed; while most studies find that PDMPs reduce opioid prescribing, some find increased mortality due to illicit sources (Bao et al., 2018; Kim, 2021; Meinhofer, 2018; Buchmueller and Carey, 2018; Alpert et al., 2020; Balestra et al., 2021). Pill mill legislation and prescribing limits (Kaestner and Ziedan, 2019; Sacks et al., 2021) generally reduced prescribing, but its impacts on patient outcomes are unknown. Donahoe (2023) and Soliman (2022) find that DEA crackdowns on pill mill prescribers reduced opioid deaths but may have increased heroin deaths. With naloxone access laws, Rees et al. (2019) find mortality improvements while Doleac and Mukherjee (2022) find modest—albeit noisy—increases in mortality. Marijuana legalization does not lead to fewer opioid deaths (Mathur and Ruhm, 2023). Overall, state laws are not associated with improved patient outcomes (Meara et al., 2016; Maclean et al., 2020). In terms of clinic openings, Corredor-Waldron and Currie (2022) find that opening of new substance use disorder treatment clinics lead to fewer drug-related ED visits, and Packham (2022) finds that opening of syringe exchange programs lead to more drug-related deaths.

[7]The national reformulation of OxyContin led to higher heroin mortality rates in states with higher pre-reformulation misuse rates (Alpert et al., 2018; Evans et al., 2019) and also more spread of hepatitis B and C (Beheshti, 2019). Moore and Schnepel (2021) find long-term reductions to mortality and crime following a sudden sustained reduction to heroin supply in Australia in the late 2000s.

number of naloxone prescriptions for opioid users. Similarly, Bounthavong et al. (2021a) found that detailed providers had lower rates of opioid-benzodiazepine coprescribing per patient. Additionally, Bounthavong et al. (2020) observed that detailed clinicians achieved a greater reduction in the proportion of patients on high-dose opioids compared to non-detailed clinicians between 2013 and 2016 (41% vs. 35% reduction). Building on this descriptive work, I systematically estimate the causal impacts of detailing on clinicians' long-term behaviors and am the first to link these clinicians behaviors to a comprehensive set of downstream patient outcomes, including pain, adverse events, and mortality.

There is a growing economics literature on why physicians deviate from clinical guidelines and the impacts of policies and interventions aimed at altering physician behavior (Abaluck et al., 2021; Currie and MacLeod, 2020; Currie et al., 2024). Schnell and Currie (2018); Doyle et al. (2010); Ly (2020); Tsugawa et al. (2018) investigate whether the medical school the physician attended can explain variation in physician and patient outcomes (e.g., patient cost, physician prescribing, etc.). My study goes beyond differences at a cross-sectional point-in-time and investigate the causal impact of *new* training to targeted providers.

A related literature has studied the impacts of pharmaceutical promotion by sales representatives on prescribing (Agha and Zeltzer, 2022; Carey et al., 2021; Grennan et al., 2021; Shapiro, 2018) and found short-term impacts on prescribing with limited evidence on patient outcomes due to a lack of data.[8] I find that academic detailing—with no financial incentives—can significantly change clinical care patterns and, to a lesser extent, also patient outcomes.[9]

The paper proceeds as follows. The next section describes the institutional details of the VHA and the academic detailing campaign. Section 3 summarizes the key data sources and section 4 describes the empirical strategy. The results are presented in section 5, beginning

[8]Relatedly, Bergman et al. (2022) show that payments by medical device companies to physicians increase hospital purchases of the same devices.

[9]Recent studies have shown that opioid-specific promotion by pharmaceutical companies worsens patient outcomes (Alpert et al., 2022; Arteaga and Barone, 2022; Zejcirovic and Fernandez, 2018; Miloucheva, 2021). However, it is unclear whether evidence-based detailing can improve these same outcomes, during the current stage of the crisis where the vast majority of overdose deaths are caused by fentanyl and illicit opioids. Most of the opioid promotion papers focus on a much earlier stage of the crisis (i.e., pre-reformulation OxyContin). My findings show that provider interventions can improve outcomes even during a stage of the crisis when overdose deaths are predominantly caused by illicit opioids (often referred to as the "third wave" CDC, 2022).

with physicians' response, followed by downstream patient outcomes. Section 6 discusses and contextualizes the program's impacts, the estimated effect sizes, and conducts a simple cost-benefit analysis of the campaign. The final section discusses and concludes.

2. Setting

2.1 Veterans and the Veterans Health Administration

The Veterans Health Administration (VHA) delivers healthcare to eligible US veterans. As the largest integrated healthcare system in the world, the VHA establishes national standards of practice and is exempt from state policies (38 C.F.R., 2020). This means that the VHA's national policies and laws have authority that supersede individual state laws such as prescription drug monitoring or naloxone access laws.

Veterans are eligible for healthcare benefits from the VHA—"veterans" hereafter—generally if they served 24 consecutive months in active military, naval, or air service or meet various disability or income criteria. Once eligible, veterans pay no premiums and face generally low copayments when receiving care at 152 VHA medical centers and over 1,000 outpatient clinics across the country. These medical centers and clinics fall into 140 different VHA stations. Each station roughly corresponds to a different catchment area for enrollment and is managed individually.[10] In addition to providing care at VHA facilities, the VHA will reimburse outside medical care typically for services they cannot provide such as emergency care (where the closest VHA hospital may be far) and some specialty care.

Primary care in the VHA is delivered by primary care teams consisting of a primary care provider (PCP; can be a physician or nurse practitioner), two support staff (typically an advanced nurse, and another vocational nurse or medical assistant) and an administrative clerk. Throughout the paper, I use the terms PCP and PCP team interchangeably, both referring to the team as a unit. Using a patient-centered model, teams provide coordinated care for all of their patients' health needs. Unlike outside the VA, all veterans receiving primary care in the VHA have a designated primary care team. Veterans are assigned a

[10]Regional differences in VA policy—to the extent that they exist—will typically be at the station-level.

primary care team at their intake visit following initial enrollment in VHA care and are generally discouraged from switching teams; primary care relationships are tracked and documented by the VA. For more details, see Currie and Zhang (2023).

VHA clinicians typically operate in a single-payer system and only work within the VHA and treat veterans. This means that VA policies will have greater influence on their actions than settings where clinicians treat patients under different payers and are subject to different policies. They are also salaried, which means that their care is not influenced by (profit-sharing) financial incentives.

Veterans have higher rates of pain and mental health comorbidities than the general population. Approximately half of all VHA veterans suffer from chronic pain (Clancy, 2015). Veterans also have higher rates of mental health conditions; for instance, among Iraq and Afghanistan veterans, 36.9% have a recent mental health diagnosis with roughly a quarter being diagnosed with PTSD and depression (Seal et al., 2009); rates of suicides among the veteran population are over 50% higher than non-veterans (VA, 2021). Opioid prescribing in the VHA peaked in 2012 and has historically been higher than outside the VHA (Hadlandsmyth et al., 2018). For the above reasons, among others (e.g., war-related reasons; Cesur et al., 2019), veterans are twice as likely to die of a drug overdose compared to the general US population (Bohnert et al., 2011). Therefore, the underlying comorbidities and risk factors of the veteran population, along with the heightened opioid prescribing in the VHA health system, make for an ideal setting to investigate the impact of policies aimed at improving opioid-related outcomes.

The VHA launched various nationwide risk mitigation policies aimed at reducing the harms of the opioid crisis in 2013. The largest of these policies is the implementation of a national Academic Detailing Service in 2015. It is important to note that while other policies were being implemented in the years around this time (e.g., opioid decision support systems), these policies were generally rolled-out nationwide in a way that was unrelated (across space and time) to academic detailing. In other words, other policies do not confound the treatment effects estimated in this paper and any violations would likely appear as differential pre-trends in the event study.

2.2 Academic Detailing Service

In response to a federal memorandum in March 2015 (Department of Veterans Affairs, 2015), the VA implemented a nationwide Academic Detailing Service program to perform educational outreach—known as academic detailing—to VA clinicians to align their practice with current guidelines for safe opioid prescribing and pain management (Sandbrink et al., 2020; Oliva et al., 2017a).

In VA, academic detailing is a multifaceted approach to improve quality of care and support front-line clinicians and other healthcare staff to improve veteran health care. Academic detailing incorporate evidence-based recommendations using "key message" discussions, comparative effectiveness evidence, patient safety and quality care, cost-effectiveness evidence, and relationship building. Academic detailing is delivered via individualized educational outreach focused on knowledge translation and clinical implementation barrier resolution. Specifically, it uses the one-on-one communication approach of the pharmaceutical industry—except with no direct link to a pharmaceutical company and no explicit or implicit financial incentives—combined with evidence-based, non-commercial aims of academic and research groups to understand clinical barriers and opportunities for improvement. Academic detailing then provides targeted interventions to decrease variability in evidence-based practice and reduce out-of-guideline practice among clinicians, and improve veteran health. Educational outreach is conducted by VA clinical pharmacists with VA clinicians in their own office and typically ranges from 20-60 minutes with an median visit length of 39 minutes. Over time, the VA academic detailing program has expanded to include non-opioid educational programs such as diabetes management and telemedicine adoption; however, opioid-related detailing is still the largest program.[11]

VA clinicians receiving opioid-related academic detailing were educated on pain management[12] (e.g., refer to alternate non-opioid pain treatment, prescribe low dosage opioids for acute pain, etc.), risk evaluation (e.g., use prescription drug monitoring programs and urine drug screens, etc.), OUD treatment[13] (e.g., how to identify, manage, and treat opioid use

[11] In the first quarter of 2022, 36.5% of academic detailing in the VA were for opioid-related programs. This number was 58.9% over the study period.

[12] See: pain management educational materials

[13] See: opioid use disorder educational materials

disorder), and harm reduction[14] (e.g., overdose recognition, naloxone prescribing, etc.). While a detailing visit may include any combination of these key messages, the intended practice change would include prescribing fewer opioids and more naloxone, improve recognition of overdose risk (via drug screens and PDMPs) and opioid use disorders, and increase treatment for OUD. In addition to education, the detailer also utilizes data on other providers practice to highlight discrepancies between individual clinicians practice and both clinical guidelines and their peers. The clinician also has access to population management tools (e.g., dashboards) which were rolled out nationally in late 2017, which they can use to review their own patient cases where treatment may not be concordant with guidelines. The academic detailer and the detailee will also discuss and identify barriers to achieving the recommended changes. See Appendix A for more details on the program and the training tools. It is important to note that due to the multifaceted nature of the training program, I am only able to identify the impact of the set of messages delivered during an average educational session, and not the precise impact of any individual message.

Whether and when a PCP team received detailing is first determined by the station they belonged in. Due to the enormous efforts required to conduct academic detailing at a national level, the implementation of the program was staggered across VA stations (Oliva et al., 2017a; Bounthavong et al., 2019). Some stations spearheaded the detailing effort earlier than others, largely based on staffing of clinical pharmacists and the degree of importance placed on academic detailing by station administrators. Figure D.1 illustrates differential implementation trends across select VA regions. While there is substantial variation across stations in detailing, three-quarters of the variation in ever being detailed at the end of the study period is explained by variation within stations. Within stations, PCPs were selected for detailing from a priority provider panel which lists providers by their number of opioid patients, high intensity opioid patients, and predicted overdose risk. Therefore, PCPs who had more opioid patients and prescribed opioids at higher rates were more likely to be detailed. It is important to note that to estimate the average treatment effect on the treated, the difference-in-differences design *does not* require that PCPs be randomly detailed, but rather that detailed PCPs' prescribing and their patient outcomes would have evolved like

[14] See: opioid overdose and naloxone educational materials

those of the never-detailed groups. I return to this in section 4.

Figure 1a displays the time series of the number of detailing visits to PCP teams. At the start of 2016, 3.5% (227) of PCP teams received academic detailing. This fraction increased to 52.9% (3,397) by the end of 2019. Of those that received detailing, the treatment is spread out over four years: 36.7% are detailed by October 2016, 64.8% are detailed by October 2017, and 88.4% are detailed by October 2018 (see Table 1). Figure 1b displays a time series of the number of opioid prescriptions written and opioid overdose mortality counts among VHA users from 2008 to 2019. Opioid prescribing peaked around 2012-2013, followed by a steady decline. Opioid overdose mortality was rising rapidly among VHA users at the start of the decade and slowed in growth and plateaued near the end of 2016. The number of naloxone kits prescribed follow detailing trends with a short lag. The extent to which the temporal patterns between academic detailing, prescribing, and mortality are causal or driven by other confounding factors requires additional investigation.

3. Data and Sample

3.1 Data Sources

To estimate the impacts of academic detailing on providers and patients, I combine multiple datasets on detailing visits, patient-clinician relationships in primary care, and electronic health records on prescriptions, medical encounters, lab tests, and mortality.

Administrative data on academic detailing visits between October 2015 and December 2019 comes from the VA Pharmacy Benefits Management. It includes physician and detailer identifiers, date and time, location, and the duration of the detailing visit. Each time a detailing visit is conducted, a record is created, and the data is stored.

As mentioned earlier, all patients in the VHA regularly receiving primary care have a designated primary care team. The VHA maintains a record of all historical primary care team members, and primary care team and patient relationships. This includes the date each patient is assigned to a PCP team and the date that relationship ended. From this data, one can construct the exact patient panel for each PCP team (i.e., list of patients each PCP is

responsible for) at any point in time.

VHA electronic health records provides data on prescriptions and medical care. This includes the identity of the prescriber, provider, patient, date and time of each prescription and encounter, diagnosis code, among others. From the prescription data, I construct counts of prescriptions, number of patients receiving prescriptions, and milligrams of morphine equivalents (MME) for opioid prescriptions. Total MME is calculated using all prescription fills, including refills; however, other medication outcomes measure number of prescriptions to better approximate physician behavior. I construct counts of serious adverse events[15] —defined as accidents including overdose poisonings, suicide attempts, and other accidents[16] using emergency department and hospitalization encounters from three sources: VHA records (occurring in VHA facilities); Medicaid claims from 2014-2015, Medicare claims (Part A, B, and D) from 2014-2019; and claims from non-VHA facilities for care that is reimbursed by the VHA.[17] These data sources provide me a more complete, but imperfect, view of veterans' medical encounters and health outcomes; it is important to note that I will not observe prescriptions or health events outside of these sources (e.g., opioids purchased using cash, privately-paid hospital care). Finally, date and cause of death linked to the veteran come from the CDC National Death Index Plus until the end of 2019.

The electronic health records also include data on lab tests (e.g., urine drug screens), and vital signs such as pain scores. I use lab tests to construct the number of urine drug screens conducted and the positivity of those tests. Pain scores are routinely measured as a "fifth vital sign" in the VA with clinical care by asking the patient about their current level of pain on a 0 to 10 scale, with 10 being the greatest pain. Using pain scores from primary care visits, I construct average pain scores for each patient-quarter. Finally, clinicians at the VHA are required to record every time they perform a prescription drug monitoring program

[15] Adverse events such as falls and accidents are often influenced by impulsivity or sedation (Oliva et al., 2017b). Opioid use is a major contributor for accidents, both correlationally (i.e., as a risk factor; Dowell et al., 2019) and causally (Betz and Jones, 2022; Eichmeyer and Zhang, 2022).

[16] Specifically, I follow the VA Office of Mental Health and Suicide Prevention definition of a "serious adverse event" using the following ICD-10 diagnosis codes: suicide and self-harm T14.91, T36-T71, X71-X83; poisoning T39-T50; toxic effects of substances T51-T65; transport and vehicle accidents V00-V99; accidental falls and exposure to mechanical forces W00-W34, W50-W52, X00-X01, Y22-Y24; Y27-Y31; drowning W65-W74, Y21.

[17] The VHA will pay for some outside care including all emergency department visits.

(PDMP) query in a standardized note template in the VHA; I construct counts of PDMP checks using this data.

3.2 Sample Construction

The main analysis sample covers all clinicians and patients in primary care in the VHA at the start of fiscal year 2015 (October 1, 2014), a full year before academic detailing begins. This includes all active primary care teams and their non-end-of-life, non-terminal-cancer patients. Primary care setting is responsible for the majority of repeat opioid prescriptions in the VA (Eichmeyer and Zhang, 2023) and the majority of academic detailing. Moreover, prior research has found that veterans enrolled in primary care engage the most with the VA, utilize more care, and include most high risk patients (Chang et al., 2020).

To deal with potential endogenous patient response in switching providers and endogenous provider response in accepting/refusing new patients, I construct a static snapshot of the members of each PCP team and patients on their panel as of October 1, 2014. This ensures one year of pre-period data to test for pre-trends; while extending the pre-period would provide a longer pre-period, primary care patient attrition becomes an issue with the static snapshot. Each health event that occurs to a given patient in my study period is attributed to their documented PCP team on October 1, 2014. For example, when studying opioid overdoses as an outcome, the variable is the number of opioid overdoses in a calendar quarter among patients on a given PCP team's patient panel on October 1, 2014. Because the PCP team and its patient panel is fixed and constructed pre-detailing, and outcomes are measured on the fixed panel of patients, I am effectively conducting an "intent-to-treat" analysis.[18]

The final analytic sample consists of 6,416 primary care teams treating a total of 5,079,919 patients (86% of all VHA users at the start of fiscal year 2015) on their primary care panels on October 1, 2014. I construct quarterly measures of each outcome variable using data from October 1, 2014 to December 31, 2019. Table 1 summarizes prescribing and clinical measures at the PCP-team-level. A total of 3,397 PCP teams ever receive academic detailing and 3,019

[18]Patient-PCP relationships are relatively stable within the VA. Among those who are alive, 70% of patients are still with their October 1, 2014 PCP at the end of 2019. Figure D.3 shows attrition of PCP patient panels. Panel b shows that there is no differential attrition among detailed PCPs after detailing.

are never-treated. On average, compared to the never detailed teams (column 2), detailed teams (column 1) prescribed more opioids, fewer naloxone, and fewer opioid agonists prior to the detailing campaign. They also had a larger patient panel (811 vs 770 patients). Male-led PCP teams were slightly more likely to be detailed. As mentioned earlier, detailing focused on PCP teams with higher opioid prescribing and more patients; however, the change in number of naloxone prescriptions, opioid prescriptions, and MME per prescription is similar across the two groups. The research design allows for presence of selection bias, but requires that the bias is constant over time. I explain this in more detail in the following section.

4. Empirical Strategy

The staggered rollout of academic detailing in the VA allows for a generalized difference-in-differences design to study its impacts. In recent years, there has been a growing literature documenting the pitfalls with the canonical two-way fixed effects model which assumes constant treatment effects either across treatment units or time (see Roth et al., 2022, for a review)—both of which may not hold in my setting. Several new estimators have been proposed, each with slightly different identifying assumptions. The main estimator utilized in this paper is Callaway and Sant'Anna (2021), which requires a weaker parallel trends assumption than other estimators such as Borusyak et al. (2022).[19] Since this assumption is untestable, I demonstrate robustness of the main findings to three alternate estimators and the canonical two-way fixed effects estimator in subsection 5.5.

The Callaway and Sant'Anna (2021) estimator relaxes the constant treatment effect (across time and units) assumption by using group-time average treatment effect on the treated as the building block. Units (PCP teams) are grouped into treatment cohorts based on when they are treated, g.

Let $Y_{it}(g)$ denote the potential outcome in quarter t if PCP i was first treated in quarter g and $Y_{it}(\infty)$ denote their potential outcome if they are never treated. The group-time average treatment effect on the treated is then: $ATT(g,t) = E[Y_{it}(g) - Y_{it}(\infty)|G_t = g]$.

[19] Unlike the generalized parallel trends assumption imposes that those treated in time g would have evolved like those in any other time g' for all periods of time, had they not been treated, Callaway and Sant'Anna (2021) only requires parallel trends from period $g-1$ onwards.

Under parallel trends and no anticipation assumptions, one can estimate $ATT(g,t)$ by comparing the expected change in outcome for physician cohort g, between the period just prior to treatment, $g-1$ and t, to that of a never-treated control group.[20] That is,

$$ATT(g,t) = E[Y_{it}(g) - Y_{i,g-1}|G_i = g] - E[Y_{it}(g) - Y_{i,g-1}|G_i = \infty]. \quad (1)$$

Equation 1 is estimated nonparametrically using sample analogs. $ATT(g,t)$ can then be aggregated across PCP teams and time to create event study coefficients based on duration length since treatment.

Baseline specification For the main baseline specification, I plot these event study coefficients (average $ATT(g,t)$ across cohort g, for different lengths since treatment) for eight quarters prior and eight quarters post treatment.[21] The 3,019 never-treated PCP teams are used as the primary control group (and use not-yet-treated teams as the control group in a robustness exercise) and no covariates controls are included. I also report the overall average treatment effect of the treatment. Observations are weighted by the size of the PCP team's patient panel on October 1, 2014, prior to academic detailing. Doubly robust standard errors are clustered at the PCP team-level. Note that to the extent there are repeat detailing visits after the first visit, I would estimate the sum of impacts stemming from the first visit (i.e., the impact of the VA program as opposed to an individual visit).

The key identifying assumption is that absent academic detailing, the detailed PCPs and their patients would have had otherwise similar trends in their practice patterns and patient outcomes. Figure D.2 plots the raw data to visually assess this assumption and provides intuition for the staggered treatment design. The black line shows that even the never-treated PCPs were experiencing secular trends in naloxone and opioid prescribing, this is consistent with both overall national (CDC, 2021; Peet et al., 2022) and VHA trends over this period (Lin et al., 2019). Treated cohorts (red, green, and blue lines) are on higher, but parallel,

[20] Callaway and Sant'Anna (2021) allow for the control group to be never-treated units or not-yet-treated units. Since roughly half of the PCP teams never receive academic detailing, they serve as a natural control group.

[21] Note that different groups will contribute to different event study coefficients. I follow Agha and Zeltzer (2022) and require that all PCP teams have at least two quarters of post-treatment data; all PCP teams have at least four quarters of pre-treatment data.

trajectories and almost immediately deviate from the trend after being detailed.

The lag event study coefficients in Figure 2-6 provide further supportive evidence that outcomes of treated and never-treated groups were evolving in parallel. I conduct a set of robustness exercises in detail in subsection 5.5.

5. Results

I begin by studying the dynamics of academic detailing, followed by its impacts on provider practice, and then its downstream impacts on patient outcomes. The treatment effects for the main outcomes are displayed in Table 2 and the full set of findings are presented graphically in event study figures in the subsequent exhibits.

Heterogeneity analysis by patient and provider characteristics, and robustness checks follow.

5.1 First Stage and Attrition

To interpret the treatment effects in this paper—intent-to-treat estimates for a fixed panel of pre-detailing patients, following the first detailing received—one needs to understand the dynamics of patient attrition and detailing over time.

Of the PCP team's patient panel in the fourth quarter of 2014, 70.1% of these patients saw their PCP that quarter. This declines gradually over the next five years to 58.1% in the fourth quarter of 2019, an attrition rate of 3.5% per year. Importantly, there is no differential attrition among detailed PCPs after detailing (see Figure D.3). This allows for an analysis studying outcomes based on pre-detailing primary care patients; all outcomes are measured in units of 1,000 pre-detailing patients.

PCP teams that receive academic detailing typically receive an initial longer detailing session, followed by consistent short follow-up sessions. In the first quarter the PCP team is detailed, they receive 1.3 detailing visits to 1.16 team members, totaling 103 minutes in length. This immediately levels off to about 0.3 visits, averaging less than 20 minutes per quarter (see Figure D.4)

5.2 Provider Response

Prescribing of naloxone, opioid analgesics, and opioid agonists

Figure 2 displays event study coefficients for the key provider prescribing outcomes. Across all six panels, the coefficients on lagged event time are precisely stable around zero. This means that PCPs who are about to be detailed were on parallel trajectories with PCPs who will never get detailed, lending credibility to the parallel trends assumption.

The impact of academic detailing on naloxone prescribing is immediate and persistent. Detailed providers increase naloxone prescribing by 0.92 prescriptions per 1,000 patients, per quarter over the first two years over a pre-policy mean of 0.45, a 200% increase (panel a). This targeted education approach is 6.3 times the impact of laws allowing pharmacists to directly prescribe naloxone to patients estimated in Smart et al. (2023).[22] The number of unique patients who receive any naloxone prescription in a quarter increase by a similar 227% (0.98 additional patients over a mean of 0.43; panel b).[23]

Detailed clinicians gradually reduce opioid prescribing (panels c and d).[24] The first quarter after academic detailing, detailing leads to 5 fewer opioid prescriptions and grows to 30 fewer prescriptions by the eighth quarter. This equates to an average treatment effect of 16.6 fewer opioid prescriptions per 1,000 patients, per quarter on a base of 269 (6.2% reduction), and 7.8 fewer patients being prescribed on a base of 134.3 (5.8% reduction). Total milligrams of morphine equivalents prescribed per quarterly declines by 7.6% (Figure D.5, panel a). PCPs partially substitute prescription opioids with referrals to alternate non-opioid pain treatment such as pain clinics and complementary and integrative health clinics which provide acupuncture, massage therapy, meditation treatments, among others. Referrals increase by 7.5% (Figure D.5, panel b). While the relative increase in alternate non-opioid pain treatment is roughly the same as the relative reduction in opioid prescribing, PCPs prescribe 20 opioid prescriptions for every referral to alternate non-opioid pain treatment. Unlike pharmaceutical

[22] Smart et al. (2023) estimate that pharmacist prescriptive authority laws increase quarterly naloxone prescriptions by 14.5 per 100,000 population.

[23] Bounthavong et al. (2019) compares stations with more vs. fewer detailed providers and conclude that a station that detailed 100% of its providers would prescribe 5.5 times more naloxone than a station that never detailed anyone.

[24] These results are not driven by PCPs changing the number of visits they perform, days they work, or patients that they treat (Table D.1).

promotion and other behavioral nudges which have shorter-lived effects, the prescribing changes are persistent; in fact, the reduction in opioid prescribing *grows* over time, persisting even three years after the detailing visit (see Figure D.6).

Stratifying patients based on their fiscal year 2014 (prior to academic detailing campaign) daily MME dosage, I find that opioid prescribing declined most for higher dose prior opioid users: there was a 6% reduction for patients with prior opioid use and a smaller 2% reduction for opioid-naïve patients (Figure 3a).[25]

Risky opioid prescribing also declines. Figure 3b shows that the prescribing declines are increasing in magnitude with dosage intensity: The number of prescriptions with greater than 90 MME per day decline by 11% and prescribing of 50-90 MME decline by 9%.[26] Lower MME prescriptions, 20-50 MME and $<$ 20 MME per day, decline by 7% and 4%, respectively. This is consistent with VA and broader CDC guidelines to limit prescribing of higher MME opioids (CDC, 2016; VA/DoD, 2017). One implication of this result is that evidence-based outreach achieves better prescribing outcomes than blunt policy instruments. For instance, broad prescribing limit laws which have been found to increase the number of opioid prescriptions alongside reducing the average prescription length (Sacks et al., 2021) and nudging letters tend to reduce both risky and guidance-adherence prescribing (Sacarny et al., 2018). Another measure for risky prescribing is having opioid and benzodiazepine on-hand at the same time—a dangerous combination even at low levels (Jones et al., 2012). Panel c of Figure D.5 shows that the number of patients with both opioids and benzodiazepines declines by 7%.[27,28] Finally, a VA-developed composite measure of opioid risk based on opioid medication and medical history also decreases (Figure D.7; see Zedler et al., 2018, for the details on the measure).

Prescribing of opioid agonists (buprenorphine and suboxone) increase but the estimates are

[25]This implies that in addition to reductions in overall opioid prescribing, initial prescribing to opioid naïve patients also declined. Without substitution, one may expect this to lead to fewer opioid abusers in both the short- and long-run (Eichmeyer and Zhang, 2022; Finkelstein et al., 2021)

[26]For comparison, Bounthavong et al. (2020) finds that providers that received academic detailing had roughly 35% fewer patients with over 100 MME prescriptions after 3 years than those who were never detailed.

[27]I measure the number of patients who have at least one day of overlapping opioid and benzodiazpine prescriptions based on the date the drug was released to the patient and the days supply on the prescription.

[28]This is roughly a third of the effect size found in (Bounthavong et al., 2021a) when comparing facilities with different proportions of detailed providers.

noisy. An additional 0.075 opioid agonist prescriptions are prescribed and 0.03 more patients receive opioid agonists, per 1,000 primary care patients, both roughly a 18% increase (panels e and f of Figure 2). Indicator for prescribing *any* opioid agonist—proxy for whether the PCP has a "X waiver" to prescribe buprenorphine—increases by a statistically insignificant 0.11pp (6%; see Figure D.5, panel d). Together, these results suggest that PCPs may have eventually increased prescribing for medication for opioid use disorders, but the magnitudes are small. This may reflect the existence of systems barriers in the VA in prescribing buprenorphine, even among credentialed prescribers (Valenstein-Mah et al., 2018).

Risk evaluation: urine drug screens and PDMP checks

In addition to changing physician prescribing, the academic detailing program aimed to improve PCP's opioid risk evaluation by conducting regular urine drug screens (UDS) and querying prescription drug monitoring program (PDMP) dashboards for at-risk patients. UDS are typically conducted to screen for adherence and potential misuse among patients on opioid therapy and PDMPs are a tool to monitor a patients' history of controlled substances.

In Figure 4a, the number of urine drug screens remains steady in the first year and then begins a gradual decline in the second year. Although this decline is minimal—less than 0.5 tests per 1,000 patients, per quarter, reflecting a mere 1% reduction——it may seem inconsistent with VA recommendations which should increase UDS screening. However, clinicians may reduce testing because fewer patients are using opioids, and those who are, appear to be adhering to their prescribed regimens. Indeed, the patients of detailed PCPs who are on opioid therapy become more likely to use their prescribed opioids as intended and less likely to test positive for non-opioid abusable substances (see Figure D.8).

In Figure 4b, the number of PDMP queries increase by 9% over a two-year period and 12% over three years (1.8 and 2.3 additional queries). While the magnitude of this effect is sizable, it is worth noting that the baseline query rate (19.2 queries per 1,000 patients) is low relative to the 134.3 patients prescribed opioids by the average PCP each quarter.

Relatedly, I do not observe any increases in measures of "drug-seeking behavior". Following proxies commonly used in the literature (Yang et al., 2015; Finkelstein et al., 2021; Eichmeyer and Zhang, 2022), I see either declines or no change in measures of having four or more

unique prescribers in a quarter ("doctor shopping"); having two prescriptions that overlap by at least 25% of the days supply ("overlapping prescription"); and five or more back pain or headache/migraine visits in a quarter ("many back pain and headaches"). Moreover, elderly patients do not appear to be substituting to opioid prescriptions in Medicare either. These findings can be seen in panels a-d of Figure D.9. This suggests that UDS screens and PDMP queries may have played a role in curtailing demand-driven opioid misuse behavior.

The VA's academic detailing program changed long-term provider behavior along most of the program's intended margins by reducing opioid prescribing, increasing naloxone prescriptions, and increasing PDMP queries. Did the program improve patient outcomes?

5.3 Downstream Outcomes

Pain

Opioid analgesics treat acute pain and prescribers often face challenges balancing pain management with opioid-related risk (National Academies of Sciences, 2017). This cost-benefit calculation depends crucially on the long-term effectiveness of opioid therapy relative to non-opioid pain therapies in reducing pain, and there is scant evidence on this relative effectiveness for a broad population[29].

I take advantage of the fact that the VA tracks and records pain scores in its electronic health records and investigate whether self-reported pain, in primary care settings, changed in response to the policy and reduced opioid prescribing.[30,31] In Figure D.10, self-reported pain remains constant for all patients with different levels of prior opioid use and I can rule out increases of more than a quarter of a percent, with 95% confidence, in average pain among patients of treated PCPs.[32]

[29]There are a handful of RCTs comparing opioid analgesics versus other forms of pain treatment in specific settings (e.g., knee pain). These studies generally have very small sample sizes with short follow-up. See Busse et al. (2018) for a review.

[30]Specifically, I average all individual pain scores for each patient-quarter and then compute the mean across all patient-quarters to obtain a PCP-quarter-level average.

[31]I observe an average of 33.4 million pain scores per year among the five million patients, 9.3 million of which are measured in primary care settings (1.8 measurements per patient-year). The effects on pain are nearly identical when I include all (non-ED) *outpatient* pain scores in addition to primary care pain scores.

[32]This exercise requires that PCPs do not alter the likelihood of measuring and recording pain scores after detailing, which is empirically validated in column 4 of Table D.1.

Figure 5 displays the impact of detailing on the distribution of patient pain scores (e.g., the fraction of pain scores reported below a certain threshold). Scores between 1-4, 5-6, and 7-10 are classified as mild, moderate, and severe pain, respectively. Consistent with the finding that average pain scores are unchanged, there are no statistically significant impacts across almost all pain thresholds. The one exception is that patients are marginally more likely to report pain scores of 9 or lower by 0.05pp on a base of 98%.

Pain scores are also stable across pain risk groups. This includes patients who will begin new pain episodes and would have started opioid therapy initiation but do not (opioid naïve patients) and those who are high dosage long-term opioid users who are slowly being tapered off prescription opioids. Moreover, changes in pain are also precisely zero among those previously diagnosed with chronic pain—which constitutes a large majority of the veteran population (Table 2). Together, this suggests that a practice of slowly reducing opioid prescribing along with a modest increase in referrals to non-opioid pain management clinics is just as effective in treating pain as higher, pre-policy levels of opioid prescribing. Put differently, PCPs are reducing opioids for precisely the patients who are not benefiting from opioid pain therapy, but may still face the opioid-related risks.

Serious Adverse Events

Towards that end, I investigate whether academic detailing impacted emergency department encounters and hospitalizations for overdose poisonings, attempted suicides, and other accidents ("serious adverse events") across VHA, Medicare, Medicaid, and VHA-paid community claims. Figure 6 shows noisy reductions in drug overdoses and a statistically significant 0.10 reduction in all serious adverse events over a base of 4.8 occurrences per 1,000 patients, per quarter (a 2.2% reduction). Longer term impacts are approximately the same (Figure D.6). The reduction in adverse events is broadly consistent with the documented reduction in the composite overdose risk index in Figure D.7.

Heterogeneity analysis shows that SAEs declined by 10% among higher dose prior opioid users ($\geq$ 20 daily MME over the prior year); see Figure D.11 and Table 2. Since higher dose prior opioid users account for only 5% of the veteran population, this means that the overall reduction is driven by high risk patients. Each academic detailing clinic visit resulted in one

fewer ED/hospitalization for a serious adverse event over the next two years, totaling 4,169 fewer events over the study period or over $51 million in cost savings to the VA (I conduct a cost-benefit analysis in a later section). These findings also suggest that a gradual reduction in prescribing of prescription opioids does not lead to serious adverse events.[33]

Mortality

Finally, panels c and d of Figure 6 investigates mortality and cause of death impacts. Academic detailing likely had small impacts on patient mortality. The coefficient on all-cause mortality is -0.08 over a mean of 7.36, a statistically insignificant 1.1% reduction. Estimated 95% confidence intervals rule out reductions (and increases) in all-cause mortality by more than 2.7%. The estimate over three years is slightly larger in magnitudes (0.126 deaths per quarter, 1.7%). The effects on drug overdose deaths are also small, if any. Both illicit and prescription opioid deaths increase by statistically insignificant amounts (Figure D.12).

5.4 Heterogeneity

Table 2 displays treatment effects for different patient populations. As mentioned earlier, higher dose prior opioid users (daily MME ≥ 20) receive the most naloxone, experience the largest opioid reductions, and the most PDMP checks. In turn, their relative reduction in serious adverse events is largest at 10%. The main effects also persist for other subpopulations such as those with chronic pain, existing opioid use disorders, and combat veterans. The estimates in the latter two groups are noisier due to smaller sample sizes. The reductions in mortality are largest for the highest prior opioid users and those with chronic pain, with statistically significant estimates for the latter.

Table D.2 displays treatment effects by characteristics of the PCP leading the team. The qualitative pattern that emerges is that detailing was effective across many different types of PCPs and not concentrated in one group. While physician-led teams prescribe more

[33]There is a concern among practitioners that opioid discontinuation and aggressive dose tapering is associated with increased risk of suicide and mental health event (Oliva et al., 2020; Agnoli et al., 2021). I add to these observational studies by providing quasi-experimental evidence that gradual reduction in prescribing of prescription opioids (which I demonstrate in subsection 6.3)—well within VA and CDC guidelines and initiated by physicians—can lead to a reduction in serious adverse events for the average patient.

opioids and naloxone than nurse practitioner-led teams (who also have full scope of practice in the VA) at baseline, the relative effect sizes in practice change and patient outcomes are approximately the same. In general, male, older, and above median salary PCPs altered their behaviors the most. For instance, above median salary PCPs reduced opioid prescribing by 23.1 (7.1%) prescriptions per 1,000 primary care patients per quarter compared to 8.6 (3.7%) prescriptions for below median salary PCPs. This means that educational outreach can alter behavior even among more senior and longer tenured PCPs who likely have more ingrained practice styles. Interestingly, the median time spent on each detailing session was roughly equal at around 39 minutes across all subgroups. This may also suggest that the results are unlikely to be driven by the fear of being observed or penalized by the VA, as this fear would likely lead to greater (and shorter-lived) responses among younger and less experienced PCPs. Finally, it is worth noting that the treatment effect on serious adverse events is largest for female-led and above median salary teams.

Finally, Table D.3 breaks down the treatment effects by states with and without must access PDMPs (MA-PDMP), following Buchmueller and Carey (2018). Although VA clinicians do not necessarily need to abide by state regulations, states with MA-PDMPs may foster a prescribing culture that spills over to VA clinicians and patients. States with MA-PDMP laws have lower baseline levels of opioid prescribing, and the treatment effects of detailing are larger for opioid prescribing, PDMP querying, and serious adverse outcomes. This suggests that there are complementarities between detailing and opioid policies that create a culture of reduced and safer prescribing.

5.5 Addressing Threats to Identification

This section conducts the range of robustness exercises addressing concerns around the key identifying assumptions. One concern is the potential for interactions between academic detailing and other opioid policies. First, it is important to note that VA clinicians are not subject to state policies because VA has federal preemption. To control for potential differential VA policies across space, I control for differential trends by facility, as well as

patient panel size, and number of predicted "high risk" patients.[34] By including facility trends I am effectively comparing PCP teams *within* a facility. The results are unchanged, and in fact slightly larger in magnitude in Table D.4.

The VA generally targeted PCP teams that were lagging on measures of safe opioid practices. This may lead to the concern that the estimated treatment effects may only be internally valid for these clinicians. However, in Table D.5, I find that even below median opioid prescribing (measured pre-detailing) teams increased naloxone prescribing and reduced opioid prescribing by large relative amounts. This suggests that the impacts of academic detailing are not just concentrated among the highest opioid prescribers.

The findings are also robust with respect to different comparison groups and alternate staggered treatment estimators. Figure D.13 uses not-yet-treated instead of never-treated PCP teams as the comparison group and the event studies follow nearly identical patterns; the main difference is that the reduction in opioid prescribing is roughly 50% greater using the not-yet-treated as controls. Figure D.14 shows that the estimators in Borusyak et al. (2022); Sun and Abraham (2021); Gardner et al. (2024); De Chaisemartin and D'haultfœuille (2023) yield qualitative similar findings to the main specification; difference-in-differences estimates are reported in Table D.6. This may be because only 13.6% of the standard two-way fixed effect estimate is derived from later versus earlier treated teams (Goodman-Bacon, 2021, see Table D.7).

A corollary of the parallel trends assumption that is required to interpret the event study estimates as the causal effect of detailing is that PCPs cannot strategically change how many patients they see or how frequently they work. In Table D.1, I demonstrate that the number of encounters, days of work, patients, and fraction of days with pain scores recorded do not change after detailing.

To address concerns around the results being spurious, I consider two placebo falsification tests. Patients who do not utilize primary care are unlikely to have improved patient outcomes. I focus on veterans who have an assigned PCP but never saw them in the year prior to the academic detailing campaign and find that although their prescriptions changed by small

[34] With control variables, the identifying assumption becomes one of conditional parallel trends; see Callaway and Sant'Anna (2021) for a discussion.

modest amounts (since they still may see the PCP after), there is no effect on SAEs or mortality (Table D.8). Next, I randomly assign PCPs treatment status such that the number of detailing visits each quarter remains the same and estimate the treatment effect. I repeat this process 1,000 times, and plot the placebo distribution of treatment effects in Figure D.15. It is unlikely that one would estimate a treatment effect of detailing to be as large as what is observed by chance. It is also worth noting that the results are unlikely to be spurious since they persist even after three years (see Figure D.6).

Finally, there may be concerns that not-treated PCPs may experience spillover effects if their peers are detailed (Agha and Zeltzer, 2022). This would violate the stable unit treatment value assumption (SUTVA) and lead to biased estimates of the impacts of detailing. To deal with spillover concerns, I follow Miguel and Kremer (2004); Baum-Snow and Ferreira (2015) and aggregate treatment units up to the primary care clinic level where spillovers are likely contained. The PCP teams work in 803 clinics, with a median of four PCP teams per clinic. Outcomes are average at the clinic-quarter-level and the clinic treatment date is the earliest date any PCP team was detailed. Figure D.16 compares 583 treated clinics to 220 never-treated clinics and finds that while the qualitative patterns still remain. For instance, naloxone prescribing increases by 130% and serious adverse events decline by 5.7%.

6. Discussion and Benchmarking

In this section, I provide context for the findings. I compare observed patient outcomes relative to expected results from the literature; benchmark physician prescribing response relative to national VA-wide changes during the time period; conduct a simple cost-benefit analysis of the impacts of detailing; quantify the degree in which detailing brought physician behavior within guidelines; and discuss scaling the program.

6.1 Observed impacts vs expected (a priori) impacts

It was not ex ante obvious that academic detailing would lead to positive opioid-related provider behaviors (Hoof et al., 2015; Meara et al., 2016). However, given that detailing improved physician prescribing, what is the expected downstream impact on patients and

how does that compare to what actually occurred? Answering this question is challenging because there are few causal estimates on how providers' opioid-related actions impact patient outcomes.

Academic detailing reduced the number of opioid prescriptions to opioid naïve patients by 4.23 prescriptions per 1,000 primary care patients (row 2 of Table 2). Using estimates from Eichmeyer and Zhang (2023) of the impact of one opioid prescription from primary care on mortality among opioid naïve patients,[35] implies a reduction of 0.164 deaths per 1,000 patients, well within the 95% confidence interval of the observed 0.086 deaths.

Rees et al. (2019) estimate that naloxone access laws (NAL) reduced opioid-related mortality by approximately 10% (95% CI: −0.06% to −19.9%). On the other hand, Doleac and Mukherjee (2022) find NAL had no significant impact on opioid-related mortality (95% CI: −7.8% to +9.8%). I estimate that academic detailing had no statistical impact on opioid overdose mortality (0.006; SE: 0.004).

6.2 VA-wide impacts and cost-benefit analysis

Academic detailing had large impacts on prescribing among individual PCPs who were detailed, but just how large were the campaign's effects on the entire VA system? I estimate that an additional 33,528 naloxone prescriptions were prescribed between October 2015 and December 2019 due to detailing (ATT multiplied by number of post quarters among all treated providers). This accounts for 24.5% of all naloxone prescribed from primary care. This estimate reflects the fact that naloxone prescriptions were rising in the VA throughout the study period. In contrast, the number of opioid prescriptions declined by approximately one million prescriptions per year in VA primary care during the study period.[36] Back-of-envelope calculations imply that 18.2% of this reduction in opioids (or 731,999 fewer prescriptions over the study period) is directly attributable to the academic detailing program.

In addition to the detailing campaign having large impacts on naloxone and opioid

[35] To the best of my knowledge, Eichmeyer and Zhang (2023) is the only paper to estimate the impact of higher opioid prescribing primary care providers on patient outcomes. The reduced form estimate in Table 5 scaled by the IV implies that one fewer opioid prescription leads to a 0.039 percentage point reduction among opioid naïve patients. As the authors point out, high prescribers may differ along other clinical margins, and thus view their estimates as an upper bound on the causal impact of opioids.

[36] Based on my calculations, but also see Figure 1b.

prescribing efforts, it had large positive financial impacts. Cost-benefit analyses suggest that detailing a new, additional PCP team yields a net benefit of $15,306 over the first two years, primarily driven by fewer ED visits and hospitalizations for serious adverse events. The details of this calculation can be found in Appendix B; note that this calculation ignores the fixed costs of operating the detailing campaign and only focuses on statistically significant outcomes (e.g., ignores potential mortality reductions) over a two-year time frame.

6.3 Prescribing response and guideline adherence

Were providers following VA's opioid-related guidelines and did academic detailing improve guideline adherence? There are two sets of quantifiable VA opioid guidelines for acute opioid patients[37] and long-term opioid therapy[38] (LTOT) patients. For new and acute opioid patients, they should be limited to opioid prescriptions with fewer than 5 days supply and fewer than 50 milligrams of morphine equivalents; for LTOT patients, they should have naloxone on-hand and be gradually tapered off of opioids (VA/DoD, 2017). To investigate guideline adherence, I plot the causal impact of detailing on guideline adherence metrics on top of baseline guideline adherence rates for the never-treated control PCP's patients (Figure D.17).

Generally, adherence to specialized opioid guidelines was already quite high by 2016 and improving. For instance, fewer than 5% of opioid naïve or acute opioid patients were prescribed more than 50 daily MME. Similarly, the fraction of LTOT patients receiving opioid tapering reached over 90% by 2019 and more than 90% of the tapering was gradual and within clinical guidelines[39]. Not surprisingly, academic detailing had small impacts on these appropriate prescribing measures. The fraction of LTOT patients with naloxone prescribed in the prior year increased from 3% in 2016 to 15% in 2019, and detailing had an additional 2.1pp effect on adherence. One place where VA providers were significantly

[37]The VA defines acute acute opioid users as those who fill an opioid prescription after no more than 30 days supply total over the prior three years and not receiving hospice/end-of-life cancer care.

[38]Following Sabety et al. (2024), this is defined as at least four consecutive quarters of 60 days supply averaging at least 25 MME per day.

[39]The VA strongly recommends "gradual tapers" of 5-20% per month (VA/DoD, 2017). This is equal to no more than 52.1% taper in MME per quarter. I calculate the fraction of patients each quarter that are within this taper threshold, conditional on being tapered.

deviating from guidelines is the number of days supply for new and acute patients; only 3-6% of prescriptions are five days or fewer and detailing only improves this statistic by 0.42pp. One caveat of this analysis is that the opioid-related guidelines studied here are very context-specific and do not apply to the many prescriber actions (e.g., whether to prescribe naloxone to high dose but non-LTOT opioid users), and do not capture non-quantifiable metrics. For example, successful tapering is not simply a function of the tapering rate, but also factors like patient-provider trust and communication.

6.4 Scaling the program

Policymakers may want to know the potential effects of academic detailing if all clinicians participate. Extrapolating treatment estimates for the entire clinical workforce may not provide reliable results due to factors such as heterogeneous treatment effects or spillover effects. I parametrically model the treatment effects of detailing to scale linearly with (and only with) the fraction of PCP teams in a facility that have already received detailing. The details of this exercise can be found in Appendix C. There does not appear to be large network effects in naloxone and opioid prescribing. Compared to detailing the first PCP of a clinic, the impact of detailing a PCP whose peers have already *all* been detailed is a statistically insignificant 0.6 more naloxone and 1.2 fewer opioid prescriptions, per 1,000 patients, per quarter. However, serious adverse events and mortality rates initially worsen with the introduction of detailing. Over time, though, detailing more primary care physicians (PCPs) shows increasing returns. One potential explanation is that patients may initially switch to other, possibly more dangerous, opioids; however, once a clinic reaches a certain threshold of safe opioid-related practices, patient outcomes improve. It may also be the case that academic detailers become more effective with experience.

7. Discussion and Conclusion

In 2015, the VA began implementing the largest opioid-related academic detailing campaign in the United States. Academic detailing was rolled-out in a staggered fashion over the next few years. This resulted in over 3,000 PCP teams—treating 2.75 million patients—receiving

training on topics around appropriate pain management, opioid risk evaluation methods, identifying and treating opioid use disorders, and harm reduction.

The detailing campaign had large impacts on provider behaviors and patient outcomes. Naloxone prescribing increased and opioid prescribing decreased, and effects lasted at least three years. Despite the decline in prescribing of opioid painkillers, patient pain was unchanged across multiple patient subpopulations. The largest impacts were on emergency department and hospitalizations for serious adverse events. Between October 2015 and December 2019, academic detailing was responsible for 4,169 fewer serious adverse events; among heavy prior users of opioids, there was a 10% reduction. This suggests that PCPs were able to use their expert judgment to reduce opioids for patients who were likely not benefiting from opioid-provided pain relief, yet faced high risks for adverse events.

What made this program successful? First, it is important to note that this program was implemented within the VA, and its outcomes may not generalize to the broader population. Opioid use, misuse, and mental health conditions are more prevalent among veterans. Patients are randomly assigned to PCPs, which may limit patient demand-side responses. VA physicians are also salaried employees, often working only in the VA, and may exhibit a greater shared commitment to the organization's initiatives.

Academic detailing effectively influenced clinician behaviors by improving clinical knowledge, beliefs, and skills. Importantly, these findings are not simply the result of oversight and monitoring by the VA ("Hawthorne effect"). Several factors support this conclusion. First, the VA does not explicitly penalize more liberal prescribing practices. Second, VA surveys indicated that over 90% of providers who received academic detailing found it informative, believed in the effectiveness of naloxone, and felt knowledgeable about its uses (Bounthavong et al., 2021b). Third, research on monitoring-related notifications have generally shown minimal or short-lived impacts on opioid prescribing.[40] Lastly, the changes in provider behavior appear to be persistent rather than temporary, particularly in opioid prescribing, where the reductions increase over time, putting detailed providers on different practice trajectories.

[40] Sacarny et al. (2016, 2022) found that letters or emails notifying higher or out-of-guideline opioid prescribers had no impact on subsequent prescribing of opioids. Navathe et al. (2022) found that individual audit feedback to high outlier opioid prescribers had no impact, but including peer comparisons did. In a meta-analysis, Ivers et al. (2012) found that audit and feedback interventions induce a modest 1.3% change in behavior.

This mirrors observed differences in prescribing patterns across graduating cohorts, reflecting differences in medical training (Schnell and Currie, 2018).

There are a few lessons learned from this VA setting that may have broader applications. First, altering outcomes through detailing by peers, such as clinical pharmacists, can be effective. Previous research has shown that improving clinical skills can outperform strict guidelines (Chan et al., 2022; Currie and MacLeod, 2020); indeed, in this VA setting, guideline adherence remained relatively unchanged. Second, heterogeneity and subsample analyses suggest that policies should specifically target the highest opioid users and high-prescribing clinicians. Third, as an integrated healthcare system, the VA can foster a culture of prescribing changes, which may be crucial. Both the MA-PDMPs and peer effects spillover analyses indicate that health outcomes improve most when many clinicians are aligned and committed to safe prescribing behaviors. Having a large number of aligned clinicians may also prevent patients from substituting to more dangerous alternatives, a common unintended consequence of many other opioid policies (Alpert et al., 2018; Evans et al., 2019).

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Figures and Tables

Table 1: Academic Detailing and PCP Statistics

	PCP Team Treatment Status:	
	Detailed	Never Detailed
	(1)	(2)
N (Number of PCP Teams)	3,397	3,019
Duration of detailing visit (minutes)	39.0 (48.6)	
Measures in 2014Q4, per 1,000 patients:		
Naloxone Rx	0.050 (0.958)	0.074 (1.708)
Δ Naloxone Rx (2014-15)	0.080 (2.042)	0.024 (1.196)
Opioid Rx	346.5 (384.4)	251.2 (337.1)
Δ Opioid Rx (2014-15)	-3.47 (160.50)	-11.79 (126.87)
MME per Rx	938.9 (344.8)	888.1 (347.6)
Δ MME per Rx (2014-15)	-22.25 (152.78)	-20.44 (171.52)
Opioid Agonist Rx	0.446 (10.591)	0.925 (40.673)
Urine Drug Screens	46.4 (68.2)	36.5 (67.6)
PDMP Queries	19.3 (99.8)	15.5 (70.4)
Patient Panel Size	810.7 (374.8)	770.4 (383.0)
Opioid naïve	607.3 (289.2)	606.6 (311.8)
Prior Daily MME $\in (0, 20)$	158.9 (90.5)	132.0 (83.8)
Prior Daily MME ≥ 20	44.5 (41.7)	31.9 (32.2)
Proportion Detailed By | Detailed		
2015Q4	0.006	
2016Q4	0.366	
2017Q4	0.648	
2018Q4	0.884	
2019Q4	1	
Physician Characteristics:		
Age	53.3 (9.3)	53.8 (9.7)
Female	0.57 (0.49)	0.60 (0.49)

Notes: This table summarizes characteristics of PCP teams based on treatment status (i.e., whether they ever receive academic detailing). Averages across PCP teams in the fourth quarter of 2014 (prior to roll-out of the academic detailing program) are displayed along with the standard deviation in parentheses. Prior opioid use is characterized by their average daily milligrams of morphine equivalent (MME) dosage over the 365 days prior to academic detailing program was initiated (fiscal year 2014). Change (Δ) in naloxone, opioid, and MME per prescription are calculated between 2014 and 2015. Detailed PCPs have more patients and prescribe more opioids than the never-detailed; however, the subsequent figures show that the trends in prescribing and patient outcomes were parallel prior to detailing.

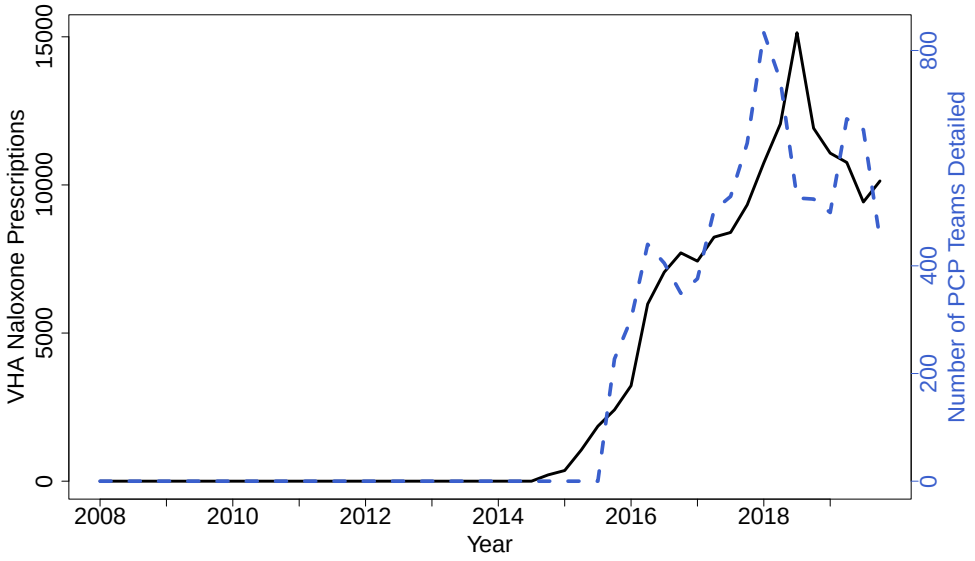
Table 2: Main and Heterogeneous Effects for Relevant Patient Subsamples

	Dependent variable:						
	Naloxone Rx (1)	Opioid Rx (2)	Agonist Rx (3)	PDMP Queries (4)	Pain Score (5)	Serious Adv. Events (6)	All-Cause Mortality (7)
Baseline Sample	0.915***	−16.611***	0.075	1.784*	−0.006	−0.103*	−0.081
(No. Patients: 5,079,919)	(0.115)	(1.970)	(0.088)	(0.924)	(0.006)	(0.052)	(0.059)
Pre-Detailing Mean:	0.447	269.406	0.434	19.221	2.469	4.791	7.359
	Patient Subsamples:						
Opioid Naïve	1.013***	−4.229***	0.093	1.735	−0.005	−0.020	−0.086
(No. Patients: 3,918,523)	(0.130)	(1.923)	(0.110)	(1.324)	(0.006)	(0.048)	(0.071)
Pre-Detailing Mean:	0.381	220.982	0.647	19.867	1.922	3.460	7.220
Daily MME: 1-20	0.425***	−25.202***	−0.001	0.930	0.003	−0.063	0.026
(No. Patients: 910,928)	(0.108)	(3.236)	(0.013)	(0.902)	(0.010)	(0.145)	(0.138)
Pre-Detailing Mean:	0.209	391.993	0.100	15.412	3.417	8.471	7.298
Daily MME: 20+	2.401***	−88.842***	0.086	5.986	0.016	−1.137***	−0.377
(No. Patients: 250,468)	(0.735)	(15.162)	(0.085)	(4.637)	(0.016)	(0.374)	(0.289)
Pre-Detailing Mean:	2.148	1666.219	0.060	67.996	4.899	11.410	9.567
Chronic Pain	0.438***	−25.509***	−0.003	1.153	0.002	−0.190***	−0.181***
(No. Patients: 2,796,034)	(0.110)	(2.498)	(0.016)	(0.737)	(0.008)	(0.091)	(0.083)
Pre-Detailing Mean:	0.299	244.610	0.096	11.525	3.134	6.910	6.243
Existing OUD	−0.061	−54.453***	−0.284	−3.101	0.056	−0.773	0.170
(No. Patients: 52,522)	(0.811)	(10.035)	(1.065)	(2.054)	(0.042)	(1.178)	(0.629)
Pre-Detailing Mean:	1.650	441.242	2.044	20.499	4.485	29.923	7.577
Combat Veterans	0.219***	−8.688***	−0.029	0.968**	0.001	−0.078	−0.023
(No. Patients: 644,985)	(0.091)	(1.225)	(0.020)	(0.503)	(0.013)	(0.105)	(0.049)
Pre-Detailing Mean:	0.086	92.112	0.152	4.367	3.000	3.956	0.906

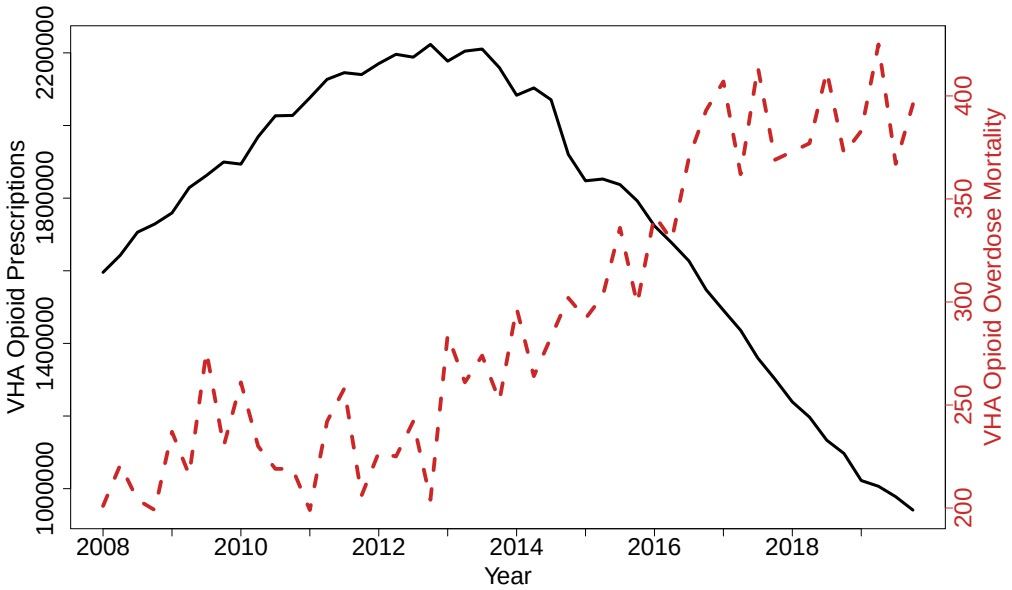
Notes: This table displays the average treatment on the treated effects and its associated standard errors from a Callaway and Sant'Anna (2021) estimator for various subsamples and select outcomes. All outcomes are measured in units of per 1,000 pre-detailing primary care patients. The outcomes are (from column 1 to 7): number of naloxone prescriptions, number of opioid prescriptions, number of agonist prescriptions, number of PDMP checks, average pain scores, number of serious adverse events (emergency department visits and hospitalizations for accidents including overdose poisonings and suicide attempts), and number of deaths per quarter among all patients falling into the sample criteria. The relevant heterogeneity margins are (in rows): based on the year prior to academic detailing (fiscal year 2014), patients with no opioid prescriptions; patients average less than 20 milligrams of morphine equivalent per day, patients with over an average of 20 MME per day; patients diagnosed with chronic pain (following Mayhew et al., 2019); those with an existing opioid use disorder diagnosis; and veterans who saw combat (theater of operations). The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Analyses are weighted by the number of patients falling into each subsample, treated by the PCP team. *p<0.1; **p<0.05; ***p<0.01.

Figure 1: Trends in Opioid Overdose Mortality, Opioid and Naloxone Prescriptions, and Number of Detailed PCP Teams

(a) VHA Naloxone Prescriptions and Teams Detailed Among Baseline Primary Care Sample

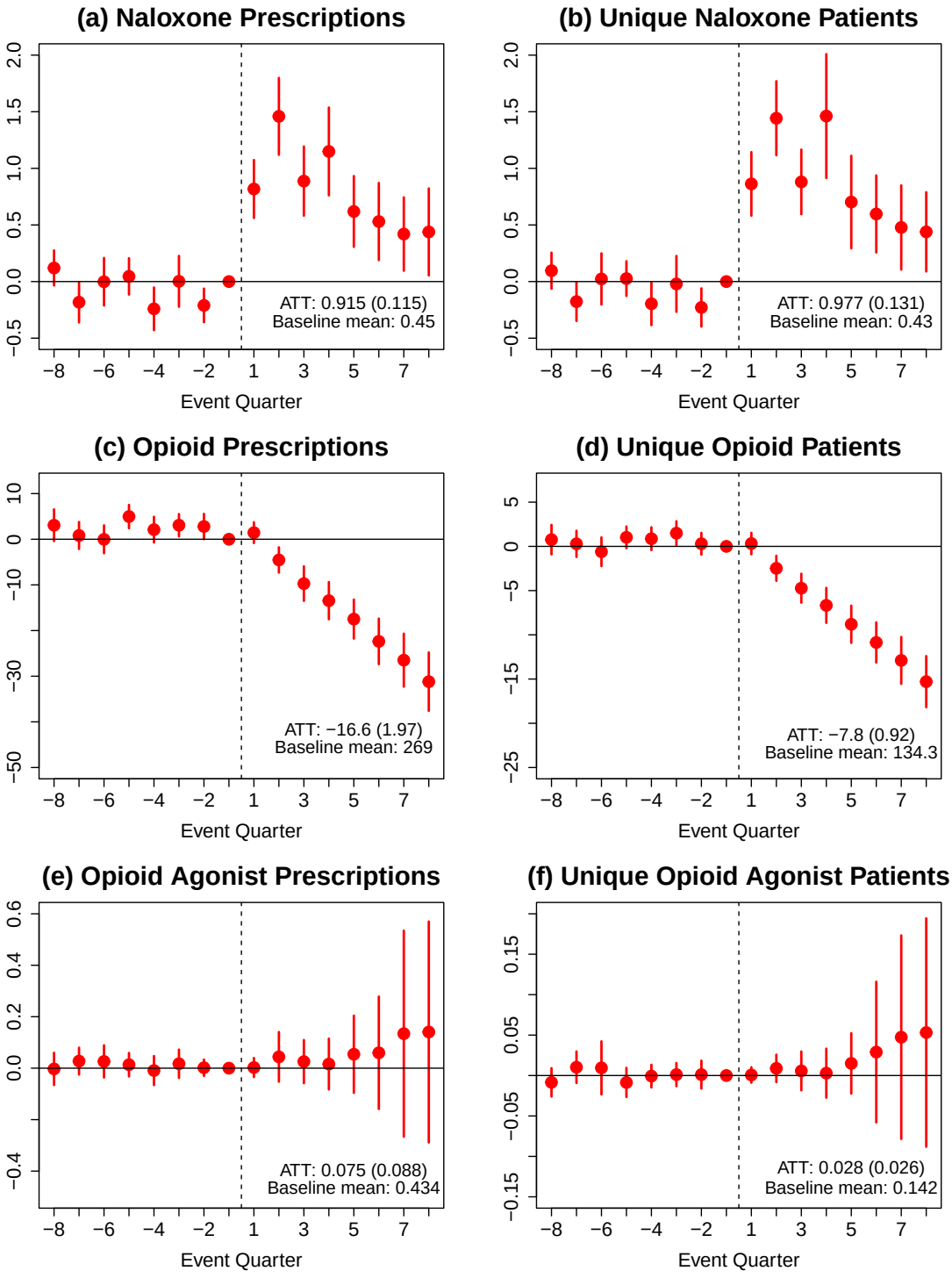


(b) VHA Opioid Prescriptions and Opioid Overdose Mortality Among All VHA Users



Notes: This figure plots time series for academic detailing visits, opioid and naloxone prescriptions, and opioid overdose mortality in the VHA at the calendar year-quarter level between 2013 and 2019. Figure 1a displays a time series of naloxone kits prescribed and filled in the solid black on the left y-axis and number of PCP teams that received opioid-related academic detailing in the dashed blue line on the right y-axis. Figure 1b displays a time series of opioid analgesics prescribed and filled at the Veterans Health Administration (VHA) in the solid black line on the left y-axis and the number of opioid overdose deaths among VHA users in the dashed red line on the right y-axis.

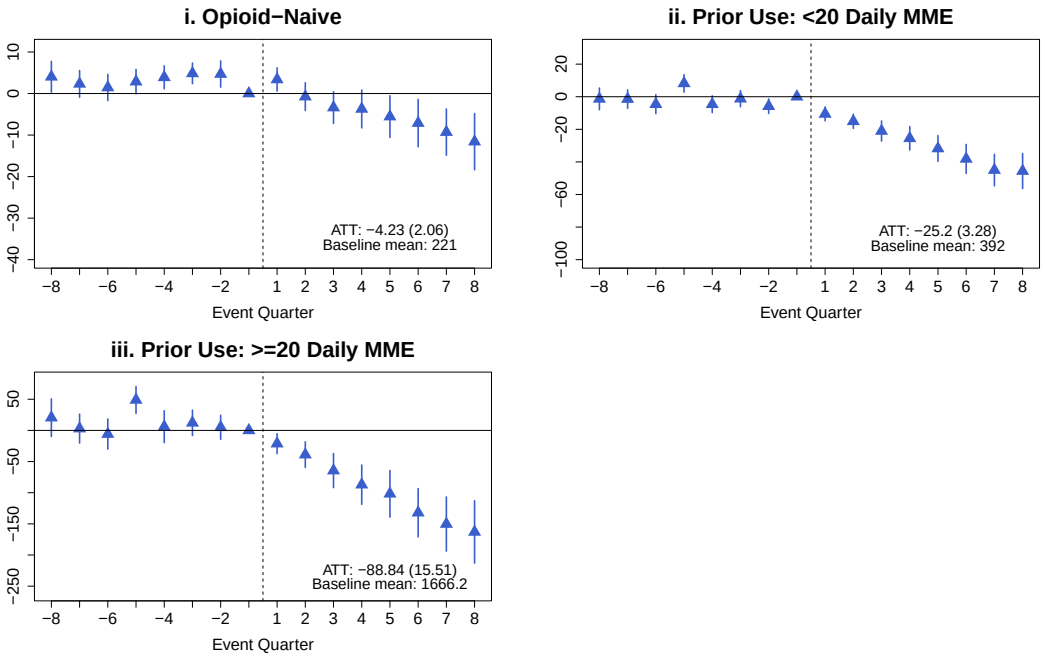
Figure 2: Physician Response: Prescription Counts and Number of Patients Prescribed



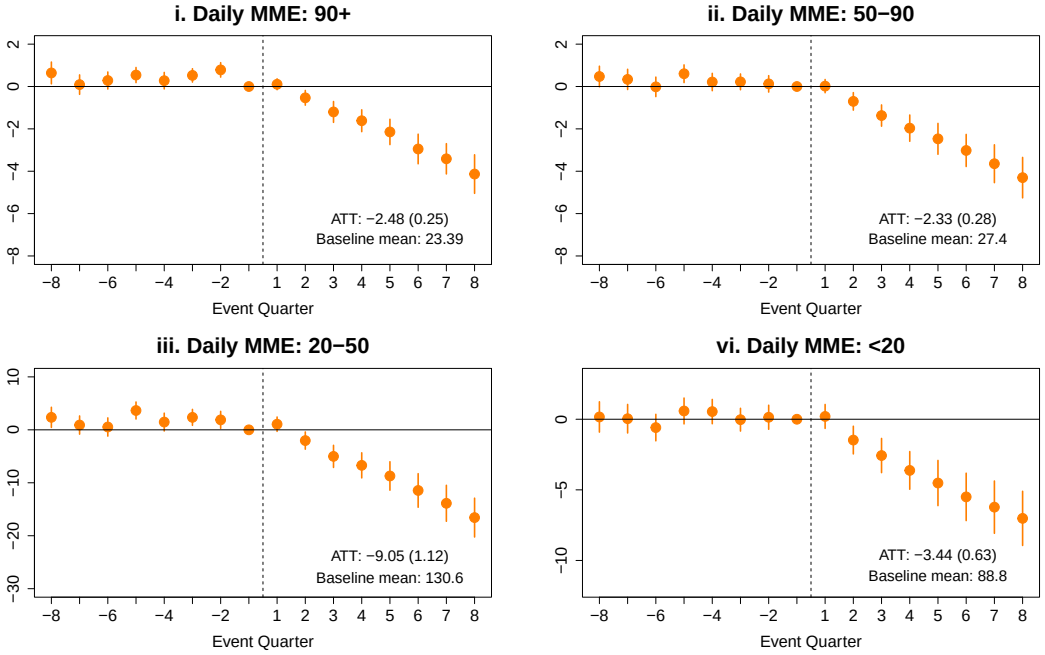
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for physician prescribing outcomes using the methodology in Callaway and Sant'Anna (2021). All outcomes are measured in units of per 1,000 pre-detailing primary care patients. Panels a, c, and e correspond to the number of prescriptions prescribed by each PCP team (to all patients each quarter) and panels b, d, and f correspond to the unique number of patients they prescribe to each quarter. All naloxone kits in the VA appear in the prescription data. The outcomes variables are constructed using all of a PCP's prescriptions, including those to patients not on their initial patient panel. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure 3: Provider Response: Heterogeneity in Opioid Prescribing by Prior Use and Opioid Dosage

(a) Number of opioid prescriptions by prior opioid use



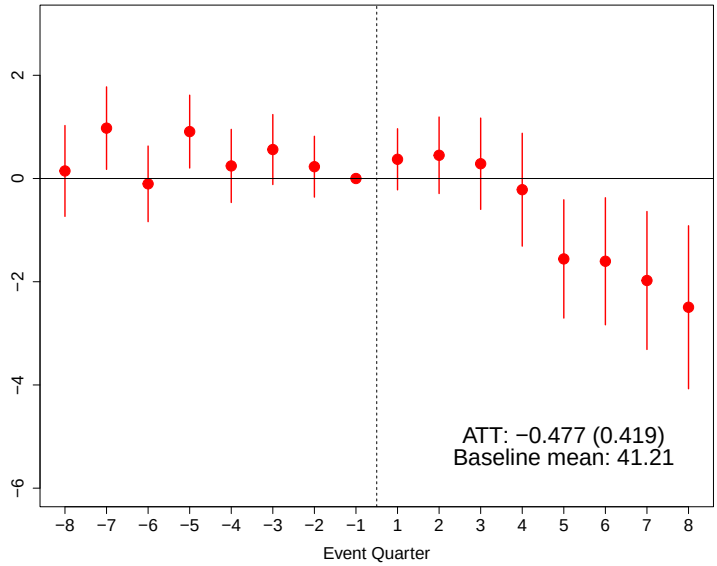
(b) Number of prescriptions by opioid dosage intensity



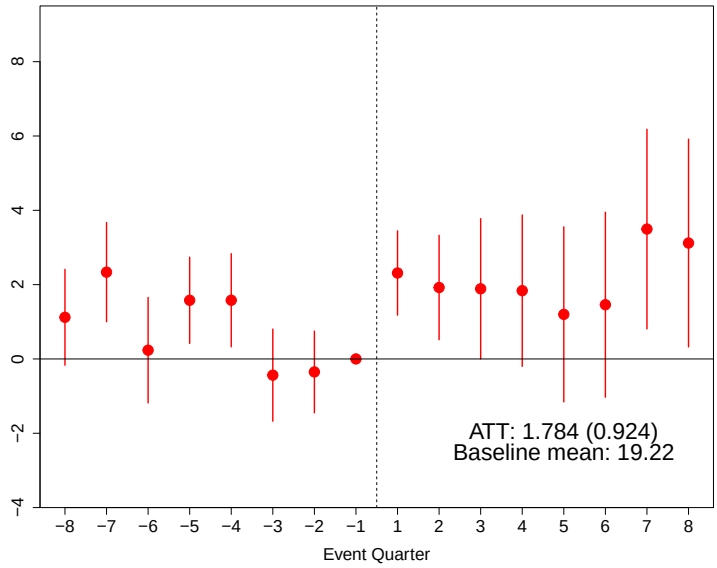
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for heterogeneity in physician opioid prescribing using the methodology in Callaway and Sant'Anna (2021). All outcomes are measured in units of per 1,000 pre-detailing primary care patients (of each risk category). Figure 3a displays total number of opioid prescriptions prescribed for patients of varying pre-policy opioid use, based on their average daily MME in fiscal year 2014. There are 3,918,523; 910,928; and 250,468 patients in each group. Figure 3b displays number of opioid prescriptions of varying opioid dosage intensity prescribed by the PCP. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure 4: Provider Response: Risk Evaluation

(a) Number of Urine Drug Screens (UDS)

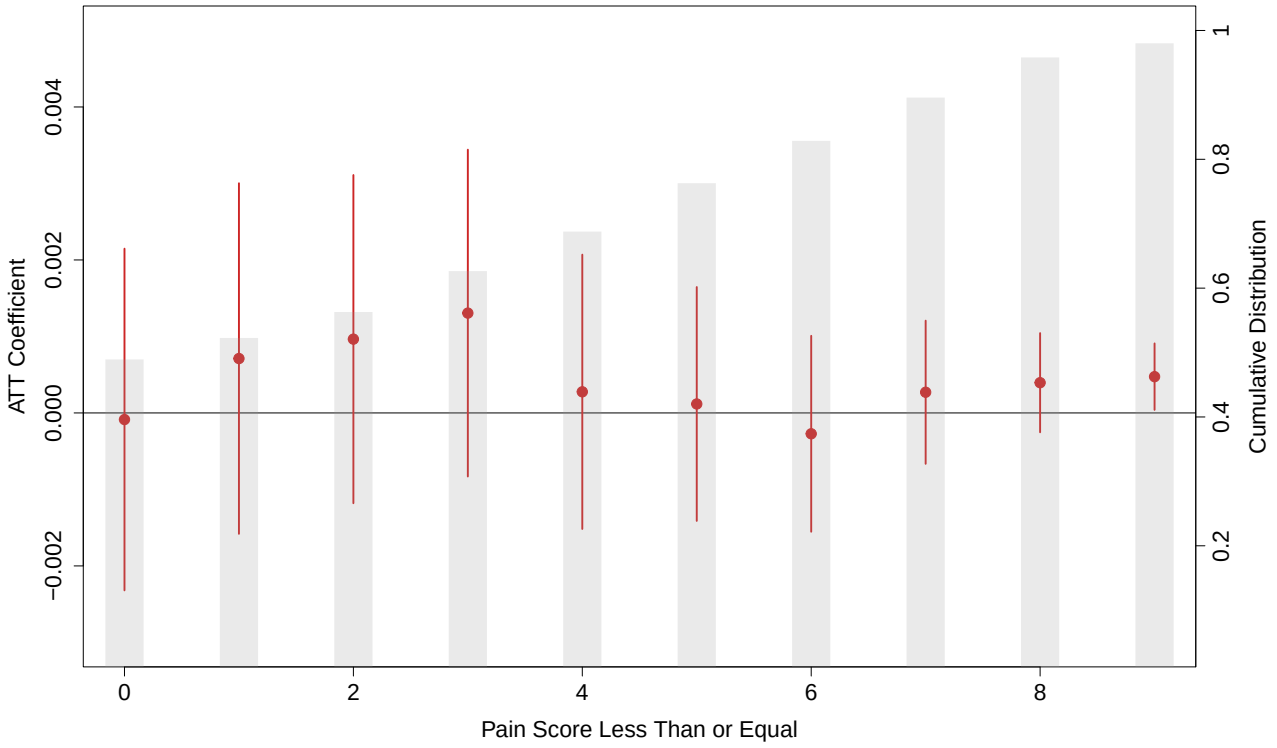


(b) PDMP Queries



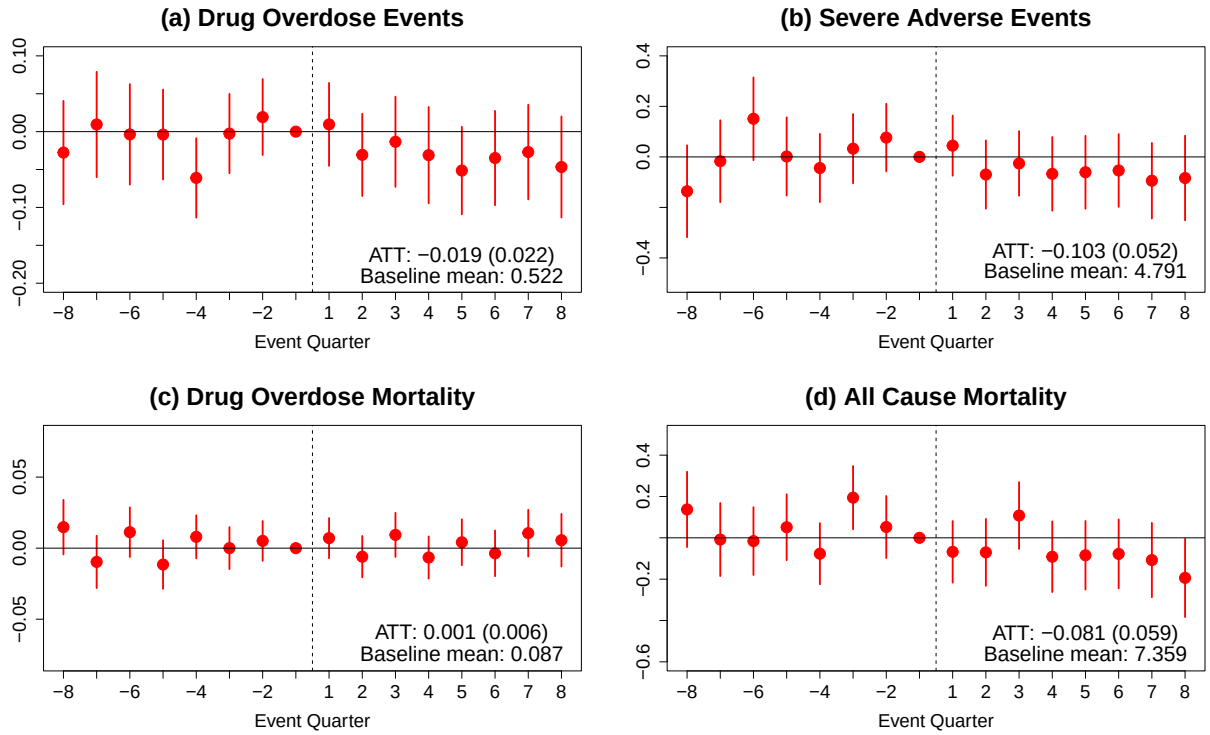
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for physician risk evaluation response using the methodology in Callaway and Sant'Anna (2021). All outcomes are measured in units of per 1,000 pre-detailing primary care patients. The outcomes in panels a, and b correspond to the number of opioid urine drug screens (morphine or metabolite in heroin/fentanyl) conducted each quarter, and the number of prescription drug monitoring program queries recorded each quarter. Clinicians are mandated by the VA to check PDMPs for opioid patients at least once a year and to record the query using a pre-populated template form. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure 5: Impact of Detailing on Pain Thresholds



Notes: This figure displays average treatment effects on the fraction of pain scores below each threshold value. For instance, the third coefficient from the left corresponds to ATT on an outcome variable of the fraction of each PCP's patient's pain scores that are no more than 2 (e.g., 0, 1, and 2) in a calendar quarter. Grey bars in the background display the cumulative distribution of pain scores (right y axis). Self-reported pain scores take values between 0, 1, . . . , 10 with 10 indicating greatest pain. Scores between 1-4, 5-6, and 7-10 are classified as mild, moderate, and severe pain. Only measurements taken in primary care (regardless of provider identity) are included. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure 6: Downstream Outcomes: Number of Drug Overdose Events, Serious Adverse Events, Mortality



Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for adverse events and mortality using the methodology in Callaway and Sant'Anna (2021). Outcome data is observed at the patient-level and then aggregated to PCP teams based on patient-PCP linkages from pre-policy documentation. All outcomes are measured in units of per 1,000 pre-detailing primary care patients. Panels a-c display counts of emergency department and hospitalization diagnosis patient-date events for drug overdoses; serious adverse events (overdoses, suicides, and accidents); deaths from drug overdoses; and deaths from all causes.mEvents occurring in VA facilities, non-VA facilities but are reimbursed by the VA, and Medicare/Medicaid claims are all included. Date and cause of death are from the CDC National Death Index Plus. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Online Appendix for

"Can Educational Outreach Improve Experts' Decision Making? Evidence from a National Opioid Academic Detailing Program"

A. VA Opioid-Related Academic Detailing

Academic detailers at the VA (trained clinician pharmacists) provide education to frontline providers to align their practice with current evidence and guidelines. This is done during face-to-face visits where the detailers use and provide educational material to facilitate discussion and promote evidence. This includes provider handouts, pocket cards, and educational material for providers to give to patients. The handouts include key messages, summaries of new research and literature, recommendations based on VA/DoD Practice Guidelines, and actionable information about treatment recommendations (Wells et al., 2016). Figure A.1 shows the front page and material for select opioid-related educational material. I provide brief summaries for opioid-related key messages below.

Pain management

- Appropriate prescribing of opioids for acute and chronic pain[1] (e.g., the risks associated with opioids[2]; effectiveness of non-opioid treatments; a stepwise approach for acute pain: non-pharmacologic before non-opioid pharmacologic approaches, before short-term use of short-acting opioids; avoid opioid-benzodiazepine coprescribing)
- Recommended opioid taper strategies and potential risks of rapid tapering/discontinuation[3]

Risk evaluation

[1]Pain management: provider material; patient material. If these links are updated and become broken, the materials can be found at the Academic Detailing Service homepage.
[2]Opioid risk: provider material.
[3]Opioid tapering: provider material; patient material.

- Importance of prescription drug monitoring program checks and VA mandates[4]: minimum once per year for all patients and every prescription for patients with OUD or on higher doses
- Urine drug screens[5]: the different types and how to interpret them; recommended frequencies (annually for all chronic opioid patients, every three months for high risk patients); different "red flags" and action plans (e.g., if patient screens positive for a drug they are not prescribed, then have a discussion about addiction treatment program)

Opioid use disorder treatment

- Identification of OUD[6]: physical signs (e.g., abscesses, rashes, murmurs, etc.) and other components such as medical, mental health and substance abuse history, etc.
- Tools for identification: urine drug screens and PDMPs
- Strategies for conversation with patient (e.g., supportive, person-first language, avoid judgmental terminology and stigmatizing the patient, etc.) and the expected symptoms with opiod withdrawal
- Efficacy and safety of buprenorphine and other medications[7]

Harm reduction

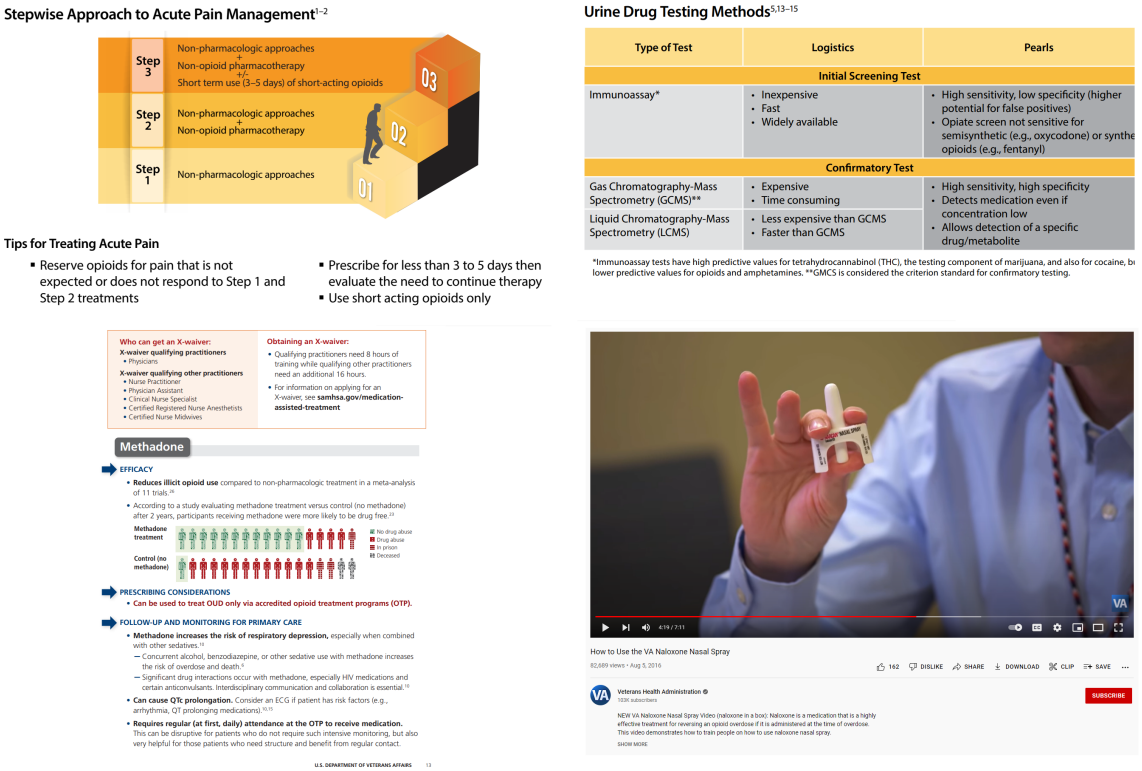
- Efficacy and safety of naloxone[8]; recommend increased prescribing of naloxone
- How to administer naloxone

[4]PDMP: provider material (slide 20).
[5]UDS: provider material (page 21-33).
[6]OUD materials: provider material, quick reference guide.
[7]Medication for OUD: patient material.
[8]Naloxone materials with videos: naloxone page.

Figure A.1: Opioid-Related Academic Detailing Material

(a) Front page of select educational material

(b) Select educational content



Notes: Panel a displays the front page of three different academic detailing educational handouts and panel b displays select material from the handouts and video resources.

B. Details of Cost-Benefit Analysis

In this appendix I provide more details of the cost-benefit calculations associated with detailing a new, additional PCP. Note that I only consider statistically significant impacts of the detailing, therefore, potential value of a statistical life saved is omitted. The table below summarizes the main pieces of the cost-benefit analysis. Estimated impacts are from my ATT estimates summed across the patient panel (i.e., summed across all patients for each PCP team, as opposed to per 1,000 primary care patients), various federal sources, and other approximations.

Item	Estimate Source	Dollar Value (2020$)
Naloxone Rx	VA Federal Supply Schedule[9]	ATT: 0.898×8 qtr $\times$ \$67.84
Opioid Rx	VA Federal Supply Schedule	ATT: -16.871×8 qtr $\times$ \$35.26
Serious Adverse Events	VA Average Cost[10]	ATT: -0.118×8 qtr $\times$ \$12,262
Detailing Cost	VA Human Resources Data[11]	Salary \$139,784 $\div$ 273 visits/year[12]
Other detailing costs	IRS Standard Mileage Rate[13]	50 miles[14] $\times$ \$0.575 per mile
	Net Benefit:	=**\$15,306.16** per visit

Totaling the items, the net benefit per detailed PCP is roughly over two years. There are a few limitations with this crude back-of-the-envelope calculation. First, I am calculating benefit associated with a marginal PCP team being newly detailed and ignoring the costs associated with starting up the detailing campaign (e.g., guideline creation, training, knowledge dissemination, dashboard maintenance, etc.). I assume that the majority of these costs are fixed, but they may have an impact on the marginal cost. Second, these are two-year calculations and ignore longer-term impacts. Figure D.6 demonstrates that the three-year

[9]This data is publicly available and reflects a schedule of prices set of federal regulatory bodies. Note that this price will be an overestimate since it does not include negotiated discounts and savings.

[10](The VA calculates average cost estimates for each encounter based on observable characteristics of the encounter (e.g., length of stay, diagnosis-related group, intensive care days, procedure codes, etc.; Wagner et al., 2003)). I average the estimates for all SAEs in FY2016 to obtain these values. The average cost per inpatient SAE encounter is \$35,362 and \$877 for emergency department SAE encounters.

[11]Average salary of a full-time equivalent academic detailer in 2020 dollars comes from VA Personnel and Accounting Integrated Data System (PAID) Data.

[12]The average full-time equivalent academic detailer details 273 visits per year.

[13]Using 2020 IRS Standard Mileage Rates: https://www.irs.gov/tax-professionals/standard-mileage-rates.

[14]Virtually all detailing visits are via car transportation. The average detailer visits three different stations in a year (the VHA is split into 140 different regions, called stations) and rarely stay overnight.

impacts of detailing are likely equally as large. Finally, the calculations are sensitive to my main estimates. If there are improvements in all-cause mortality that are imprecisely estimated, then this net benefit is grossly underestimated.

C. Scaling The Program

In this appendix, I provide details on the empirical specification that parametrically models spillovers. Specifically, I assume that peer effects are constrained within primary care clinics and scale linearly with the fraction of PCP teams in a facility that have already received detailing:

$$Y_{it} = \beta Treated_{it} + \lambda FractionDetailed_{it} + \gamma Treated_{it} \times FractionDetailed_{it} + \alpha_i + \phi_t + \epsilon_{it}. \quad (2)$$

In Equation 2, $Treated_{it}$ is a treatment indicator for units (quarters) where the team has already been detailed and $FractionDetailed_{it}$ is the (leave-out) fraction of teams within team i's facility that have already been detailed by date t. This model assumes that spillovers are constrained to within the same VA facility, an assumption that is analogous to assuming spillovers only occur within a certain radius or aggregate block in spatial settings (Miguel and Kremer, 2004; Baum-Snow and Ferreira, 2015). As is the case with standard two-way fixed effects models, the estimates of α_i and ϕ_t fixed effects are contaminated by the post-treatment period. To deal with this, I implement a two step approach à la Borusyak et al. (2022) and Gardner et al. (2024) where the fixed effects are estimated using pre-treatment and never-treated observations and the residualized outcomes are then regressed on the remaining explanatory variables. The parameters of interest, β tell us the direct effect of academic detailing if there are no spillovers or no other teams in their facility have been treated, and $\beta + \gamma$ tells us the total effect of academic detailing if every team is detailed. The results of this exercise are presented in Table C.1.

There does not appear to be large spillover effects in naloxone and opioid prescribing. Compared to detailing the first PCP of a clinic, the impact of detailing a PCP whose peers have all already been directly treated is a statistically insignificant 0.608 more naloxone and 1.243 fewer opioid prescriptions. This could suggest that the value of detailing on prescribing is concentrated in the direct effect, or that peer practice behaviors are generally unobserved in primary care (unlike hospital team settings). Interestingly, the number of PDMP checks are declining with the degree of prior detailing. This might suggest that the perceived value of PDMP checks diminishes if the majority of your peers are engaging in safer opioid practices,

and you assume others are checking PDMPs.

Finally, serious adverse events and mortality initially increase when only one PCP is detailed, but declines when a greater fraction of PCPs are detailed within a facility. This might suggest that patients may initially substitute to other—perhaps more fatal—opioids and experience adverse outcomes; however, with a large quantity of naloxone prescriptions and/or sufficiently strict opioid prescribing culture, patient outcomes improve with detailing. If this is true, then it suggests that there are increasing returns to opioid-related academic detailing in the VA. However, it is important to note that this exercise has strong parametric assumptions. It is also possible that academic detailers improve their impacts as they gain more experience detailing, or that the early PCP teams who were detailed, were particularly non-responsive to detailing.

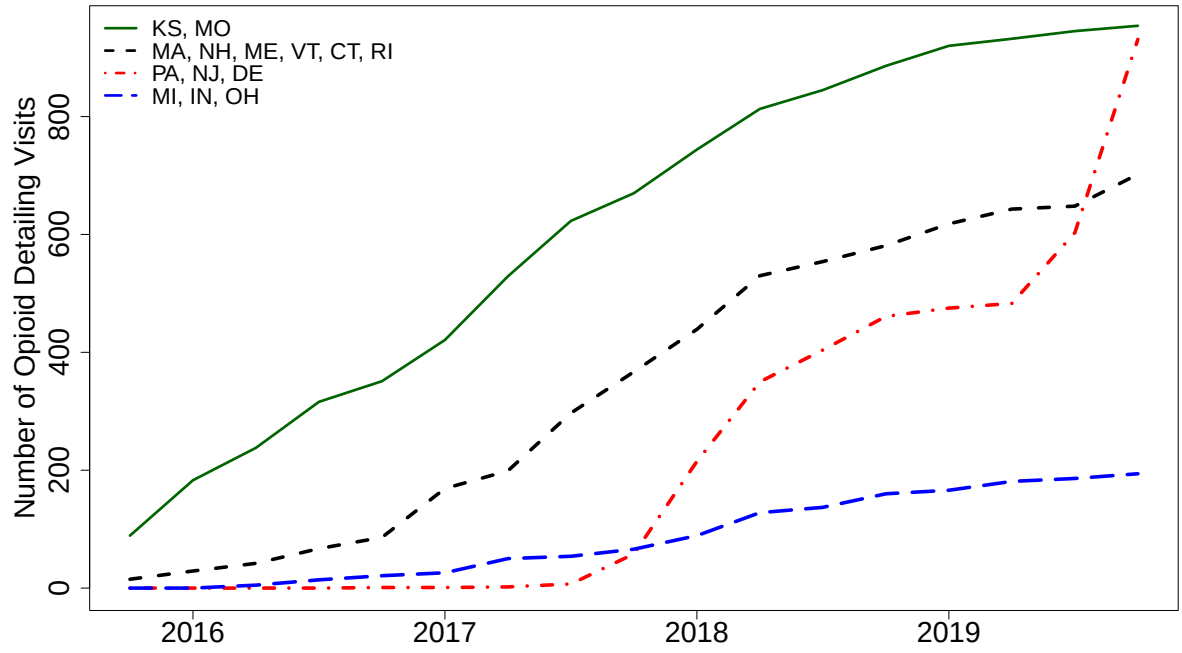
Table C.1: Modeling Peer Spillovers

	Dependent variable:						
	Naloxone	Opioids	Agonists	PDMPs	Pain	SAEs	Death
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Treated_{it}$	0.935^{***}	-17.821^{**}	0.257	10.553^{**}	0.122	0.301^{***}	0.240^{***}
	(0.233)	(7.251)	(0.217)	(4.859)	(0.099)	(0.092)	(0.076)
$Treated_{it} \times$	0.608	-1.243	-0.171	-16.984^{***}	-0.046	-0.700^{***}	-0.262^{**}
$FractionDetailed_{it}$	(0.374)	(10.143)	(0.254)	(6.060)	(0.161)	(0.136)	(0.111)
Pre-Detailing Mean	0.447	269.406	0.434	19.221	2.469	4.791	7.359

Notes: This table displays the impacts of academic detailing on a number of main outcomes after modeling for peer spillovers parametrically; the estimated equation is Equation 2. $Treated_{it}$ denotes treatment status: one if the team has been detailed by quarter t and zero otherwise (not yet detailed or will never be detailed). $FractionDetailed_{it}$ denotes the leave-out fraction of PCP teams that have received detailing in PCP i's clinic by calendar quarter t. Robust standard errors are clustered at the PCP team level. *p<0.1; **p<0.05; ***p<0.01.

D. Additional Exhibits

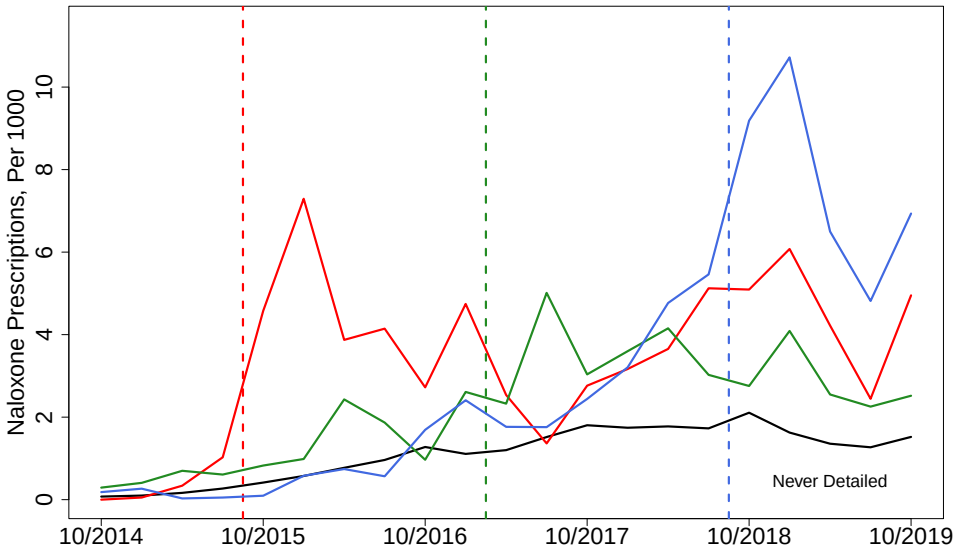
Figure D.1: Example of Staggered Implementation Across Stations



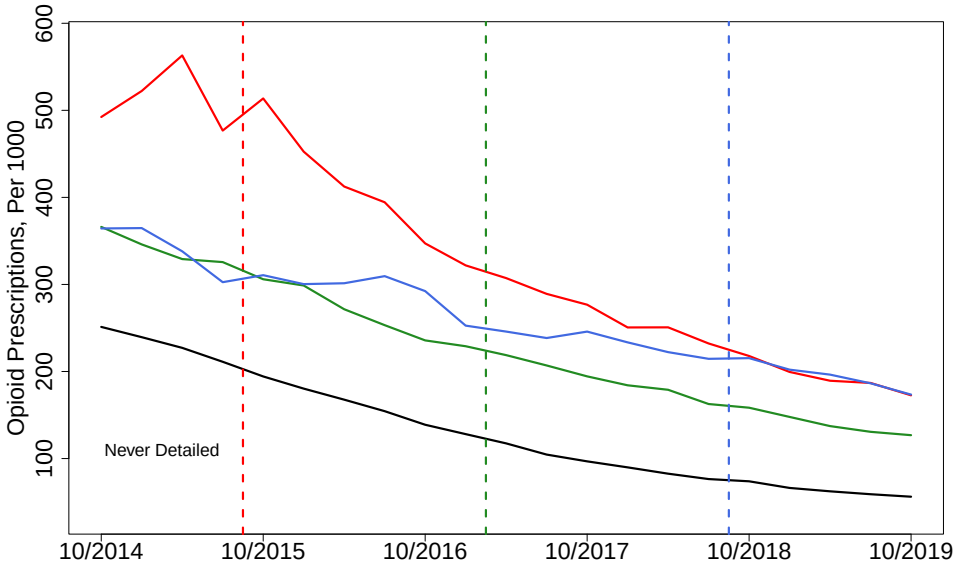
Notes: This figure displays the number of opioid-related academic detailing visits from October 2015 to December 2019 across four select Veterans Integrated Services Networks (VISNs) which are similar to regions. The VA is split into 22 different VISNs.

Figure D.2: Time Series: Physician Responses by Quarter of Treatment (Cohort)

(a) Naloxone Prescribing

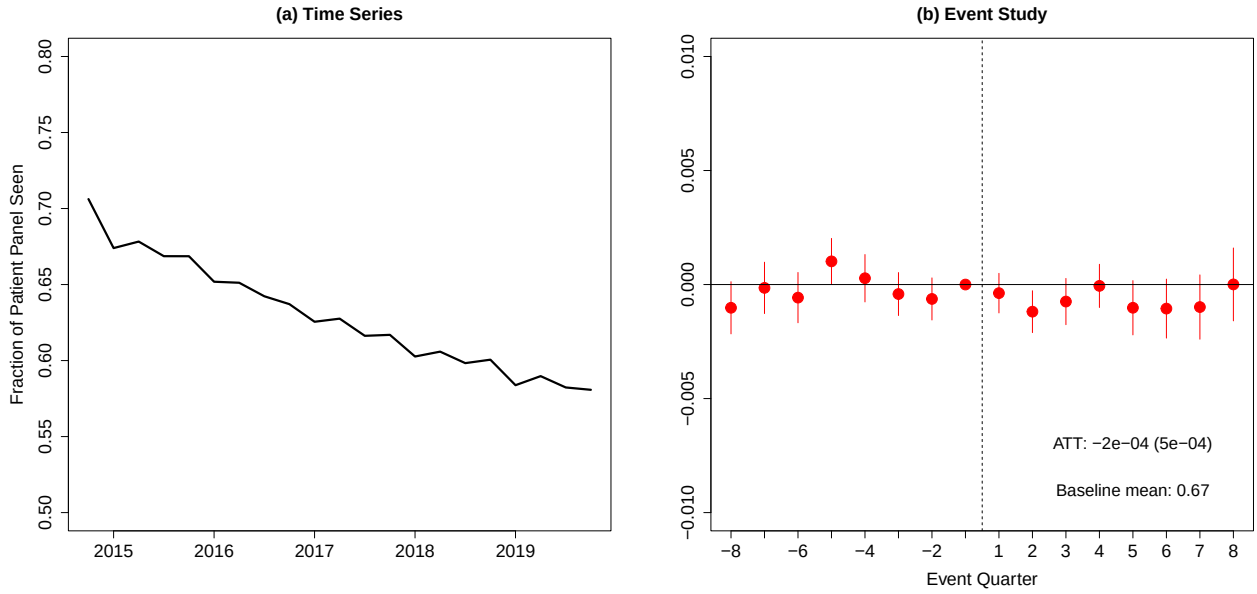


(b) Opioid Prescribing



Notes: This figure plots the raw data of naloxone prescribing and opioid prescribing per 1,000 primary care patients for PCP teams of four cohorts. PCPs who first received academic detailing in the fourth quarter of 2015 (red), first quarter of 2017 (green), fourth quarter of 2018 (blue), and those who never receive detailing (black). The three dashed vertical lines correspond to the quarter each cohort was treated.

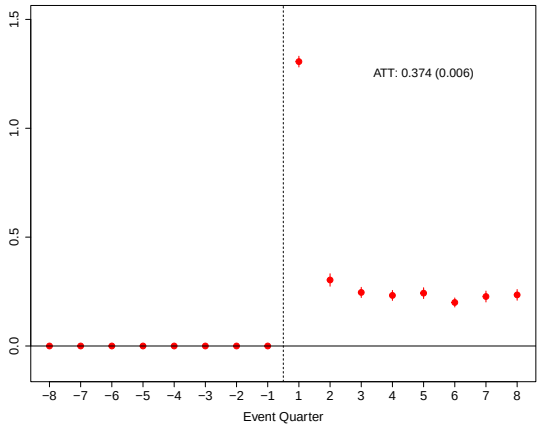
Figure D.3: Attrition of Patient Panel



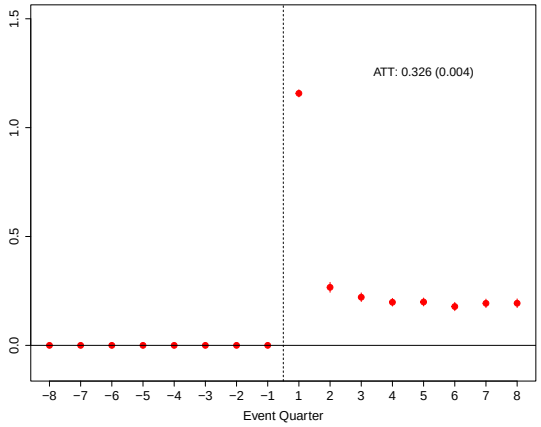
Notes: Panel a shows the fraction of each PCP's patient panel that they see each quarter between 2014Q4 and 2019Q4. Panel b shows how the fraction of the patient panel seen each quarter changes (or does not change) after academic detailing in an event study format following the methodology in Callaway and Sant'Anna (2021).

Figure D.4: Dynamics of Detailing Following First Detailing Event

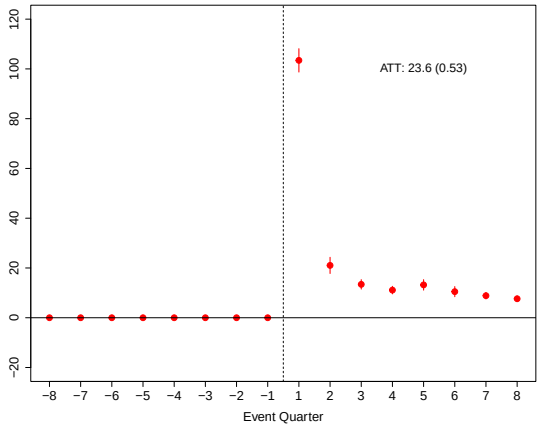
(a) Number of Detailing Visits



(b) Number of PCP Team Members Detailed

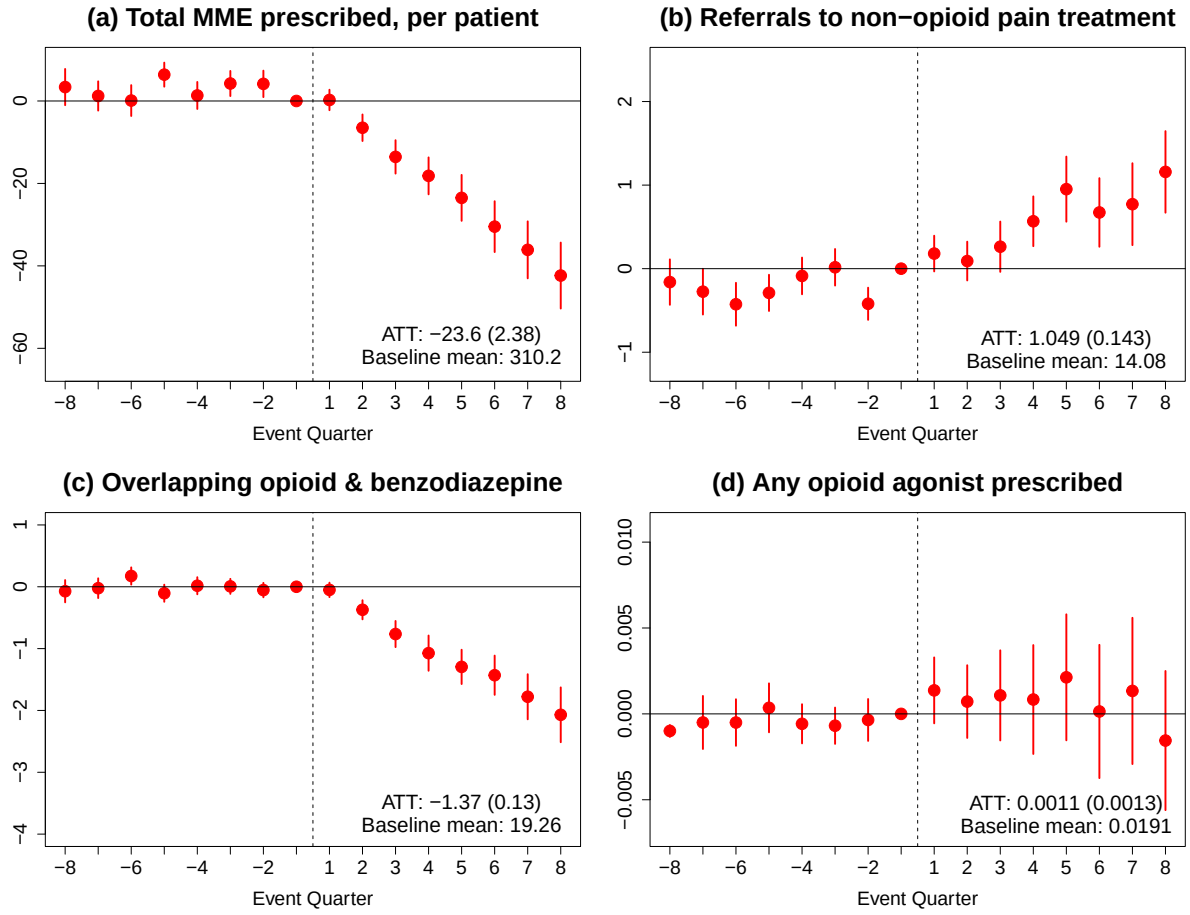


(c) Detailing Duration, in Minutes



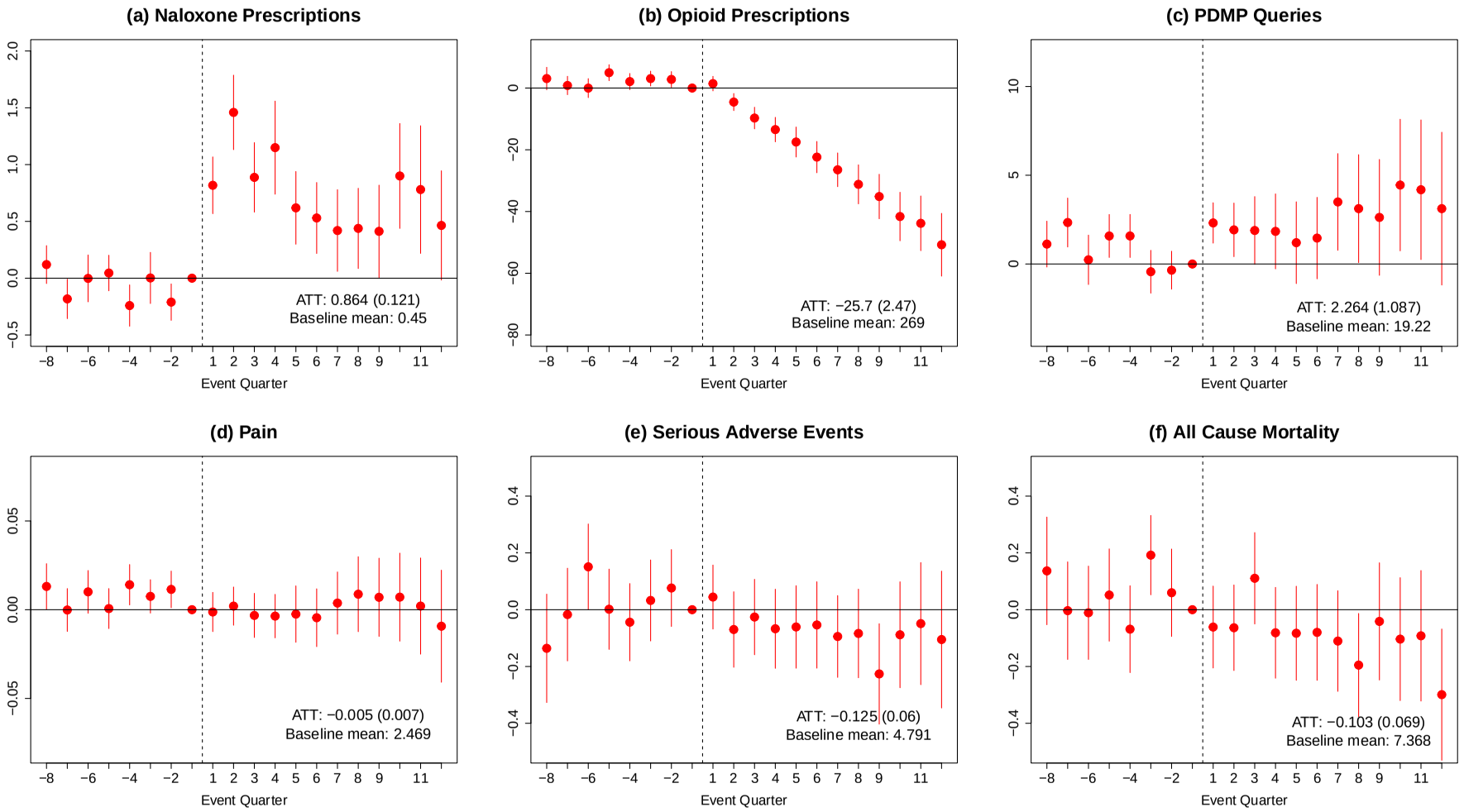
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for physician risk evaluation response using the methodology in Callaway and Sant'Anna (2021). Panel a shows the number of unique detailing visits, panel b shows the number of primary care team members that are detailed, and panel c shows the total number of minutes detailed. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.5: Additional Physician Response Margins



Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for other physician prescribing outcomes using the methodology in Callaway and Sant'Anna (2021). Panels a, b, c, and d correspond to total milligrams of morphine equivalents (MME) prescribed each quarter, number of referrals to alternate non-opioid pain treatment (e.g., pain clinic, acupuncture, physical therapy, etc.) centers, the number of patients with overlapping opioid and benzodiazepine prescriptions, and an indicator for prescribing any opioid agonist (a proxy for having an X-waiver), respectively. Other than panel a which is measured per patient, panels b-d are measured in units of per 1,000 pre-detailing primary care patients. Overlapping opioid and benzodiazepine prescriptions are calculated based on the date the medication was released to the patient and the days supply on that prescription. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

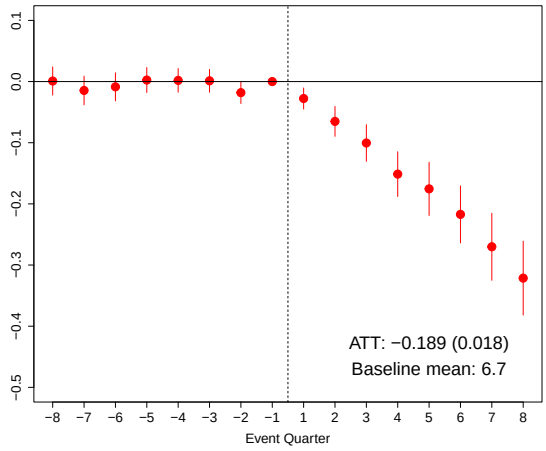
Figure D.6: Three-Year Horizons for Select Main Outcomes



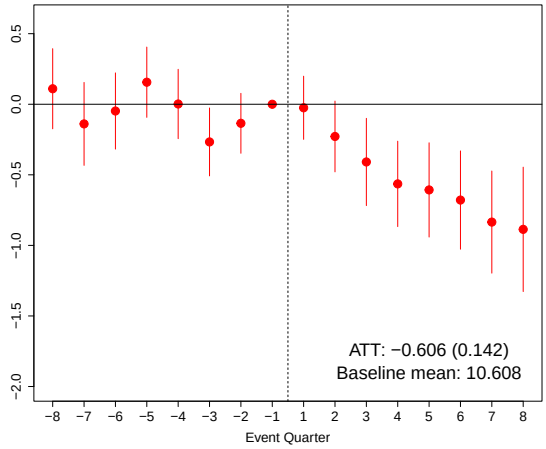
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for select outcomes using the methodology in Callaway and Sant'Anna (2021). Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients. Serious adverse events include those occurring in VA facilities, non-VA facilities but are reimbursed by the VA, and Medicare/Medicaid claims are included. The second row (panels d-f) display counts of patients dying from all-causes. Patients are categorized into three groups based on their average daily milligrams of morphine equivalents (MME) in the year prior to academic detailing policy (fiscal year 2014). There are 3,918,523; 910,928; and 250,468 patients in each group. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.7: Physician-Induced Changes to "*Risk Index for Overdose or Serious Opioid-Induced Respiratory Depression*" (RIOSORD), Among a Fixed Patient Population

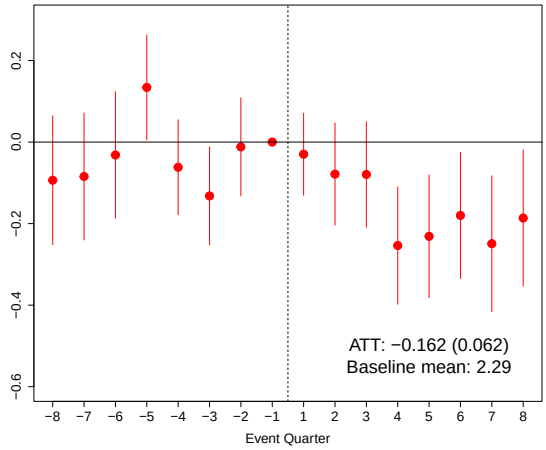
(a) Average patient RIOSORD index



(b) Number of "high risk" patients



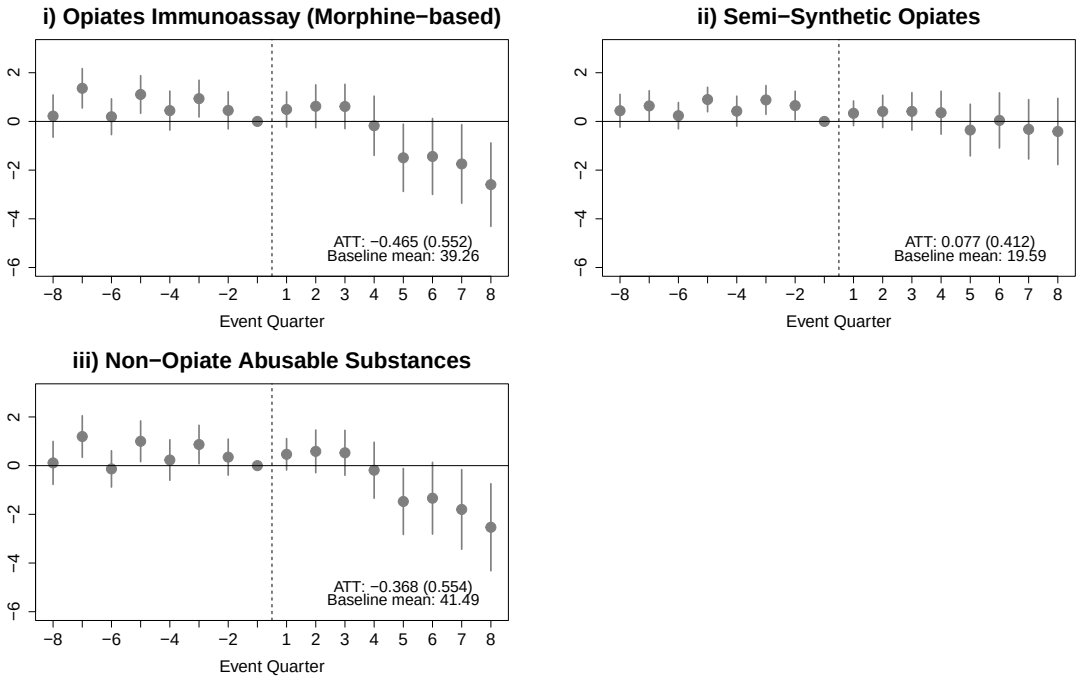
(c) Number of "very high risk" patients



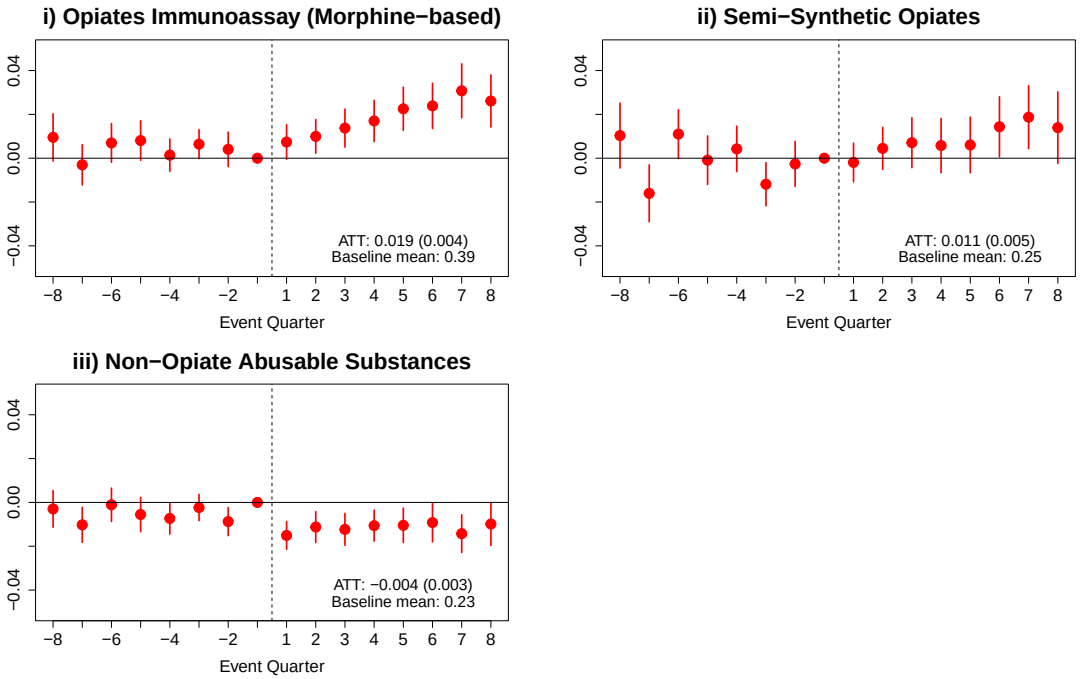
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for opioid overdose risk measures using the methodology in Callaway and Sant'Anna (2021). Measures of patient overdose risk comes from a VA predictive algorithm called "risk of overdose or serious opioid-induced respiratory depression" (RIOSORD) which classifies patients into different risk tiers. The algorithm is shown to have strong predictive power (Zedler et al., 2018). Patient RIOSORD risk is calculated each quarter for a *fixed patient panel* for each PCP based on pre-policy PCP-patient relationships. Figure D.7a displays the average RIOSORD index score across patients of a given PCP. Figure D.7b displays the number of high risk patients the PCP has each quarter; 2.27% of high risk patients go on to overdose within one year in the data. Figure D.7c displays the number of very high risk patients the PCP has each quarter; 2.84% of very high risk patients go on to overdose within one year in the data. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.8: Urine Drug Screens, By Type

(a) Urine Drug Screens Per 1,000 Patients, By Type

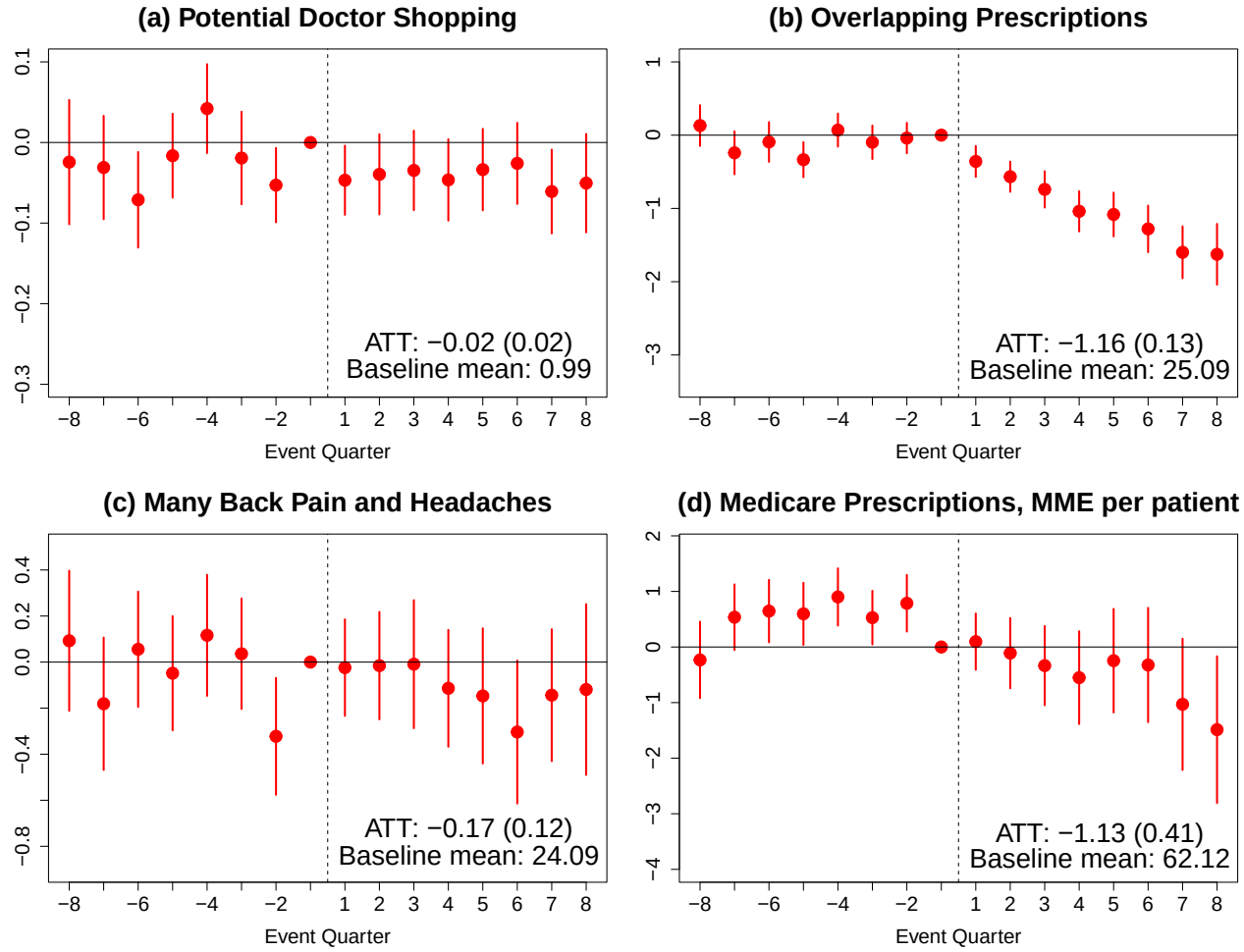


(b) Positivity Rate of Urine Drug Screens, By Type



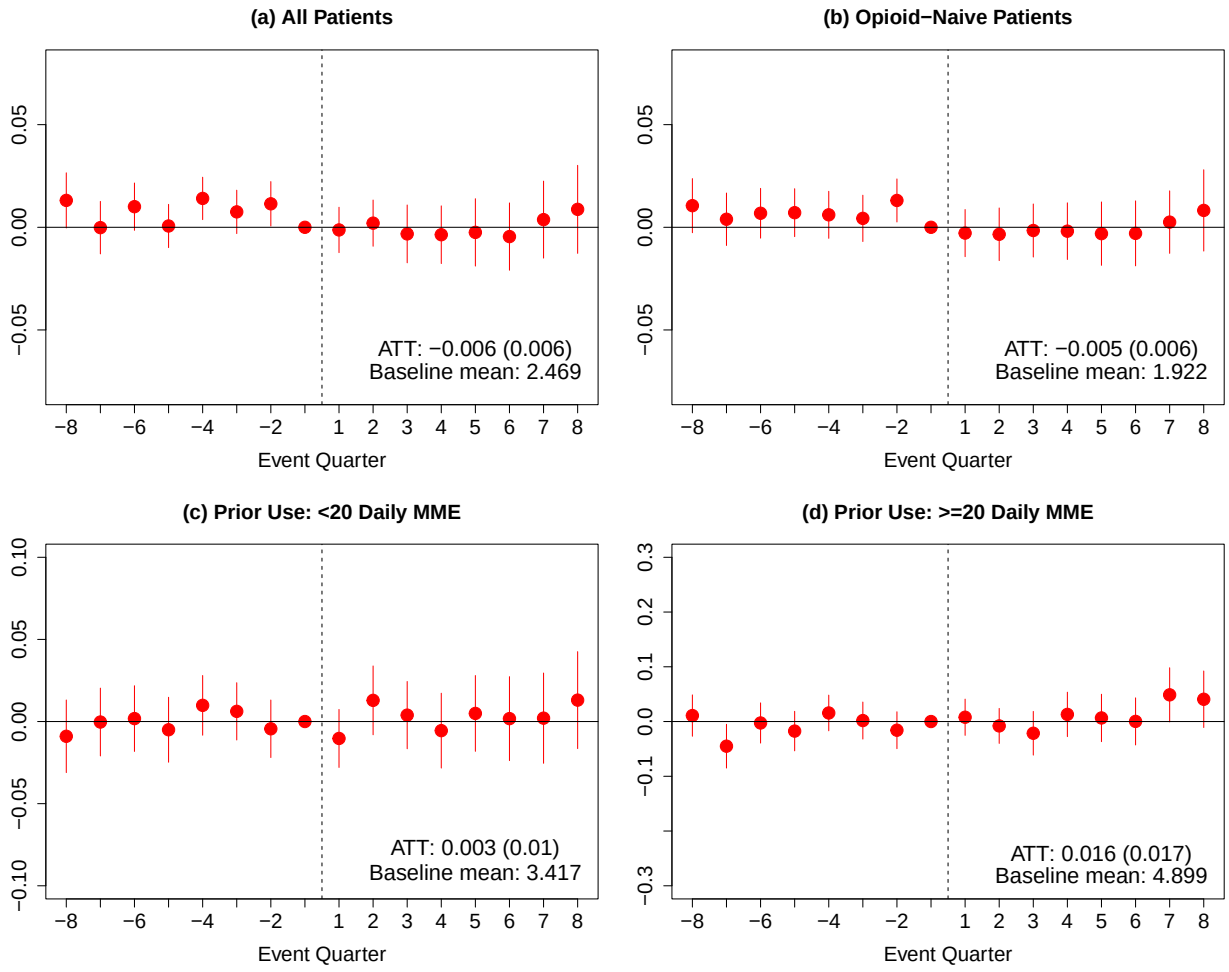
Notes: Panel a plots the number of ordered urine drug screens by type of screen, per 1,000 primary care patients. Panel b plots the positivity rate by type of screen. The staggered difference-in-differences methodology in Callaway and Sant'Anna (2021) is employed. The types of urine drug screens are: i) generic opiates immunoassay (which screens for codeine, morphine, and naturally occurring opiates), ii) semi-synthetic opiate screens (screens for hydrocodone, oxycodone, etc.), iii) non-opioid abusable substances (e.g., amphetamines, barbiturates, benzodiazepines, etc.). The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.9: Proxies for "Drug-Seeking" Behavior



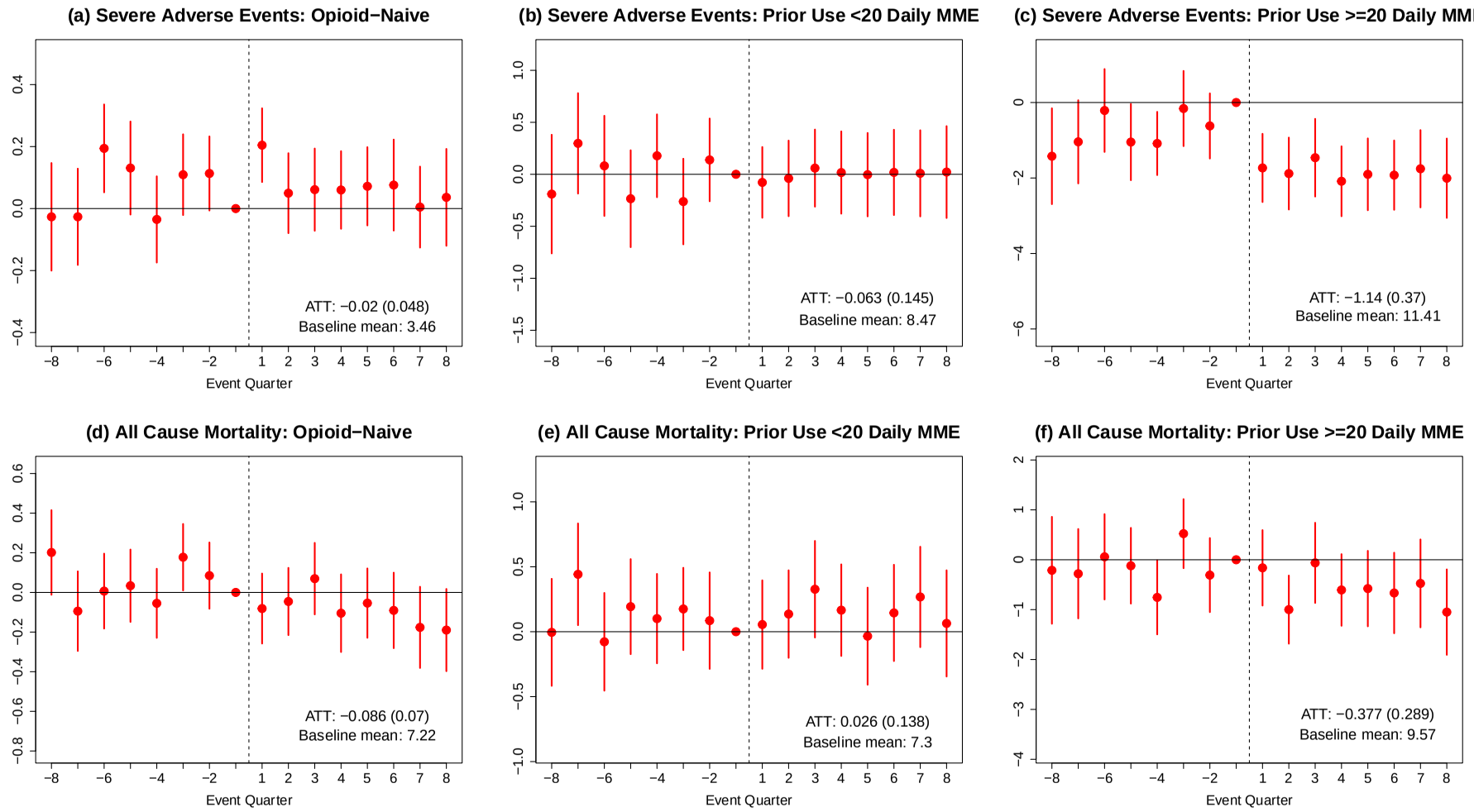
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for proxies for "drug-seeking" behavior using the methodology in Callaway and Sant'Anna (2021). These proxies—following Finkelstein et al. (2021); Eichmeyer and Zhang (2022)—are: a) four or more unique opioid prescribers in a quarter ("doctor shopping"); b) two prescriptions that overlap by at least 25% of the days ("overlapping prescriptions"); c) five or more back pain and headache/migraine diagnoses in a quarter ("many back pain and headaches"); and d) total milligrams of morphine of Medicare opioid prescriptions. All outcomes are measured in units of per 1,000 pre-detailing primary care patients. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.10: Self-Reported Pain Scores



Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for self-reported patient pain scores by prior opioid use using the methodology in Callaway and Sant'Anna (2021). Self-reported pain scores take values between 0, 1, . . . , 10 with 10 indicating greatest pain. Only measurements taken in primary care (regardless of provider identity) are included. Patients are categorized into three groups based on their average daily milligrams of morphine equivalents (MME) in the year prior to academic detailing policy (fiscal year 2014). There are 3,918,523; 910,928; and 250,468 patients in each group. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

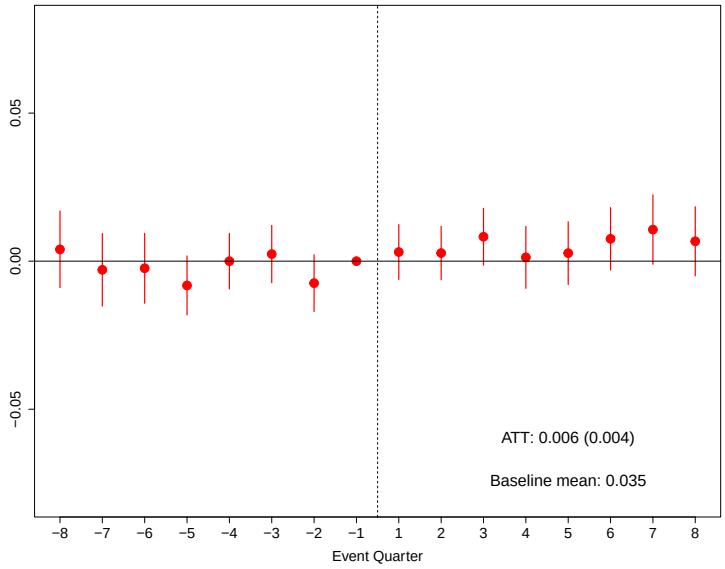
Figure D.11: Downstream Outcomes by Pre-Policy Opioid Use



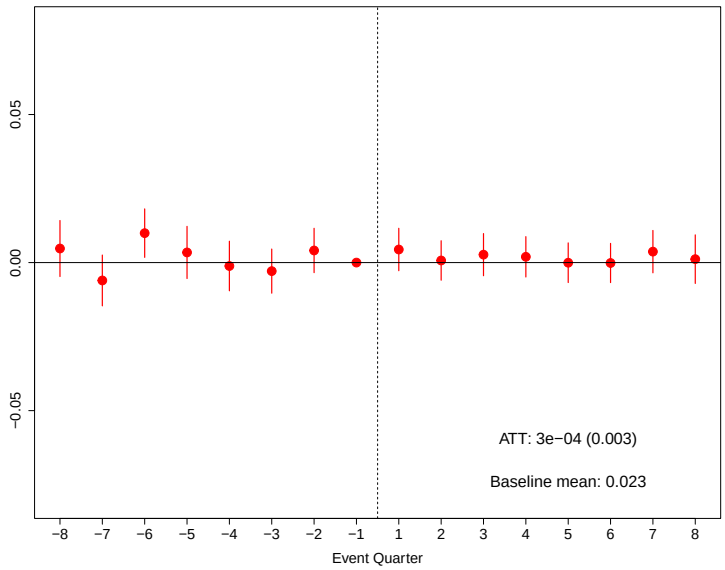
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for downstream outcomes (analogous to Figure 6) by prior opioid use using the methodology in Callaway and Sant'Anna (2021). All outcomes are measured in units of per 1,000 pre-detailing primary care patients. The first row (panels a-c) display counts of emergency department and hospitalization diagnosis patient-date events serious adverse events (overdoses, suicides, and accidents). Events occurring in VA facilities, non-VA facilities but are reimbursed by the VA, and Medicare/Medicaid claims are included. The second row (panels d-f) display counts of patients dying from all-causes. Patients are categorized into three groups based on their average daily milligrams of morphine equivalents (MME) in the year prior to academic detailing policy (fiscal year 2014). There are 3,918,523; 910,928; and 250,468 patients in each group. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.12: Opioid Overdose Deaths, By Type of Opioid

(a) Illicit Opioid Deaths

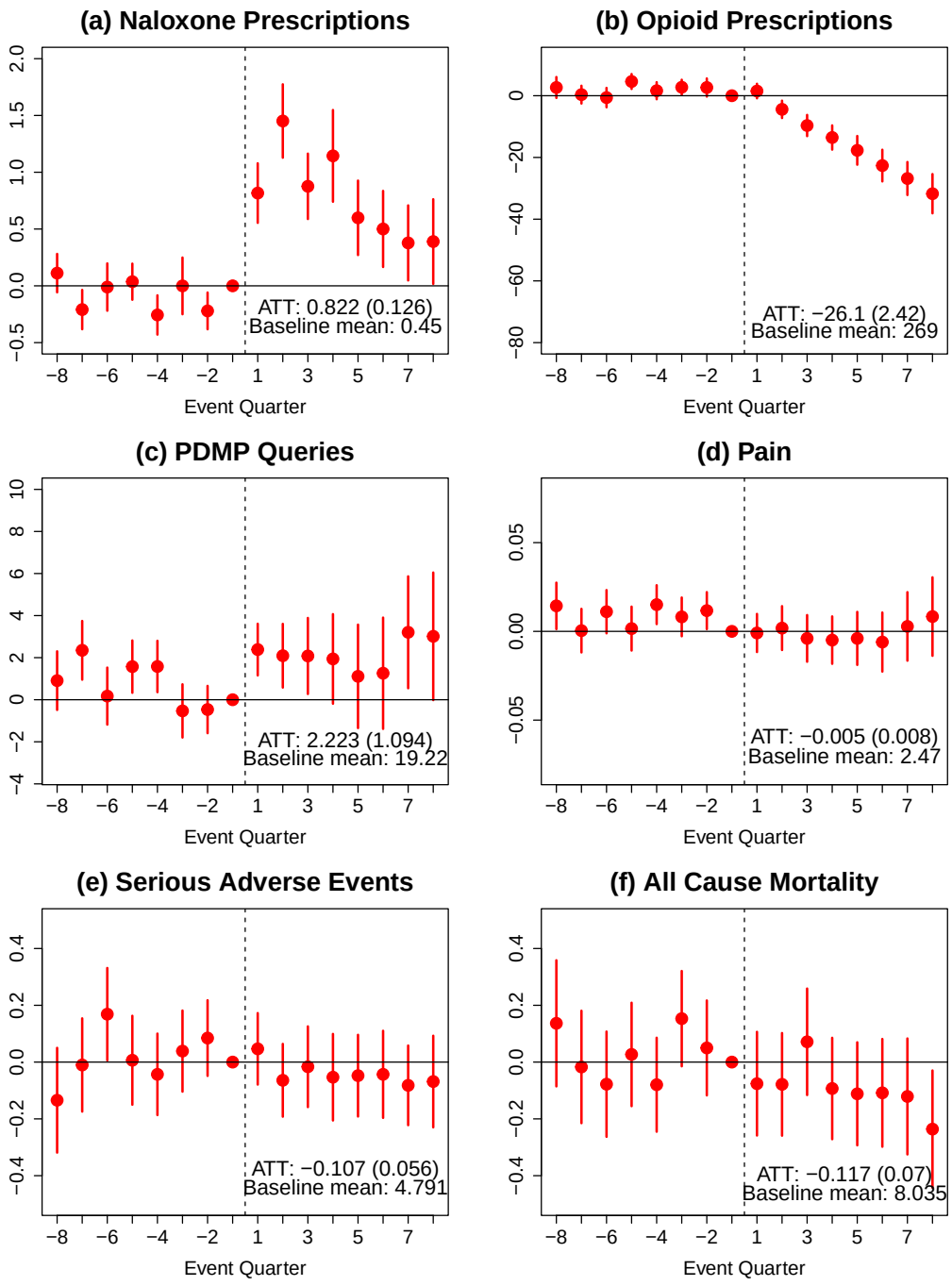


(b) Prescription Opioid Deaths



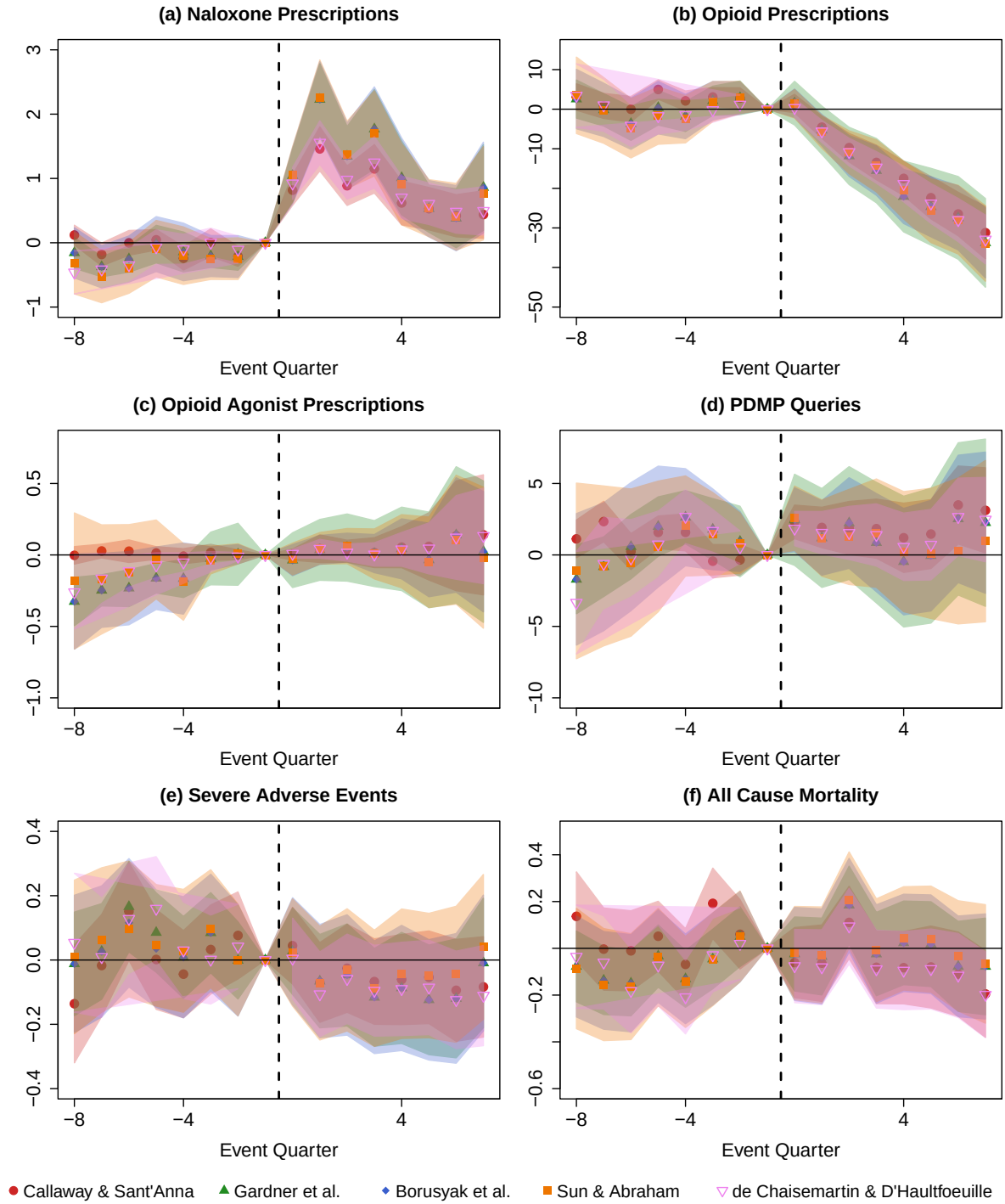
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for deaths by illicit opioids (heroin and synthetic non-methadone opioids; ICD10 T40.1 and T40.4 cause of death codes) and prescription opioids, per 1,000 primary care patients, using the methodology in Callaway and Sant'Anna (2021). The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Figure D.13: Select Main Outcomes Using Later Treated (Not-Yet-Treated) as Control Group



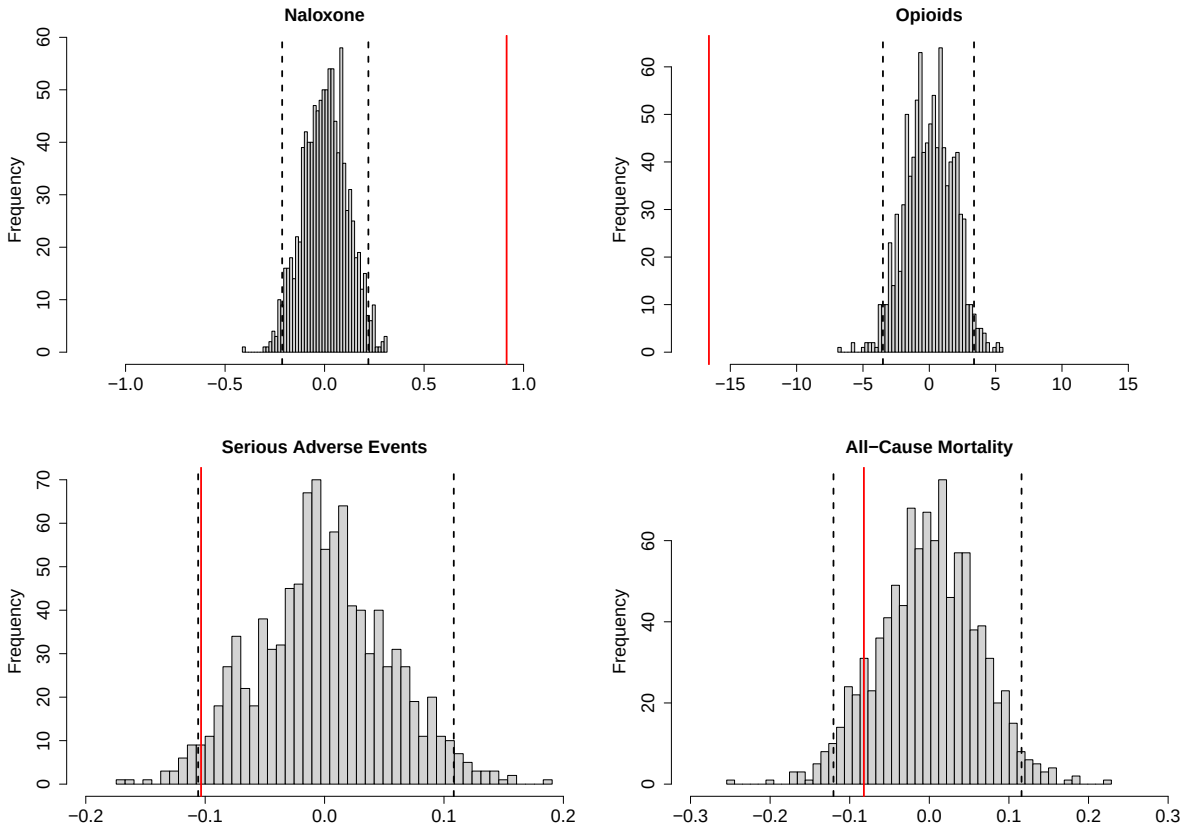
Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for select main outcomes with later (not-yet-treated) treated PCP teams as the control group using the methodology in Callaway and Sant'Anna (2021). Recall that the main specifications only use never-treated patients as the control group. Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients.

Figure D.14: Alternate Staggered Treatment Difference-in-Differences Estimators



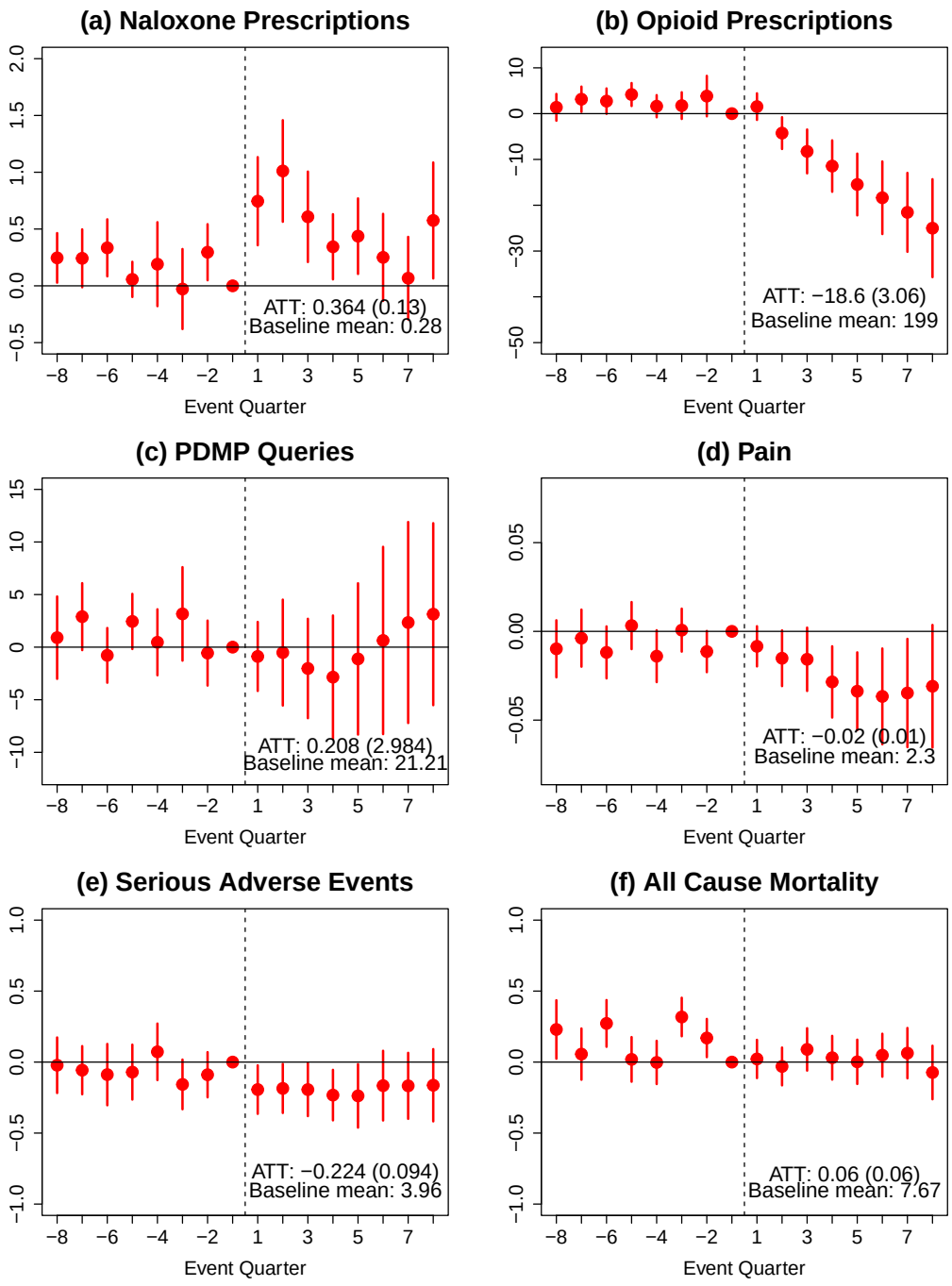
Notes: This figure plots the event study coefficients and associated 95% confidence bands based on various estimators: Callaway and Sant'Anna (2021), Gardner et al. (2024), Borusyak et al. (2022), Sun and Abraham (2021), and De Chaisemartin and D'haultfœuille (2023). The main outcomes are: number of naloxone prescriptions, opioid prescriptions, opioid agonist prescriptions, PDMP query checks, serious adverse events, and number of patient deaths from all causes. All outcomes are measured in units of per 1,000 pre-detailing primary care patients.

Figure D.15: Falsification Permutation Test



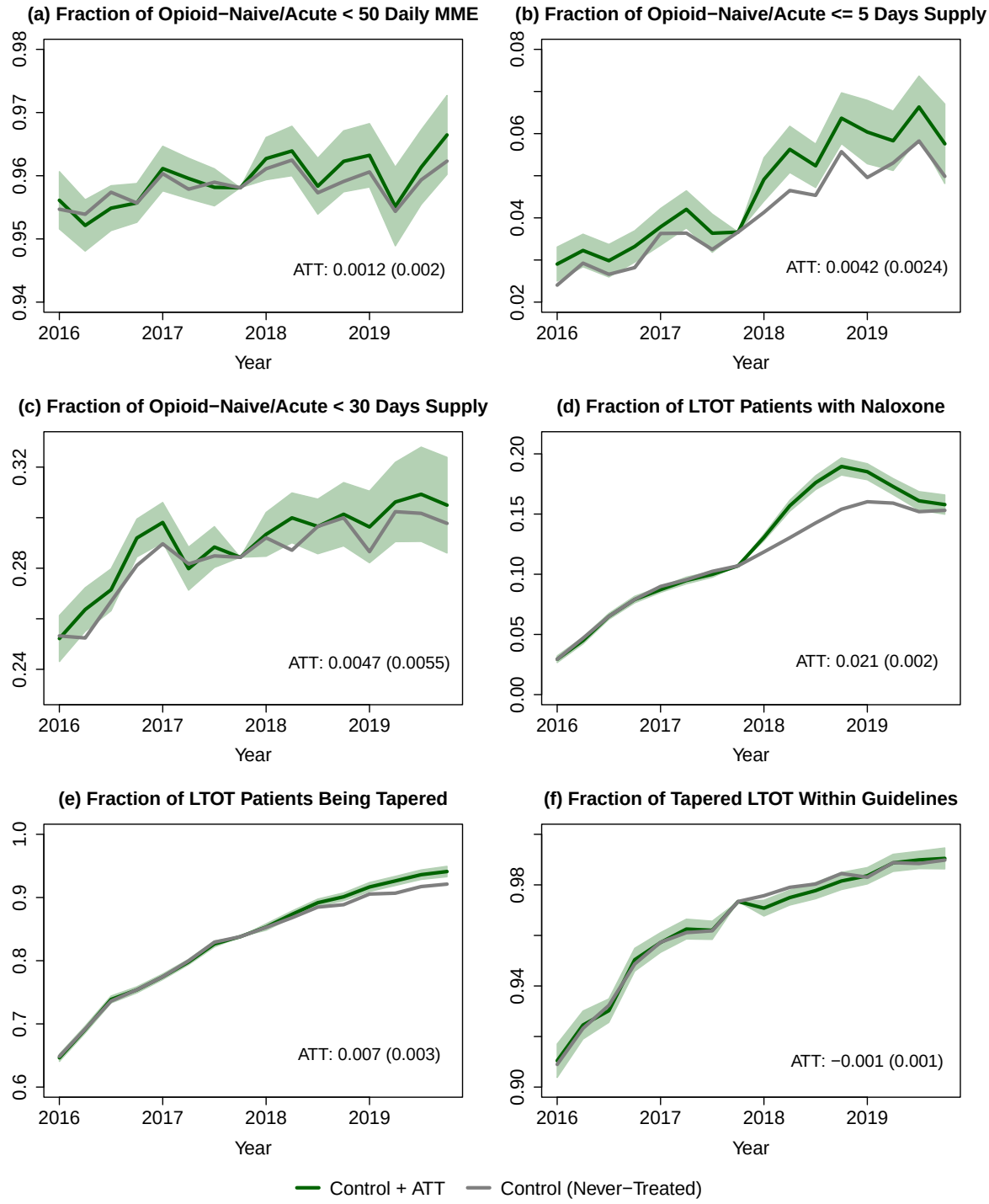
Notes: This figure plots the results of a falsification permutation exercise where PCPs are randomly assigned treatment (detailing) status such that the number of PCPs detailed each quarter is consistent with what is actually observed. For each randomization, the baseline treatment estimate is stored. This procedure is repeated 1,000 times and the distribution of the treatment estimates are plotted. The two dash lines correspond to the top and bottom 2.5% of the treatment values and the solid red line corresponds to the actual treatment effect. Note that the figures for naloxone and opioids are zoomed out so the actual treatment value fits in the figure; the test statistic for these two outcomes is approximately 8.

Figure D.16: Exploring SUTVA: Treating Primary Care Clinics as an Unit



Notes: This figure displays event study coefficients of average treatment effects on the treated by length of exposure in quarters for select outcomes using the methodology in Callaway and Sant'Anna (2021), aggregating PCP teams to primary care clinics. PCP teams are assigned to their primary care clinic (803 clinics) and the average of that clinic (per 1,000 pre-detailing primary care patients) is calculated; their treatment date is the earliest date that any PCP team is detailed. There are 220 never-treated clinics (none of the PCP teams receive detailing). Outlier clinics with more than 50 PCP teams are dropped.

Figure D.17: Quantifying Changes in Opioid-Related Guideline Adherence Rates



Notes: This figure plots rates of opioid-related guideline adherence over the academic detailing period for the control (never-treated) and the treated groups. The gray line displays the average of each outcome (guideline metric) between 2016 and 2019 among the never-treated PCPs. The green line displays the control average plus the eight quarters lead and lag event study coefficients obtained from Callaway and Sant'Anna (2021). Panels a-c display the fraction of a PCP's opioid naïve and acute opioid patients (defined as having an opioid prescription following a three-year period where the patient was never prescribed over 30 days supply total) who are never prescribed more than 50 daily milligrams of morphine equivalents (MME), more than 5 days supply, and more than 30 days supply in a quarter. Panels d-f display the fraction of a PCP's long-term opioid therapy (LTOT; defined as four consecutive quarters of 60 or more days supply averaging at least 25 daily MME) patients who have had at least one naloxone prescription in the prior year, are receiving fewer opioids (measured via total MME) than the previous quarter, and are receiving no more than a 51.2% reduction in total MME over the previous quarter. The VA recommends an upperbound of no more than 20% tapering per month which equals 51.2% per quarter. Patients are grouped into opioid naïve and acute opioid or LTOT patients based on pre-detailing (fiscal year 2014) measures. There are 4,281,222 opioid naïve or acute opioid patients and 333,247 LTOT patients. Average treatment effect on the treated (ATT) over the eight post quarters are reported along with doubly robust standard errors in parentheses.

Table D.1: Encounters: PCP Teams Do Not Meaningfully Alter Number of Visits, Encounter Days, Patients Treated, or Likelihood of Recording Pain Scores

	Dependent variable:			
	Visits (Counts)	Encounter Days (Counts)	Patients (Counts)	Frac. Visits w/ Pain Score
	(1)	(2)	(3)	(4)
ATT	−17.43	0.88***	−1.97	0.0020
	(11.59)	(0.12)	(5.75)	(0.0011)
Pre-Detailing Mean	2,184.9	69.0	1,059	0.73

Notes: This table displays the average treatment on the treated effects and its associated standard errors from a Callaway and Sant'Anna (2021) estimator for various subsamples and select outcomes. The outcomes, at the PCP-quarter-level, are (from column 1 to 4): number of unique patients, number of encounter days, number of unique patients, fraction of patient primary care encounter days that have a pain score taken and recorded. The comparison group is the never-treated group and doubly robust standard errors and 95% confidence intervals are reported/displayed. Analyses are weighted by the number of patients falling into each subsample, treated by the PCP team. *p<0.1; **p<0.05; ***p<0.01.

Table D.2: Main and Heterogeneous Effects for Relevant PCP Team Subsamples

	Dependent variable:						
	Naloxone Rx	Opioid Rx	Agonist Rx	PDMP Queries	Pain Score	Serious Adv. Events	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All PCP Teams	0.915***	−16.611***	0.075	1.784*	−0.006	−0.103*	−0.081
(No. Teams: 6,416)	(0.115)	(1.970)	(0.088)	(0.924)	(0.006)	(0.052)	(0.059)
Pre-Detailing Mean:	0.447	269.406	0.434	19.221	2.469	4.791	7.359
	PCP Team Subsamples:						
Physician-Led Teams	0.910***	−19.689***	0.092	1.802*	−0.005	−0.079	−0.074
(No. Teams: 4,725)	(0.133)	(2.342)	(0.112)	(0.994)	(0.007)	(0.061)	(0.070)
Pre-Detailing Mean:	0.429	299.810	0.589	18.037	2.492	4.785	7.464
Nurse Practitioner-Led	1.288***	−16.832***	−0.001	2.121	−0.006	−0.170	−0.109
(No. Teams: 1,485)	(0.311)	(4.506)	(0.011)	(2.394)	(0.015)	(0.127)	(0.171)
Pre-Detailing Mean:	0.421	186.915	0.003	27.012	2.386	4.731	7.104
Male-Led Teams	0.919***	−20.451***	0.133	3.176***	−0.007	−0.021	−0.020
(No. Teams: 2,460)	(0.185)	(2.692)	(0.216)	(1.401)	(0.010)	(0.077)	(0.101)
Pre-Detailing Mean:	0.476	301.017	0.964	18.071	2.469	4.691	7.696
Female-Led Teams	0.822***	−11.122***	0.043	1.661	−0.009	−0.138*	−0.120
(No. Teams: 3,413)	(0.149)	(2.326)	(0.054)	(1.174)	(0.008)	(0.076)	(0.088)
Pre-Detailing Mean:	0.425	246.699	0.092	18.119	2.472	4.843	7.168
Younger (<55) Teams	0.788***	−12.644***	0.004	5.017***	−0.003	−0.114	−0.031
(No. Teams: 2,959)	(0.188)	(2.479)	(0.061)	(1.354)	(0.009)	(0.085)	(0.095)
Pre-Detailing Mean:	0.376	275.337	0.294	18.321	2.487	4.811	6.946
Older (≥ 55) Teams	0.868***	−20.998***	0.166	1.734	−0.007	0.009	−0.144
(No. Teams: 2,685)	(0.178)	(3.030)	(0.207)	(1.267)	(0.009)	(0.076)	(0.100)
Pre-Detailing Mean:	0.521	267.261	0.702	20.367	2.471	4.750	7.831
Below Median Salary	0.878***	−8.597***	−0.019	1.812	−0.012	−0.064	−0.105
(No. Teams: 2,953)	(0.177)	(2.570)	(0.058)	(1.381)	(0.009)	(0.082)	(0.105)
Pre-Detailing Mean:	0.340	229.823	0.167	18.341	2.437	4.749	7.069
Above Median Salary	0.929***	−23.146***	0.154	3.025***	−0.003	−0.130*	−0.054
(No. Teams: 2,952)	(0.177)	(2.750)	(0.167)	(1.141)	(0.009)	(0.076)	(0.090)
Pre-Detailing Mean:	0.592	325.839	0.777	19.236	2.533	5.042	7.569

Notes: This table displays the average treatment on the treated effects and its associated standard errors from a Callaway and Sant'Anna (2021) estimator for various PCP team subsamples and select outcomes. PCP team subsamples are classified based on the PCP's characteristics and the number of PCP teams are reported. Physician led teams include both medical doctors (M.D.) and doctor of osteopathic medicine (D.O.). Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients. The outcomes are (from column 1 to 7): number of naloxone prescriptions, number of opioid prescriptions, number of agonist prescriptions, number of PDMP checks, average pain scores, number of serious adverse events (emergency department visits and hospitalizations for accidents including overdose poisonings and suicide attempts), and number of deaths per quarter among all patients falling into the sample criteria. The treatment group is the specific PCP team subsample and the comparison group is all never-treated PCP teams; 95% confidence intervals are reported/displayed. Analyses are weighted by the number of patients treated by the PCP team. I do not observe characteristics for some PCPs. *p<0.1; **p<0.05; ***p<0.01.

Table D.3: Effects by Must-Access PDMP States

	Dependent variable:						
	Naloxone Rx	Opioid Rx	Agonist Rx	PDMP Queries	Pain Score	Serious Adv. Events	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MA-PDMP	−0.147	−30.415***	0.017	8.019***	−0.022	−0.306***	−0.262
(No. Teams: 1,198)	(0.399)	(4.833)	(0.185)	(3.575)	(0.016)	(0.128)	(0.182)
Pre-Detailing Mean:	0.347	226.994	0.320	48.179	2.362	4.777	8.584
No MA-PDMP	1.127***	−13.508***	0.086	0.071	−0.003	−0.065	−0.077
(No. Teams: 5,218)	(0.111)	(2.111)	(0.115)	(1.166)	(0.007)	(0.059)	(0.075)
Pre-Detailing Mean:	0.469	279.143	0.461	14.681	2.494	4.794	7.907

Notes: This table displays the average treatment on the treated effects and its associated standard errors from a Callaway and Sant'Anna (2021) estimator for PCP teams located in states with must-access PDMP laws, and those without. There are 10 must-access PDMP states by the end of 2013 (Buchmueller and Carey, 2018). Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients. Analyses are weighted by the number of patients treated by the PCP team. *p<0.1; **p<0.05; ***p<0.01.

Table D.4: Controlling for Covariate-Specific Trends

		Sequentially adding controls:		
	Baseline	+ Station	+ Panel Size Quartile Bins	+ # High Risk Patients Quartile Bins
	(1)	(2)	(3)	(4)
Naloxone Rx	0.915***	0.929***	0.940***	0.933***
	(0.111)	(0.117)	(0.119)	(0.112)
Opioid Rx	−16.611***	−16.782***	−16.915***	−15.657***
	(1.870)	(2.021)	(1.967)	(1.893)
Agonist Rx	0.075	0.079	0.078	0.083
	(0.093)	(0.092)	(0.092)	(0.099)
PDMP Queries	1.784*	1.908***	2.126***	1.857***
	(0.924)	(0.841)	(0.854)	(0.924)
Pain Score	−0.006	−0.006	−0.007	−0.005
	(0.006)	(0.006)	(0.006)	(0.007)
SAEs	−0.103*	−0.105*	−0.109***	−0.113**
	(0.052)	(0.052)	(0.053)	(0.057)
Mortality	−0.081	−0.088	−0.091	−0.092
	(0.059)	(0.064)	(0.063)	(0.061)

Notes: This table presents the baseline ATT for the main outcomes and ATT after controlling for covariate-specific time trends (conditional parallel trends in Callaway and Sant'Anna, 2021). Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients. Column 1 displays the baseline ATT with no controls ("two-way fixed effects only") and columns 2-4 sequentially add station, panel size (in quartile files), and number of high risk patient (in quartile bins) specific fixed effects. Doubly robust standard errors are displayed in parentheses. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Observations are weighted by the PCP team's patient panel size.

Table D.5: Effects by Pre-Detailing Opioid Prescribing

	Dependent variable:						
	Naloxone Rx	Opioid Rx	Agonist Rx	PDMP Queries	Pain Score	Serious Adv. Events	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Above Median	1.255***	−41.936***	0.108*	3.237***	−0.008	−0.107	−0.091
(No. Teams: 3,208)	(0.166)	(2.773)	(0.060)	(1.285)	(0.008)	(0.077)	(0.080)
Pre-Detailing Mean:	0.700	465.647	0.710	25.804	2.577	5.385	7.547
Below Median	0.457***	−17.977***	0.163	−0.191	−0.003	−0.099	−0.071
(No. Teams: 3,208)	(0.141)	(1.619)	(0.215)	(0.974)	(0.009)	(0.059)	(0.075)
Pre-Detailing Mean:	0.193	73.165	0.159	12.637	2.361	4.197	7.188

Notes: This table displays the average treatment on the treated effects and its associated standard errors from a Callaway and Sant'Anna (2021) estimator for PCP teams that were prescribing above and below median daily total MME per patient (2.1mg). Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients. Analyses are weighted by the number of patients treated by the PCP team.*p<0.1; **p<0.05; ***p<0.01.

Table D.6: Robustness to Alternate Difference-in-Differences Estimators

	Callaway & Sant'Anna (1)	Borusyak et al. (2)	de Chaisemartin & D'Haultfoeuille (3)	Gardner et al. (4)	Sun & Abraham (5)	Two-Way FE (6)
Naloxone Rx	0.915***	1.308***	0.901***	1.126***	0.939***	1.165***
	(0.105)	(0.103)	(0.116)	(0.095)	(0.115)	(0.059)
Opioid Rx	−16.61***	−18.58***	−15.86***	−14.35***	−15.68***	−12.17***
	(1.90)	(1.61)	(1.81)	(2.29)	(1.86)	(0.93)
Agonist Rx	0.075	0.152***	0.048	0.136	0.071	0.128***
	(0.087)	(0.060)	(0.065)	(0.099)	(0.075)	(0.054)
PDMP	1.784**	0.312	1.572*	1.868	1.663	1.627***
	(0.922)	(0.836)	(0.898)	(1.230)	(1.148)	(0.609)
SAEs	−0.103**	−0.128***	−0.081	−0.195***	−0.101*	−0.154***
	(0.053)	(0.036)	(0.054)	(0.040)	(0.053)	(0.030)
Mortality	−0.082	−0.002	−0.077	0.003	−0.077	0.017
	(0.065)	(0.037)	(0.064)	(0.036)	(0.062)	(0.034)

Notes: This table displays the aggregated average treatment effect on the treated based on six different estimators from columns 1 to 6: Callaway and Sant'Anna (2021), Borusyak et al. (2022), De Chaisemartin and D'haultfœuille (2023), Gardner et al. (2024), Sun and Abraham (2021), and the canonical two-way fixed effects estimator. The main outcomes are: number of naloxone prescriptions, opioid prescriptions, opioid agonist prescriptions, PDMP query checks, serious adverse events, and number of patient deaths from all causes. All outcomes are measured in units of per 1,000 pre-detailing primary care patients.

Table D.7: Difference-in-Differences: Goodman-Bacon Decomposition

		Dependent variable:					
	Weight	Naloxone	Opioids	PDMPs	Pain	SAEs	Deaths
Earlier vs Later Treated	0.154	0.682	−18.12	0.551	−0.004	−0.121	−0.009
Later vs Earlier Treated	0.136	0.976	19.84	0.658	−0.007	−0.014	0.049
Treated vs Untreated	0.709	0.105	−21.19	3.023	−0.007	−0.187	0.042

Notes: This table estimates results from the difference-in-differences decomposition following Goodman-Bacon (2021). The decomposition shows the weight placed on various treated vs control group comparisons in the canonical two-way fixed effects model and the estimate from each comparison.

Table D.8: Falsification Test: Patients with No Primary Care Visits in Year Prior to Detailing Campaign (FY2014)

	Outcome:						
	Naloxone	Opioids	Agonist	PDMPs	Pain	SAEs	Deaths
ATT	0.027***	−0.603***	0.014	0.148***	−0.001	0.010	0.434
	(0.012)	(0.239)	(0.021)	(0.065)	(0.019)	(0.074)	(0.154)
Mean Dep. Var	0.001	6.258	0.017	0.146	-	1.538	9.755
No. Patients:	780,047	780,047	780,047	780,047	780,047	780,047	780,047

Notes: This table presents ATT from Callaway and Sant'Anna (2021) for patients who did not have any primary care visit in the year prior to detailing campaign (FY2014). Patients of detailed PCPs are compared to those who are not detailed. Doubly robust standard errors are displayed in parentheses. Baseline mean is calculated in the fourth quarter of 2014, prior to academic detailing. Only pain scores taken from primary care are used and are thus its baseline mean is missing. Other than pain, all outcomes are measured in units of per 1,000 pre-detailing primary care patients. Observations are weighted by the PCP team's patient panel size.