Information Technology, Improved Access, and Use of Prescription Drugs*

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Abstract

We estimate the effects of health information technology designed to improve access to medication while limiting overuse through easier prescription renewal and improved information provision. We focus on benzodiazepines, which are commonly prescribed and effective but potentially addictive medications. We study the staggered rollout of a nationwide electronic prescribing system over four years in Finland and use population-wide, individual-level administrative data sets. We find that e-prescribing increases average benzodiazepine use due to increased prescription renewals. The increase is most pronounced for younger patients. While e-prescribing can benefit the health of elderly patients and may succeed in balancing the access-overuse trade-off, it can also have unintended health harms for younger patients, a population at a higher risk of mental and behavioral health disorders.

Keywords: Information technology, electronic prescribing, medication access, overuse, prescription renewal
JEL Codes: H51, H75, I12, I18

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1 Introduction

Ensuring access to health care is a central policy goal worldwide (WHO Human Rights 2022). Policy measures to improve access include lowering out-of-pocket costs and non-financial barriers that prevent patients from seeking the care they need. Such unmet needs for care are common in European and other high-income countries, particularly among population groups at a higher risk of poor health and lower social status (Eurostat 2021; Hawks et al. 2020; Patel and Prince 2010).

Although access-improving policies are intended to mitigate unmet care needs, they can also expose some patients to the overuse of medical services, with fewer health benefits than health harms. The overuse of medical services is a widely recognized problem worldwide (Brownlee et al. 2017). This is particularly true in the context of prescription medications with the potential for addiction and misuse—a pressing public health concern in Europe (Hockenhull et al. 2021; Novak et al. 2016) and the U.S. (UNODC 2017). Hence, improving access to medical services without exposing patients to overuse is a challenging but important trade-off to balance.

We examine a large-scale public policy of health information technology adoption designed to improve access to medication while simultaneously limiting overuse: the adoption of a nationwide and fully interoperable electronic prescribing (e-prescribing) system that digitizes all prescriptions and their renewal requests in Finland. E-prescribing improves medication access by making it easier for patients to renew prescriptions without necessarily having to visit a physician in-person. By reducing patients' hassle costs in prescription renewal, e-prescribing lowers the barriers for obtaining essential medications but can also expose some patients to medication overuse and unintended health harms. However, as e-prescribing also provides physicians with better information on a patient's prescription history through a centralized e-prescription database, it can prevent medication overuse and related health harms.

We study how the information technology adoption balances the access-overuse trade-off for patients treated with benzodiazepines, which are commonly prescribed, effective, but also potentially addictive mental health and insomnia medications. We use the plausibly exogenous rollout of the nationwide e-prescribing system across all Finnish municipalities over the years 2010–2013 and population-wide, individual-level administrative data sets on benzodiazepine prescriptions and hospital discharges during 2007–2014. Using a difference-in-differences strategy, we estimate the effects of the access-improving technology on benzodiazepine use and downstream health outcomes.

Benzodiazepines have characteristics that make them relevant for studying the access-overuse

trade-off in medical services. Benzodiazepines are included in the World Health Organization's (WHO) 2021 Model List of Essential Medicines and are therefore intended to be always accessible in well-functioning health care systems. Accordingly, and reflecting the high prevalence of mental disorders and insomnia, benzodiazepines are among the most widely used psychotropics in high-income countries (Olfson et al. 2015; Votaw et al. 2019). When appropriately prescribed and used, benzodiazepines can provide health benefits because they are a highly effective treatment for often disabling disorders, such as anxiety, panic disorder, and insomnia (Hirschtritt et al. 2021). When overused or misused, benzodiazepines can cause adverse drug effects such as poisoning and physical dependence, with increased tolerance over time.[1] Long-term use of benzodiazepines increases the risk of these health harms (Hirschtritt et al. 2021), and this is what prescription renewals can facilitate.

Our intention-to-treat (ITT) estimates show that the nationwide e-prescribing system has little effect on the probability of initiating benzodiazepine treatment at the extensive margin.[2] In contrast, at the intensive margin, we find that the total amount (duration) of benzodiazepine use per patient increases by 3% and there is also a 7% increase in the long-term use of benzodiazepines after the adoption of e-prescribing. These increases at the intensive margin of benzodiazepine use result from increased prescription renewals, consistent with e-prescribing improving access to medication through easier renewal.

We also find substantial response heterogeneity in the effects of the technology adoption across different age groups. The quantitative magnitude of the increase in the total amount of benzodiazepine use is over twice as large for younger patients (aged 18–39) as for the elderly (age over 65). Despite the improved access, we find little substantive evidence of improvements in patients' general health outcomes such as emergency department visits and mental health outcomes.[3] Rather, we demonstrate that hospitalizations for certain adverse drug effects—which measure health harms related to overuse or misuse—increase substantially in the younger population, but decrease among the elderly.

Overall, we find that e-prescribing is particularly effective in improving access to medication for younger patients, who have higher rates of unmet health needs and mental health disorders

[1] Non-adherence (not following the recommendations from a health care provider) refers to taking medication more or less than recommended by a physician and it also includes prescription drug misuse. Non-adherence is common for patients with major psychiatric disorders (Semahegn et al. 2018).

[2] The take-up of e-prescriptions was voluntary during our observation period. Approximately 50% of benzodiazepine prescriptions were issued electronically on average one year after the technology adoption.

[3] There is a temporary decrease in hospitalizations for younger patients during the first year of adoption when the increase in their benzodiazepine use was still relatively small.

(Alonso et al. 2007; Kullgren et al. 2012; Kessler et al. 2010). However, as younger patients are also at a higher risk of prescription drug misuse (CDC 2019), improved access may expose some of them to medication overuse and unintended health harms. In contrast, for the elderly, we find that e-prescribing can prevent health harms from adverse drug effects, consistent with an improvement in information provision and potential success in balancing the access-overuse trade-off.

We contribute to the literature studying the effects of health information technologies. Only little large-scale evidence of these effects exists, since nationwide health information systems are rare and costly to implement, and high-quality administrative data are often limited to a specific region, payer, or policy program, such as Medicare fee-for-service. Existing research has evaluated the effects of electronic medical records (EMRs) (Miller and Tucker 2011; Agha 2014; McCullough et al. 2016; Atasoy et al. 2017, 2019) and prescription drug monitoring programs (PDMPs) (Buchmueller and Carey 2018; Grecu et al. 2019; Kim 2021; Ellyson et al. 2022). EMRs and PDMPs are, however, information-improving technologies. In contrast, we study a nationwide, interoperable e-prescribing system that improves both medication information and access. Our paper complements an earlier study on the nationwide e-prescribing system showing how information integration enhances physician coordination in the co-prescribing of harmful non-addictive drug combinations (Böckerman et al. 2023). Our paper focuses on a distinct economic question: how technology adoption balances the access-overuse trade-off, which is particularly salient for patients treated with psychotropics and addictive medications. When considered in combination, these two papers allow us to draw broader policy conclusions on e-prescribing and health information technologies.

More broadly, our findings on the relative importance of access and information are novel contributions to the literature on health care and welfare program design, access, and targeting. Research on health care access has mainly focused on the impacts of prices, information, and changes in the availability of health care and treatment options (Cohen et al. 2015; Alpert et al. 2018; Hamilton et al. 2018). In contrast, we study the impacts of health information technology affecting access, overuse, and targeting through reductions in hassle costs and improvements in information provision. Thus, we also contribute to the literature on ordeal mechanisms examining how transaction or hassle costs borne by participants can help with program targeting (Nichols and Zeckhauser 1982; Zeckhauser 2021; Finkelstein and Notowidigdo 2019; Iizuka and Shigeoka 2022). As suggested by our results, reducing the hassle costs of prescription renewal without an in-person physician visit improves medication access but may weaken monitoring and targeting for some patients using high-risk medications — despite of better prescription information.

2 Institutional Background

2.1 Finnish Health Care System

Finland has a decentralized, tax-financed health care system, in which the National Health Insurance Scheme (NHI) covers all Finnish residents. The public sector overwhelmingly dominates the provision of health care services.[4] By law, municipalities ($N = 304$ in 2014) are responsible for organizing primary care for their residents at the local level. Each municipality also belongs to one of the 20 hospital districts that organize specialized (hospital) health care. The resources for public sector health care services are rationed and waiting times are typically long (Keskimäki et al. 2019).

Public primary care is provided by municipalities, and every resident of the municipality is entitled to its primary care services. Patients usually visit the geographically closest primary care units in their municipality rather than those more distant. Unlike health care systems in some other countries, no law requires or enables physician choice in primary care in Finland. Consequently, patients have limited influence on which physician they are assigned to and are limited in choosing the physician who treats them and prescribes medication.

Because service delivery and decisions related to organizing health care services are distributed across distinct regional providers (municipalities), the health care system in Finland is highly fragmented. Fragmentation led to health information systems that were incompatible with each other and operated independently within a region or even a single health care unit. In 1995, the Finnish government set an ambitious policy goal of integrating and digitizing health care services nationwide (Hyppönen et al. 2015). A nationwide fully interoperable e-prescribing system with easier renewal of prescriptions and e-prescription information accessible by all health care providers was a central element of this policy.

2.2 Mechanisms Related to E-prescribing

E-prescribing is widely used but understudied health information technology that digitizes prescriptions and transfers information between physicians and pharmacies and allows them to electronically request prescription renewals.[5] Below we describe the key mechanisms through which interoperable

[4] In 2014, public primary and specialized health care accounted for approximately 50% of Finland's health care expenditures. In contrast, private health care covered by NHI accounted for only 5% of health care expenditure, and employer-sponsored health care provided by the private sector accounted for 3% ofexpenditure. (THL 2021). The remaining 42% of expenditure comes mainly from pharmaceuticals and long-term care for the elderly.

[5] A renewal is the generation of a new prescription based on a previous prescription. Prescriptions can be renewed without an in-person physician visit and e-prescribing made this much easier. In some countries, patients can also electronically request prescription refills. This means that they can order a new supply of medication without an

nationwide e-prescribing systems can affect prescription drug use and downstream health outcomes.

E-prescribing and Access.—E-prescribing systems can improve medication access by making it easier for patients to renew their existing prescriptions. Before e-prescribing, a patient had to deliver an existing paper prescription at a health care unit or pharmacy for prescription renewals and renewed prescriptions were transferred between physicians and pharmacies, for example, by fax or mail.

After e-prescribing, the patient did not have to schedule an in-person physician visit for a prescription renewal; instead the patient could make a renewal request by contacting a health care unit by phone. The request can be also made via a pharmacy, which automatically transmits it to the health care unit through a computer interface.[6] In Finland, the patient cannot influence which physician the renewal request is passed to in a health care unit, and the request may be received by someone other than the physician who originally issued the prescription (Kanta 2022). After physician approval, the digital prescription is readily available and the patient can fill the prescription at any pharmacy in the country. The patient can also receive a text message informing them when the renewed prescription is available. E-prescribing therefore reduces the time and other hassle costs of prescription renewal, such as eliminating the risk of lost (paper) prescriptions. We expect the access channel to be stronger for patients who would not renew their prescriptions because the higher hassle costs are too high.

Health care systems generally permit prescription renewals for psychotropics and some controlled substances such as benzodiazepines. For example, the U.K. health care system permits prescription renewals for Schedule IV controlled substances, such as most benzodiazepines, with the normal periods of prescription validity (PSNC 2019). In Finland, benzodiazepine prescriptions can be renewed within 16 months from the issue date (Kanta 2018). Importantly, the evidence from Finnish primary care shows that issuing or renewing prescriptions without an in-person physician consultation is more common for psychotropics compared to many other groups of prescription drugs (Saastamoinen et al. 2008).

E-prescribing and Information.—Interoperable nationwide e-prescribing systems also improve the exchange of prescription information both within and across provider organizations. In contrast to providers' pre-existing incompatible and incomplete health information (such as EMR) systems,

in-person physician visit for an existing prescription. When a prescription has expired or has no medication or refills left, it has to be renewed. In Finland, patients can renew, but not refill, prescriptions.

[6]Some e-prescribing systems or online pharmacies in other countries permit patients themselves to make electronic renewal requests. In Finland, electronic renewal requests were introduced into the e-prescribing system in 2015, which is outside of our observation period.

the nationwide e-prescribing system provides physicians with access to a patient's complete e-prescription history.[7] Thus, the system reduces the likelihood of a physician not knowing about the patient's previous prescriptions. The benefit of improved information can, however, be relatively small in the first year after the adoption of the e-prescribing system, because the system only includes information on the e-prescription history and it takes time for the e-prescription data to accumulate in the system.

Net Effects of E-prescribing.—The net effects of e-prescribing (improved access and information) on prescription drug use and downstream health outcomes are ambiguous *ex ante*. Improved access through easier renewal should increase the total amount or duration of medication use per patient at the intensive margin. By increasing persistence with essential medical treatment, e-prescribing can improve patient health. Easier renewal without an in-person physician visit can, however, also expose some patients to medication overuse and unintended health harms.

Improved information on a patient's prescription history through a centralized e-prescription database can, on the other hand, reduce the risk of medication overuse. Prescription information can help physicians to pay attention to the health benefits and harms of medications such as adverse drug effects. Consequently, physicians may prescribe more medication to patients who are expected to benefit from additional medication, and less medication to those at risk of medication overuse and health harms.[8] Thus, improved information can improve health outcomes and prevent health harms from adverse drug effects, with ambiguous effects on medication use *ex ante*.

2.3 Staggered Adoption of Nationwide E-prescribing System

We evaluate the rollout of the nationwide e-prescribing system across all municipalities in Finland. The unified standards and interoperability of the fully integrated nationwide system enable access to a centralized prescription database that has the records of all filled and unfilled e-prescriptions for all physicians and pharmacies involved in a patient's care. This access, however, requires a patient's permission.[9] The system includes all pharmacies and providers (public or private), and

[7]The Finnish e-prescribing system does not record past paper prescriptions or information on diagnostic and related notes taken by physicians during the appointment. The information about diagnostic and related notes taken by physicians is recorded and available only locally in the health care unit treating the patient. Notably, the e-prescribing system does not contain warnings on controlled substances or other decision-supporting tools for physicians. Online Appendix Figure A2 in Böckerman et al. (2023) illustrates the prescription information available in the Finnish health care provider setting.

[8]Physicians may use information in deciding whether to renew an existing prescription, switch to a different medication or initiate a new medical treatment.

[9]The Finnish law enacted on April 2014 made it possible for physicians to access information on prescriptions for central nervous system drugs without a patient's permission. In practice, physicians were obligated to act in

enables them to electronically prescribe and renew prescriptions.

We focus on the adoption of e-prescribing in primary care for three reasons. First, prescription renewal and related preventable harms are pertinent in primary care settings worldwide (Duncan et al. 2014; Price et al. 2017). Second, the literature has shown that primary care physicians write most prescriptions, especially for benzodiazepines (Cascade and Kalali 2008). Third, in Finland, there was substantial regional variation in the adoption time of e-prescribing in (public) primary care, stemming in part from the fragmented nature of the primary care system and the decentralization of its organization across municipalities (Section 2.1).

Figure 1 documents the staggered adoption of the e-prescribing system across all municipalities and over the course of four years (2010–2013) before the system became mandatory in public health care in 2014. The figure shows the earliest municipality adoption time at the half-year level, and we also use this level of precision in our estimations. Even though there was some geographical clustering in the policy adoption, the adoption time still varied substantially across regions.[10] The e-prescribing system was first adopted in 2010 by the sixth largest municipality in Finland, and by the first half of 2013 all municipalities had adopted the new system.

According to our government expert interviews, the regional variation in the adoption time was driven mainly by difficulties in integrating the e-prescribing system with the pre-existing information technology systems in local health care units, not by regional differences in patient outcomes. The adoption was gradual across municipalities, because the implementation of a national and fully standardized system required substantial investments in information technology infrastructure, tailoring software, and a skilled workforce in each municipality. To support the findings from the government expert interviews and the credibility of our research design, Böckerman et al. (2023) show that the adoption time is unrelated to municipality-level covariates such as measures of prescription drug use and morbidity in the pre-adoption period.

2.4 Benzodiazepine Market

Benzodiazepines are one of the most widely used psychotropics in high-income countries (Olfson et al. 2015). They are commonly used in the adult population to treat mental health disorders

accordance with the law from November 1, 2015 onwards, which is outside of our observation period.

[10] In practice, these clusters are caused by municipalities being affiliated with one of the hospital districts that coordinate some of their specialized care activities. This clustering is not a threat for identification of the effects, because there is also relevant variation for identification within hospital districts. The clustering can, however, affect statistical inference. For this reason, we show the robustness of our standard error estimates for the geographic clustering of the policy adoption at the hospital district level (Section 6.3).

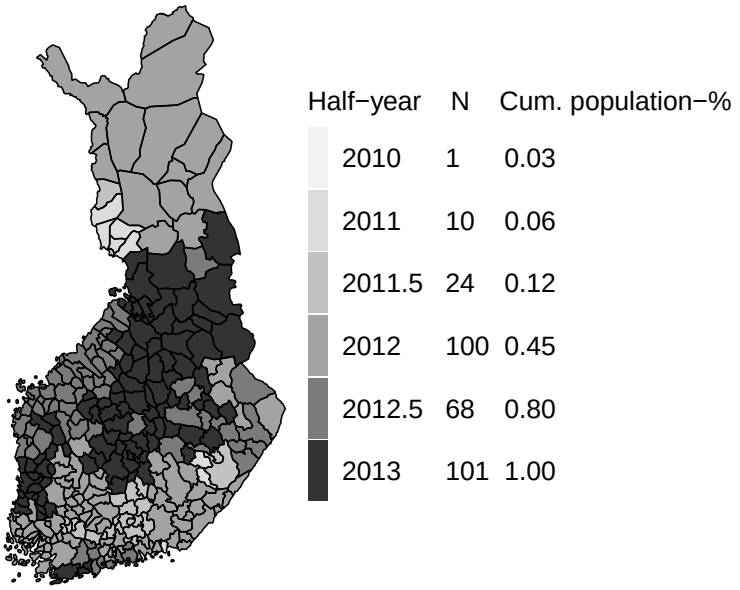


FIGURE 1: E-prescribing Adoption Half-Year in Municipalities

Notes: The figure plots the half-year when e-prescribing was adopted by a municipality in the primary care setting. The figure also shows the number of municipalities and the cumulative population share by adoption half-year. Source: Finnish Institute for Health and Welfare, and Statistics Finland: Population Statistics.

and insomnia. In Finland, the top five active ingredients (benzodiazepine drugs) based on 2014 sales measured in euros were alprazolam (e.g., Xanax), diazepam (e.g., international brand name Valium), oxazepam (e.g., Serax), temazepam (e.g., Restoril), and zopiclone (e.g., Imovane) (Fimea 2015).[11] Notably, nearly 10% of all Finnish adults had used benzodiazepines in 2014 (Kurko et al. 2018). For comparison, the prevalence of benzodiazepine use within a year has reached 20% in France (Airagnes et al. 2019), approximately 10% in Norway (Holm et al. 2012), and 5% for U.S. adults (Olfson et al. 2015).

Benzodiazepines are effective medications for treating often disabling disorders such as anxiety, panic attacks, insomnia or sleeping disorders, as well as depression when anxiety is involved (Quagliato et al. 2018; Hirschtritt et al. 2021).[12] Thus, the appropriate use of benzodiazepines can improve patient health outcomes, for example reducing hospital admissions related to mental disorders.

Health harms through adverse drug effects indicate medication overuse. Benzodiazepines may

[11]The wholesale value of benzodiazepines was EUR 13.7 million in that year, with a market share of approximately 17% of the wholesale value of all psycholeptics.

[12]Benzodiazepines are also used to treat other conditions and disorders such as epilepsy, alcohol withdrawal, and chronic pain (Cheatle and Shmuts 2015).

cause sedation, a decline in cognitive functions and delirium (Lader 2011). Benzodiazepine poisoning is characterized by excessive sedation for example, and may result after an overdose and the use of medication in large amounts. Moreover, long-term use of benzodiazepines may lead to physical dependence and abuse, with strong withdrawal symptoms and increased tolerance over time (Lader 2011; Votaw et al. 2019). Clinical treatment guidelines generally recommend not using benzodiazepines for more than 2–4 weeks (FCCG 2022). Despite these guidelines and health harms, long-term use of benzodiazepines is common in Finland (Kurko et al. 2018) and generally in Europe (Huerta et al. 2016).

Because mental and behavioral health disorders are on the rise globally, benzodiazepines are a relevant drug class for studying how a public policy of health information technology adoption succeeds in balancing the access-overuse trade-off in medical services. Misuse of benzodiazepines is prevalent in Europe and the U.S., and these medications are commonly involved in poisonings, overdose deaths, and emergency department visits related to non-medical misuse of prescription drugs (Jones and McAninch 2015), especially when combined with alcohol and opioids.[13] However, research on medication misuse has mostly focused on the opioid epidemic in the U.S. and policies such as the adoption of information technologies aimed at curbing it (Maclean et al. 2022; Buchmueller and Carey 2018; Ellyson et al. 2022). Notably, global consumption of opioids is concentrated in the U.S. (PPSG 2015). In Finland, opioid prescribing is heavily regulated and opioid consumption is much smaller compared to benzodiazepines (Fimea 2015). More generally, less focus has been placed on other important potentially addictive psychotropics such as benzodiazepines, their impact in countries other than the U.S., and the role of access-improving policies in causing the overuse or misuse of these medications.

3 Data

We use comprehensive, individual-level de-identified administrative data sets for patients treated with benzodiazepines to analyze their prescription drug use, renewals, and downstream health outcomes at the intensive margin. We also use de-identified individual-level data on the entire Finnish

[13]There is no systematic information on the size of the illicit market for benzodiazepines in Finland (Rönkä and Markkula 2020). According to our interview with an expert at the Police of Finland, the total number of seized benzodiazepine tablets was 517,000 in 2021, and there has been an increase in the total number of seized tablets in recent years. To date, a substantial and increasing fraction of seized benzodiazepine tablets come from unofficial online purchases. Thus, the regional availability of illicit drugs is much less important now. We show later the robustness of our baseline results to controlling for municipality-specific linear time trends that capture, for example, the general changes in regional illicit markets (Section 6.3).

adult population to study their first-time benzodiazepine use at the extensive margin. We define benzodiazepine patients as those who have at least one dispensed benzodiazepine prescription in the years 2007–2014.[14] We focus on adults who are at least 18 years of age because the prevalence of benzodiazepine use is remarkably low among individuals younger than 18 years of age, who only represent approximately 2% of all of our observations. We construct all our variables for each individual (patient) and half-year period to find a balance between the accuracy of the adoption time of e-prescribing and observing variation in benzodiazepine use and downstream health outcomes.[15] Next, we provide an overview of our data sets and describe the main variable construction. Details on the drug classes and ICD-10 diagnosis codes used for variable construction are in Online Appendix A.

3.1 Measures for Benzodiazepine Use

We use prescription data from the Social Insurance Institution of Finland. The data include all benzodiazepine prescriptions dispensed at Finnish pharmacies and covered by NHI over the period 2007–2014.[16] The de-identified data record for each patient includes the date of birth (age), the date of death (mortality), and the municipality of residence based on the 2014 municipality classification. These data also include records for each dispensed prescription, with the coded patient and physician identifiers, the Anatomical Therapeutic Chemical (ATC) code, the prescription date, the strength of the drug, the route of administration, and the number of defined daily doses (DDD) dispensed.

We identify individual prescriptions based on the unique patient and physician identifiers, the ATC code (active ingredient), and the prescription date. We define a prescription as renewed if the prescribed drug is essentially the same as the two previous prescriptions with the same ATC code, strength, and adminstrative route, and the renewal is made within 16 months (renewal of an electronic prescription for benzodiazepines must be requested within this time period in Finland). If a prescription is not renewed, we define it as new. Our results are robust to the exclusion of the

[14] We use this rather loose definition of benzodiazepine patients because prescription renewal and health outcomes can sometimes materialize long after the initial prescription (e-prescriptions for benzodiazepines must be renewed within 16 months). However, this loose definition comes at the expense of precision (in our data, 8% of patients fill only a single prescription and the average number of prescriptions is 10).

[15] Note that the time difference between two subsequent benzodiazepine prescriptions is 129 days on average. Moreover, our benzodiazepine use (health) outcomes include zeros from half-year periods in which a patient does not have a benzodiazepine prescription (hospitalization).

[16] Our prescription data do not, however, include prescriptions given in hospitals, nursing homes, and other institutions such as palliative care clinics, where benzodiazepines are also commonly used (Malagaris et al. 2022; Peralta et al. 2022; Fimea 2015).

16-month interval rule (Section 6.3).[17]

We measure the effects of e-prescribing at the intensive margin of benzodiazepine use, that is, the total amount (duration) of medication use per patient. However, this measurement is challenging because the amount of a medication needed to produce a given effect varies across benzodiazepine drugs. For example, 15 mg of diazepam is approximately equivalent to 3 mg of lorazepam, according to the national treatment guidelines (FCCG 2022). To address this challenge, we use the World Health Organization's (WHO) DDD measure. DDD is defined as the assumed average maintenance dose per day of a drug used for its main indication in adults, providing us with a standardized unit of measurement for different types of benzodiazepines. We calculate the number of dispensed DDDs of benzodiazepine prescriptions, which is our primary measure of benzodiazepine use at the intensive margin.

We also calculate the number of dispensed prescriptions. In contrast to the number of dispensed DDDs, this measure is rather coarse because it does not capture changes in an important aspect of medication use at the intensive margin: the total amount of medication use.[18] We calculate these two measures separately for renewed and new prescriptions. To better understand the adjustment at the intensive margin, we also use additional outcomes such as those related to the long-term use of benzodiazepines (Section 6.1).

To measure the extensive margin of benzodiazepine use, we combine the prescription data with another data set from Statistics Finland using commonly coded individual identifiers. This another data set contains information on the entire adult population in Finland, also including those individuals who did not have a benzodiazepine prescription during the observation period. Using the combined data sets, we calculate the indicator of having a benzodiazepine prescription and the indicator of first-time benzodiazepine use in the entire adult population. We define a first-time user as an individual who did not have a benzodiazepine prescription during the previous 16 month-period in the prescription data. To account for left censoring, the first 16 months are excluded from the data, implying that the first biannual period for this variable is the second half of 2008 (H2:2008).

[17] We also confirmed the robustness to defining a renewal based on the previous prescription or three previous prescribing events within a 16-month interval.

[18] For example, assume that a patient fills one prescription at a pharmacy (the number of prescriptions is one). If the prescription contains one tablet of 5 mg diazepam to be taken three times a day for five days, the actual daily dose is 15 mg (3 is multiplied by 5 mg). As the theoretical DDD of the drug per day is 10 mg, then each day we have 1.5 DDDs per day (= 15 mg/10 mg). In total, the number of DDDs dispensed is 7.5 DDDs (5 days multiplied by 1.5 DDDs), corresponding to 7.5 days of *theoretical* use (10 mg per day). The number of DDDs also reflects the *actual* duration of medication use (5 days) as well as its relative amount (daily dose intensity of medical therapy), that is, the ratio of actual to theoretical daily dose (15 mg/10 mg).

3.2 Measures for Patient Health Outcomes

We also use hospital discharge data from the Finnish Institute for Health and Welfare, which contain comprehensive information on Finnish public hospital admissions and discharges from 2007 through 2014. The de-identified data record includes coded patient identifiers, the diagnosis (ICD-10 code), the date of discharge, and the patient's municipality of residence. Using the uniquely coded patient identifiers in both the hospital discharge and prescription data, we identify hospitalizations for benzodiazepine patients to analyze their downstream health outcomes in each biannual period.

However, even with our rich data it is challenging to comprehensively measure and distinguish downstream health outcomes related to appropriate use or overuse of benzodiazepines, in part because mental and behavioral health disorders generally cannot be fully cured and thus the focus of the treatment is on management of the disorder and its symptoms (Maclean 2019). We rely on the literature (Buchmueller and Carey 2018; Chen et al. 2022) to construct several medical service-related health outcomes, which are potentially associated with appropriate use and medication overuse in our setting. To gain an overview of the benzodiazepine patients' downstream health outcomes, we calculate the number of their emergency department visits, the total number of hospital visits, and an indicator of hospitalization for specific health conditions, including diagnoses of mental and behavioral disorders (henceforth mental disorders for brevity).

In addition to these general and mental health outcomes, we construct proxies for health harms from adverse drug effects and medication overuse. We calculate the indicators of the diagnoses of prescription drug abuse (PDA) disorder and prescription drug poisoning for hospitalizations. Prescription drug poisoning may result from an unintentional or intentional overdose. Prescription drug abuse is more specifically related to physical dependence and can be prevented by investigating patients' prescription histories (NIDA 2023). Although hospitalizations for prescription drug poisonings and abuse might not be exclusively attributed to benzodiazepine use,[19] both are positively correlated with the number of DDDs of benzodiazepine prescriptions (Online Appendix Figure A1). We supplement these two measures with an indicator of hospitalization with a diagnosis of other possible side effects of benzodiazepines, such as sedation, poor coordination, and cognitive function decline.

[19]These hospitalizations might result from a combination of factors such as the concurrent use of alcohol and prescription drugs.

4 Evidence on Prescribing and Health Patterns

General Patterns.—Table 1 reports the summary statistics on total benzodiazepine use and downstream health outcomes during our observation period 2007–2014. Panel A shows total benzodiazepine use and renewals per patient at the intensive margin. Adult patients purchased in total over 800 DDDs on average during the observation period. This corresponds to a theoretical use of benzodiazepines for over 800 days per patient in total or 800/8 = 100 days per patient and year.[20] The average total number of dispensed prescriptions per patient was 10. Renewed prescriptions constitute an overwhelming fraction (77%) of all dispensed benzodiazepine prescriptions. For comparison, prescription renewals are commonly issued and account for as much as 80% of prescription drug use in the U.K. (Avery 2011; Duncan et al. 2014). Panel B shows total benzodiazepine use at the extensive margin and reveals that the use of benzodiazepines is very common in the Finnish adult population: 21% of the total adult population had at least one benzodiazepine drug prescription during our observation period.

Panel C shows benzodiazepine patients' health patterns. Patient mortality is 16% on average. As expected, mortality is much higher for older patients (Online Appendix Table A1), which is likely most directly related to pain treatment in palliative care as opposed to mental health care. Moreover, 26% of benzodiazepine patients receive hospital diagnoses of mental disorders at least once during the observation period. Panel D shows that the average age of benzodiazepine patients is only a little higher (55 years) than the average age of the general Finnish adult population (49 years).[21]

Age Heterogeneity.—We study differences in the use of benzodiazepines and downstream health outcomes in the different age groups. Figure 2 documents the flexible age profiles for our main measure of total benzodiazepine use at the intensive margin: the yearly number of dispensed DDDs per patient and by age for three years (2007, 2010, and 2014) to detect possible changes in consumption patterns over time before and after the e-prescribing rollout (Online Appendix Figure A2 shows the profile for the number of prescriptions).

Figure 2 shows that the use of benzodiazepines, as measured by the number of DDDs, is more concentrated among older patients, consistent with earlier findings (Olfson et al. 2015). For patients above age 55, there also was a substantial decrease in the use of benzodiazepines between

[20] In the prescription-level data, the average DDD per prescription is 86 (SD 99).

[21] Compared with benzodiazepines, the use of hypertension and cholesterol-lowering medications, for example, is even more concentrated among the elderly population (Jackson et al. 2005), making it challenging to generalize the results to the broader (non-elderly) population.

TABLE 1: Summary Statistics for Overall Outcomes Among Benzodiazepine Patients and All Finnish Adults

	Mean	SD
Panel A. Intensive margin of benzodiazepine use (N = 1,019,405 patients)		
Total DDDs	828.64	1,666.342
Total renewed DDDs	678.654	1,439.961
Total new DDDs	149.986	355.212
Total number of rx	9.584	14.431
Total number of renewed rx	7.405	12.824
Total number of new rx	2.18	2.703
Share taking benzodiazepines	1	
Panel B. Extensive margin of benzodiazepine use (N=4,802,180 individuals)		
Share taking benzodiazepines at any time	0.212	
Share taking benzodiazepines only once	0.058	
Panel C. Health outcomes (N = 1,019,405 patients)		
Share of patients who die	0.156	
Total ED visits	5.048	10.11
Total hospital visits	24.515	49.223
Share with a mental or behavioral disorder	0.255	
Share with PDA diagnosis	0.012	
Share with rx poisoning	0.024	
Share with other side effects	0.115	
Panel D. Characteristics (2007)		
Age (benzodiazepine patients)	55	18
Age (all Finnish individuals)	49	18

Notes: "Benzodiazepine patients" refers to all adult patients who fill at least one benzodiazepine prescription during the observation period 2007–2014. Note that 27% of patients fill only a single prescription during the observation period (the average number of prescriptions is 10). "All Finnish adults" refers to all Finnish residents older than 18 years of age. The values depict the overall values during 2007–2014 with the exception of age, which was the age measured in 2007.

2010 and 2014, the two years between which e-prescribing was rolled out. A decline in long-term benzodiazepine use has also been documented in previous research in Finland (Kurko et al. 2018). Prescribing behavior for benzodiazepines has evolved over time, and that could be because of changes to mental health prescribing practices. However, Figure 2 also shows that the decrease in benzodiazepine use was much smaller among younger patients. In fact, we find that for those aged under 20, the number of DDDs increased over time.

Figure 3 documents the age profiles for the selected adverse health outcomes and shows that younger patients have much higher rates of hospitalizations for mental and behavioral disorders, prescription drug abuse, and prescription drug poisoning than other age groups (Panels B–D). Moreover, younger adults (under 40 years of age) also experienced a substantial increase in the prevalence of these adverse health outcomes and the number of emergency department visits from 2007 to 2014. Emergency department visits increased also for elderly patients (age over 65), but not as much as for younger adults.

Mental disorders are one of the highest disease burdens in Finland, and they disproportionally affect younger adults (Patana 2014). We document that younger adult patients use benzodiazepines less, despite their higher rates of mental and behavioral health disorders. Younger adults have higher rates of unmet health needs and face major barriers in accessing health and mental care despite the universal health insurance system and low financial barriers to health care access (Kullgren et al. 2012; Patana 2014; Vanheusden et al. 2008; Alonso et al. 2007). As a result, younger adults may more frequently underuse medications, which could worsen their mental health. However, the long-term use of potentially addictive drugs can lead to medication overuse or misuse, which can cause health harms. This can be particularly concerning for the younger adult population because they are at a higher risk of prescription drug misuse (CDC 2019). Access barriers seem to be less of an issue for older patients as they already more commonly use medications and thus we expect the information channel to have a larger effect for them than for the younger patients. These descriptive patterns motivate the analyses of response heterogeneity in the effects of e-prescribing in different age groups.

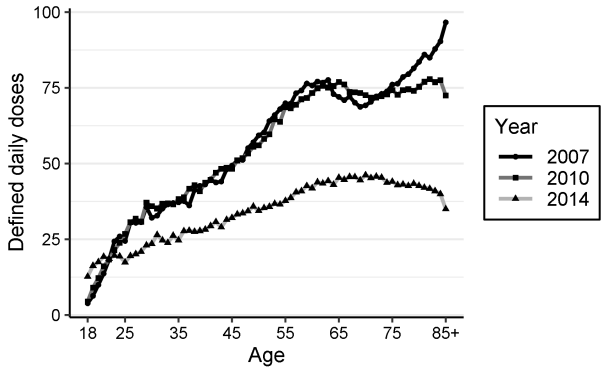
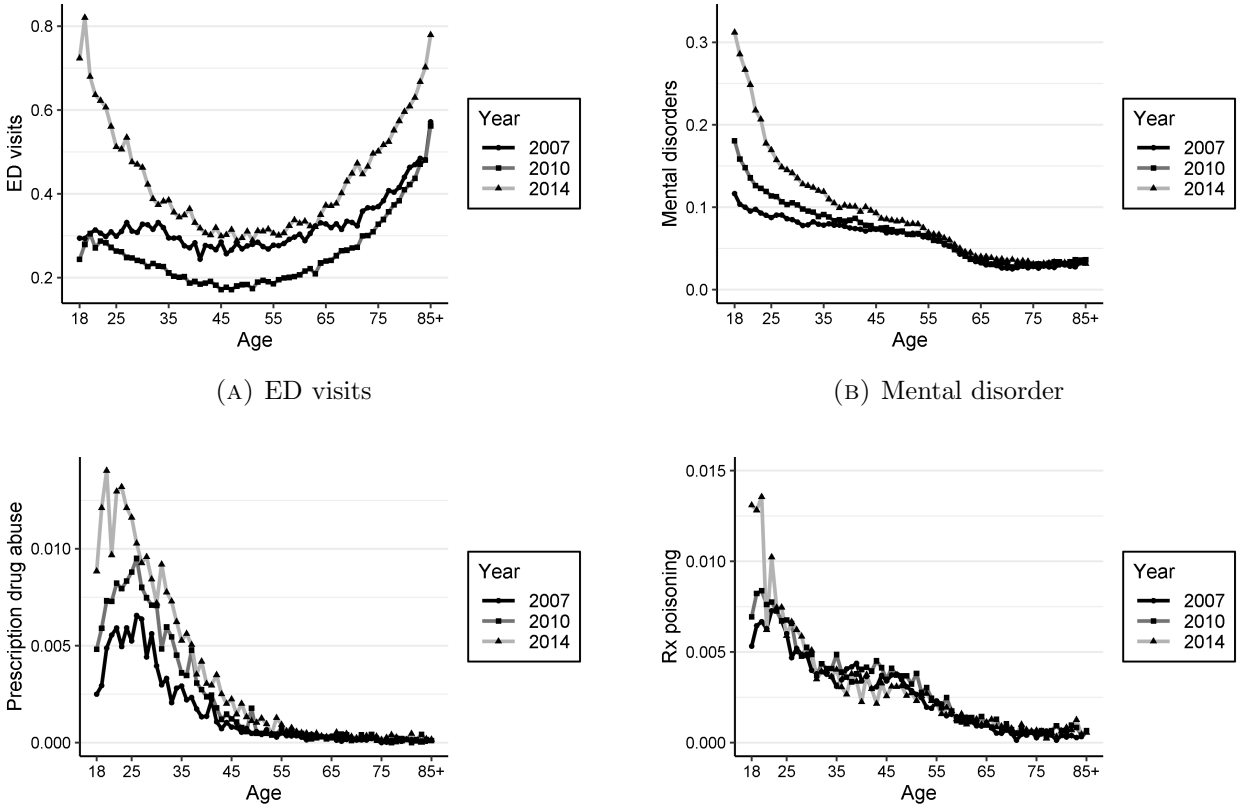


FIGURE 2: Yearly Benzodiazepine Use-Age Relationships at Intensive Margin: Number of Defined Daily Doses

Notes: The figure is based on aggregated patient biannual-level panel data. The mean total number of defined daily doses is calculated for each year (2007, 2010, 2014).



(A) ED visits

(B) Mental disorder

(C) Prescription drug abuse

(D) Rx poisoning

FIGURE 3: Yearly Health Outcome-Age Relationships Among Benzodiazepine Patients

Notes: The figures are based on aggregated patient biannual-level panel data. The mean total number of emergency department visits (Panel A) and the probability of a hospital diagnosis (Panels B–D) are calculated for each year (2007, 2010, 2014). "Mental disorder" refers to the diagnosis of mental and behavioral disorders. "Rx poisoning" refers to prescription drug poisoning.

5 Empirical Approach and Identification

Baseline Specification.—We estimate the effects of a nationwide e-prescribing system on benzodiazepine use and downstream health outcomes, using comprehensive individual (patient) biannual-level administrative data and a difference-in-differences (DiD) design based on the staggered rollout of the system across all municipalities over four years. Because e-prescribing was adopted at different times across municipalities, and all municipalities eventually adopted the technology, individuals in later-treated municipalities are used as controls for individuals in early-treated municipalities in estimating the average treatment effects. We estimate DiD models using the following two-way fixed effects (TWFE) specification:[22]

$$y_{imt} = \rho \mathbb{1}[t - E_m \geq 0] + \alpha_i + \gamma_t + \epsilon_{imt}, \tag{1}$$

where y_{imt} is a benzodiazepine-related outcome such as the number of DDDs for individual i in municipality m at time t (a period of six months). $t - E_m$ denotes the half-year periods relative to the time period of adopting e-prescribing in the individual's municipality of residence m, E_m, and $\mathbb{1}[t - E_m \geq 0]$ denotes the post-adoption indicator. We include individual and time fixed effects, α_i and γ_t, to control for individual- and time-specific factors such gender, age, and general trends in prescribing behavior.[23] We cluster the standard errors at the municipality level ($N = 304$).

The take-up of e-prescriptions by individual patients and physicians was voluntary during the 2007–2014 observation period. Hence, our approach identifies the intention-to-treat (ITT) effect of the e-prescribing policy (ρ in Equation (1)) using variation across municipalities in the adoption time. This holds to the extent that in the absence of the e-prescribing rollout, the outcomes would have evolved under parallel trends in municipalities adopting the technology at different times.

Parallel Trends Assumption and Dynamic Patterns.—One might worry about the plausibility of the parallel trends assumption in our setting, as the outcomes might have evolved differently across municipalities depending on their adoption time. Based on the descriptive and institutional evidence, the adoption time is unrelated to pre-existing, time-varying outcomes at the municipality level (Section 2.3). To conduct further visual inspections of potential pre-trends and the dynamic

[22] We follow individuals in the relevant population over time, starting after they turn 18 years until they die, making the data an unbalanced panel. Note that for benzodiazepine use and health outcomes at the intensive margin, we use all Finnish adults with at least one benzodiazepine prescription over the observation period as the relevant population ("benzodiazepine patients"). For the extensive margin outcomes, we use all Finnish adults as the relevant population (Section 3).

[23] The results do not change much if we use municipality instead of individual fixed effects.

effects of e-prescribing, we also estimate the following event study specification for individual i in municipality m in period t:

$$y_{imt} = \sum_{k} \delta_k \mathbb{1}[t - E_m = k] + \alpha_i + \gamma_t + \epsilon_{imt}, \tag{2}$$

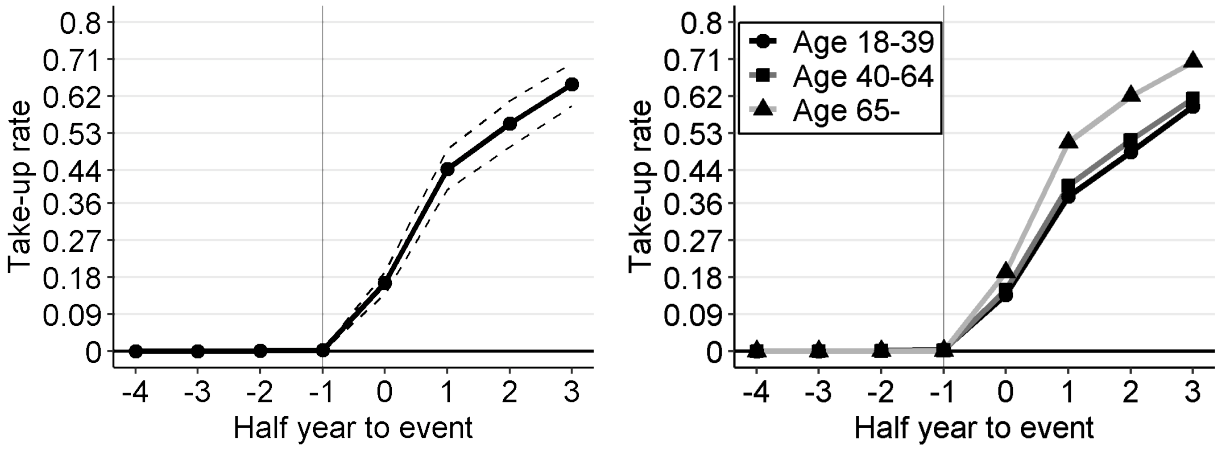
where the negative values of k indicate the pre-adoption periods and the positive values indicate the post-adoption periods. The coefficients δ_k for the pre-adoption periods $k < 0$ capture a possible pre-existing trend in the outcome variable, while the coefficients δ_k for the post-adoption periods $k \geq 0$ represent the period-specific dynamic effects of e-prescribing on the outcome. We normalize the coefficient for the indicator one period before adoption to zero, $\delta_{-1} = 0$. When there are no never-treated units in the sample, two relative time coefficients have to be normalized to avoid multicollinearity between t and E_i (Borusyak et al. 2023). Hence, in addition to $\delta_{-1} = 0$, we normalize the coefficient for the most negative (minimum) relative time indicator to zero, $\delta_{-5} = 0$, so that the coefficients for the relative time indicators can be interpreted as the mean differences from the average values of the outcomes in two specific relative periods (-1 and -5) prior to the treatment (Baker et al. 2022).[24]

Following Sun and Abraham (2021), we trim the event study graphs by analyzing the data up to five relative time periods prior to the adoption ($k = -5$) and three periods after the adoption ($k = 3$), since our data are unbalanced in relative time for some treatment units. Following a fairly balanced set of municipalities over time around the adoption mitigates changes in the composition of municipalities in distant periods and the effect of individual municipalities (early- and late-treated municipalities) on the event study coefficients.[25]

Potential Biases in TWFE models and Robustness for Treatment Effect Heterogeneity.——Although the TWFE regression similar to the one in Equation (1) is the workhorse model in the staggered DiD settings, it is not guaranteed to be a consistent estimator without a relatively strong assumption about the constant treatment effect (de Chaisemartin and D'Haultfœuille 2020; Borusyak et al. 2023; Callaway and Sant'Anna 2021). Specifically, if the treatment effect varies over time, negative weights could arise for later-treated units, potentially biasing the average treatment effect estimate downwards or upwards (Goodman-Bacon 2021; Baker et al. 2022). We address the concerns regarding potential negative weights by performing robustness checks and conclude that

[24] Binning the endpoints in the event study is an alternative approach to dropping an additional pre-treatment indicator (Borusyak et al. 2023; Schmidheiny and Siegloch 2019).

[25] Trimming also implies that the post-treatment (the pre-treatment) periods are relatively short for the first (the last) treatment units.



(A) All patients (B) By age group

FIGURE 4: Conditional Take-up Rate of E-prescriptions

Notes: The figures plot the coefficient estimates from different event study regressions using prescription-level data. Panel A shows the results for all ages and Panel B by age group (18–39, 40–64 and at least 65 years old). The outcome is a binary variable equal to one if the benzodiazepine prescription is issued electronically. Event time is the biannual period relative to the period of e-prescribing adoption by the patient's municipality of residence. The omitted period is −1. The regressions include only event dummies and do not use any additional controls. The dashed lines (Panel A) are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

negative weighting is not an issue in our application (Section 6.3). We also address the concerns about the reliability (and precision) of the TWFE estimator by employing the efficient estimator proposed by Roth and Sant'Anna (2023). Besides being efficient and robust for treatment effect heterogeneity, the estimator is computationally less demanding than many other heterogeneity-robust estimators in our application based on large individual-level data sets containing millions of observations.[26]

Take-up of E-prescriptions.—The estimated ITT effect of the e-prescribing policy may underestimate the average treatment effect on treated (ATT) because the take-up of the new technology by individuals was voluntary. Fortunately, we can use our prescription-level data to study the take-up rate of e-prescriptions by individual patients or their physicians after the patients' municipality of residence adopted e-prescribing in primary care. Figure 4 shows that the take-up rate increases sharply after adoption (Panel A): one year after adoption, approximately 50% of benzodiazepine prescriptions are issued electronically, after which the number grows gradually to around 60–70%. The take-up rate is also very similar in the three age groups, with only a slightly higher take-up

[26]Similar to other DiD and event study estimators developed for staggered research designs, such as Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfœuille (2020), the estimator by Roth and Sant'Anna (2023) is based on comparisons between newly treated and not-yet or never-treated units.

among the elderly patients (Panel B). We conclude that low take-up rates or differences in take-up rates across age groups are unlikely to explain our findings.

6 Results

We report our results on the effects of e-prescribing on benzodiazepine use in Section 6.1 and downstream health outcomes in Section 6.2 based on the baseline TWFE specification presented in Equation (1). We present only the most relevant dynamic patterns using the event study plots from Equation (2) in the main text and, for brevity, include the remaining figures in the Online Appendix. In addition to the average effects, we also explore the response heterogeneity of e-prescribing across different age groups (18–39, 40–64, and 65 years and older).[27] Finally, we show the robustness of our results for alternative specifications and estimators, study additional mechanisms, and conduct a placebo test (Section 6.3).

6.1 Effects on Prescription Drug Use

Defined Daily Doses at the Intensive Margin.—Table 2 reports the effect estimates on the total amount of benzodiazepine use per patient at the intensive margin.[28] We find that the use of benzodiazepines, as measured by the number of DDDs increases by 3% on average compared to the outcome mean after the adoption of e-prescribing (Column 1 of Panel A). In absolute terms, the average increase is approximately 2 DDDs, corresponding to 2 days of theoretical use.

Panels B–D of Table 2 reveal a substantial response heterogeneity in the effects of e-prescribing. The quantitative magnitude of the increase in benzodiazepine use is over twice as large for the younger as for the elderly patients (2.4 versus 1 DDDs or 8% versus 1%). The estimated event study coefficients in Figure 5 show that the increase is gradual in each age group, coinciding with the increasing take-up rate of e-prescribing over time (Figure 4). Importantly, they show little evidence of deviations from the parallel trends assumption.

Mechanism: Improved Access through Easier Renewal.—Consistent with e-prescribing improving access to medication through easier renewal, we find that the increase in the total amount of

[27]Note that we do not include age as a control variable in our baseline specification because the variation in it is absorbed by individual and time fixed effects. Nevertheless, we checked that the age composition did not change after e-prescribing by regressing patient age on post-adoption indicator and municipality (instead of patient) fixed effects and time fixed effects. The coefficient estimate for the post-adoption indicator was equal to zero (-0.000) and statistically insignificant (SE: 0.024, mean age: 56.654).

[28]Recall that benzodiazepine patients are defined as those who have at least one dispensed benzodiazepine prescription in the years 2007–2014.

benzodiazepine use per patient results from renewed, as opposed to new prescriptions (Columns 3-4 of Table 2 and Online Appendix Figure A3).[29] We also find that the increase in the number of renewed DDDs is much larger for the younger patient group (8%) than for the age groups of 40–64 years (4%) and over 65 years (2%). This finding is expected because benzodiazepine use is already more widespread among older patients.

Number of Prescriptions at the Intensive Margin.—Next, we present the results on the alternative measure of benzodiazepine use at the intensive margin: the number of prescriptions per patient. We find that the number of prescriptions increases gradually over time for younger patients, with an increase of 4% one year after the adoption (Online Appendix Figure A4). The corresponding DiD estimate is, however, statistically insignificant, ruling out an effect larger than 3% based on the 95% confidence intervals (Column 4 of Table 2). For the elderly patients, the estimated effect is negative (2%) and statistically significant despite the increase in the number of DDDs. Next we study changes in individual prescriptions to explain these patterns and to provide more comprehensive evidence of the effects of e-prescribing.

Long-term Use and Prescribing Interval Using Prescription-level Data.—In Online Appendix Table A2, we present additional results on the long-term use of benzodiazepines and prescribing interval, using raw prescription-level data. We follow Kurko et al. (2015) and the definition used by the WHO (1996) and define long-term use of benzodiazepines as at least six months' theoretical use (180 dispensed DDDs) and at least two separate drug purchases dispensed at a pharmacy per prescription. Along with a high number of DDDs, multiple purchases per prescription indicate long-term use and the need for additional doses of benzodiazepines, despite potential health harms.

We find that e-prescribing increases the long-term use of benzodiazepines by 14% for younger patients (Column 4) and by 6–7% for the groups of 40–64 years and over 65 years.[30] The increase in long-term use results from increased renewals (Columns 5 and 6). For younger patients, prescribing also became more frequent, as shown by a 2% decrease in the prescribing interval (Column 7). In contrast, for the elderly, physicians issued longer prescriptions (an increase of 2% in the number of DDDs) and less frequently (an increase of 1% in the prescribing interval), with a fewer number of new DDDs (a decrease of 4%), leading to a smaller number of prescriptions shown in Table 2.

[29] New (non-renewed) prescriptions include, for example, prescriptions for a new strength of medication or new treatment episode (no previous prescriptions or previous prescription written more than 16 months ago).

[30] Using prescription-level data, we also show that the estimated effects on the number of DDDs of all, renewed, and new prescriptions are similar and even more precisely estimated to those obtained using the patient biannual-level panel data (Columns 1–3). We also confirm that our effect estimates on the long-term use of benzodiazepines are very similar to those obtained using the patient biannual-level data, and both estimates are also statistically significant (Online Appendix Table A3).

TABLE 2: Effects of E-Prescribing on Intensive Margin of Benzodiazepine Use

	DDDs (1)	Renewed DDDs (2)	New DDDs (3)	Number of rx (4)
Panel A. All ages				
Post-adoption	1.838***	1.764***	0.074	−0.005
	(0.421)	(0.463)	(0.113)	(0.004)
Mean outcome	55.694	45.614	10.081	0.644
Observations	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18-39				
Post-adoption	2.396***	1.974***	0.422**	0.007
	(0.684)	(0.577)	(0.197)	(0.005)
Mean outcome	30.342	23.307	7.035	0.445
Observations	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40-64				
Post-adoption	2.093***	1.934**	0.159	−0.003
	(0.680)	(0.802)	(0.175)	(0.004)
Mean outcome	57.504	47.085	10.419	0.680
Observations	6,742,280	6,742,280	6,742,280	6,742,280
Panel D. Age over 65				
Post-adoption	1.018**	1.267***	−0.249	−0.013***
	(0.415)	(0.371)	(0.161)	(0.005)
Mean outcome	68.051	56.638	11.414	0.714
Observations	5,340,589	5,340,589	5,340,589	5,340,589

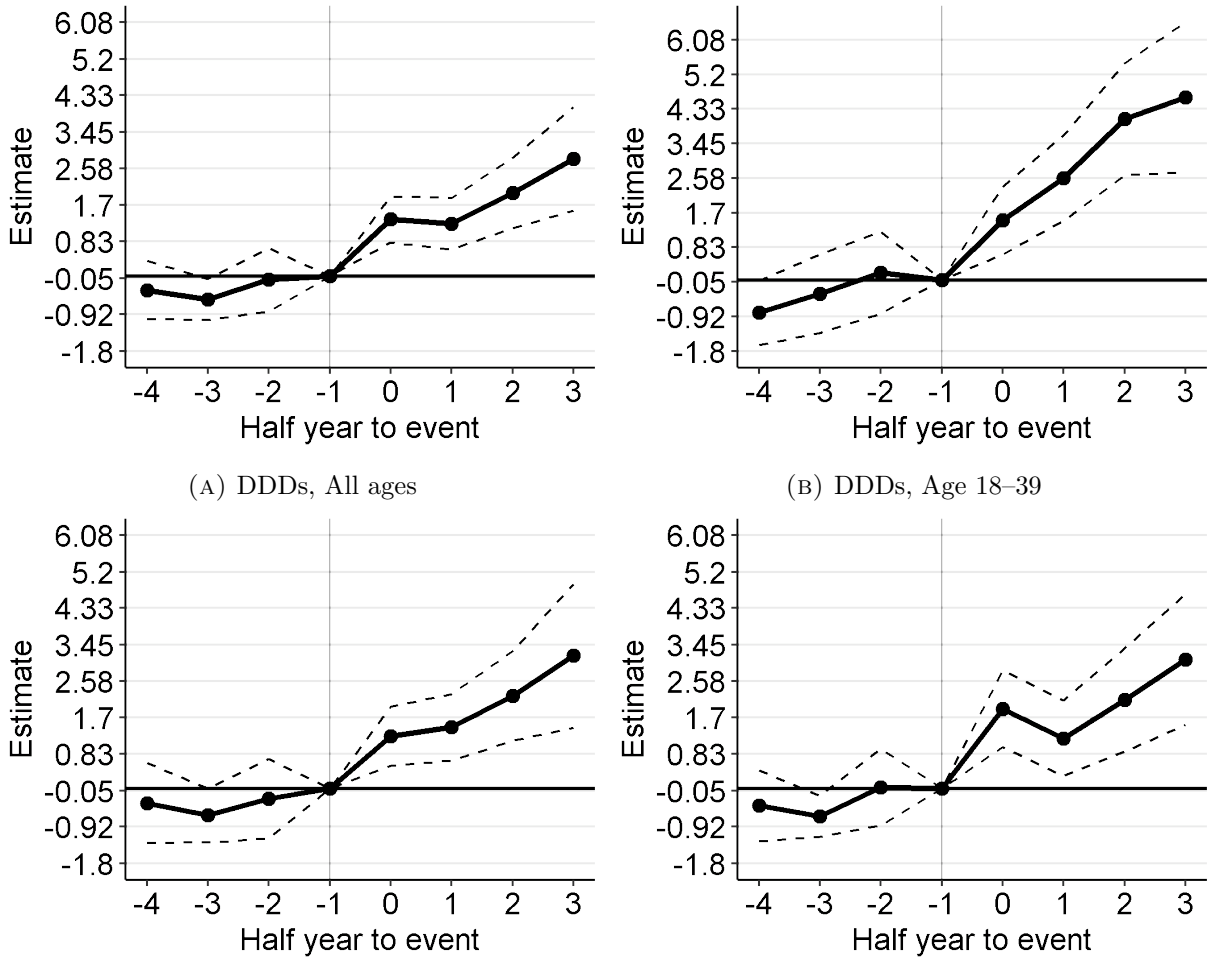
Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Panel A shows the results for all ages, Panel B for the age group under 18–39, Panel C for the age group 40–64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE 3: Effects of E-Prescribing on Extensive Margin of Benzodiazepine Use (Multiplied by 100)

	All ages		Age 18–39		Age 40–64		Age over 65	
	Benzo use	First-time use	Benzo use	First-time use	Benzo use	First-time use	Benzo use	First-time use
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-adoption	−0.012	0.006	0.050*	0.015	−0.023	0.007	−0.102	−0.004
	(0.031)	(0.010)	(0.029)	(0.012)	(0.037)	(0.012)	(0.068)	(0.016)
Mean outcome	7.362	0.859	2.735	0.716	7.404	0.880	14.124	1.026
Observations	69,545,285	56,827,149	23,629,599	19,285,434	29,931,704	24,238,003	15,983,982	13,303,712

Notes: Each column shows parameter estimates from a separate regression using aggregated individual biannual-level panel data for the Finnish adult population. Time fixed effects and individual fixed effects are included in all models. The effect on the probability of benzodiazepine use is estimated for the whole observation period (from H1:2007 to H2:2014), whereas the probability of first-time benzodiazepine use is estimated for H2:2008 to H2:2014 (due to left censoring). Standard errors are clustered at the municipality level and shown in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Extensive Margin Adjustment.—E-prescribing can also lead to adjustments at the extensive margin of benzodiazepine use through the information channel (Section 2.2); improved information on the patient's prescription history of other drugs than benzodiazepines might help the physician to learn about the potential harms (benefits) of benzodiazepines, and thus negatively (positively) impact the physician's decision to initiate benzodiazepine treatment. We combine our prescription data with the entire Finnish adult population data, including also all individuals who did not have a benzodiazepine prescription during the observation period, to study the potential effects on benzodiazepine use and first-time use at the extensive margin. This type of analysis, only rarely conducted at the individual level in the literature because of data limitations, complements our intensive margin results by using comprehensive individual-level data on benzodiazepine users and non-users who potentially become first-time users. We find that benzodiazepine use increases by 2% in the younger Finnish adult population; however, the point estimate for first-time use is statistically insignificant. For the elderly, the extensive margin point estimates are negative, statistically insignificant and are small in magnitude (decreases of less than 1%). (Table 3 and Online Appendix Figures A5 and A6.)



(A) DDDs, All ages

(B) DDDs, Age 18–39

(C) DDDs, 40–64

(D) DDDs, Over 65

FIGURE 5: Intensive Margin Adjustment: Number of Defined Daily Doses

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

6.2 Effects on Health Outcomes

Our results above reveal that e-prescribing increased the total amount of benzodiazepine use, with a larger impact for younger patients than for the elderly. If e-prescribing increased the appropriate use of benzodiazepines and succeeded in balancing the access-overuse trade-off, we would expect patients' downstream health outcomes to improve, alongside with the increased benzodiazepine use. On the other hand, if e-prescribing increased the overuse of benzodiazepines and the health harms outweighed the health benefits through adverse drug effects, patients' health outcomes may have deteriorated.

General and Mental Health Outcomes.—We first focus our attention on the general and mental health outcomes. Column 2 of Table 4 shows that e-prescribing decreases the total number of hospital visits by 7% and 3% for the age groups of 18–39 and 40–64 years, respectively. However, the corresponding event study plots in Figure 6 show that this decrease is detected only in the short term, during the first year of adoption. The estimated DiD effect on the number of emergency department visits is statistically insignificant (Column 1 of Table 4), similar to the corresponding event study estimates, which are noisy with wide confidence intervals (Online Appendix Figure A7).[31] The estimates for the probability of hospitalization for mental or behavioral health disorders are, however, less noisy, but statistically insignificant (Online Appendix Figure A8), similar to the results for most of the other general health outcomes.[32]

Health Harms from Adverse Drug Effects.—We then focus our attention on proxy measures for health harms from adverse drug effects and medication overuse. We find that e-prescribing increases younger patients' probability of hospitalization for prescription drug abuse and prescription drug poisoning by approximately 11-12% compared to the mean, showing that e-prescribing had unintended health harms for younger patients (Columns 4 and 5 in Table 4). The effects on prescription drug abuse and poisonings are consistent with each other, but the latter effect is more precisely estimated. The increase in poisonings is also gradual and approximately twice as large after the first year of adoption based on the event study estimates (Figure 7).

In contrast, for the elderly, we find that e-prescribing reduces the probability of prescription

[31] The 95% confidence intervals of the DiD estimates, for example, for all patients on average allow us to rule out effects larger than 14%.

[32] We also explored the effects on mortality and the effect estimates are statistically insignificant (Column 1 of Online Appendix Table A4). These results are as expected, given that death is an extreme outcome and quite rare in age groups other than the elderly. However, we also find statistically insignificant effects on more specific health outcomes of hospitalizations for anxiety, panic disorder, depression, and sleeping disorders (Columns 2–5). The only exception is a statistically significant 35% decrease in the probability of a hospitalization for panic disorders in the elderly population.

TABLE 4: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes (Multiplied by 100)

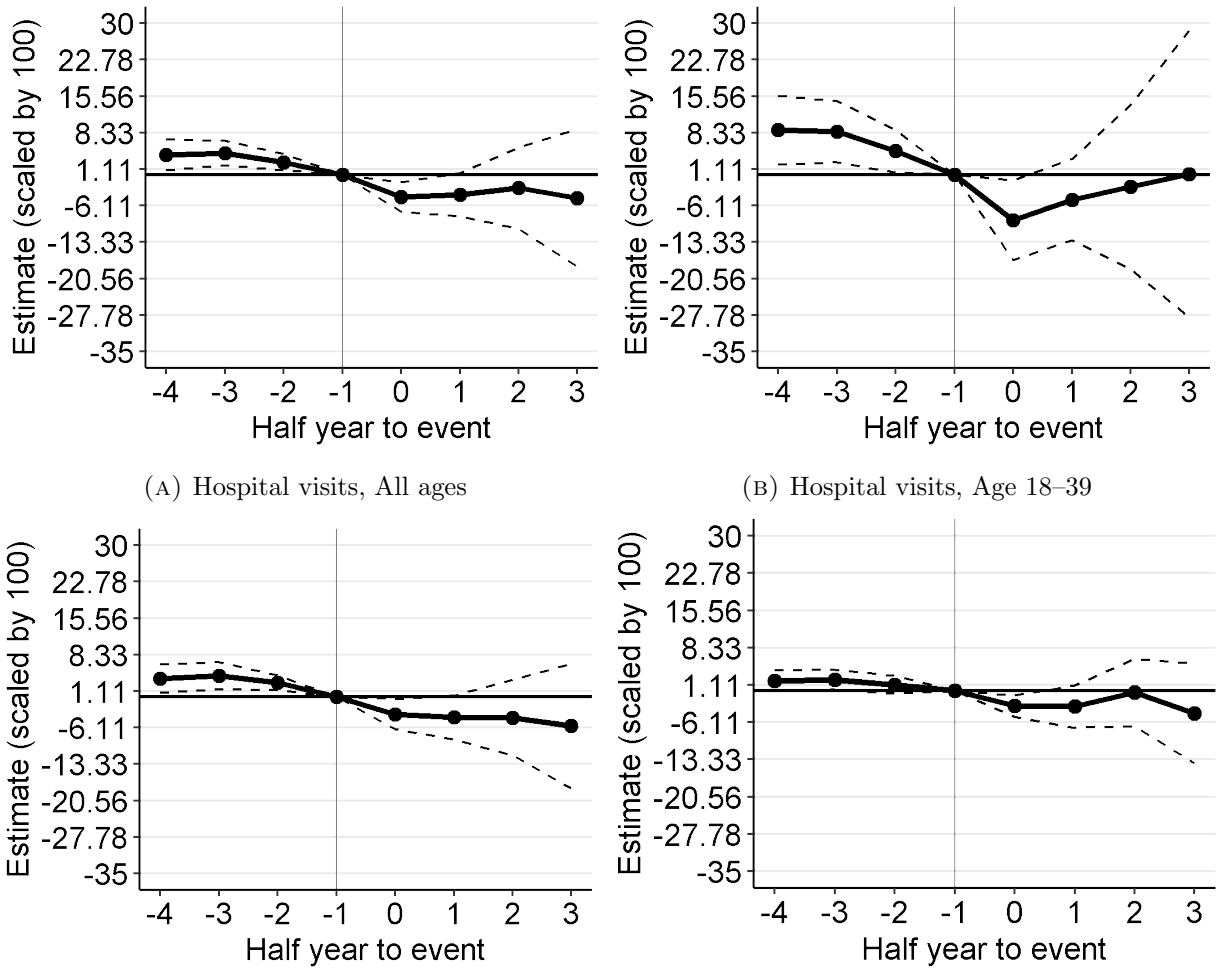
	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All ages						
Post-adoption	−0.517	−6.103**	−0.327	0.010	0.015*	−0.008
	(2.142)	(2.594)	(0.329)	(0.009)	(0.009)	(0.058)
Mean outcome	33.925	164.768	6.363	0.166	0.240	1.157
Observations	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18-39						
Post-adoption	1.085	−12.101***	−0.837	0.067	0.062***	0.012
	(2.955)	(4.052)	(0.742)	(0.044)	(0.024)	(0.023)
Mean outcome	32.984	182.878	11.174	0.603	0.529	0.299
Observations	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40-64						
Post-adoption	−0.131	−5.162*	−0.312	−0.004	−0.000	0.002
	(1.976)	(2.661)	(0.354)	(0.006)	(0.012)	(0.031)
Mean outcome	26.297	151.715	6.615	0.082	0.245	0.583
Observations	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280
Panel D. Age over 65						
Post-adoption	−1.709	−3.462	−0.064	−0.006*	0.006	−0.026
	(1.938)	(2.279)	(0.084)	(0.003)	(0.008)	(0.115)
Mean outcome	44.100	170.789	3.268	0.020	0.066	2.378
Observations	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Panel A shows the results for all ages, Panel B for the age group under 18–39, Panel C for the age group 40–64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

drug abuse by 30% and the estimated effect is statistically significant at the 10% level (Column 4 in Table 4 and Online Appendix Figure A9). The point estimates for prescription drug poisonings are, however, positive and statistically insignificant for the elderly. The possible increase in prescription drug poisonings might reflect a modest increase in the total amount of their benzodiazepine use after e-prescribing, whereas hospitalizations more specifically related to physical dependence and prescription drug abuse appear to be more easily prevented with better prescription information. Although imprecisely estimated, our results on hospitalizations related to other side effects of benzodiazepines (e.g., sedation and a decline in cognitive functions) also suggest a gradual decrease in these relatively prevalent health harms for the elderly (Online Appendix Figure A10). However, it is difficult to make strong conclusions based on the statistically insignificant estimates.

In conclusion, we find a few statistically significant improvements in the general and mental health outcomes of benzodiazepine patients after e-prescribing. Nevertheless, the health information technology decreased hospitalizations for certain adverse drug effects among the elderly, indicating that improved information provision can mitigate health harms from medication overuse. Conversely, for younger patients, hospitalizations for certain adverse drug effects increased gradually after e-prescribing, coinciding with a disproportionate rise in their benzodiazepine use due to improved medication access after e-prescribing (Section 6.1).[33]

[33]However, we find that e-prescribing led to fewer hospital visits for younger patients during the first year of adoption when the increase in their benzodiazepine use was still relatively small (Figure 5). In the second year, their benzodiazepine use increased further, leading to health harms from medication overuse (Figure 7).



(A) Hospital visits, All ages

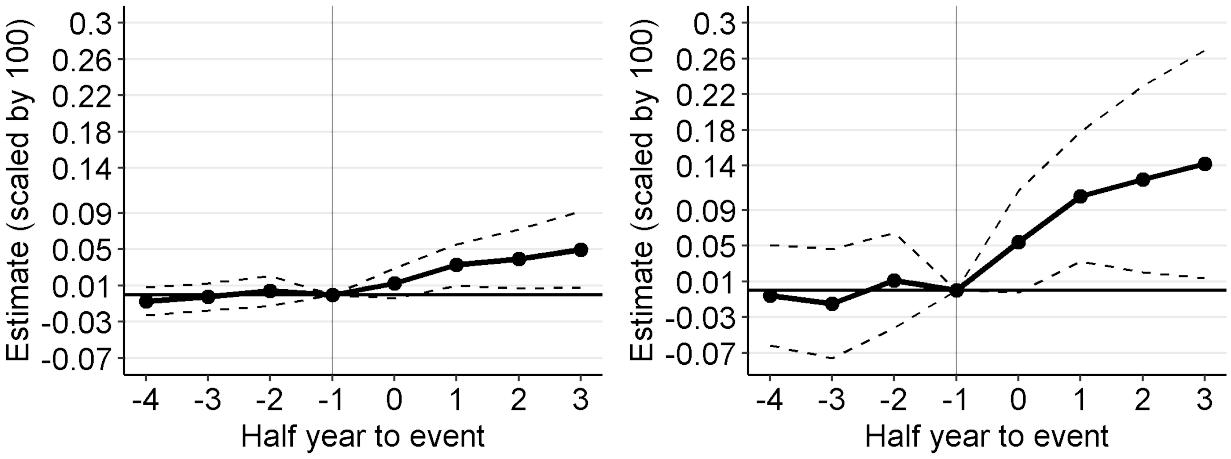
(B) Hospital visits, Age 18–39

(C) Hospital visits, 40–64

(D) Hospital visits, Over 65

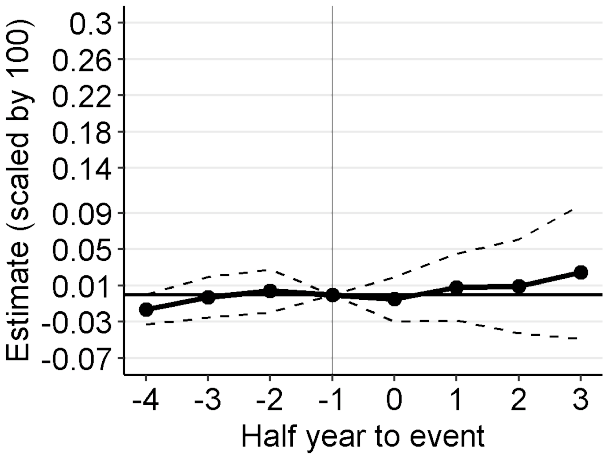
FIGURE 6: Hospital visits

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

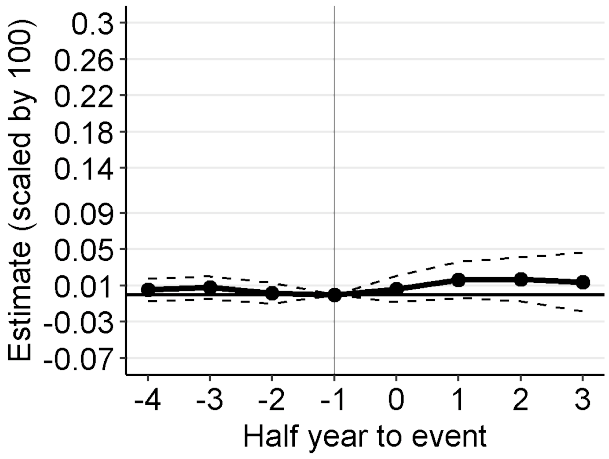


(A) Rx poisoning, All ages

(B) Rx poisoning, Age 18–39



(C) Rx poisoning, 40–64



(D) Rx poisoning, Over 65

FIGURE 7: Prescription Drug Poisoning

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

6.3 Robustness and Additional Mechanisms

Alternative Specifications.—We test the robustness of our results by using alternative specifications in both the estimations and samples. First, we exclude those who die during the observation period. Second, we restrict our data to periods when the last-treated municipalities had not yet adopted e-prescribing and thus act as "clean controls" for early-treated municipalities.[34] (Online Appendix Tables A5 and A6.) Third, we cluster standard errors at the hospital district, rather than at the municipality level (see Section 2.3). Fourth, we exclude patients who switched municipalities during the observation period and could cause contamination bias in the treatment effect estimates. (Online Appendix Tables A7 and A8.) Fifth, we estimate specifications using physician fixed effects as in Dubois and Tunçel (2021), based on our prescription-level data, to evaluate the role of unobserved heterogeneity across physicians in their prescribing decisions (Online Appendix Table A9). Sixth, we use an alternative definition of new versus renewed prescription without the 16-month cutoff (Online Appendix Table A10, Online Appendix Figures A11 and A12). Our results remain similar to our baseline results in all these alternative specifications.

Potential Biases in TWFE models and Robustness for Treatment Effect Heterogeneity.—We evaluate potential biases and assumptions in the TWFE models (Online Appendix Section D). First, using the decomposition method of Goodman-Bacon (2021), we show that possible negative weighting does not bias the treatment effect estimates in our setting and that the DiD estimates are similar for the early- and late-treated units (Online Appendix Tables A11 and A12). Second, we use the efficient DiD estimator proposed by Roth and Sant'Anna (2023) to show the robustness of our results to treatment effect heterogeneity and to address low-power concerns in the baseline estimates (Online Appendix Tables A13 and A14 and Online Appendix Figures A13–A16). Our results are not sensitive to using alternative heterogeneity-robust DiD estimators.[35] Third, we establish the robustness regarding undetected parallel trends and noise by controlling for municipality-specific linear time trends in the TWFE model, following Freyaldenhoven et al. (2023) (Online Appendix Tables A15 and A16), and by applying the tools proposed by Roth (2022) (Online Appendix Figures A17-A20). We conclude that an undetected pre-trend due to low statistical power is an unlikely explanation of our results.

[34]Some of the estimates are more imprecisely estimated than in the baseline specifications. This is to be expected because the specification shortens the post-adoption period and thus puts more weight on short-term effects, even though the estimated long-term effects are often larger.

[35]We find that the estimated effects are similar or somewhat larger and more precise than those obtained using the baseline TWFE specifications.

Further Age-based Heterogeneity.—Online Appendix Table A17 shows no major differential responses to e-prescribing when patients under 40 years of age are separated into two additional age groups (aged 18-25 and 26-39). Compared to the means, the increases in the number of DDDs and the probability of prescription drug poisoning are slightly larger for those aged 18-25 than for those aged 26-39 (increases of 11% versus 7% and 14% versus 9%, respectively). Moreover, there is a similar 7% decrease in patient hospitalizations in both age groups.[36]

Additional Mechanism: Potential Role of Improved Diagnosing.—Improved information on a patient's prescription history after the adoption of e-prescribing in primary care may enhance the prescribing physician's ability to diagnose mental health disorders and identify adverse drug effects. Thus, referrals and hospitalizations for these conditions might also increase, which could cause upward bias in our health effect estimates.[37] Online Appendix Table A18 shows the results excluding diagnoses for hospital visits where the referrals are obtained on the same day, and potentially from the same physicians, as the benzodiazepine prescriptions (less than 1% of all diagnoses). The results remain intact and they are clearly not driven by potential improvements in the diagnosing of medical conditions.

Additional Mechanism: Use of Other Medications.—E-prescribing can also affect the use of other medications by benzodiazepine patients that could affect their downstream health outcomes. We use additional data on benzodiazepine patients' prescriptions for a group of widely used antidepressants SSRIs (selective serotonin reuptake inhibitors). These are non-addictive medications and can be either substitutes or complements for benzodiazepines in treating anxiety, for example. We hypothesize that SSRI use decreases and benzodiazepine use increases if physicians substitute SSRIs for benzodiazepines and both SSRI and benzodiazepine use increase if these two drugs are used as complements. We find that there are no significant effects for the use of SSRIs on average (Online Appendix Table A19). For the patients aged 18–39, there is a small statistically significant increase in the number of SSRI prescriptions (2%), but not in the number of DDDs.

Placebo Regressions.—We estimate placebo regressions for a health outcome that should not have been affected by e-prescribing or improved diagnosing: diagnosis of diseases of the appendix. This condition is quite prevalent, especially among younger individuals, and not correlated with

[36]Moreover, the take-up rate of e-prescriptions does not differ between the two age groups (Online Appendix Figure A21).

[37]After e-prescribing, mental health-related hospital visits might also increase with the increased use of benzodiazepines because benzodiazepines are used to treat these conditions. On the other hand, as the patient can receive prescriptions more easily (from primary care and/or without an in-person visit), e-prescribing can also *lower* their need to show up at a hospital and be diagnosed with a mental health condition to receive a prescription. If this were the case, our point estimate for mental health effects would likely be conservative and lower than the true effect.

socioeconomic status, making it a good candidate for placebo regressions. We find that the effect estimates for these placebo regressions are not statistically significant and the point estimates are close to zero (Online Appendix Table A20).

7 Conclusion

This paper studies a large-scale public policy designed to improve medication access while limiting overuse. Our analysis is based on the staggered rollout of a nationwide, fully standardized, and interoperable e-prescribing system across all municipalities in Finland. We use comprehensive administrative data sets on hospital discharges and prescriptions for effective but also potentially addictive medications, benzodiazepines. Our empirical approach allows us to provide evidence on how the adoption of health information technology balances the access-overuse trade-off by making prescription renewal easier for patients while providing physicians with better prescription information through a centralized e-prescription database.

Our results are consistent with e-prescribing improving access to medication through easier renewal. We find that e-prescribing increases the total amount of benzodiazepine use per patient due to increased prescription renewals. The increase in benzodiazepine use is over twice as large for younger patients (aged 18–39) as for the elderly (age over 65). We provide further suggestive evidence that the information technology adoption can benefit the health of the elderly due to improved information provision, but it can also increase the risk of medication overuse and health harms for younger patients due to improved medication access. Thus, the ability of e-prescribing to balance the access-overuse trade-off depends on whether the improved access to medication, characterized by easier renewals without an in-person physician visit, offsets the benefits of improved information provision for physicians.[38]

Easier renewal and improved information are the core features of e-prescribing systems globally and relevant for any repeat users of prescription drugs. Our findings based on benzodiazepines, a drug class that is widely prescribed in most high-income countries, are most directly relevant to users of psychotropics and potentially addictive medications, for whom balancing the access-overuse trade-off is particularly challenging. However, our study has some important limitations.

[38]Medication overuse or over-prescribing might be related to insufficient patient monitoring, communication, and health status examination when authorizing prescriptions without in-person patient contact (Mehrotra et al. 2013; U.S. Drug Enforcement Administration 2023). Moreover, physicians may not use new e-prescription information in health harm prevention because the time and hassle costs of information acquisition may be too large (Woodford 2012; Gabaix 2014) or because they undervalue the expected benefits of using new information (Gagnon-Bartsch et al. 2017; Schwartzstein 2014).

We estimate the reduced-form health effects of e-prescribing for benzodiazepine patients, which may result from changes in the use of other prescription drugs. Because we focus on high-risk medical treatments, benzodiazepines, it is unclear whether our conclusions on the health effects of e-prescribing apply to other types of drug classes. In this regard, easier renewal could lead to improvements in managing the long-term medical treatment of chronic diseases, with a low risk of medication overuse and potential health benefits that substantially outweigh any health harms. Further research on other drug classes is needed to fully understand the effects of e-prescribing technology.

Empirical research in economics has largely overlooked factors that influence joint physician-patient decisions. Our results suggest that the conditions under which joint decisions are taken may critically affect patient outcomes. Information technology improves access and patient convenience but may impair communication and interaction between physicians and patients and expose some patients to medication overuse. Studies of other emerging technologies and markets from the perspective of optimal policy design, along with studies focusing on physician prescribing behavior, are other key areas for future research.

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Information Technology, Improved Access, and Use of Prescription Drugs — Online Appendix

Petri Böckerman, Mika Kortelainen, Liisa T. Laine, Mikko Nurminen, and Tanja Saxell

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A ATC and ICD-10 Codes for Variable Constructions

A.1 Prescribing outcomes

Benzodiazepine and SSRI ATC codes used from the Prescription Data:

- Benzodiazepines: N05BA01, N05BA02, N05BA04, N05BA06, N05BA09, N05BA12, N05CD02, N05CD07, N05CD08, N05CF
- SSRI: N06AB03, N06AB04, N06AB05, N06AB06, N06AB08, N06AB10.

A.2 Health outcomes

We construct our medical service-related health outcomes from hospital discharge data and diagnoses associated with hospital visits.[39] We list Finnish ICD-10 diagnosis codes and other details for the health outcome construction below.

- *Emergency department visit* is identified based on the following information associated with each hospital visit:
  - Type of admission: emergency duty
  - Referral type: the patient arrived at care without a referral, such as emergency duty
  - Reason for seeking care: emergency duty or acute care
  - Service branch: emergency duty visit
  - Procedures and interventions: intensive care
  - Specialty of care: emergency medicine
- *Hospital visits* include all hospital visits regardless of the diagnosis.
- *Mental disorder* is based on the fifth chapter of ICD-10 "Mental and behavioral disorders" containing the ICD-10 codes F00–F99.
- *Prescription drug abuse disorder (PDA) diagnosis* is constructed by grouping multiple diagnosis codes measuring prescription drug abuse (such as *abuse of benzodiazepines and opioids*). We consider diagnoses with the following ICD-10 codes:
  - Opioid-related disorders (F11)
  - Sedative-, hypnotic-, or anxiolytic-related disorders (F13)

[39] We use primary diagnoses in the hospital discharge data because they are recorded accurately and the quality of the recording of secondary diagnoses has raised some concerns in validation studies (Sund 2012).

  - Other stimulant-related disorders (F15)
  - Other psychoactive substance-related disorders (F19)

  However, not all of the aforementioned diagnoses measure active prescription drug misuse or abuse. The Finnish ICD-10 classification contains codes that indicate that the patient is currently participating in a controlled rehabilitation program, or uses drug withdrawal medication. Therefore, we exclude the following diagnoses from the group of prescription drug abuse disorders:

  - Opioid dependence, uncomplicated (F11.20); Opioid dependence, in remission (F11.21); Opioid dependence with intoxication (F11.22); Opioid dependence with withdrawal (F11.23)
  - Sedative, hypnotic or anxiolytic dependence, uncomplicated (F13.20); Sedative, hypnotic or anxiolytic dependence, in remission (F13.21); Sedative, hypnotic or anxiolytic dependence with intoxication (F13.22); Sedative, hypnotic or anxiolytic dependence with withdrawal (F13.23)
  - Other psychoactive substance dependence, uncomplicated (F19.20); Other psychoactive substance dependence, in remission (F19.21); Other psychoactive substance dependence with intoxication (F19.22); Other psychoactive substance dependence with withdrawal (F19.23)

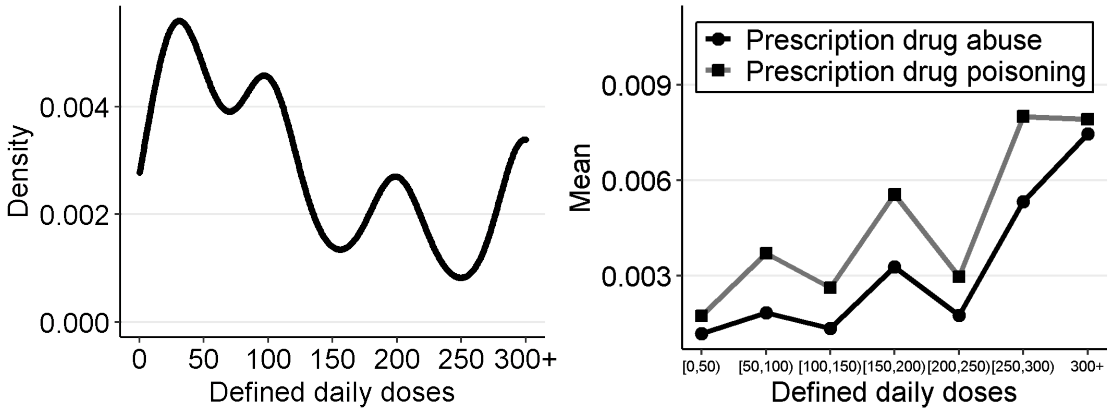
- *Prescription drug poisoning diagnosis* is identified using the (Finnish) ICD-10 code T36. This diagnosis code includes any poisoning from prescription drugs. A prescription drug poisoning including adverse effect of and underdosing (or overdosing) of drugs, medicaments and biological substances.

- *Other side effects* are measured based on diagnoses with the following ICD-10 codes:

  - Hypersomnia (G47.1)
  - Ataxia, unspecified (R27.0); Other lack of coordination (R27.8)
  - Somnolence (R40.0); Stupor (R40.1); Anterograde amnesia (R41.1); Other amnesia (R41.3); Other and unspecified symptoms and signs involving cognitive functions and awareness (R41.8); Dizziness and giddiness (R42); Malaise and fatigue (R53)
  - Fracture of neck of femur (S72.0); Pertrochanteric fracture (S72.1); Subtrochanteric fracture (S72.2)

B Main Specification: Additional Figures and Tables

B.1 Figures



(A) Density of defined daily doses (excluding zeros)

(B) Defined daily doses and adverse health outcomes

FIGURE A1: Defined Daily Doses and Their Relationship With Prescription Drug Abuse and Poisoning

Notes: Panel A of the figure plots a smoothed density of the biannual number of defined daily doses (here, zeros are excluded to better illustrate variation in the outcome). Panel B plots the mean probabilities of prescription drug abuse and poisoning (y-axis) by the bin of defined daily doses shown on the x-axis.

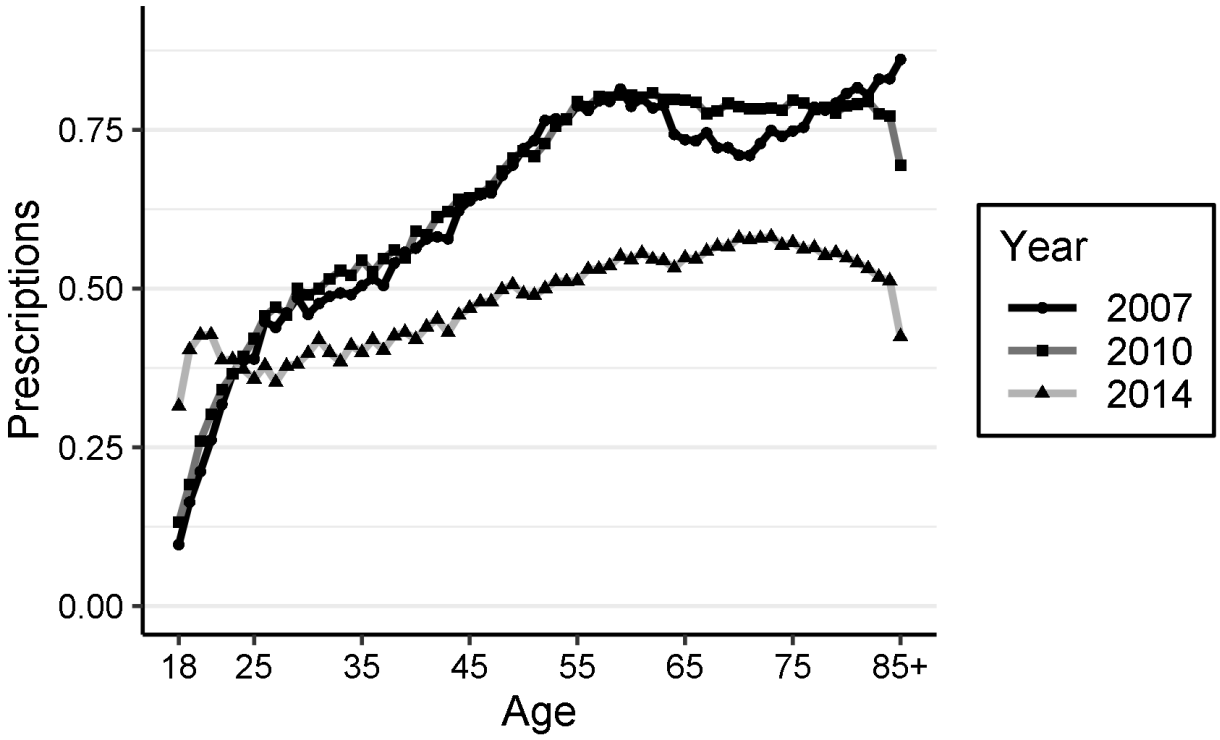
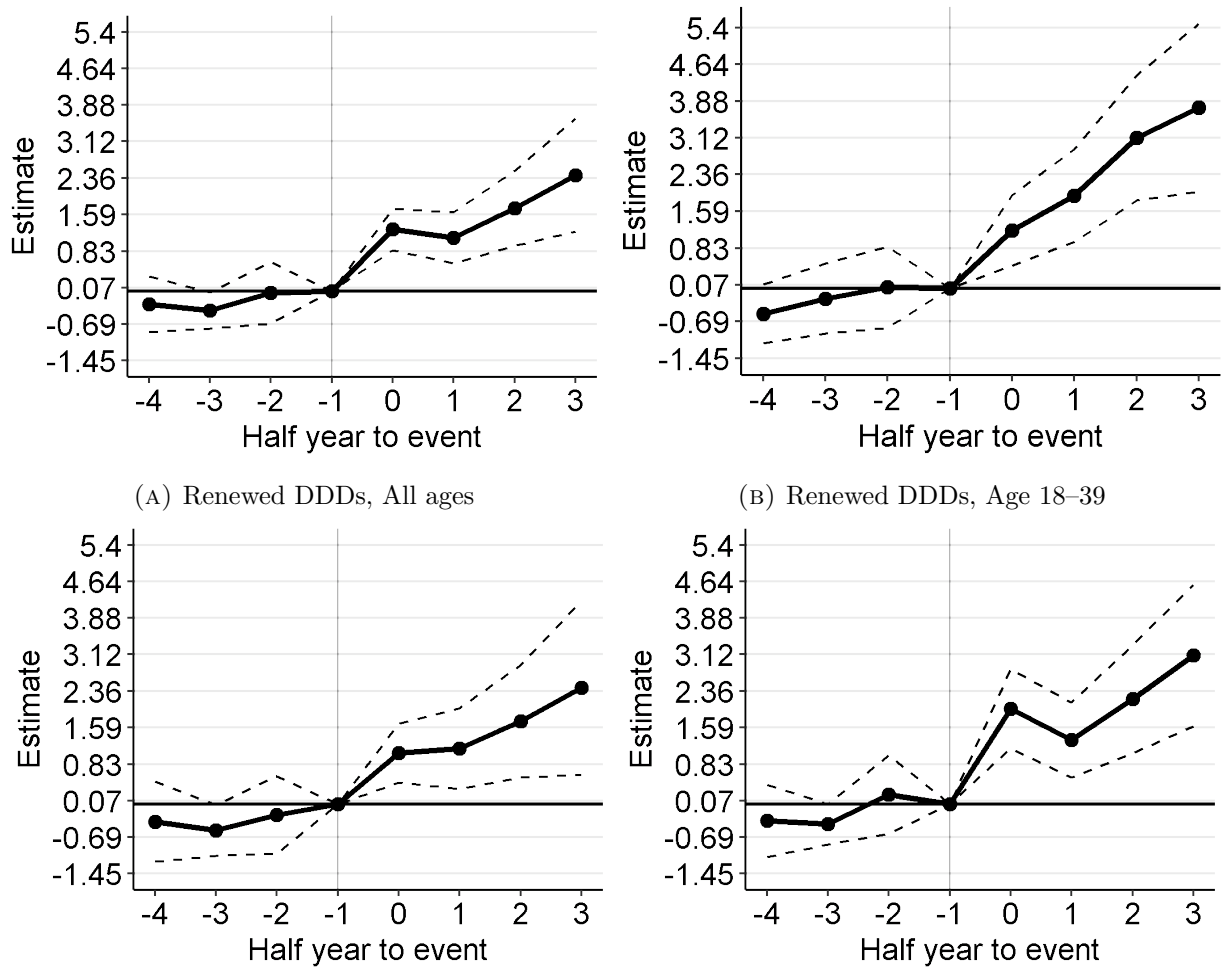


FIGURE A2: Yearly Benzodiazepine Use-Age Relationships at Intensive Margin: Number of All Prescriptions

Notes: The figures are based on aggregated patient biannual-level panel data. The mean total number of prescriptions is calculated for each year (2007, 2010, 2014).



(A) Renewed DDDs, All ages

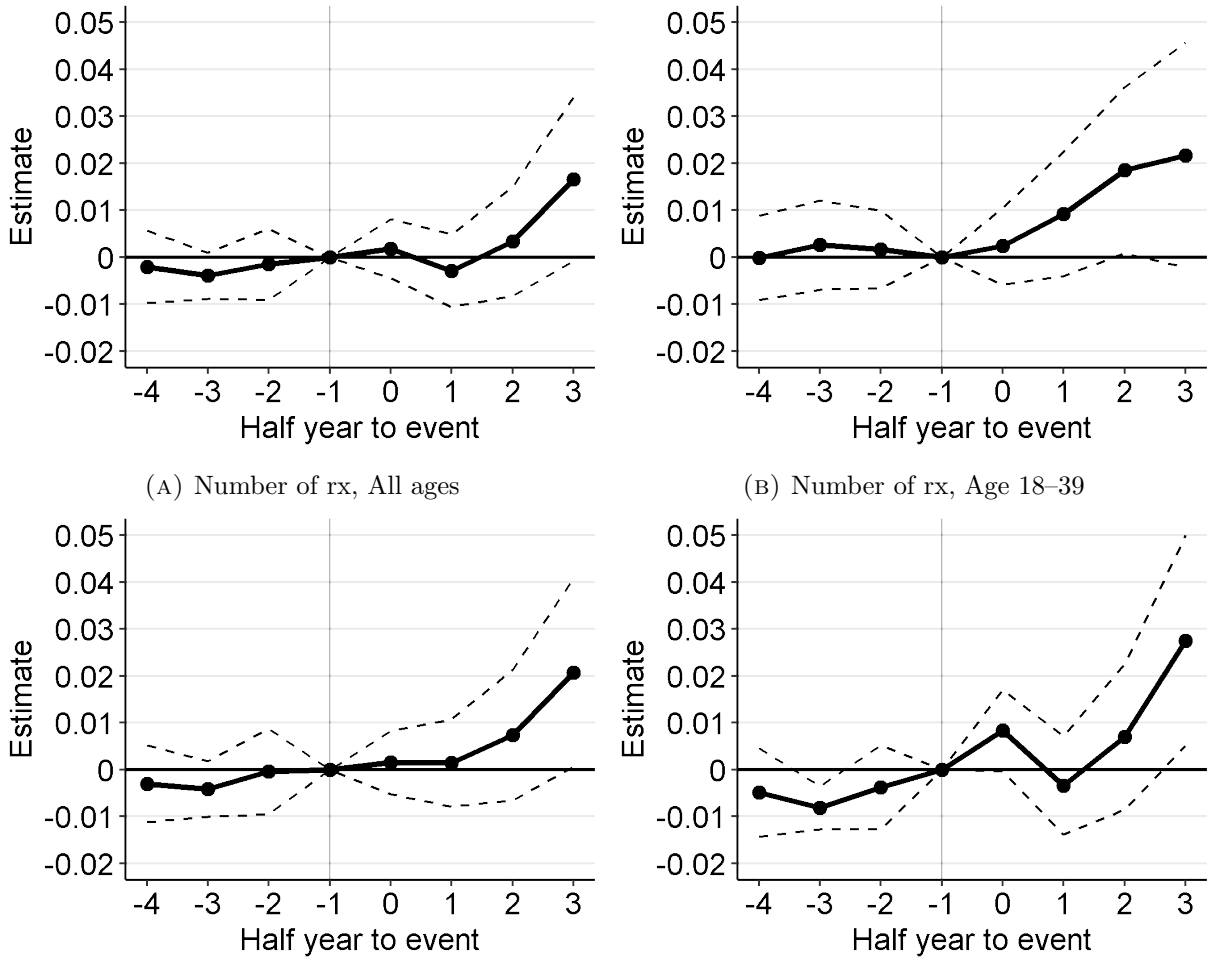
(B) Renewed DDDs, Age 18–39

(C) Renewed DDDs, 40–64

(D) Renewed DDDs, Over 65

FIGURE A3: Renewed Defined Daily Doses

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Number of rx, All ages

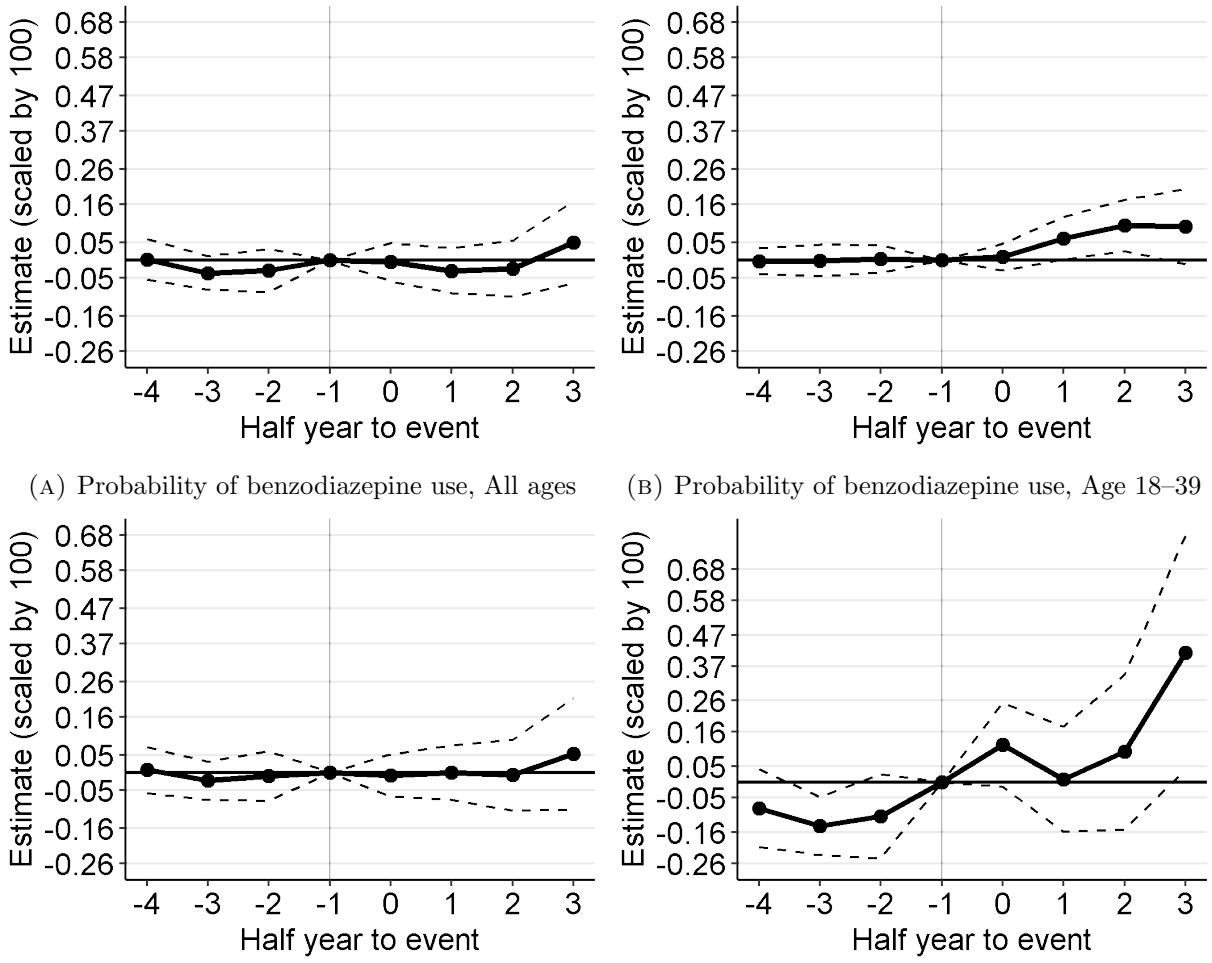
(B) Number of rx, Age 18–39

(C) Number of rx, 40–64

(D) Number of rx, Over 65

FIGURE A4: Intensive Margin Adjustment: Number of Prescriptions

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Probability of benzodiazepine use, All ages

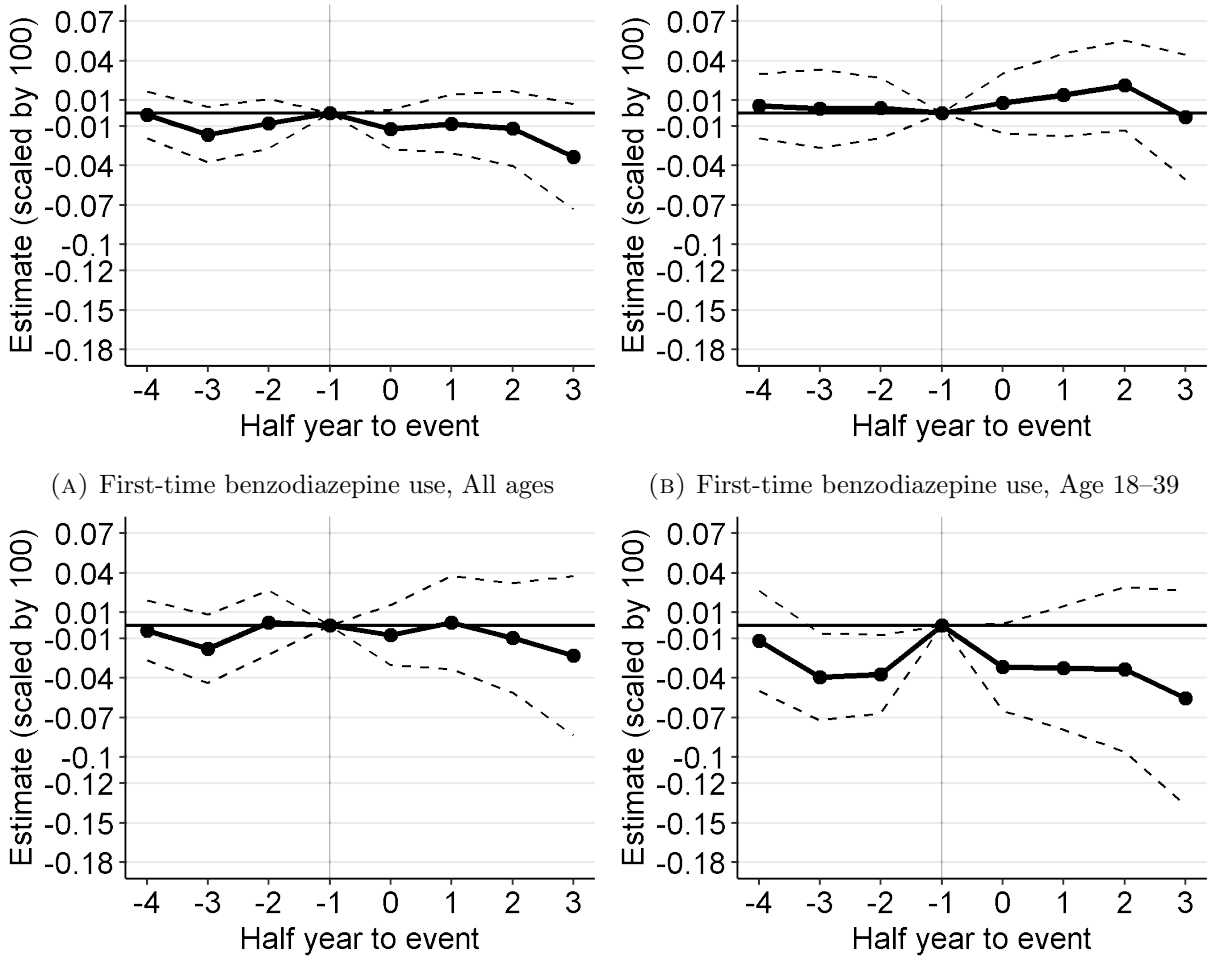
(B) Probability of benzodiazepine use, Age 18–39

(C) Probability of benzodiazepine use, 40–64

(D) Probability of benzodiazepine use, Over 65

FIGURE A5: Extensive Margin Adjustment: Probability of Benzodiazepine Use

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated individual biannual-level panel data for the Finnish adult population trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and individual fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) First-time benzodiazepine use, All ages

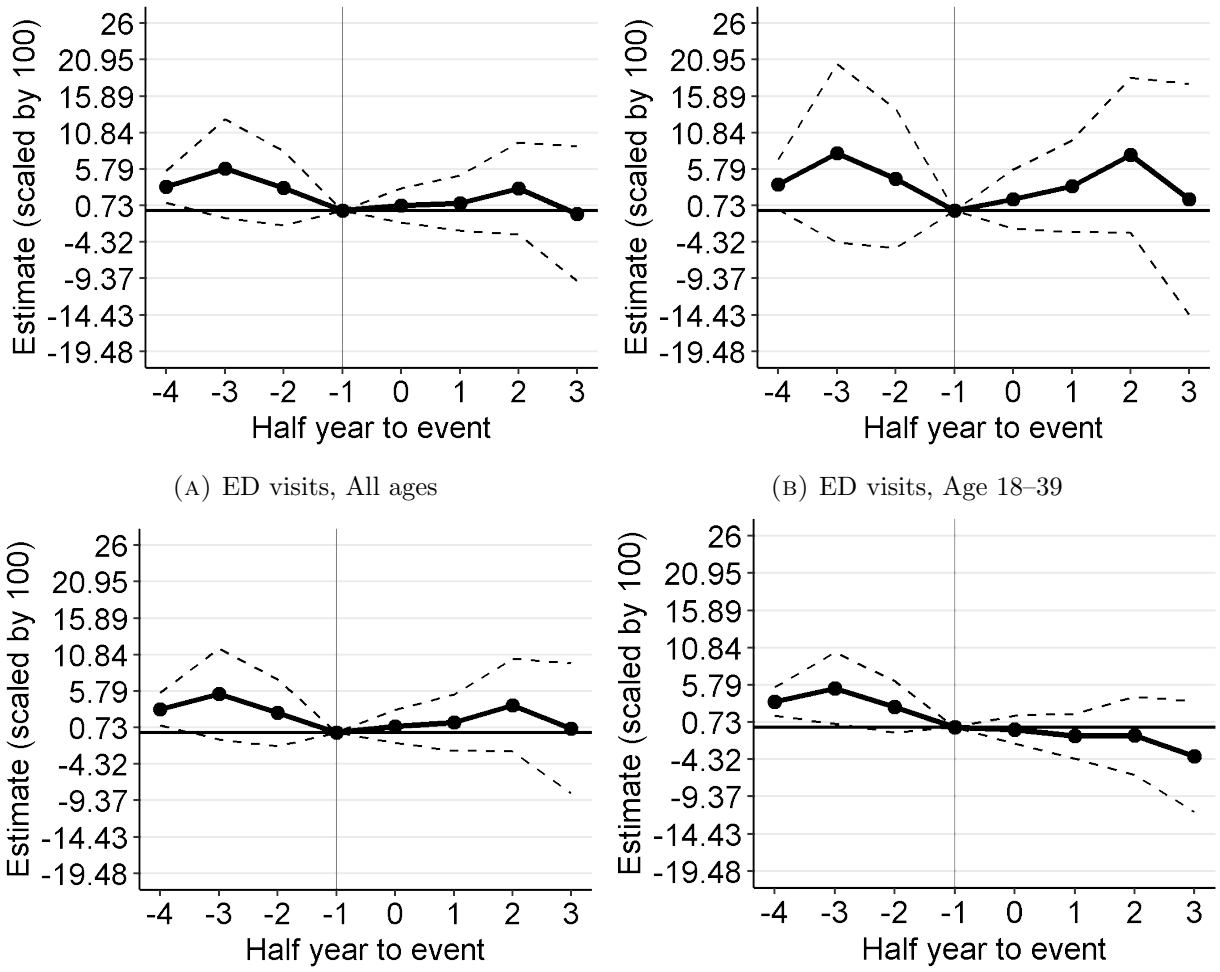
(B) First-time benzodiazepine use, Age 18–39

(C) First-time benzodiazepine use, 40–64

(D) First-time benzodiazepine use, Over 65

FIGURE A6: Extensive Margin Adjustment: Probability of First-Time Benzodiazepine Use

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated individual biannual-level panel data for the Finnish adult population trimmed between relative time periods −5 and 3. The data used in the estimations are from 2008h2 to 2014h2 because of left censoring. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and individual fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) ED visits, All ages

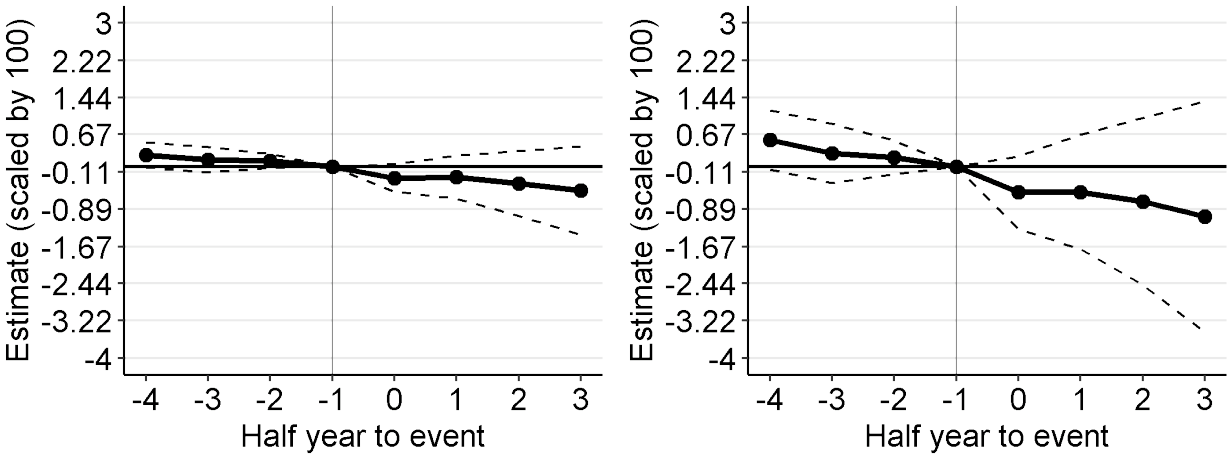
(B) ED visits, Age 18–39

(C) ED visits, 40–64

(D) ED visits, Over 65

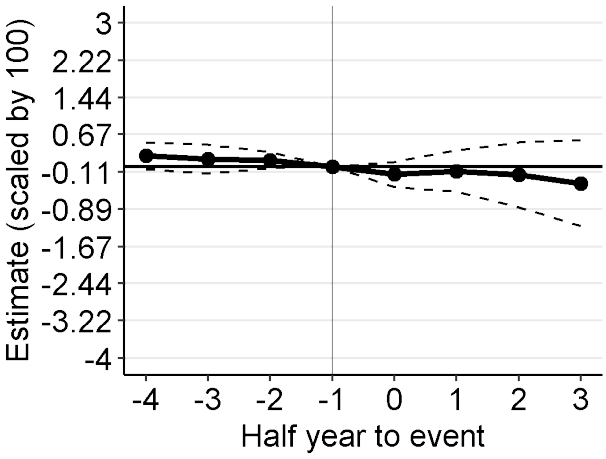
FIGURE A7: Emergency Department Visits

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

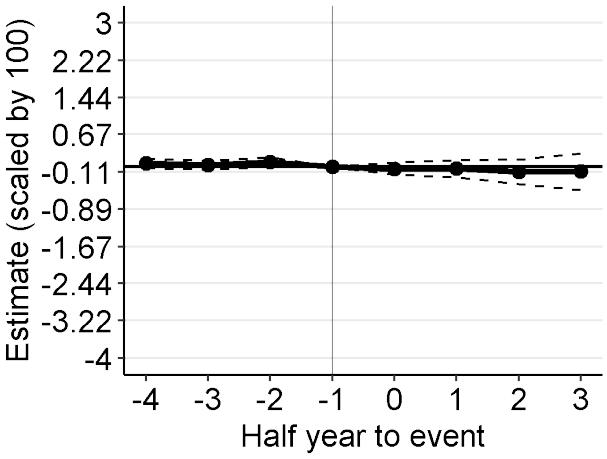


(A) Mental disorder, All ages

(B) Mental disorder, Age 18–39



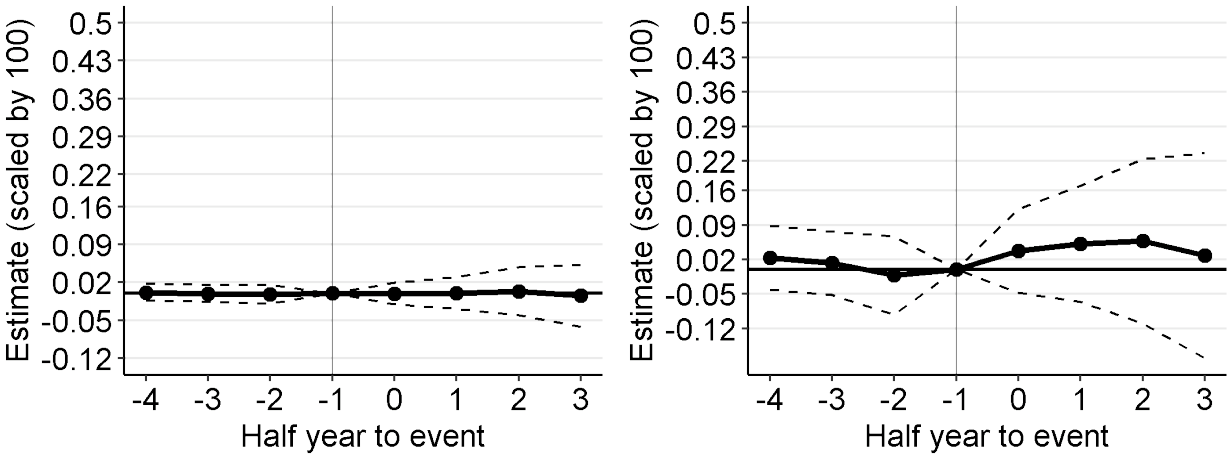
(C) Mental disorder, 40–64



(D) Mental disorder, Over 65

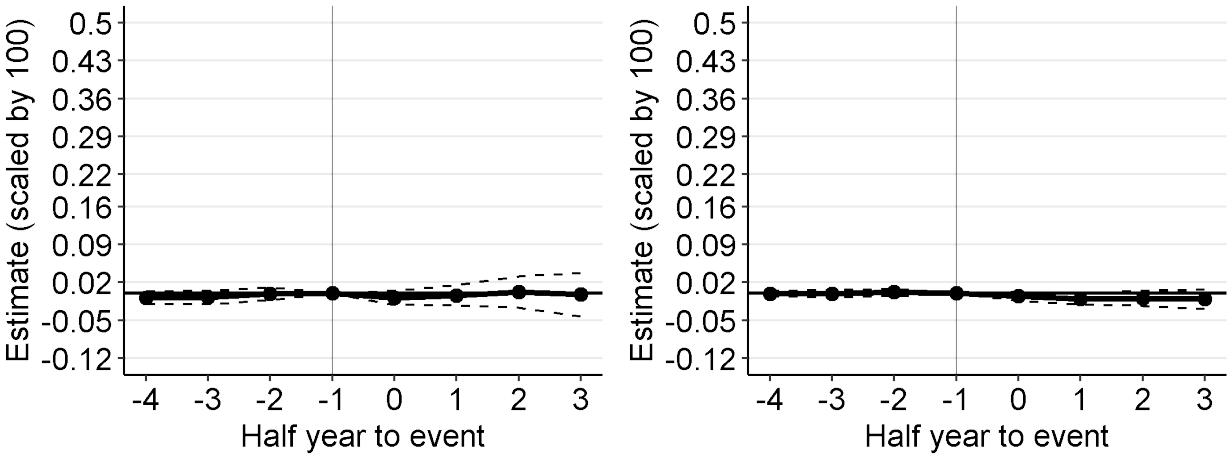
FIGURE A8: Mental and Behavioral Health

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) PDA diagnosis, All ages

(B) PDA diagnosis, Age 18–39

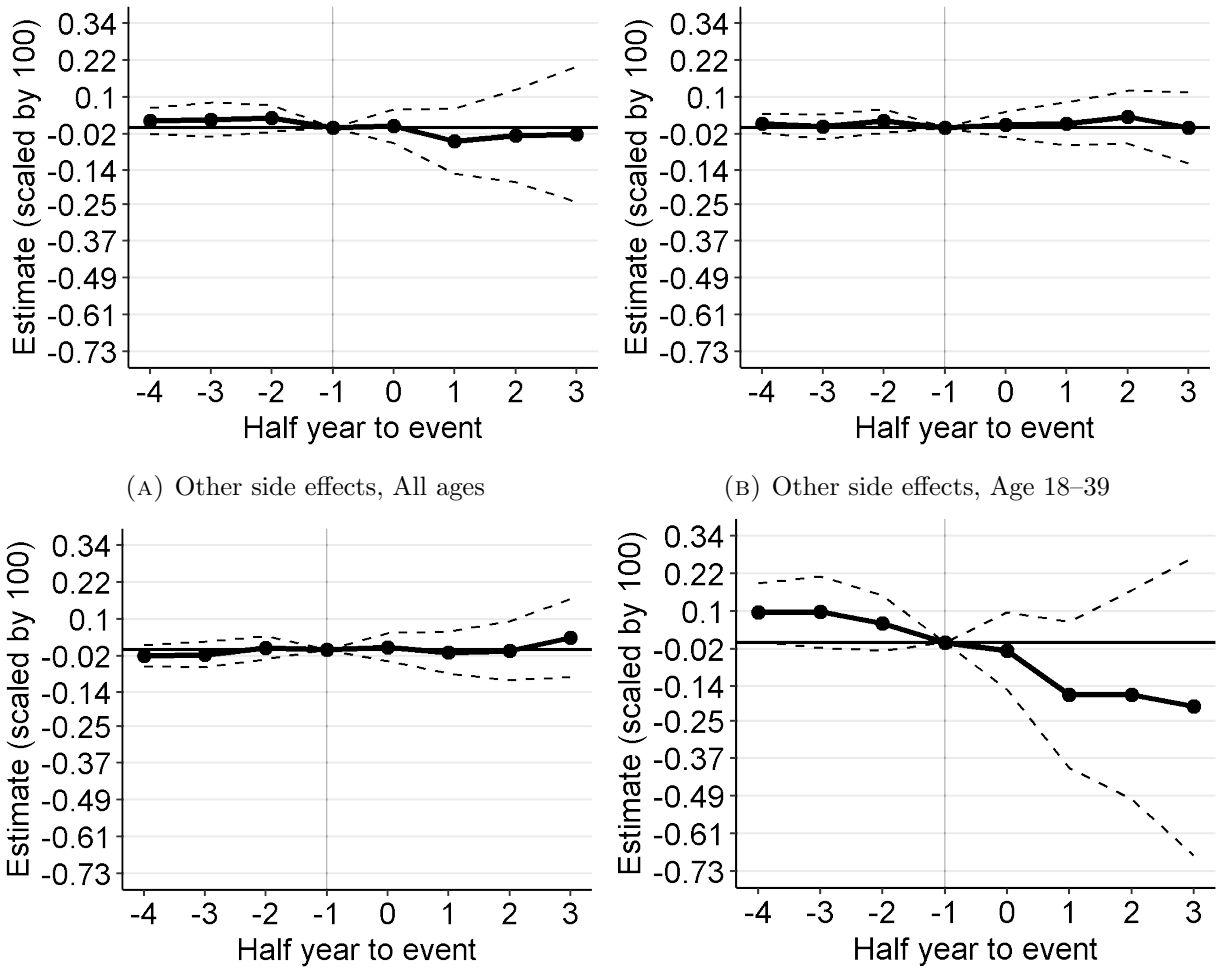


(C) PDA diagnosis, 40–64

(D) PDA diagnosis, Over 65

FIGURE A9: Prescription Drug Abuse Diagnosis

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Other side effects, All ages

(B) Other side effects, Age 18–39

(C) Other side effects, 40–64

(D) Other side effects, Over 65

FIGURE A10: Other Side Effects

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

B.2 Tables of Additional Outcomes

TABLE A1: Mortality Rates Among Benzodiazepine Patients

	All ages (1)	Ages 18–39 (2)	Age 40–64 (3)	Age over 65 (4)
Share of patients who die	0.156	0.015	0.054	0.279
Unique individuals	1,019,405	247,168	536,328	452,041

Notes: Values depict the overall values for benzodiazepine patients during the observation period 2007–2014.

TABLE A2: Effects of E-Prescribing on Composition and Duration of Individual Prescriptions

	Main outcomes			Additional outcomes			
	DDDs	Renewed DDDs	New DDDs	Long-term use	Long-term use, renewed rx	Long-term use, new rx	Prescribing interval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All ages							
Post-adoption	2.543***	2.586***	−0.043	0.007***	0.008***	−0.001	0.849
	(0.360)	(0.381)	(0.165)	(0.001)	(0.001)	(0.000)	(0.543)
Mean outcome	86.466	70.817	15.649	0.097	0.081	0.016	128.893
Observations	9,768,925	9,768,925	9,768,925	9,768,925	9,768,925	9,768,925	8,754,560
Panel B. Age 18-39							
Post-adoption	3.661***	3.008***	0.653*	0.008**	0.007**	0.001	−2.435*
	(1.061)	(0.991)	(0.356)	(0.004)	(0.003)	(0.001)	(1.439)
Mean outcome	68.316	52.497	15.818	0.058	0.048	0.010	112.649
Observations	1,396,770	1,396,770	1,396,770	1,396,770	1,396,770	1,396,770	1,181,859
Panel C. Age 40-64							
Post-adoption	2.110***	2.111***	−0.001	0.005***	0.005***	0.000	0.826
	(0.444)	(0.526)	(0.245)	(0.001)	(0.001)	(0.000)	(0.648)
Mean outcome	84.466	69.137	15.328	0.087	0.072	0.014	119.778
Observations	4,510,421	4,510,421	4,510,421	4,510,421	4,510,421	4,510,421	4,063,208
Panel D. Age over 65							
Post-adoption	2.142***	2.717***	−0.575**	0.008***	0.010***	−0.002***	1.156*
	(0.416)	(0.426)	(0.227)	(0.002)	(0.002)	(0.001)	(0.663)
Mean outcome	95.366	79.404	15.963	0.122	0.103	0.020	144.917
Observations	3,861,734	3,861,734	3,861,734	3,861,734	3,861,734	3,861,734	3,509,493

Notes: Each column shows parameter estimates from a separate regression using prescription-level data. The outcomes are the number of defined daily doses (column 1), the number of renewed defined daily doses (column 2), the number of new defined daily doses (column 3), the indicator of long-term use, defined as the number of defined daily doses at least 180 and at least 2 separate drug purchases per prescription (column 4), the indicator of long-term use for a renewed prescription (column 5), the indicator of long-term use for a new prescription (column 6), and the prescribing interval, defined as the number of days between the focal and previous prescription (from the second prescription onward) (column 7). Panel A shows the results for all ages, Panel B for the age group under 18–39, Panel C for the age group 40–64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE A3: Effects of E-Prescribing on Long-Term Use of Benzodiazepine at Intensive Margin, Using Patient-Biannual Level Data

	All ages	Age 18–39	Age 40–64	Age over 65
	(1)	(2)	(3)	(4)
Post-adoption	0.004***	0.003***	0.003***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Mean outcome	0.052	0.017	0.046	0.079
Observations	15,167,056	3,084,187	6,742,280	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. The outcome is the indicator of long-term use, defined as the number of defined daily doses at least 180 and at least 2 separate drug purchases per prescription. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE A4: Effects of E-Prescribing on Benzodiazepine Patients' Additional Health Outcomes (Multiplied by 100)

	Mortality (1)	Anxiety (2)	Panic disorder (3)	Depression (4)	Sleep disorder (5)
Panel A. All ages					
Post-adoption	−0.024	−0.053	−0.012	−0.095	−0.007
	(0.027)	(0.063)	(0.011)	(0.134)	(0.008)
Mean outcome	1.046	1.152	0.132	2.264	0.088
Observations	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18-39					
Post-adoption	0.017	−0.130	−0.030	−0.258	−0.017
	(0.013)	(0.176)	(0.036)	(0.293)	(0.016)
Mean outcome	0.118	2.858	0.391	4.206	0.140
Observations	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40-64					
Post-adoption	−0.003	−0.038	−0.005	−0.091	−0.007
	(0.016)	(0.054)	(0.009)	(0.159)	(0.010)
Mean outcome	0.429	1.010	0.099	2.581	0.094
Observations	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280
Panel D. Age over 65					
Post-adoption	−0.053	−0.021	−0.008**	0.003	−0.001
	(0.034)	(0.022)	(0.003)	(0.039)	(0.006)
Mean outcome	2.361	0.345	0.023	0.744	0.049
Observations	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. The outcomes are the mortality indicator (column 1) and the indicators of hospitalizations for particular health conditions (diagnoses): anxiety (ICD-10 F40-F48; column 2), panic disorder (ICD-10 F410; column 3), depression (ICD-10 F32, F33; column 4), and sleep disorder (ICD-10 G470, G472, G478, G479, F51; column 5). Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

C Additional Specifications, Robustness, Mechanisms, and Placebo Regression Test

C.1 Exclusion of Deceased Patients and Last-Treated Municipalities

TABLE A5: Robustness of Effects on Benzodiazepine Use for Excluding Deceased Patients and Last-Treated Municipalities

	DDDs		Renewed DDDs		New DDDs		Number of rx	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All ages								
Post-adoption	1.868***	1.631***	1.762***	1.675***	0.106	−0.044	−0.006	−0.004
	(0.448)	(0.388)	(0.486)	(0.458)	(0.107)	(0.206)	(0.004)	(0.005)
Mean outcome	52.724	59.993	43.620	48.355	9.104	11.638	0.624	0.681
Observations	13,650,613	11,604,223	13,650,613	11,604,223	13,650,613	11,604,223	13,650,613	11,604,223
Panel B. Age 18-39								
Post-adoption	1.868***	2.143***	1.762***	1.906***	0.106	0.237	−0.006	0.005
	(0.448)	(0.693)	(0.486)	(0.632)	(0.107)	(0.193)	(0.004)	(0.006)
Mean outcome	52.724	31.607	43.620	24.033	9.104	7.573	0.624	0.456
Observations	13,650,613	2,423,853	13,650,613	2,423,853	13,650,613	2,423,853	13,650,613	2,423,853
Panel C. Age 40-64								
Post-adoption	1.756***	1.881***	1.736***	1.795**	0.021	0.086	−0.009**	−0.002
	(0.455)	(0.514)	(0.546)	(0.717)	(0.157)	(0.294)	(0.004)	(0.005)
Mean outcome	59.532	61.996	49.736	50.012	9.797	11.984	0.679	0.722
Observations	10,604,738	5,190,270	10,604,738	5,190,270	10,604,738	5,190,270	10,604,738	5,190,270
Panel D. Age over 65								
Post-adoption	1.086**	0.739	1.225***	1.149**	−0.138	−0.410	−0.017***	−0.009
	(0.428)	(0.579)	(0.398)	(0.450)	(0.145)	(0.274)	(0.005)	(0.006)
Mean outcome	66.470	74.632	56.585	60.975	9.885	13.657	0.709	0.764
Observations	4,173,112	3,990,100	4,173,112	3,990,100	4,173,112	3,990,100	4,173,112	3,990,100
Exclude died patients	✓		✓		✓		✓	
Exclude last-treated municipalities		✓		✓		✓		✓

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Columns 1, 3, 5, and 7 exclude patients who died during the observation period 2007–2014. Columns 2, 4, 6, and 8 use data from periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. *p<0.1; **p<0.05; ***p<0.01.

TABLE A6: Robustness of Effects on Health Outcomes for Excluding Deceased Patients and Last-Treated Municipalities (Multiplied by 100)

	ED visits		Hospital visits		Mental disorder		PDA diagnosis		Rx poisoning		Other side effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. All ages												
Post-adoption	−0.296	0.197	−5.143**	−5.661	−0.350	−0.124	0.012	0.018*	0.016**	0.015	−0.013	0.005
	(2.000)	(2.766)	(2.429)	(3.934)	(0.352)	(0.302)	(0.010)	(0.010)	(0.008)	(0.012)	(0.045)	(0.075)
Mean outcome	28.283	31.905	150.782	159.372	6.317	6.180	0.169	0.156	0.232	0.245	0.881	1.123
Observations	13,650,613	11,604,223	13,650,613	11,604,223	13,650,613	11,604,223	13,650,613	11,604,223	13,650,613	11,604,223	13,650,613	11,604,223
Panel B. Age 18-39												
Post-adoption	−0.296	1.408	−5.143**	−12.423**	−0.350	−0.481	0.012	0.103**	0.016**	0.062**	−0.013	0.018
	(2.000)	(3.655)	(2.429)	(5.339)	(0.352)	(0.662)	(0.010)	(0.048)	(0.008)	(0.024)	(0.045)	(0.029)
Mean outcome	28.283	30.760	150.782	172.916	6.317	10.489	0.169	0.559	0.232	0.528	0.881	0.276
Observations	13,650,613	2,423,853	13,650,613	2,423,853	13,650,613	2,423,853	13,650,613	2,423,853	13,650,613	2,423,853	13,650,613	2,423,853
Panel C. Age 40-64												
Post-adoption	−0.635	0.251	−3.308	−5.069	−0.206	−0.098	−0.003	−0.003	0.005	−0.003	−0.021	0.018
	(1.763)	(2.548)	(2.317)	(4.179)	(0.241)	(0.325)	(0.004)	(0.006)	(0.008)	(0.017)	(0.053)	(0.035)
Mean outcome	27.194	25.212	142.531	148.537	4.971	6.448	0.054	0.074	0.157	0.252	1.050	0.576
Observations	10,604,738	5,190,270	10,604,738	5,190,270	10,604,738	5,190,270	10,604,738	5,190,270	10,604,738	5,190,270	10,604,738	5,190,270
Panel D. Age over 65												
Post-adoption	−1.665	−0.489	−2.105	−2.260	−0.088	−0.037	−0.003	−0.005	0.005	0.007	−0.051	−0.016
	(1.723)	(2.300)	(2.010)	(2.978)	(0.087)	(0.108)	(0.003)	(0.004)	(0.006)	(0.008)	(0.095)	(0.155)
Mean outcome	33.414	41.307	146.551	165.238	2.837	3.214	0.019	0.018	0.056	0.064	1.845	2.350
Observations	4,173,112	3,990,100	4,173,112	3,990,100	4,173,112	3,990,100	4,173,112	3,990,100	4,173,112	3,990,100	4,173,112	3,990,100
Exclude died patients	✓		✓		✓		✓		✓		✓	
Exclude last-treated municipalities		✓		✓		✓		✓		✓		✓

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Columns 1, 3, 5, 7, 9, 11 exclude patients who died during the observation period 2007–2014. Columns 2, 4, 6, 8, 10, 12 use data from periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

C.2 Clustering Standard Errors at Hospital District Level and Excluding Patients Who Switch Municipalities

TABLE A7: Robustness of Effects on Benzodiazepine Use for Standard Errors Clustering at Hospital District Level and Excluding Patients With Multiple Municipalities

	DDDs		Renewed DDDs		New DDDs		Number of rx	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All ages								
Post-adoption	1.838***	1.723***	1.764***	1.714***	0.074	0.009	−0.005	−0.007
	(0.459)	(0.423)	(0.529)	(0.479)	(0.148)	(0.124)	(0.005)	(0.004)
Mean outcome	55.694	56.548	45.614	46.391	10.081	10.158	0.644	0.644
Observations	15,167,056	13,242,972	15,167,056	13,242,972	15,167,056	13,242,972	15,167,056	13,242,972
Panel B. Age 18-39								
Post-adoption	2.396***	2.490***	1.974***	2.096***	0.422***	0.393*	0.007	0.007
	(0.582)	(0.712)	(0.522)	(0.614)	(0.144)	(0.207)	(0.005)	(0.005)
Mean outcome	30.342	29.380	23.307	22.663	7.035	6.717	0.445	0.424
Observations	3,084,187	2,165,200	3,084,187	2,165,200	3,084,187	2,165,200	3,084,187	2,165,200
Panel C. Age 40-64								
Post-adoption	2.093***	1.899***	1.934**	1.771**	0.159	0.128	−0.003	−0.004
	(0.759)	(0.669)	(0.910)	(0.799)	(0.211)	(0.188)	(0.005)	(0.004)
Mean outcome	57.504	56.677	47.085	46.376	10.419	10.301	0.680	0.667
Observations	6,742,280	5,980,332	6,742,280	5,980,332	6,742,280	5,980,332	6,742,280	5,980,332
Panel D. Age over 65								
Post-adoption	1.018**	1.009**	1.267***	1.276***	−0.249	−0.267	−0.013**	−0.014***
	(0.470)	(0.405)	(0.466)	(0.358)	(0.175)	(0.167)	(0.006)	(0.005)
Mean outcome	68.051	67.937	56.638	56.486	11.414	11.451	0.714	0.711
Observations	5,340,589	5,097,440	5,340,589	5,097,440	5,340,589	5,097,440	5,340,589	5,097,440
Hospital district level clustering	✓		✓		✓		✓	
Patients with multiple municipalities excluded		✓		✓		✓		✓

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Columns 1, 3, 5, and 7 cluster standard errors at the hospital district level and show them in parentheses. Columns 2, 4, 6, and 8 exclude patients with multiple municipalities and show standard errors clustered at the municipality level in parentheses. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

TABLE A8: Robustness of Effects on Health Outcomes for Standard Errors Clustering at Hospital District Level and Excluding Patients With Multiple Municipalities (Multiplied by 100)

	ED visits		Hospital visits		Mental disorder		PDA diagnosis		Rx poisoning		Other side effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. All ages												
Post-adoption	−0.517	−0.561	−6.103**	−5.436**	−0.327	−0.236	0.010	0.007	0.015	0.010	−0.008	−0.008
	(3.216)	(2.088)	(2.698)	(2.600)	(0.391)	(0.287)	(0.010)	(0.007)	(0.009)	(0.008)	(0.062)	(0.061)
Mean outcome	33.925	33.210	164.768	160.332	6.363	5.701	0.166	0.118	0.240	0.188	1.157	1.224
Observations	15,167,056	13,242,972	15,167,056	13,242,972	15,167,056	13,242,972	15,167,056	13,242,972	15,167,056	13,242,972	15,167,056	13,242,972
Panel B. Age 18-39												
Post-adoption	1.085	0.946	−12.101***	−11.903***	−0.837	−0.651	0.067	0.067*	0.062***	0.057**	0.012	0.008
	(4.102)	(3.015)	(3.445)	(4.345)	(0.846)	(0.704)	(0.043)	(0.038)	(0.022)	(0.025)	(0.024)	(0.022)
Mean outcome	32.984	28.937	182.878	168.818	11.174	9.954	0.603	0.487	0.529	0.410	0.299	0.271
Observations	3,084,187	2,165,200	3,084,187	2,165,200	3,084,187	2,165,200	3,084,187	2,165,200	3,084,187	2,165,200	3,084,187	2,165,200
Panel C. Age 40-64												
Post-adoption	−0.131	0.006	−5.162*	−4.384*	−0.312	−0.260	−0.004	−0.004	−0.000	−0.007	0.002	0.010
	(3.035)	(1.920)	(3.063)	(2.584)	(0.425)	(0.327)	(0.006)	(0.005)	(0.013)	(0.012)	(0.035)	(0.031)
Mean outcome	26.297	25.387	151.715	148.516	6.615	6.246	0.082	0.069	0.245	0.212	0.583	0.571
Observations	6,742,280	5,980,332	6,742,280	5,980,332	6,742,280	5,980,332	6,742,280	5,980,332	6,742,280	5,980,332	6,742,280	5,980,332
Panel D. Age over 65												
Post-adoption	−1.709	−1.687	−3.462	−3.608	−0.064	−0.050	−0.006**	−0.005	0.006	0.007	−0.026	−0.031
	(2.940)	(1.903)	(2.557)	(2.282)	(0.108)	(0.081)	(0.003)	(0.003)	(0.009)	(0.008)	(0.122)	(0.112)
Mean outcome	44.100	44.204	170.789	170.591	3.268	3.256	0.020	0.019	0.066	0.065	2.378	2.394
Observations	5,340,589	5,097,440	5,340,589	5,097,440	5,340,589	5,097,440	5,340,589	5,097,440	5,340,589	5,097,440	5,340,589	5,097,440
Hospital district level clustering	✓		✓		✓		✓		✓		✓	
Patients with multiple municipalities excluded		✓		✓		✓		✓		✓		✓

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Columns 1, 3, 5, 7, 9 and 11 cluster standard errors at the hospital district level and show them in parentheses. Columns 2, 4, 6, 8, 10 and 12 exclude patients with multiple municipalities and show standard errors clustered at the municipality level in parentheses. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

C.3 Specification with Physician Fixed Effects

TABLE A9: Robustness for Physician Fixed Effects: Effects of E-Prescribing on Composition of Individual Prescriptions

	DDDs		Renewed DDDs		New DDDs	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All ages						
Post-adoption	2.962***	2.207***	2.834***	2.254***	0.129	−0.047
	(0.405)	(0.354)	(0.420)	(0.379)	(0.169)	(0.172)
Mean outcome	86.466	86.466	70.817	70.817	15.649	15.649
Observations	9,768,925	9,768,925	9,768,925	9,768,925	9,768,925	9,768,925
Panel B. Age 18-39						
Post-adoption	3.220***	3.481***	2.737***	2.884***	0.484	0.597
	(0.989)	(1.132)	(0.971)	(0.970)	(0.383)	(0.477)
Mean outcome	68.316	68.316	52.497	52.497	15.818	15.818
Observations	1,396,770	1,396,770	1,396,770	1,396,770	1,396,770	1,396,770
Panel C. Age 40-64						
Post-adoption	2.715***	1.776***	2.551***	1.818***	0.165	−0.042
	(0.500)	(0.413)	(0.570)	(0.501)	(0.192)	(0.247)
Mean outcome	84.466	84.466	69.137	69.137	15.328	15.328
Observations	4,510,421	4,510,421	4,510,421	4,510,421	4,510,421	4,510,421
Panel D. Age over 65						
Post-adoption	2.834***	1.833***	3.119***	2.333***	−0.286	−0.500**
	(0.383)	(0.365)	(0.403)	(0.420)	(0.209)	(0.254)
Mean outcome	95.366	95.366	79.404	79.404	15.963	15.963
Observations	3,861,734	3,861,734	3,861,734	3,861,734	3,861,734	3,861,734
Physician FE	✓	✓	✓	✓	✓	✓
Patient FE		✓		✓		✓

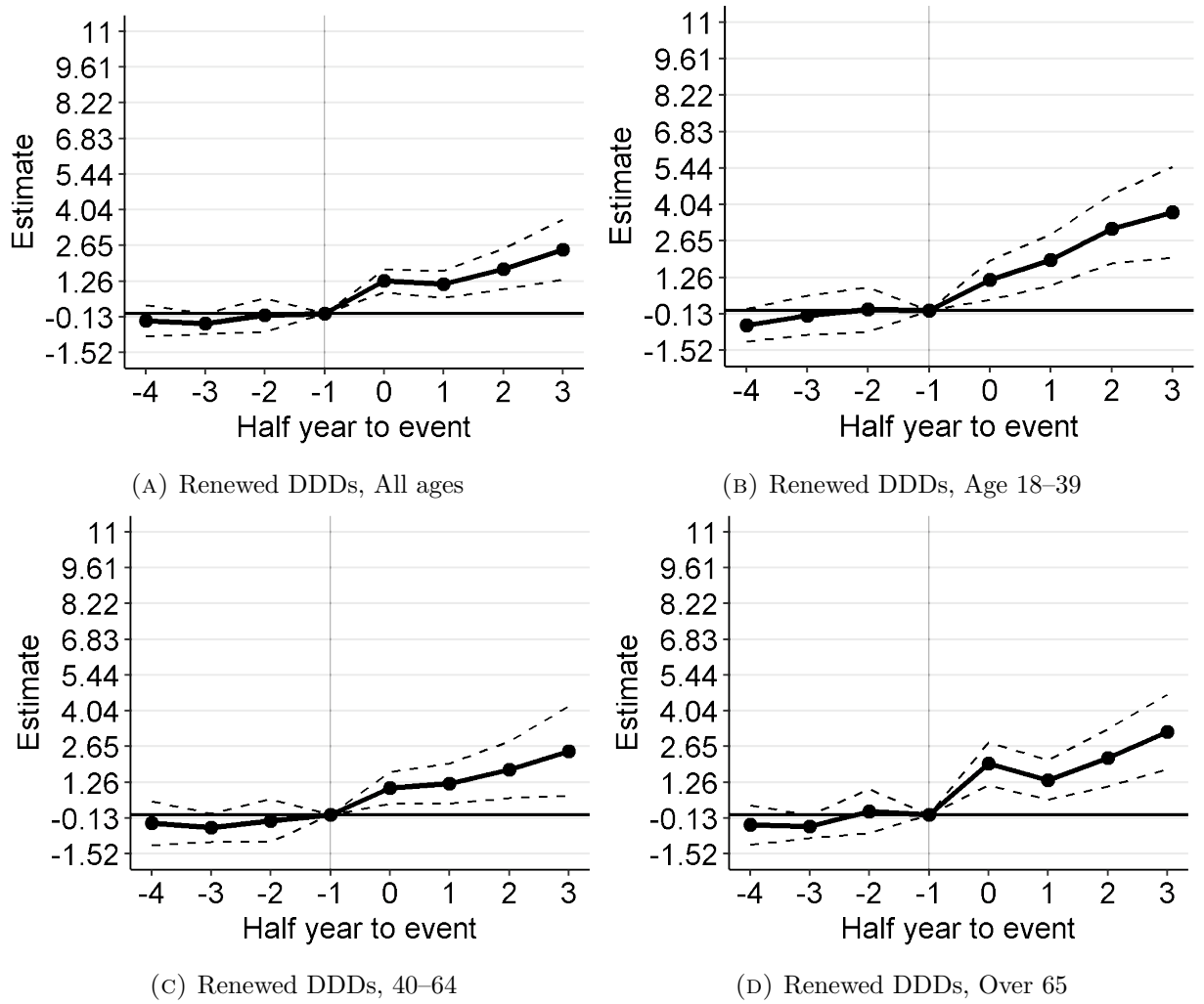
Notes: Each column shows parameter estimates from a separate regression using prescription-level data. The outcomes are the number of defined daily doses (columns 1 and 2), the number of renewed defined daily doses (columns 3 and 4), and the number of new defined daily doses (columns 5 and 6). Panel A shows the results for all ages, Panel B for the age group under 18–39, Panel C for the age group 40–64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects and physician fixed effects. Columns 2, 4 and 6 additionally control for patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

C.4 Alternative Definition of Renewed versus New Prescriptions

TABLE A10: Robustness of Effects at Intensive Margin for Alternative Definition of Renewed versus New Prescriptions and Timing of Renewal

	All ages		Age 18–39		Age 40–64		Age over 65	
	Renewed DDDs	New DDDs	Renewed DDDs	New DDDs	Renewed DDDs	New DDDs	Renewed DDDs	New DDDs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-adoption	1.817***	0.022	2.004***	0.397**	1.983**	0.110	1.336***	−0.319*
	(0.475)	(0.122)	(0.588)	(0.177)	(0.803)	(0.172)	(0.376)	(0.192)
Mean outcome	46.566	9.126	23.709	6.618	48.020	9.484	57.929	10.122
Observations	15,167,056	15,167,056	3,084,187	3,084,187	6,742,280	6,742,280	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. In calculating the number of renewed and new DDDs, we use an alternative definition of renewal without the 16-month cutoff (in Finland, benzodiazepine prescriptions can be renewed within 16 months from the issue date). In this case, we define a prescription as renewed if the prescribed drug is essentially the same as measured by the ATC code, strength, and the route of administration as that in any of the two previous prescriptions. Otherwise, we define a prescription as new. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.



(A) Renewed DDDs, All ages

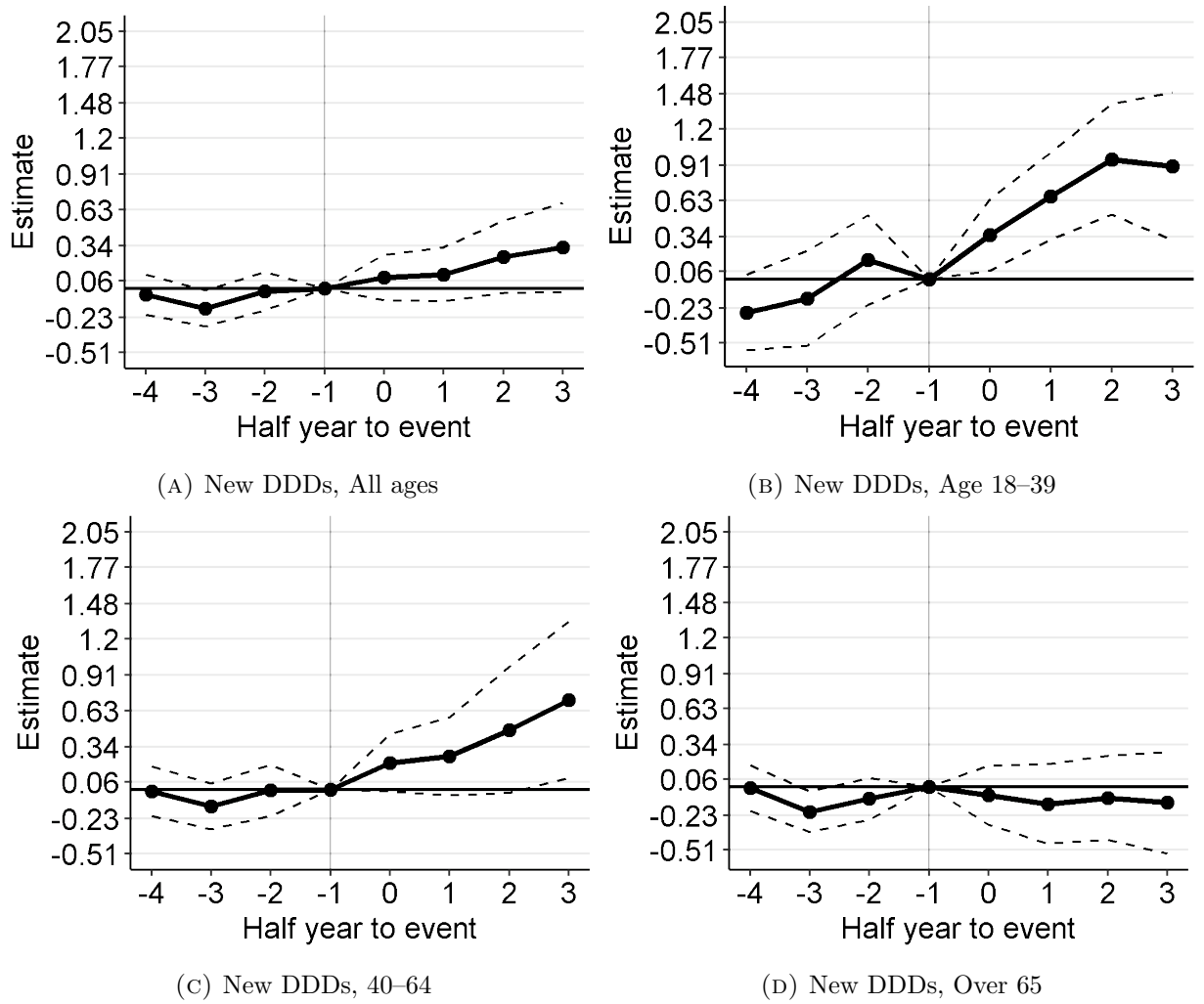
(B) Renewed DDDs, Age 18–39

(C) Renewed DDDs, 40–64

(D) Renewed DDDs, Over 65

FIGURE A11: Robustness for Alternative Definition of Renewed versus New Prescriptions: Renewed DDDs

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. In calculating the number of renewed DDDs, we use an alternative definition of renewal without the 16-month cutoff (in Finland, benzodiazepine prescriptions can be renewed within 16 months from the issue date). In this case, we define a prescription as renewed if the prescribed drug is essentially the same as measured by the ATC code, strength, and the route of administration as that in any of the two previous prescriptions. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) New DDDs, All ages

(B) New DDDs, Age 18–39

(C) New DDDs, 40–64

(D) New DDDs, Over 65

FIGURE A12: Robustness for Alternative Definition of Renewed versus New Prescriptions: New DDDs

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. In calculating the number of new DDDs, we use an alternative definition of renewal without the 16-month cutoff (in Finland, benzodiazepine prescriptions can be renewed within 16 months from the issue date). In this case, we define a prescription as renewed if the prescribed drug is essentially the same as measured by the ATC code, strength, and the route of administration as that in any of the two previous prescriptions. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

D Robustness for Treatment Effect Heterogeneity and Possible Violations of Parallel Trends Assumption

Two-way fixed effects (TWFE) regression is widely used for difference-in-differences designs, but in staggered settings it is a consistent estimator only under the assumption of constant treatment effect. We next evaluate the sensitivity of our baseline results for heterogeneity-robust estimation. We also implement test statistics and tools to investigate the parallel trends assumption in more detail.

Goodman-Bacon Decomposition.—Goodman-Bacon (2021) shows that, in the case of a staggered adoption where the treatment occurs at different times across units, the TWFE DiD estimator is a weighted average of all possible individual two-period/two-group DiD estimators in the data. In our setting, patients in later-treated municipalities are used as controls *before* the treatment for patients in early-treated municipalities, and patients in early-treated municipalities *after* the treatment are used as controls for patients in later-treated municipalities. This leads to a potential concern regarding the estimation of treatment effects for later-treated municipalities in the case of the time-varying treatment effects. This feature could induce negative weights for later-treated groups as those units are compared to already-treated units, potentially biasing the DiD estimates even away from the true sign of the estimates. To mitigate these concerns, we conduct several robustness checks that are set out below.

First, as described in the main text (Section 6.3), we estimated the DiD regressions for benzodiazepine use and downstream health outcomes using data for periods when the last-treated municipalities have not yet adopted e-prescribing (thereby using the last-treated municipalities as "clean controls"). This helps us to mitigate potential bias in the DiD estimates as some of the later versus early comparisons are excluded from the data. The shortcoming of this approach, however, is that it narrows the comparison window of early-treated units after the treatment takes place and thus puts more weight on short-term effects (Callaway and Sant'Anna 2021). We still find that the results are similar to the baseline results (Online Appendix Tables A5 and A6, Section C.1).

Second, we perform an explicit decomposition of the summed weights and average DiD estimates for early- versus later-treated groups and later- versus early-treated groups as described by Goodman-Bacon (2021) to evaluate how much weight is being placed on "forbidden" comparison groups of already-treated units and how removing these comparisons would change the results.[40]

[40] We use the *bacondecomp* package available for R and Stata for estimation.

Instead of using patient biannual-level data, we compute all 2×2 DiD estimates separately for each age group and adoption time using data aggregated to the municipality biannual-level averages in order to reduce computational burden. We control for half-year fixed effects and municipality, instead of patient fixed effects. As the current software package for the actual empirical implementation of Goodman-Bacon (2021) does not allow for population weights in the regressions when performing the full decomposition, our estimates are not fully comparable to the baseline estimates obtained using patient biannual-level data. Nevertheless, the results should give an idea of whether using early-treated units as a control group is a concern in our setting.

Online Appendix Tables A11 and A12 show the results for the municipality-level DiD estimates and the decompositions of the summed weights. Based on these results, we conclude that negative weighting is not a concern in our application, as the estimates for earlier versus later are very similar to later versus earlier for most outcomes and samples. This is especially the case for the outcomes on benzodiazepine use (DDDs, renewed DDDs, new DDDs, number of prescriptions) and health (mental disorder, PDA diagnosis, other side effects). Although not fully comparable, our conclusions on the effects of e-prescribing based on these alternative treatment groups and aggregated data remain fairly similar to those drawn from the baseline estimates using patient biannual-level data. Thus, the results are not sensitive to the aggregation of the patient-level data to the municipality level.

TABLE A11: Goodman-Bacon Decomposition of Equally Weighted TWFE Estimates of Benzodiazepine Use at the Intensive Margin

	DDDs (1)		Renewed DDDs (2)		New DDDs (3)		Number of rx (4)	
	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.
Panel A. All ages								
Earlier vs Later Treated	0.683	1.623	0.683	1.444	0.683	0.18	0.683	-0.015
Later vs Earlier Treated	0.317	1.883	0.317	1.698	0.317	0.184	0.317	-0.014
Mean outcome	58.987	58.987	48.975	48.975	10.013	10.013	0.681	0.681
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864
Panel B. Age 18–39								
Earlier vs Later Treated	0.683	3.637	0.683	3.174	0.683	0.463	0.683	0.018
Later vs Earlier Treated	0.317	4.687	0.317	3.696	0.317	0.991	0.317	0.023
Mean outcome	29.252	29.252	22.704	22.704	6.548	6.548	0.424	0.424
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864
Panel A. Age 40–64								
Earlier vs Later Treated	0.683	2.255	0.683	1.565	0.683	0.69	0.683	-0.011
Later vs Earlier Treated	0.317	1.984	0.317	1.606	0.317	0.377	0.317	-0.013
Mean outcome	59.190	59.190	48.949	48.949	10.241	10.241	0.697	0.697
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864
Panel A. Age over 65								
Earlier vs Later Treated	0.683	0.245	0.683	0.845	0.683	-0.6	0.683	-0.025
Later vs Earlier Treated	0.317	1.565	0.317	1.706	0.317	-0.141	0.317	-0.021
Mean outcome	68.554	68.554	57.462	57.462	11.092	11.092	0.747	0.747
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864

Notes: Each model shows a Goodman-Bacon decomposition of two-way fixed effects (TWFE) estimates from a separate regression using aggregated municipality biannual-level balanced data on benzodiazepine patients. In TWFE, each observation is weighted equally (currently, the method does not allow for population weighting). Each regression controls for calendar time (half-year) fixed effects and municipality fixed effects.

TABLE A12: Goodman-Bacon Decomposition of Equally Weighted TWFE Estimates of Benzodiazepine Patients' Health Outcomes (Multiplied by 100)

	ED visits		Hospital visits		Mental disorder		PDA diagnosis		Rx poisoning		Other side effects	
	(1)		(2)		(3)		(4)		(5)		(6)	
	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.
Panel A. All ages												
Earlier vs Later Treated	0.683	-2.413	0.683	-6.108	0.683	-0.119	0.683	0.008	0.683	0.015	0.683	-0.006
Later vs Earlier Treated	0.317	-0.816	0.317	-2.749	0.317	-0.104	0.317	0.004	0.317	-0.007	0.317	-0.108
Mean outcome	35.462	35.462	157.572	157.572	5.632	5.632	0.092	0.092	0.192	0.192	1.323	1.323
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864
Panel B. Age 18–39												
Earlier vs Later Treated	0.683	-3.36	0.683	-10.168	0.683	0.287	0.683	0.079	0.683	0.036	0.683	-0.078
Later vs Earlier Treated	0.317	3.575	0.317	1.984	0.317	-0.086	0.317	0.074	0.317	-0.021	0.317	-0.069
Mean outcome	33.700	33.700	174.207	174.207	10.707	10.707	0.445	0.445	0.502	0.502	0.336	0.336
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864
Panel A. Age 40–64												
Earlier vs Later Treated	0.683	-2.644	0.683	-11.241	0.683	-0.243	0.683	0	0.683	0.012	0.683	-0.016
Later vs Earlier Treated	0.317	0.319	0.317	-4.375	0.317	-0.069	0.317	-0.001	0.317	-0.018	0.317	-0.035
Mean outcome	26.837	26.837	149.143	149.143	6.553	6.553	0.055	0.055	0.228	0.228	0.586	0.586
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864
Panel A. Age over 65												
Earlier vs Later Treated	0.683	-1.885	0.683	-0.624	0.683	-0.109	0.683	-0.009	0.683	0.002	0.683	0.029
Later vs Earlier Treated	0.317	-2.951	0.317	-0.58	0.317	-0.08	0.317	-0.008	0.317	0.001	0.317	-0.165
Mean outcome	44.648	44.648	161.329	161.329	3.069	3.069	0.016	0.016	0.059	0.059	2.374	2.374
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864

Notes: Each model shows a Goodman-Bacon decomposition of two-way fixed effects (TWFE) estimates from a separate regression using aggregated municipality biannual-level balanced data. In TWFE, each observation is weighted equally (currently, the method does not allow for population weighting). Each regression controls for calendar time (half-year) fixed effects and municipality fixed effects. For scaling purposes, all coefficients ("Est.") and means are multiplied by 100.

Roth and Sant'Anna (2023) Efficient Estimator—We use the efficient DiD estimator proposed by Roth and Sant'Anna (2023), because it has three important advantages in our application. First, it is robust to potential treatment effect heterogeneity across treatment units and over time in staggered designs. Second, the efficient estimator can provide more precise estimates than those based on TWFE models and other DiD-based methods. Third, its algorithm is computationally less demanding than many other heterogeneity-robust estimators in our application, which uses large individual-level data sets with millions of observations.

The efficient estimator by Roth and Sant'Anna (2023) also has relevant disadvantages and limitations. First, the efficient estimator relies on the assumption that the timing of the treatment assignment is random or quasi-random. Note that this is a stronger identification assumption than the standard parallel trends assumption. Second, the current software package (*staggered* in R) for the actual empirical implementation of the efficient estimator requires a balanced panel; that is, estimation requires that all 16 periods are observed for all individuals in each age group. This

restriction implies that in age group 18–39, for example, an individual is excluded from the age group-specific balanced data if the individual is younger than 18 or older than 39 at any time during our observation period. Third, the software package does not allow for the clustering of standard errors at the municipality level. This implies that in our application, the (non-clustered) standard errors are most likely underestimated. In contrast, using TWFE we are able to cluster the standard errors at the municipality level, which is also the level of relevant policy variation in our application.

Online Appendix Tables A13 and A14 show the point estimates using the efficient estimator by Roth and Sant'Anna (2023). The effects are similar or even larger (and more precisely estimated) than those obtained using TWFE. For example, for younger patients, the number of DDDs increases by 12% and this increase is driven by renewed prescriptions (Online Appendix Table A13, Figure A13).[41] We find that there is only little improvement in their general health outcomes, most notably a short-term reduction in hospitalizations for younger patients (Online Appendix Figure A14). However, we also find significant increases in adverse effects related to prescription drug abuse and poisonings (Online Appendix Table A14, Figures A15 and A16).

[41] We estimate the event study coefficients using Roth and Sant'Anna (2023) for the relative time periods between -5 and 2 to have a sufficiently large number of treatment and comparison groups in every period. Note that in this case, not yet treated municipalities act as clean controls, and thus the estimation relies on data from periods before the last treated municipalities adopted e-prescribing (H1:2007-H2:2012). For this reason, we can follow many municipalities (or their individuals) for a relatively short period of time during post-adoption. Also, only one normalization is needed in this event study specification, in contrast to the baseline specification based on two normalizations in relative time periods -5 and -1 (Equation (2)).

TABLE A13: Roth and Sant'Anna (2023) Estimator for Evaluating Effects of E-Prescribing on Intensive Margin of Benzodiazepine Use

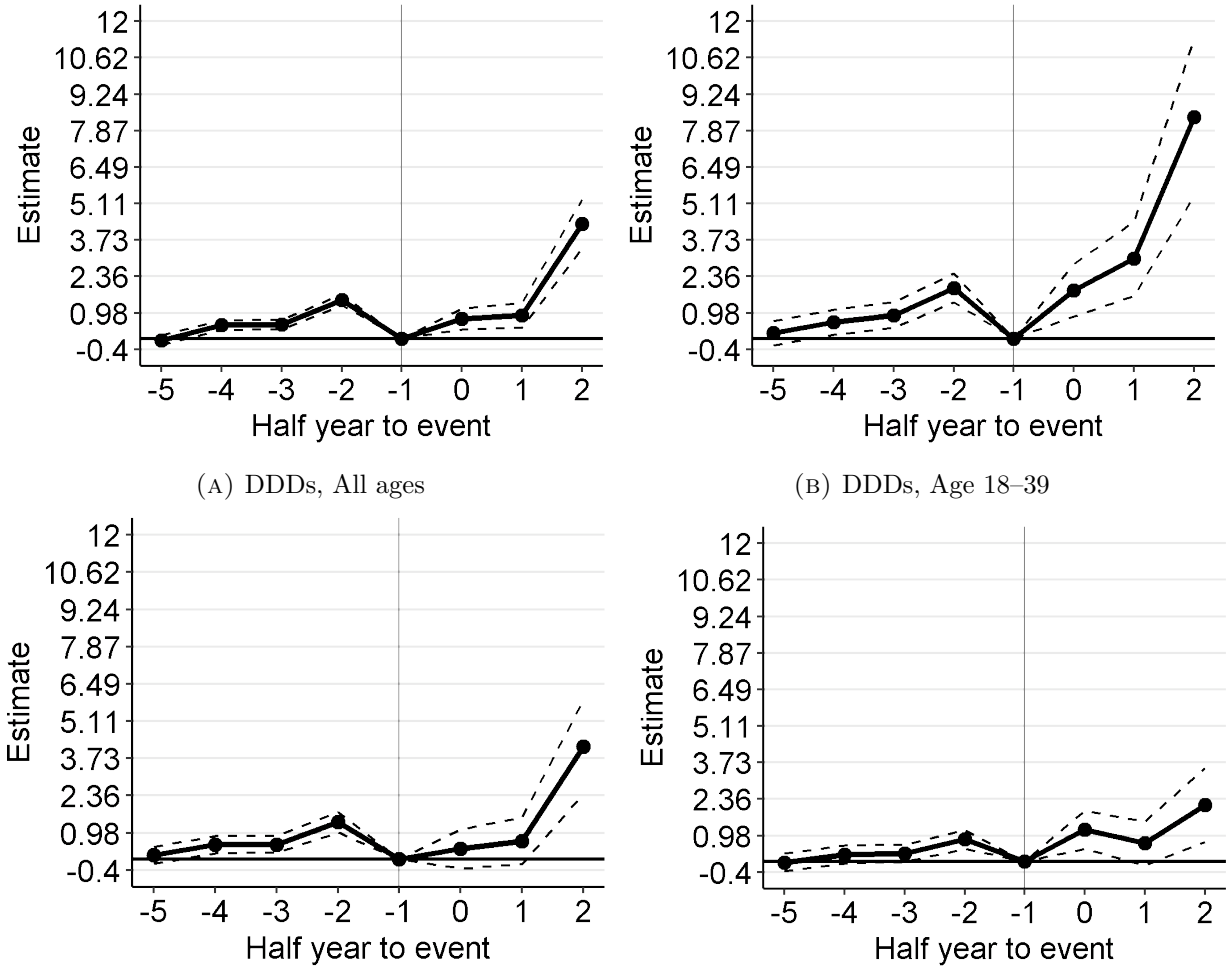
	DDDs (1)	Renewed DDDs (2)	New DDDs (3)	Number of rx (4)
Panel A. All ages				
Post-adoption	1.656	1.419	0.42	-0.012
	(0.203)	(0.186)	(0.075)	(0.002)
Mean outcome	56.548	46.391	10.158	0.644
Observations	13,242,972	13,242,972	13,242,972	13,242,972
Panel B. Age 18–39				
Post-adoption	3.458	2.643	1.096	0.015
	(0.597)	(0.519)	(0.229)	(0.006)
Mean outcome	29.380	22.663	6.717	0.424
Observations	2,165,200	2,165,200	2,165,200	2,165,200
Panel C. Age 40–64				
Post-adoption	1.474	1.251	0.382	-0.006
	(0.373)	(0.34)	(0.145)	(0.003)
Mean outcome	55.864	45.601	10.263	0.664
Observations	5,585,941	5,585,941	5,585,941	5,585,941
Panel D. Age over 65				
Post-adoption	1.39	1.329	0.328	-0.025
	(0.337)	(0.319)	(0.109)	(0.003)
Mean outcome	67.937	56.486	11.451	0.711
Observations	5,097,440	5,097,440	5,097,440	5,097,440

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level balanced panel data and the econometric approach by Roth and Sant'Anna (2023). The data include only those patients for whom we observe all periods (balanced data) and who have only one municipality (adoption date). Fixed effects for patients and half-years are included in all models. Note that the current software package for the empirical implementation of the estimation algorithm does not allow clustering for standard errors. Standard errors are shown in parentheses.

TABLE A14: Roth and Sant'Anna (2023) Estimator for Evaluating Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes (Multiplied by 100)

	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All ages						
Post-adoption	0.766	-2.495	0.015	0.04	0.022	-0.08
	(0.179)	(0.695)	(0.035)	(0.005)	(0.008)	(0.019)
Mean outcome	33.210	160.332	5.701	0.118	0.188	1.224
Observations	13,242,972	13,242,972	13,242,972	13,242,972	13,242,972	13,242,972
Panel B. Age 18–39						
Post-adoption	1.668	-2.806	0.442	0.261	0.067	0.019
	(0.577)	(3.319)	(0.13)	(0.032)	(0.035)	(0.027)
Mean outcome	28.937	168.818	9.954	0.487	0.410	0.271
Observations	2,165,200	2,165,200	2,165,200	2,165,200	2,165,200	2,165,200
Panel C. Age 40–64						
Post-adoption	1.992	-4.018	-0.033	0.004	0.009	-0.005
	(0.308)	(1.076)	(0.066)	(0.007)	(0.015)	(0.024)
Mean outcome	25.091	147.822	6.417	0.072	0.220	0.549
Observations	5,585,941	5,585,941	5,585,941	5,585,941	5,585,941	5,585,941
Panel C. Age over 65						
Post-adoption	-0.977	0.301	-0.108	-0.001	0.012	-0.221
	(0.327)	(0.981)	(0.055)	(0.005)	(0.007)	(0.052)
Mean outcome	44.204	170.591	3.256	0.019	0.065	2.394
Observations	5,097,440	5,097,440	5,097,440	5,097,440	5,097,440	5,097,440

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level balanced panel data and the econometric approach by Roth and Sant'Anna (2023). The data include only those patients for whom we observe all periods (balanced data) and who have only one municipality (adoption date). Fixed effects for patients and half-years are included in all models. Note that the current software package for the empirical implementation of the estimation algorithm does not allow clustering for standard errors. Standard errors are shown in parentheses.



(A) DDDs, All ages

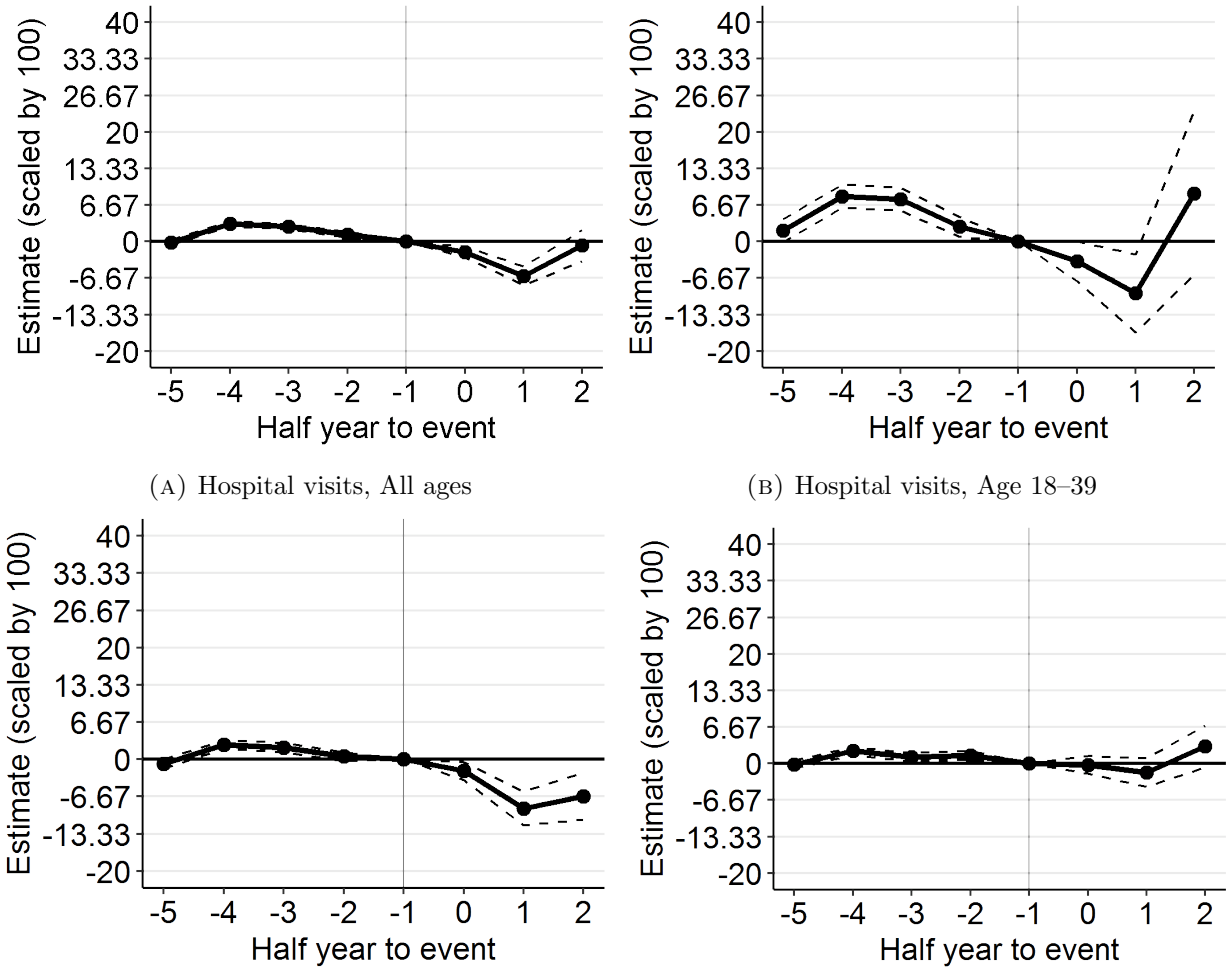
(B) DDDs, Age 18–39

(C) DDDs, Age 40–64

(D) DDDs, Age over 65

FIGURE A13: Robustness to Treatment Effect Heterogeneity at Intensive Margin: Number of Defined Daily Doses

Note: The figures plot the efficient Roth and Sant'Anna (2023) estimates from event study regressions using aggregated patient biannual-level balanced panel data. The data include only those patients for whom we observe all periods (balanced data) and who have only one municipality (adoption date). Fixed effects for patients and half-years are included in all models. Note that the current software package for the empirical implementation of the estimation algorithm does not allow clustering for standard errors.



(A) Hospital visits, All ages

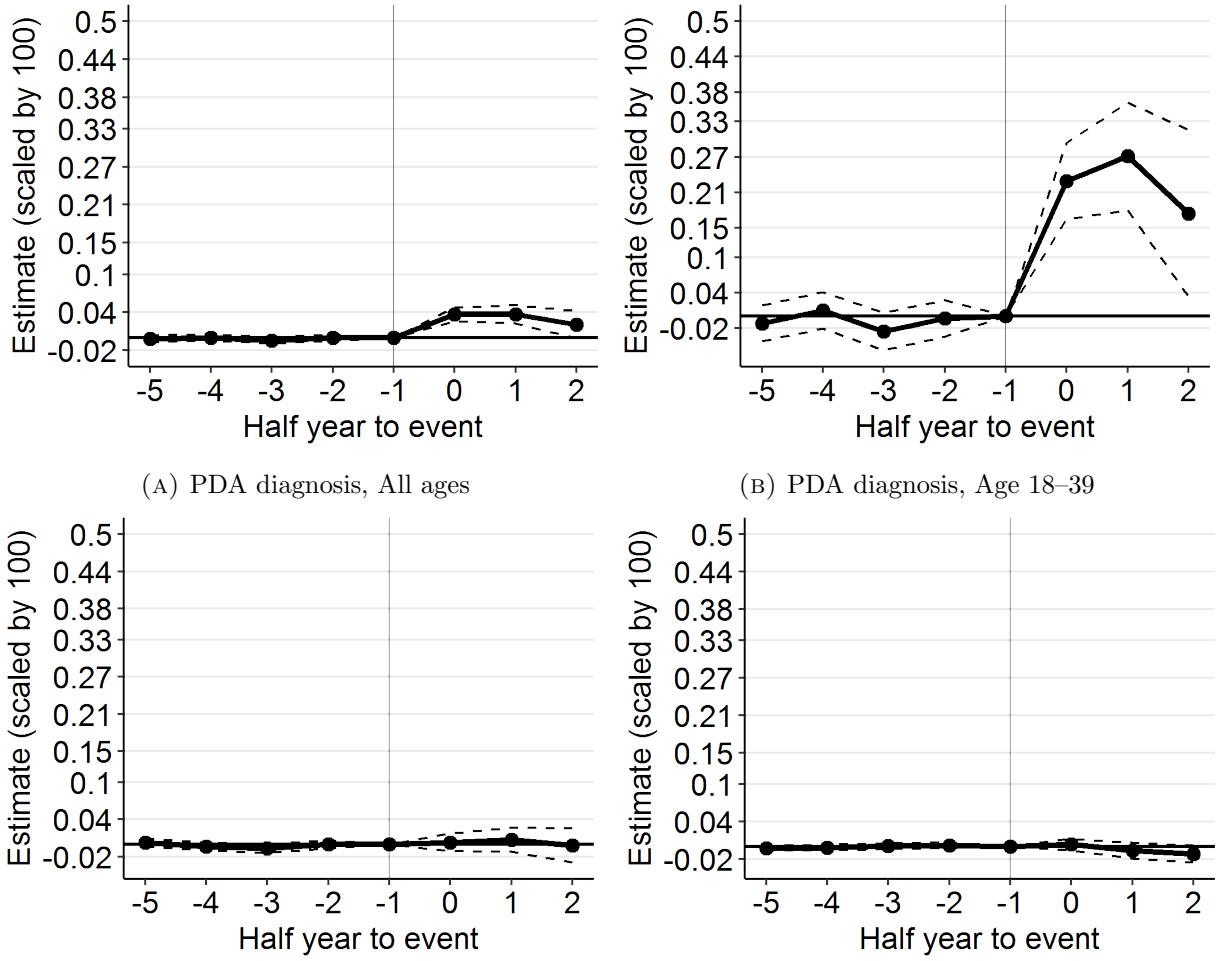
(B) Hospital visits, Age 18–39

(C) Hospital visits, Age 40–64

(D) Hospital visits, Age over 65

FIGURE A14: Robustness to Treatment Effect Heterogeneity at Intensive Margin: Hospital Visits

Note: The figures plot the efficient Roth and Sant'Anna (2023) estimates from event study regressions using aggregated patient biannual-level balanced panel data. The data include only those patients for whom we observe all periods (balanced data) and who have only one municipality (adoption date). Fixed effects for patients and half-years are included in all models. Note that the current software package for the empirical implementation of the estimation algorithm does not allow clustering for standard errors.



(A) PDA diagnosis, All ages

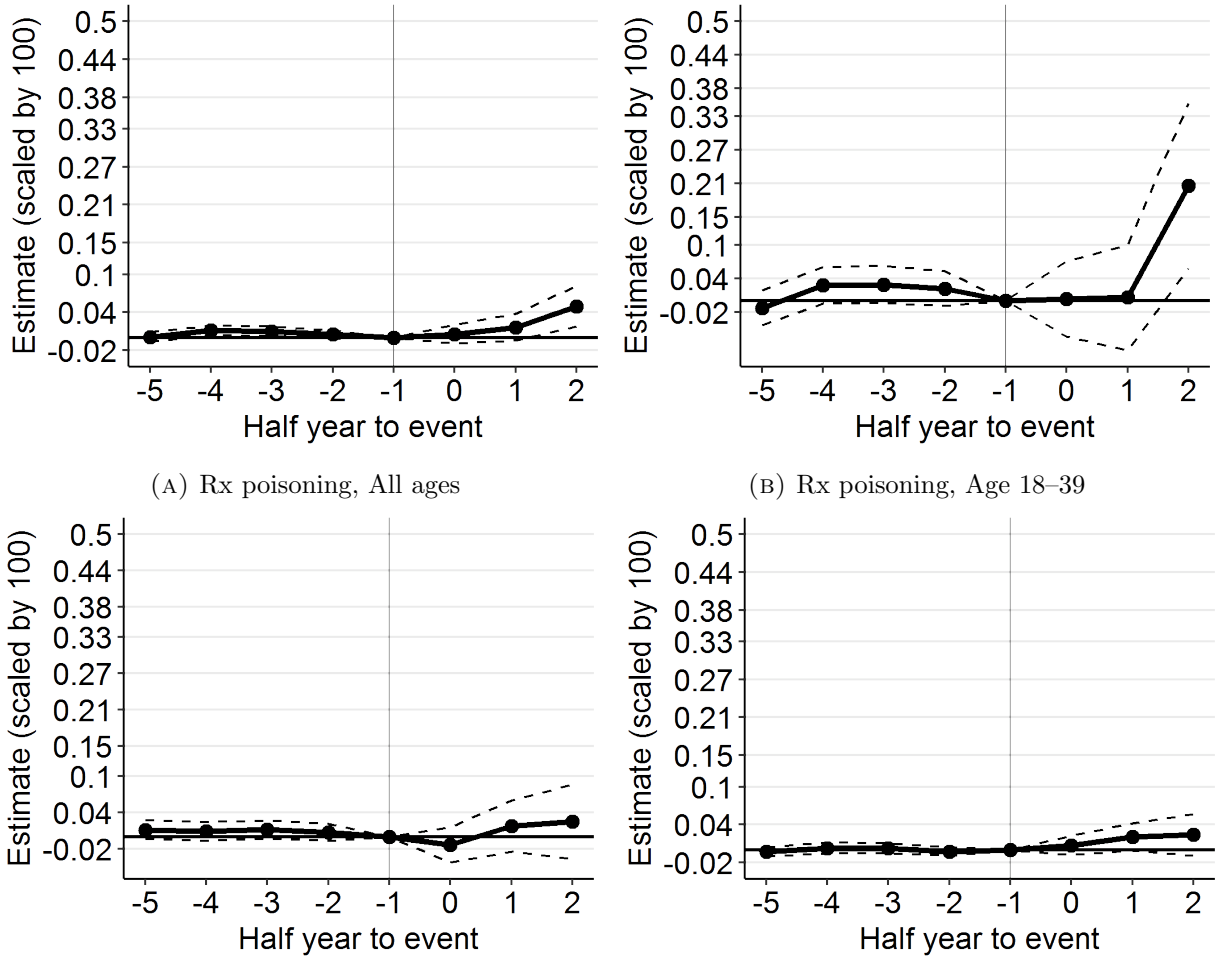
(B) PDA diagnosis, Age 18–39

(C) PDA diagnosis, Age 40–64

(D) PDA diagnosis, Age over 65

FIGURE A15: Robustness to Treatment Effect Heterogeneity: Prescription Drug Abuse (PDA) Diagnosis (Multiplied by 100)

Note: The figures plot the efficient Roth and Sant'Anna (2023) estimates from event study regressions using aggregated patient biannual-level balanced panel data. The data include only those patients for whom we observe all periods (balanced data) and who have only one municipality (adoption date). We normalize coefficients for one relative time period to zero (−1). Fixed effects for patients and half-years are included in all models. Note that the current software package for the empirical implementation of the estimation algorithm does not allow clustering for standard errors.



(A) Rx poisoning, All ages

(B) Rx poisoning, Age 18–39

(C) Rx poisoning, Age 40–64

(D) Rx poisoning, Age over 65

FIGURE A16: Robustness to Treatment Effect Heterogeneity: Prescription Drug Poisoning (Multiplied by 100)

Note: The figures plot the efficient Roth and Sant'Anna (2023) estimates from event study regressions using aggregated patient biannual-level balanced panel data. The data include only those patients for whom we observe all periods (balanced data) and who have only one municipality (adoption date). We normalize coefficients for one relative time period to zero (−1). Fixed effects for patients and half-years are included in all models. Note that the current software package for the empirical implementation of the estimation algorithm does not allow clustering for standard errors.

Addressing Limitations of Pre-trends Testing—The econometric literature has highlighted that even though visual and statistical tests for evaluating the validity of the parallel trends assumption are simple and widely used in empirical research, these tests also have notable limitations. For example, because of low statistical power it is possible that the pre-trend tests (visual or statistical) fail to reject differences in trends (Freyaldenhoven et al. 2023; Roth 2022). For this reason, we implement the following two procedures to address the potential limitations of standard pre-trends testing.

First, following Freyaldenhoven et al. (2023) and Jacobson et al. (1993), we estimate the DiD parameters by further controlling for a municipality m-specific linear time trend, ω_{mt}. Specifically, we estimate the following TWFE DiD specification:

$$y_{imt} = \rho \mathbb{1}[t - E_m \geq 0] + \alpha_i + \gamma_t + \omega_{mt} + \epsilon_{imt}. \tag{A1}$$

The estimated specification (A1) is otherwise the same as our baseline TWFE specification (1) with the individual and time fixed effects (α_i and γ_t), but the model now also includes the municipality-specific linear time trends, which are added as an interaction between munici-pality fixed effects and calendar time as a continuous variable (ω_{mt}). Because ω_{mt} allows for arbitrary permanent heterogeneity between municipalities in both the levels and linear trends of their unobserved characteristics, we can use it to adjust for the counterfactual difference in trends. Therefore, nonzero pre-trends are not required.

The results in Online Appendix Tables A15 and A16 reveal that our conclusions for the effects of e-prescribing remain mainly intact. Even the changes in the point estimates for both benzodiazepine use and health outcomes are small compared to our baseline estimates.

TABLE A15: Robustness for Controlling Municipality-Specific Linear Time Trend: Effects of E-Prescribing on Intensive Margin of Benzodiazepine Use

	DDDs (1)	Renewed DDDs (2)	New DDDs (3)	Number of rx (4)
Panel A. All ages				
Post-adoption	1.662***	1.623***	0.04	-0.007
	(0.444)	(0.43)	(0.09)	(0.004)
Mean outcome	55.694	45.614	10.081	0.644
Observations	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18–39				
Post-adoption	2.034***	1.617***	0.417**	0.004
	(0.62)	(0.489)	(0.201)	(0.005)
Mean outcome	30.342	23.307	7.035	0.445
Observations	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40–64				
Post-adoption	1.934**	1.855**	0.078	-0.003
	(0.758)	(0.827)	(0.159)	(0.004)
Mean outcome	56.744	46.353	10.392	0.677
Observations	6,311,289	6,311,289	6,311,289	6,311,289
Panel D. Age over 65				
Post-adoption	1.061***	1.24***	-0.179	-0.014***
	(0.367)	(0.33)	(0.144)	(0.005)
Mean outcome	68.051	56.638	11.414	0.714
Observations	5,340,589	5,340,589	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Panel A shows the results for all ages, Panel B for the age group under 18–39, Panel C for the age group 40–64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects, patient fixed effects and the municipality-specific linear trend. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

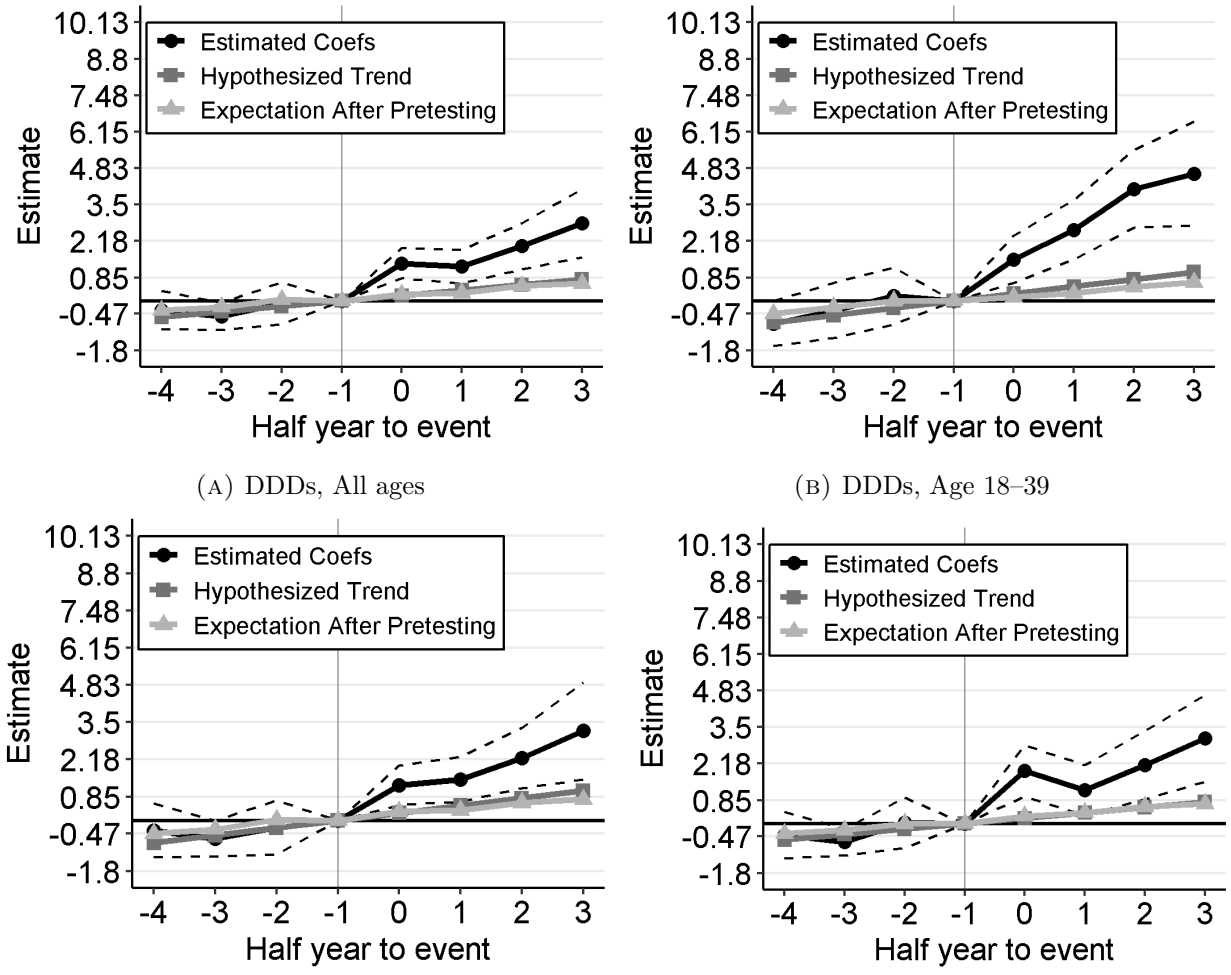
TABLE A16: Robustness for Controlling for Municipality-Specific Linear Time Trend: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes (Multiplied by 100)

	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All ages						
Post-adoption	-0.354	-6.856***	-0.307	0.004	0.005	-0.024
	(1.88)	(2.559)	(0.343)	(0.008)	(0.008)	(0.042)
Mean outcome	33.925	164.768	6.363	0.166	0.240	1.157
Observations	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18–39						
Post-adoption	1.682	-13.47**	-0.718	0.044	0.037	0.006
	(2.997)	(5.38)	(0.811)	(0.041)	(0.025)	(0.019)
Mean outcome	32.984	182.878	11.174	0.603	0.529	0.299
Observations	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40–64						
Post-adoption	0.226	-5.816***	-0.35	-0.005	-0.011	-0.01
	(1.758)	(2.229)	(0.377)	(0.008)	(0.012)	(0.025)
Mean outcome	26.064	151.281	6.805	0.086	0.255	0.561
Observations	6,311,289	6,311,289	6,311,289	6,311,289	6,311,289	6,311,289
Panel C. Age over 65						
Post-adoption	-2.061	-4.559**	-0.054	-0.006	0.005	-0.052
	(1.759)	(2.037)	(0.084)	(0.003)	(0.008)	(0.086)
Mean outcome	44.100	170.789	3.268	0.020	0.066	2.378
Observations	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Panel A shows the results for all ages, Panel B for the age group under 18–39, Panel C for the age group 40–64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects, patient fixed effects and the municipality-specific linear trend. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

Second, we apply the tools proposed by Roth (2022) to evaluate potential low-power issues in the pre-trend tests and calculate the likely distortions from pre-testing under the researcher-hypothesized violations of parallel trends. To empirically implement these tools, we use a *pretrends* R package for Roth (2022) and test statistics based on our baseline TWFE event study estimates. We first hypothesized the existence of a pre-trend as a linear violation of the parallel trend that a pre-trends test would detect a specified fraction of the time (50% power). Online Appendix Figures A17-A20 visualize the hypothesized linear trends in dark gray. Along with the hypothesized trend,

the figures also show the estimated coefficients and their confidence intervals (dark dots and dashed lines), as well as the expected value of the coefficients conditional on passing the pre-test under the hypothesized trend (light gray). Graphical inspection of the selected main estimated event study coefficients and the hypothesized trends points to the conclusion that an undetected linear pre-trend due to low power is unlikely. Importantly, the estimated coefficients based on our TWFE model follow a different pattern than the coefficients estimated conditionally on passing the hypothesized pre-trend.



(A) DDDs, All ages

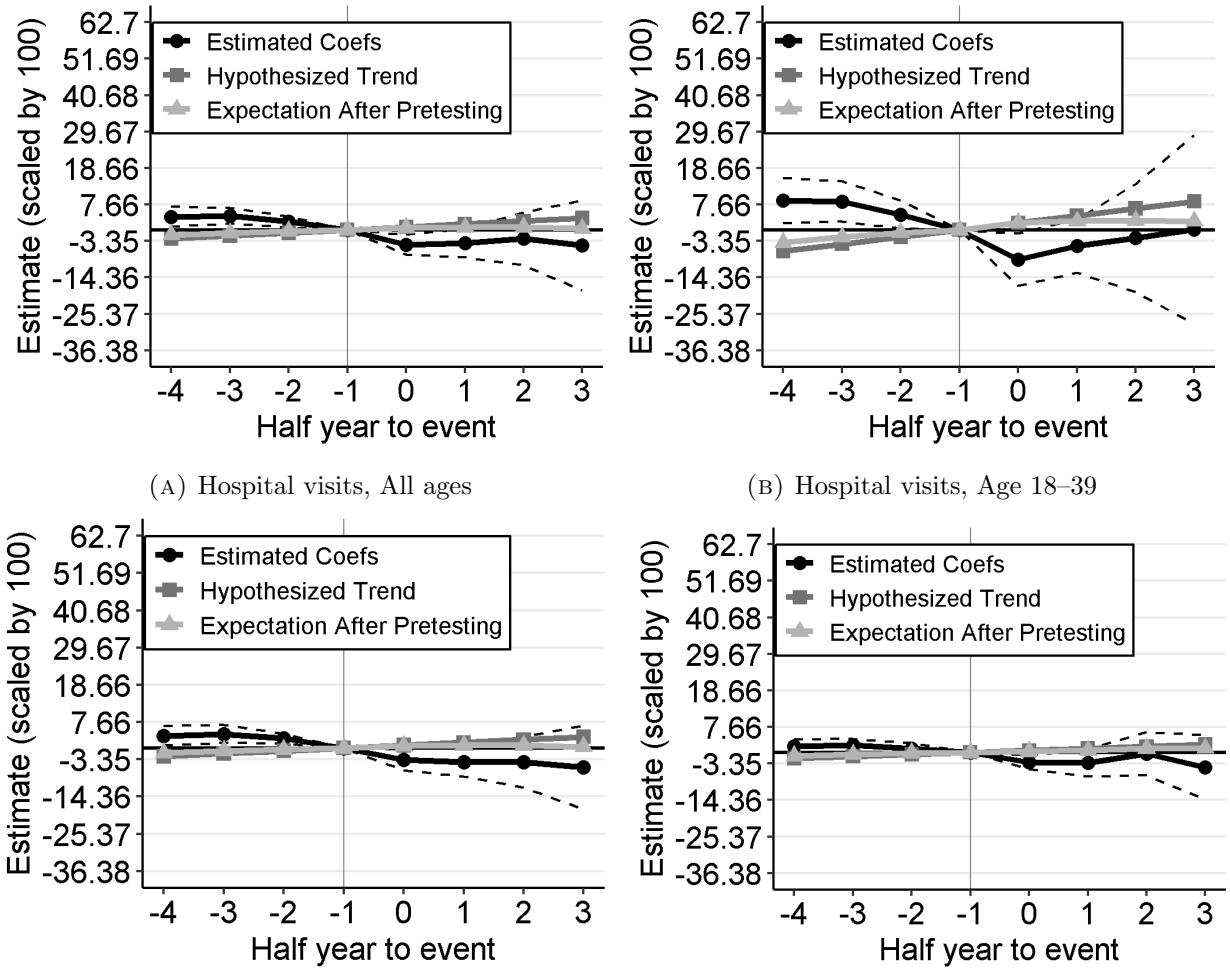
(B) DDDs, Age 18–39

(C) DDDs, Age 40–64

(D) DDDs, Age over 65

FIGURE A17: Baseline TWFE Estimates and Hypothesized Trend: Number of Defined Daily Doses

Note: The figures plot the baseline TWFE estimates and their confidence intervals from event study regressions using aggregated patient biannual-level panel data against the hypothesized trend (50% power).



(A) Hospital visits, All ages

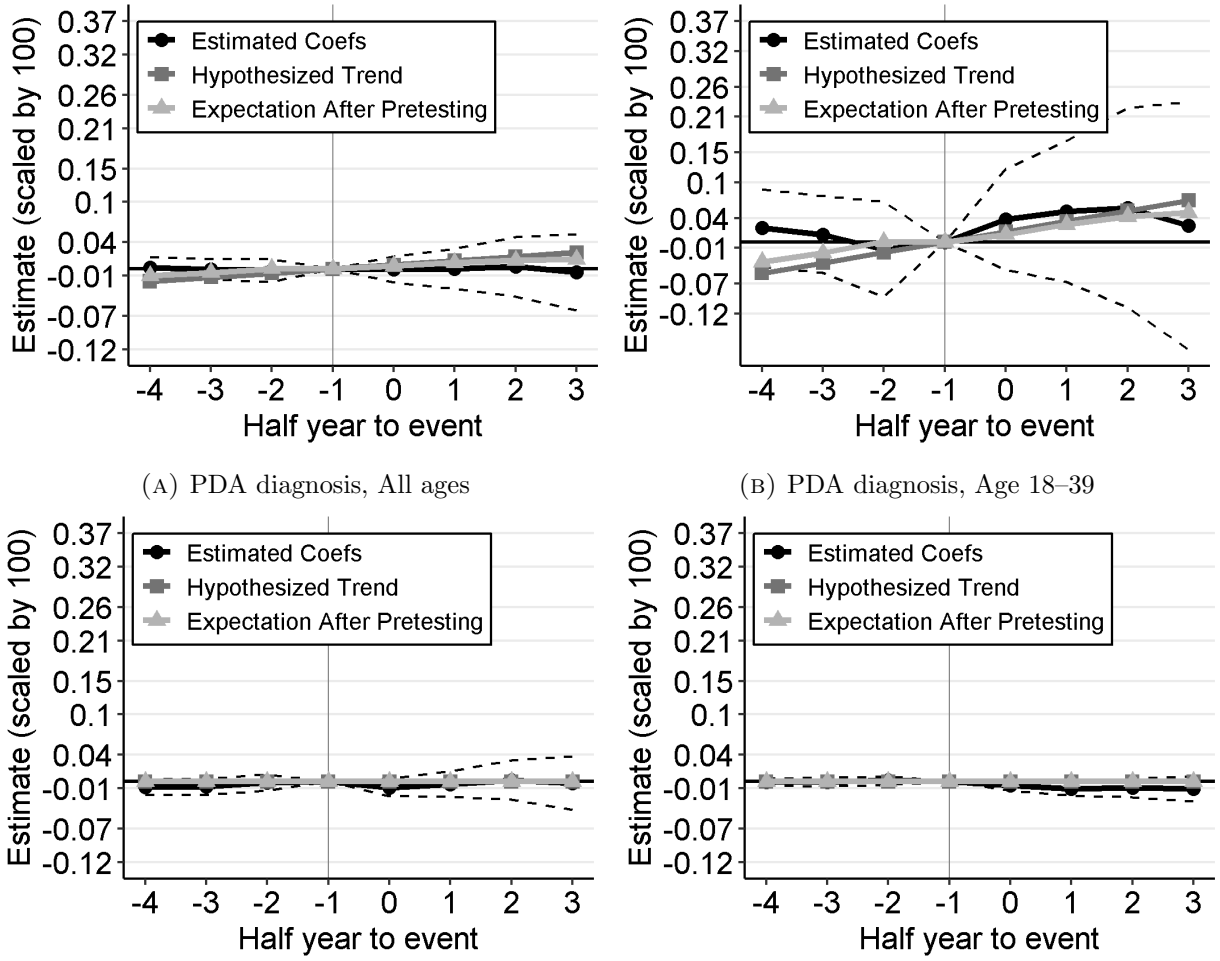
(B) Hospital visits, Age 18–39

(C) Hospital visits, Age 40–64

(D) Hospital visits, Age over 65

FIGURE A18: Baseline TWFE Estimates and Hypothesized Trend: Hospital visits

Note: The figures plot the baseline TWFE estimates and their confidence intervals from event study regressions using aggregated patient biannual-level panel data against the hypothesized trend (50% power).



(A) PDA diagnosis, All ages

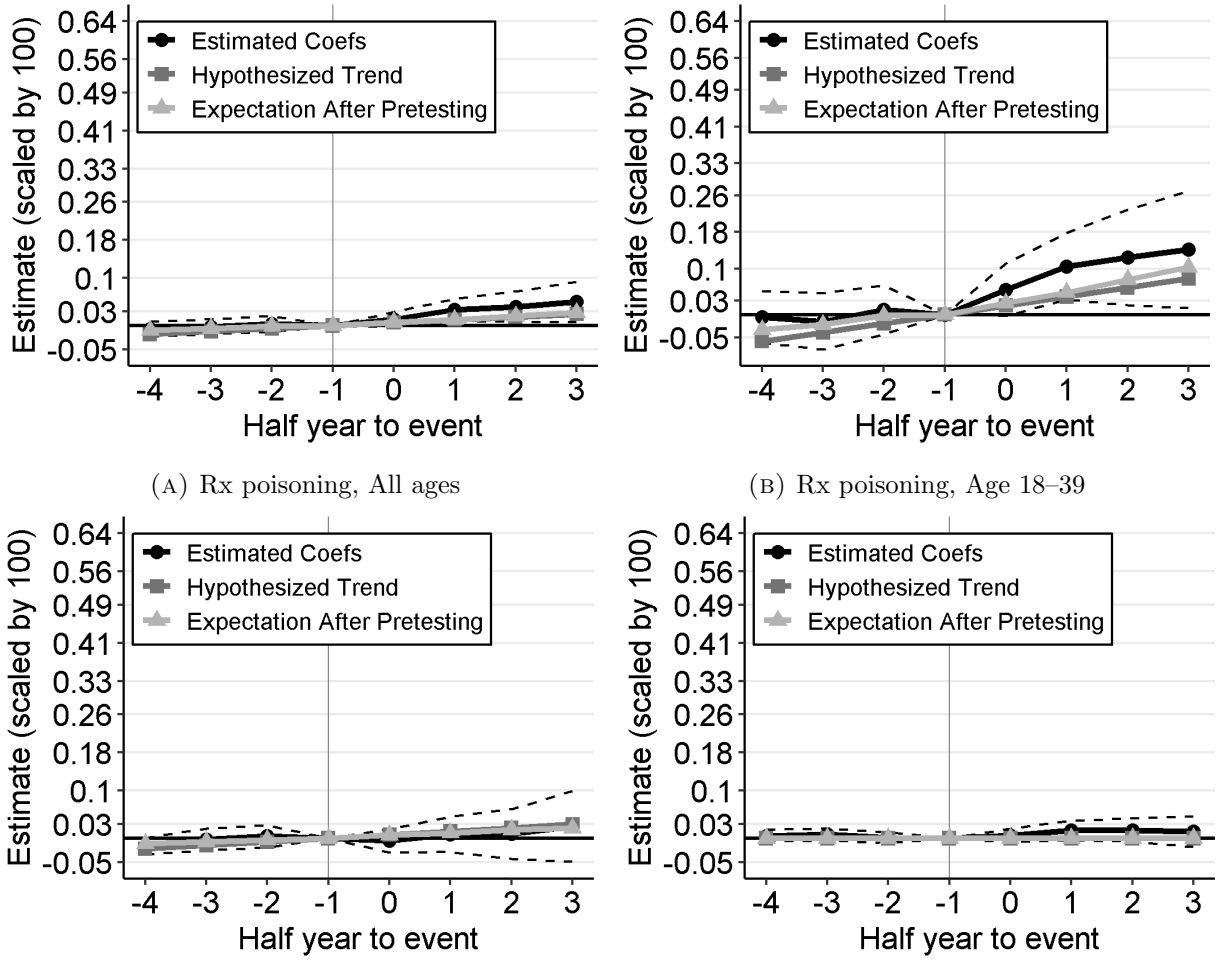
(B) PDA diagnosis, Age 18–39

(C) PDA diagnosis, Age 40–64

(D) PDA diagnosis, Age over 65

FIGURE A19: Baseline TWFE Estimates and Hypothesized Trend: Prescription Drug Abuse (PDA) Diagnosis (Multiplied by 100)

Note: The figures plot the baseline TWFE estimates and their confidence intervals from event study regressions using aggregated patient biannual-level panel data against the hypothesized trend (50% power).



(A) Rx poisoning, All ages

(B) Rx poisoning, Age 18–39

(C) Rx poisoning, Age 40–64

(D) Rx poisoning, Age over 65

FIGURE A20: Baseline TWFE Estimates and Hypothesized Trend: Prescription Drug Poisoning (Multiplied by 100)

Note: The figures plot the baseline TWFE estimates and their confidence intervals from event study regressions using aggregated patient biannual-level oanel data against the hypothesized trend (50% power).

E Additional Age Heterogeneity

TABLE A17: Effects of E-Prescribing on Selected Benzodiazepine Use and Health Outcomes at Intensive Margin, Ages 18–25 and 26–39

	DDDs	Renewed DDDs	ED visits	Hospital visits	PDA diagnosis	Rx poisoning
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Age 18-25						
Post-adoption	2.050**	1.458*	1.105	−14.541**	0.064	0.109*
	(0.933)	(0.771)	(3.898)	(7.320)	(0.068)	(0.066)
Mean outcome	17.994	12.541	37.100	201.200	0.800	0.800
Observations	752,758	752,758	752,758	752,758	752,758	752,758
Panel B. Age 26-39						
Post-adoption	2.476***	2.120***	1.011	−11.983***	0.050	0.034
	(0.748)	(0.643)	(2.589)	(3.925)	(0.049)	(0.024)
Mean outcome	34.328	26.783	31.700	177.000	0.500	0.400
Observations	2,331,429	2,331,429	2,331,429	2,331,429	2,331,429	2,331,429
Multiplied by 100			✓	✓	✓	✓

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, the coefficients, standard errors, and means in columns 3–6 are multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

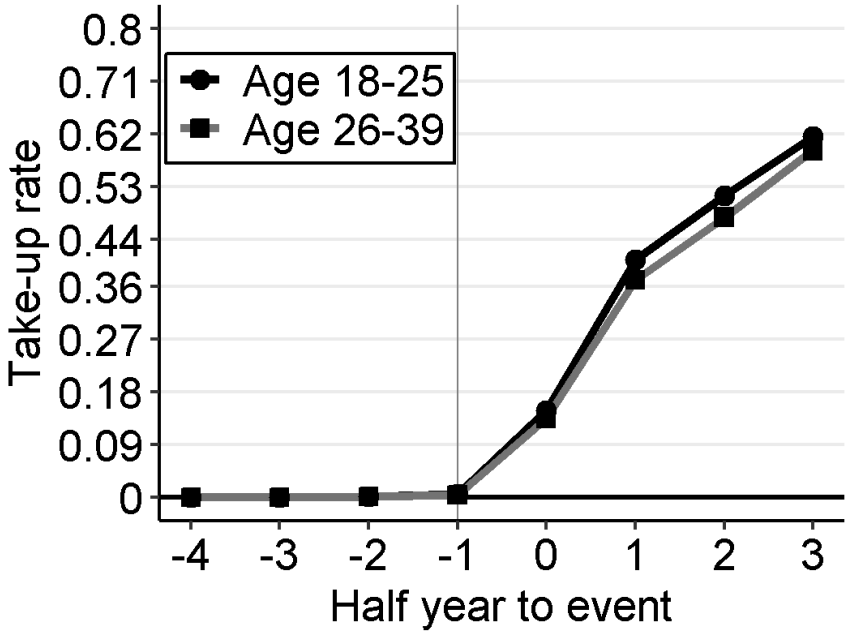


FIGURE A21: Conditional Take-up Rate of E-prescriptions, Ages 18–25 and 26–39

Notes: The figure plots the coefficient estimates from different event study regressions using prescription-level data. The outcome is a binary variable equal to one if the benzodiazepine prescription is issued electronically. Event time is the biannual period relative to the period of e-prescribing adoption by the patient's municipality of residence. The omitted period is −1. The regressions include only event dummies and do not use any additional controls.

F Additional Mechanisms

F.1 Potential Role of Improved Diagnosing

TABLE A18: Robustness for Improved Diagnoses: Effects of E-Prescribing on Benzodiazepine Patients' Selected Health Outcomes, Hospital Referral Arrival Dates with Coincidental Benzodiazepine Prescribing Dates Excluded from Outcomes (Multiplied by 100)

	Mental disorder (1)	PDA diagnosis (2)	Rx poisoning (3)	Other side effects (4)
Panel A. All ages				
Post-adoption	−0.331	0.009	0.015*	−0.009
	(0.328)	(0.009)	(0.009)	(0.057)
Mean outcome	6.338	0.165	0.240	1.155
Observations	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18-39				
Post-adoption	−0.851	0.065	0.062***	0.014
	(0.736)	(0.043)	(0.024)	(0.022)
Mean outcome	11.122	0.599	0.529	0.299
Observations	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40-64				
Post-adoption	−0.313	−0.004	0.000	0.001
	(0.353)	(0.006)	(0.012)	(0.030)
Mean outcome	6.588	0.082	0.245	0.581
Observations	6,742,280	6,742,280	6,742,280	6,742,280
Panel D. Age over 65				
Post-adoption	−0.065	−0.006*	0.006	−0.028
	(0.083)	(0.003)	(0.008)	(0.114)
Mean outcome	3.259	0.020	0.066	2.375
Observations	5,340,589	5,340,589	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. For these outcomes, diagnoses with referral arrival dates to hospital care that are coincidental with benzodiazepine prescribing dates are marked as zero instead of one. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

F.2 Use of Other Medications

TABLE A19: Effects of E-Prescribing on Benzodiazepine Patients' SSRI Use

	All ages		Age 18–39		Age 40–64		Age over 65	
	DDDs (1)	Number of rx (2)	DDDs (3)	Number of rx (4)	DDDs (5)	Number of rx (6)	DDDs (7)	Number of rx (8)
Post-adoption	0.238	0.001	0.488	0.005***	0.170	−0.000	0.239	0.000
	(0.159)	(0.001)	(0.336)	(0.002)	(0.259)	(0.001)	(0.168)	(0.001)
Mean outcome	24.444	0.141	31.905	0.213	28.616	0.152	14.869	0.086
Observations	15,167,056	15,167,056	3,084,187	3,084,187	6,742,280	6,742,280	5,340,589	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. The number of defined daily doses of SSRI prescriptions ("DDDs") and the number of SSRI prescriptions ("Number of rx") are outcomes for benzodiazepine patients. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

G Placebo Regressions

TABLE A20: Placebo Regressions: Effects of E-Prescribing on Benzodiazepine Patients' Appendix Disease Diagnosis (Multiplied by 100)

	All ages (1)	Ages 18–39 (2)	Age 40–64 (3)	Age over 65 (4)
Post-adoption	0.004	0.014	0.001	0.000
	(0.004)	(0.010)	(0.007)	(0.005)
Mean outcome	0.073	0.126	0.073	0.041
Observations	15,167,056	3,084,187	6,742,280	5,340,589

Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficients, standard errors, and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.