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

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Abstract

We estimate the effects of information technology designed to improve access to medication while limiting overuse. We focus on benzodiazepines, commonly prescribed and effective but 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 an increase in benzodiazepine use on average due to increased prescription renewals. The effect is most pronounced among younger patients. We find little evidence of improvement in their general health outcomes but observe substantial increases in diagnoses of prescription drug abuse disorders and poisonings. Our results show robust evidence that easier access may lead to medication overuse.

Keywords: Information technology, electronic prescribing, medication access, overuse, repeat prescribing
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 commonplace in Europe and other developed countries, particularly in vulnerable population groups, defined as those at higher risk of poor health or social status (Eurostat 2021; Hawks et al. 2020; Patel and Prince 2010). Unmet needs exist for treatment of both mental and physical disorders (WHO 2004; OECD 2009) and when left untreated, disorders can develop into more serious health problems that are even costlier to treat (Kisely et al. 2006).

Even though access-improving policies are intended to mitigate unmet care needs, they can also lead some patients to overuse of medical care, with fewer health benefits than health harms. Overuse of medical care is a considerable problem worldwide (Brownlee et al. 2017), creating wasteful health care spending and health harms to patients. Harms from overuse are especially pronounced in the misuse or abuse of addictive medications such as benzodiazepines and opioids—an increasingly 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 care without exposing patients to overuse is a challenging but important trade-off to balance.

We examine a large-scale public policy designed to improve access to medication while simultaneously limiting overuse: the adoption of a nationwide, fully interoperable, and standardized electronic prescribing (e-prescribing) system that digitizes all prescriptions and their renewal requests in Finland. E-prescribing improves medication access by reducing patients' hassle costs in obtaining repeat prescriptions without necessarily having to visit a physician face-to-face. E-prescribing can help patients to continue their medical treatment by making it easier to renew their prescriptions. Thus, e-prescribing can increase medication demand among patients with high health returns, but it can also expose some patients to medication overuse. Because the e-prescribing system also provides physicians with more comprehensive information on a patient's prescription history through a centralized prescription database, it can thereby prevent them from renewing prescriptions for patients who may be overusing medications.

We study the access-overuse trade-off based on the information technology adoption for patients treated with benzodiazepines, which are commonly prescribed but also addictive mental health

and insomnia medications.[1] We estimate the effects of e-prescribing on benzodiazepine use and related health outcomes by using a difference-in-differences (DiD) approach based on the plausibly exogenous rollout of the new technology across all Finnish municipalities over the years 2010–2013. We use population-wide, individual-level administrative data on benzodiazepine prescriptions and hospital discharges during 2007–2014 to measure medication use and related health outcomes that can capture benefits from appropriate use and harms from medication overuse.

Benzodiazepines have characteristics that make them relevant for studying the access-overuse trade-off in medical care. First, benzodiazepines are included in the World Health Organization's (WHO) 2021 Model List of Essential Medicines, which is a set of medicines selected based on disease prevalence and public health relevance, evidence of efficacy and safety profile, and comparative cost-effectiveness. Benzodiazepines are thus intended to always be 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 developed countries (Olfson et al. 2015; Votaw et al. 2019).[2]

Second, benzodiazepines provide health benefits when used appropriately but can cause harms if overused. Benzodiazepines can be a highly effective treatment for often disabling disorders, such as anxiety, panic disorder, and insomnia when used appropriately, and for a short period of time (Tibrewal et al. 2021). Ensuring appropriate use of benzodiazepines and other psychotropics is a crucial but also challenging undertaking in health care systems (Ribeiro and Schlindwein 2021; Semahegn et al. 2018).[3] When overused or misused, benzodiazepines can negatively affect health and lead to addiction and abuse, with strong withdrawal symptoms and increased tolerance over time. Long-term use of benzodiazepines increases the risk of these adverse health effects (Hirschtritt et al. 2021; EMCDDA 2022) and this is exactly what easier access and repeat prescriptions can facilitate.

Policy makers have stressed that the adoption of digital solutions such as e-prescribing can improve health care provision. Despite the widespread adoption of e-prescribing in Europe, the U.S., Canada, and Australia, for example, there is little credible causal evidence on the effects

[1] Research on the effects of information technology on controlled substance prescribing behavior has focused on opioid prescribing in the U.S. (Buchmueller and Carey 2018; Ellyson et al. 2022). Global consumption of opioids is, however, concentrated in the U.S. (PPSG 2015). In Finland, opioid prescribing is heavily regulated and their consumption is much smaller compared to benzodiazepines (Fimea 2015).

[2] Our data show that 20% of the Finnish adult population has had at least one benzodiazepine prescription during our observation period. Importantly, repeat prescriptions constitute approximately 80% of benzodiazepine use.

[3] Non-adherence (not following the recommendations from a health care provider) is particularly common for patients suffering from mental disorders (Semahegn et al. 2018). Non-adherence means taking medication more or less than recommended by a physician and includes also prescription drug abuse.

of e-prescribing on medication use, overuse and related health outcomes. While overuse has been widely documented in the literature across several countries and many types of medical services (Brownlee et al. 2017), there is only limited evidence on policies and mechanisms creating overuse in health care (Einav et al. 2023), and also the link between digital solutions and overuse remains unclear.

We document the effects of the nationwide e-prescribing system at the intensive and extensive margins of benzodiazepine use. Specifically, the intention-to-treat (ITT) estimates of the e-prescribing policy show a 3% increase in the duration or amount of benzodiazepine use per patient on average. There is also a 7% increase in the long-term use of benzodiazepines after the adoption of e-prescribing.[4] In contrast to the significant adjustments at the intensive margin, we find little impact on the probability of benzodiazepine use in the general Finnish adult population at the extensive margin.

We also use our patient-level data to examine heterogeneous effects across the different age groups. In particular, younger adults tend to use benzodiazepines less despite of having more mental health problems (Kessler et al. 2010; Olfson et al. 2017). In line with this finding, younger adults have higher rates of unmet health needs, with higher barriers to access (Alonso et al. 2007; Kullgren et al. 2012), which can cause underuse of essential medications. On the other hand, younger adults are at higher risk of addiction, exposing them to medication overuse. Thus, younger adults are a salient target for the e-prescribing policy to improve medication access while limiting overuse.

We find that the quantitative magnitude of the increase at the intensive margin is considerably larger for younger patients (age 18–39 years). The duration or amount of their benzodiazepine use increases by 6% and there is also a 12% increase in the long-term use of benzodiazepines after the adoption of e-prescribing. These increases in benzodiazepine use result from repeat, rather than new prescriptions and are consistent with our hypothesis that e-prescribing improves access to medication by making renewal easier.

Despite the large increase in benzodiazepine use, we find no evidence of improvements in general health outcomes such as mortality or emergency department visits for younger patients. Rather, after the first year of the technology's adoption, diagnoses of prescription drug abuse disorders and poisonings increase by approximately 20% in the younger patient population. In effect, improved access to medication (e-prescribing) may increase medication overuse and misuse in this vulnerable

[4]The take-up of e-prescriptions was voluntary during our observation period. One year after adoption, approximately 50% of benzodiazepine prescriptions were issued electronically on average.

patient population, which is at greater risk of mental health and behavioral health problems.[5]

Our results reveal unintended consequences of increasingly popular information technology. Reducing patients' hassle costs or "ordeals" to obtain repeat medication through digitization of prescriptions improves access to medication but can simultaneously worsen medication overuse. Digitization and easier renewal without face-to-face consultation may weaken physician-patient interaction and joint decision-making in treatment decisions, which are essential for monitoring and preventing potential overuse. With this study, we provide new insights into e-prescribing psychotropics and addictive substances. Our results also have broader relevance for policy makers in deciding how to improve access to medications that may also potentially harm health.

Our study contributes to three strands of literature. First, we contribute to the literature on welfare and health care program design, access, and targeting. Research on health care access has mainly focused on how access is affected by 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). Unlike our study, this strand of literature does not investigate information technology or the hassle costs of the prescribing process, a prominent non-price mechanism affecting access and targeting.

Second, our study complements research on ordeal mechanisms in welfare and health care program design, which investigates how imposing differential transaction costs on participants help with program targeting (Nichols and Zeckhauser 1982; Zeckhauser 2021). These mechanisms were recently studied in the context of the Supplemental Nutrition Assistance Program (SNAP) (Finkelstein and Notowidigdo 2019) and pediatric health care (Iizuka and Shigeoka 2022). Reducing the hassle costs associated with prescription renewal weakens targeting, as we show in our results, and is consistent with the findings of the ordeal mechanisms in other settings.

Third, we contribute to the literature on the effects of health information technology by studying the access-overuse trade-off based on a large-scale policy intervention and using population-wide, individual-level administrative data. There is very little large-scale evidence on the effects of health information technologies, since nationwide 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. The literature has analyzed 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;

[5]Our conclusions are robust to using alternative econometric specifications, subsamples, accounting for individual patient heterogeneity (fixed effects) as well as recently developed methods for staggered DiD designs (Goodman-Bacon 2021; Roth and Sant'Anna 2022).

Ellyson et al. 2022). EMRs and PDMPs are, however, information-improving technologies, whereas e-prescribing directly affects both information and medication access. Previous evidence is mostly from the U.S., where non-standardized and incompatible health information systems limit the scope of technology adoption and information exchange between different providers. In contrast, our study focuses on a nationally interoperable and standardized system, that enables prescription renewal and allows all providers to exchange comprehensive information between them.

2 Institutional Background

We examine the effects of a nationwide e-prescribing system in Finland designed to improve medication access while limiting overuse, with a specific focus on patients treated with mental health and insomnia medications, benzodiazepines. In this section, we describe the relevant institutional background related to our empirical analysis.

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.[6] 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 20 hospital districts that organize specialized medical care. The resources for public sector health care services are rationed and waiting times are typically long.

The primary care system is based on municipal health centers, and every resident of the municipality is entitled to its health 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 is 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

[6] In 2014, public primary and specialized (hospital) health care accounted for approximately 50% of health care costs. In contrast, private health care covered by NHI accounted for only 5% of the health care costs and employer-sponsored health care provided by the private sector accounted for 3% of the costs (THL 2021). The remaining 42% of the costs mainly come from pharmaceuticals and the long-term care for the elderly.

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 e-prescribing system with improved information and easier renewal of prescriptions were central elements of this policy.

2.2 Mechanisms Related to E-prescribing

E-prescribing–a health information technology that digitizes prescriptions, renewal (or refill) requests, and transfers information on these between physicians and pharmacies–is widely used but understudied.[7] Below we describe the key mechanisms through which interoperable nationwide e-prescribing systems can affect prescription drug use and related 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 have a face-to-face consultation; instead the patient could make a renewal request by contacting a health care unit by phone. The renewal request can be also made via a pharmacy, which automatically transmits the renewal to the health care unit through a computer interface.[8] Importantly, 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 could also receive a text message that inform them 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.

Health care systems generally permit repeat prescriptions or refills for psychotropics and some controlled substances such as benzodiazepines. For example, the U.K. health care system permits

[7] In many health care settings, the terms prescription "renewal" (repeat) and "refill" are used interchangeably. Prescriptions can contain refills and can be refilled multiple times. When a prescription has expired or has no refills left, it has to be renewed. A renewal is the generation of a repeat prescription based on a previous prescription. Both refills and renewals can be ordered and generated without face-to-face consultation. In Finland, patients can renew, but not refill, prescriptions. This means a patient can order a repeat supply of medication without necessarily having to visit a physician face-to-face.

[8] 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.

repeat prescriptions 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, evidence from Finnish primary care shows that issuing or repeating prescriptions without physician consultation is more common for psychotropics in comparison to many other groups of prescription drugs (Saastamoinen et al. 2008).

E-prescribing and Information.—E-prescribing also improves prescription information. In contrast to providers' pre-existing incompatible and incomplete health information (such as EMR) systems, nationwide e-prescribing system provides physicians with access to a patient's complete e-prescription history; this information is illustrated in Online Appendix Figure A2 in the Finnish health care provider setting.[9] If e-prescribing is implemented as an interoperable system (as in Finland), it improves information exchange both within and across provider organizations. Thus, the system reduces the likelihood of a physician not knowing about the patient's previous prescriptions. The benefit of improved information is, however, expected to be small in the first year after the adoption of e-prescribing, because the historical e-prescription data are not yet in the system.

Net Effects of E-prescribing.—The net effects of e-prescribing on prescription drug use and related health outcomes are ambiguous. Easier renewal (the access mechanism) can increase the intensive margin of prescription drug use, which is, the duration or number of daily doses dispensed per patient. Easier renewal can improve patient health by increasing adherence to prescribed treatment and an appropriate use of the medication. Easier renewal can, however, also increase medication overuse or even misuse for some patients who do not need an additional supply of medication. Thus, these patients can be prone to adverse health outcomes from such improved access.

Similar to the mechanism of easier renewal, we expect more comprehensive information on prescription history to be particularly relevant for existing prescription drug users at the intensive margin. E-prescribing can also affect first-time use or initiation of drug therapy at the extensive margin, for example, through switching between different medications. Therefore, the e-prescribing system with its easier renewal and improved information has no clear benefits for the first-time users who does not have previous e-prescriptions. For existing users or patients, improved information on

[9]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 that is treating the patient. Notably, the e-prescribing system does not contain flags for controlled substances or other decision supporting tools for physicians.

their prescriptions can help physicians pay attention to the adverse effects of previously prescribed medications and thus prevent their renewal and avoid writing another prescription for potentially overused medications.

2.3 Staggered Adoption of the 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 patient's care. This access, however, requires a patient's permission.[10] The system includes all pharmacies and providers (public or private), and 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 preventable harms from repeat medications 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 of the 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 for the policy adoption, the adoption time still varied substantially across regions.[11] 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 the difficulties in integrating the e-prescribing system with the pre-existing

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

[11] 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 (Section 6.3).

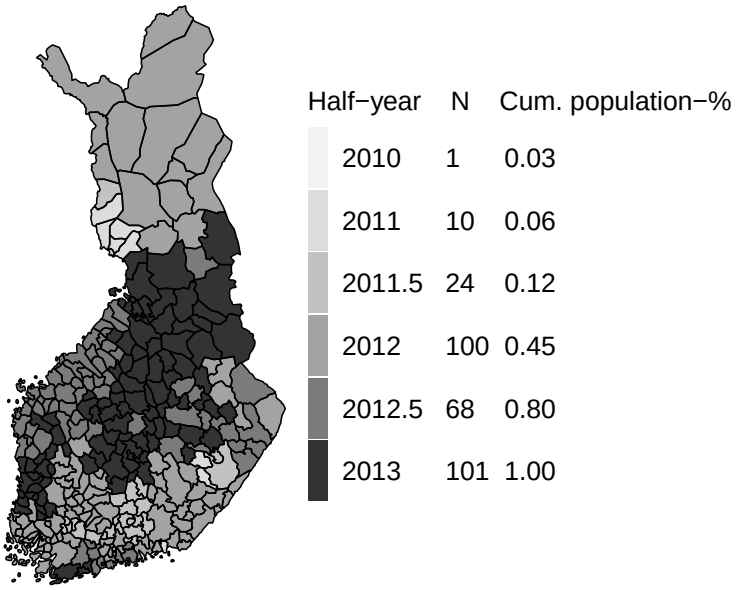


FIGURE 1: E-prescribing Adoption Half-Year in Municipalities

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: The Finnish Institute for Health and Welfare, and Statistics Finland: Population Statistics.

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 to information technology infrastructure, tailoring software, and a skilled workforce in each municipality. To corroborate the findings from the government expert interviews and the credibility of our research design, we show in Online Appendix Section B 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 developed countries (Olfson et al. 2015). They are commonly used in the adult population to treat mental health problems and insomnia. In Finland, the top five active ingredients (benzodiazepine drugs) based on 2014 sales 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). The wholesale value of benzodiazepines was 13.7 million euros in that year, with a market share of approximately 17% of the wholesale value of all psycholeptics. Notably, nearly 10% of all Finnish

adults were benzodiazepine users 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 problems, as well as depression when anxiety is involved (Quagliato et al. 2018).[12] Thus, the appropriate use of benzodiazepines can improve patient health outcomes such as reduce the likelihood of an emergency department admission related to severe anxiety (Tibrewal et al. 2021).

Health harms through adverse drug effects are indicators of medication overuse. Benzodiazepines may cause sedation, a decline in cognitive functions and delirium, for example (Lader 2011). Importantly, long-term use of benzodiazepines may lead to physical dependence, abuse, overdose or drug poisoning, with strong withdrawal symptoms and increased tolerance over time (Lader 2011; Votaw et al. 2019). Clinical treatment guidelines generally recommend benzodiazepines not to be used 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 highly relevant drug category for public policies to improve medication access while limiting their overuse. Misuse of benzodiazepines is also prevalent in Europe and the U.S., and these medications are commonly involved in 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] Recent research on medication misuse has mostly focused on the opioid epidemic in the U.S. and a broad array of policies aimed at curbing it (Maclean et al. 2022). Less focus has been placed on other important addictive psychotropics such as benzodiazepines, their impact in countries other than the U.S., and the role of access policies in causing the overuse or misuse of these medications.

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

[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 of the 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 tables 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 the regional illicit markets (Section 6.3).

3 Data

We use comprehensive administrative data sets for patients treated with addictive medications, benzodiazepines, to analyze their (repeat) prescription drug use and health outcomes at the intensive margin. We also study the first-time use in the general Finnish adult population at the extensive margin using population-wide, individual-level administrative data. 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 underage individuals (younger than 18 years of age), who only represented approximately 2% of all observations. We provide an overview of our data sets and describe the main variables used in our analyses. Details on the drug classes and diagnosis codes used for health outcomes construction are in Online Appendix A.

3.1 Benzodiazepine Use Outcomes and Characteristics

We use administrative prescription data from the Social Insurance Institution of Finland. The data include all of benzodiazepine prescriptions dispensed at Finnish pharmacies and covered by the National Health Insurance plan over the period 2007–2014. The data record for each patient includes the date of birth (age), the date of death, and the municipality of residence based on the 2014 municipality classification. Additionally, these data include records for each dispensed prescription, which have 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 that have 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).[15] Notably, a repeat prescription is often from a different physician than the previous prescription(s)

[14] We use this rather loose definition of benzodiazepine patients because prescription renewal and health outcomes can sometimes be realized long after the initial prescription (e-prescriptions for benzodiazepines have to 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] Our renewal measure captures typical patterns of obtaining repeat prescriptions. For example, a patient first obtains a prescription for A and then for B, after which she obtains a repeat prescription of A, and then of B. Our results are robust to the exclusion of the 16-month interval rule (Section 6.3). We have also confirmed robustness for defining a renewal based on the previous prescription or three previous prescribing events within a 16-month interval.

because the patient cannot influence which physician receives the renewal request in a health care unit. If a prescription is not renewed, we define it as new.

We are interested in measuring the effects of e-prescribing on the intensive margin of benzodiazepine use, that is, the duration or amount of medication use by a given set of patients. However, measuring benzodiazepine use is challenging because benzodiazepine drugs each have of different strength and potency. In other words, the amount of a medication needed to produce a given effect is different, depending on the specific drug. 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. The DDD measure is a well-established, international metric of medication use, and it is widely used in drug consumption studies and statistics (Gisev and Sluggett 2019). DDD is defined as the assumed average maintenance dose per day of a drug used for its main indication (a particular disease such as anxiety) in adults, providing us with a standardized unit of measurement for different types of benzodiazepines. Using DDD as the standard unit measurement, we calculate our primary measure of benzodiazepine use at the intensive margin: the number of dispensed DDDs of benzodiazepine prescriptions per patient and half-year period.[16]

The number of prescriptions is another measure of medication use that has been used in previously published empirical research, for example, due to the lack of access to DDDs data. Thus, we also calculate the number of dispensed prescriptions per patient and half-year period. In contrast to the number of dispensed DDDs, this coarse measure of the number of prescriptions, however, does not capture changes in important aspects of medication use at the intensive margin: the duration or amount of medication use.[17] We calculate these two measures separately for repeat 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 (see Section 6 for details).

We also analyze the extensive margin of benzodiazepine use per individual and half-year period. For this analysis, we combine the prescription data with another data set on the full Finnish adult

[16]We use a period of six months (a half-year) to find a balance between the accuracy of the adoption time of e-prescribing and observing variation in benzodiazepine use and related health outcomes; the time difference between two subsequent benzodiazepine prescriptions is 136 days on average in the data.

[17]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 that should be taken three times per 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).

population from Statistics Finland using commonly coded individual identifiers. Our first extensive margin outcome is the indicator of having a benzodiazepine prescription during a half-year period. The second outcome is the indicator of a first-time benzodiazepine use during a half-year period. We define a first-time user as an individual who does 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).

3.2 Patient Health Outcomes

Following Buchmueller and Carey (2018), we also construct various patient health outcomes for a sample of benzodiazepine patients. From the prescription data, we calculate our first general health outcome: a mortality indicator that equals one if the patient passed away in a given six-month period.

We use administrative hospital discharge data from the Finnish Institute for Health and Welfare to construct the patients' other health outcomes. The hospital discharge data contain comprehensive information on their hospital admissions and discharges from 2007 through 2014. The de-identified data record include coded patient identifiers, the diagnosis (ICD10 code), the date of discharge, and the patient's municipality of residence.

We rely on prior research to construct a broad set of health outcomes for the sample of benzodiazepine patients. Even with rich data, it is challenging to comprehensively measure and distinguish health effects from appropriate use or overuse of benzodiazepines.[18] We calculate the biannual number of emergency department visits and the biannual number of hospital visits per patient. We use these variables, together with the aforementioned mortality indicator, as general measures of patient health. Emergency department and hospital visits are less extreme outcomes than mortality and may more easily capture health problems caused, for example, by mental illness or overuse of benzodiazepines.

We also construct health outcomes based on a patient's hospital discharge(s) for particular health conditions within a period of six months. We consider diagnoses of a broad class of mental and behavioral disorders (henceforth mental disorders for brevity). We also consider diagnoses of

[18] As stated in the previous literature, measuring the effects on mental and behavioral health disorders (including serious mental illness and substance use disorders) is challenging. The difficulty arises from the fact that the disorders generally cannot be fully cured and thus the focus of the treatment is on management of the disorder and its symptoms (Maclean 2019).

prescription drug abuse disorders and poisonings, as well as diagnoses related to the other side effects of benzodiazepines such as sedation, poor coordination, and decline in cognitive functions. Notably, the diagnosis-based health outcomes that we use in our analysis of adverse effects of benzodiazepines are verified by physicians, following the national treatment guidelines.

4 Evidence on Prescribing and Health Patterns

General Findings.—Table 1 reports the summary statistics on total benzodiazepine use and related health outcomes during our observation period 2007–2014. Panel A shows total benzodiazepine use and renewals per patient at the intensive margin. It reveals that adult patients purchased a 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 $800/8 \approx 100$ days per patient and year.[19] The average total number of dispensed prescriptions per patient was 10. Renewed prescriptions constitute an overwhelming fraction (over 80%) of all dispensed benzodiazepine prescriptions. For comparison, repeat prescriptions 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 21% of the total adult population had at least one benzodiazepine drug prescription during our observation period. Thus, the use of benzodiazepines is very common in the Finnish adult population as it is in many other countries in Europe.

Panel C shows benzodiazepine patients' key health outcomes. Notably, patient mortality is substantial (16% on average). The prevalence of hospital diagnoses of mental and behavioral disorders is also at the high level: 26% of benzodiazepine patients receive these diagnoses at least once during our observation period. Panel D shows that the average age of benzodiazepine patients is only little higher (age 55) than the average age of the general Finnish adult population (age 49).[20]

Age Differences.—Motivated by the access barriers and higher rates of mental and behavioral disorders among younger adults (Kessler et al. 2010; Kullgren et al. 2012; Kurko et al. 2015a; NIDA 2016), we study differences in the use of benzodiazepines and related health outcomes in the different age groups. Figure 2 documents the flexible age profiles for our main measure of total

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

[20] 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	1666.342
Total renewed DDDs	678.654	1439.961
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" refer to all adult patients who fill at least one benzodiazepine prescription. Note that 27% of patients fill only a single prescription over the observation period 2007–2014 (the average number of prescriptions is 10). "All Finnish adults" refer to all Finnish residents older than 18 of age. Values depict the overall values during the observation period with the exception of age, which was the age measured in 2007.

benzodiazepine use at the intensive margin: the yearly number of dispensed DDDs per patient and by age (Online Appendix Figure A3 shows the profile for the number of prescriptions). The profiles are presented for three years (2007, 2010, and 2014) to detect possible changes in the consumption patterns over time before and after the e-prescribing rollout (2010–2014).

Figure 2 shows that the number of DDDs increases sharply by age; that is, the use of benzodiazepines is more concentrated among older patients, similar to findings from earlier studies (Olfson et al. 2015). There also was a significant decrease in the use of benzodiazepines over time (from 2010 to 2014), which has 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, we also find that the decrease in benzodiazepine use was much smaller among younger patients. In fact, 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 mental and behavioral disorder, prescription drug abuse, and prescription drug poisoning diagnoses (Panels B–D). Moreover, younger adults (under 40 years of age) have also experienced a substantial increase in the prevalence of these adverse health outcomes and the number of emergency department visits from 2007 to 2014. Importantly, this increase in adverse health outcomes coincides with the adoption of e-prescribing in Finland.

To conclude, mental and behavioral health problems are one of the highest disease burdens in Finland, and they disproportionally affect young adults (Patana 2014). We found that younger patients use benzodiazepines less, despite higher rates of mental and behavioral health problems. Younger patients may face major barriers in accessing health and mental health care (Kullgren et al. 2012; Patana 2014; Vanheusden et al. 2008) and because of this situation, they may have higher rates of unmet health needs (Alonso et al. 2007).[21] Thus, they may more frequently underuse medications, which could worsen their mental health. On the other hand, medication overuse or misuse can cause significant health harms among younger patients because they are at much higher risks of prescription drug abuse and poisonings. These descriptive patterns motivate our empirical analyses of health information technology adoption and the heterogeneity analyses of the effects in different parts of the age distribution.

[21] Financial barriers to access are relatively small in the Finnish single-payer, national health insurance system.

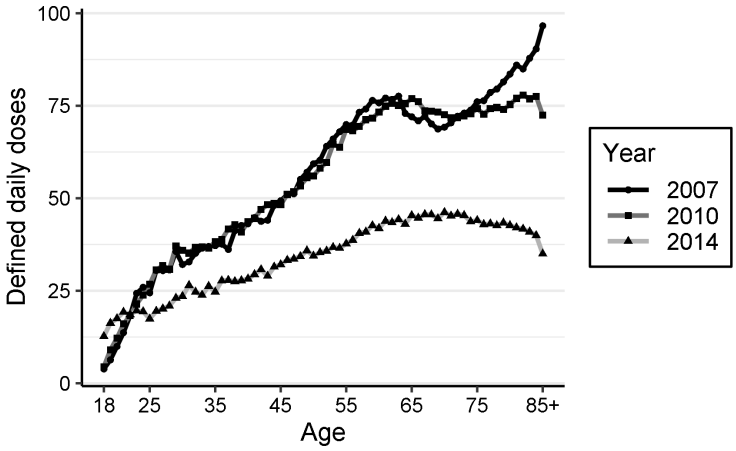
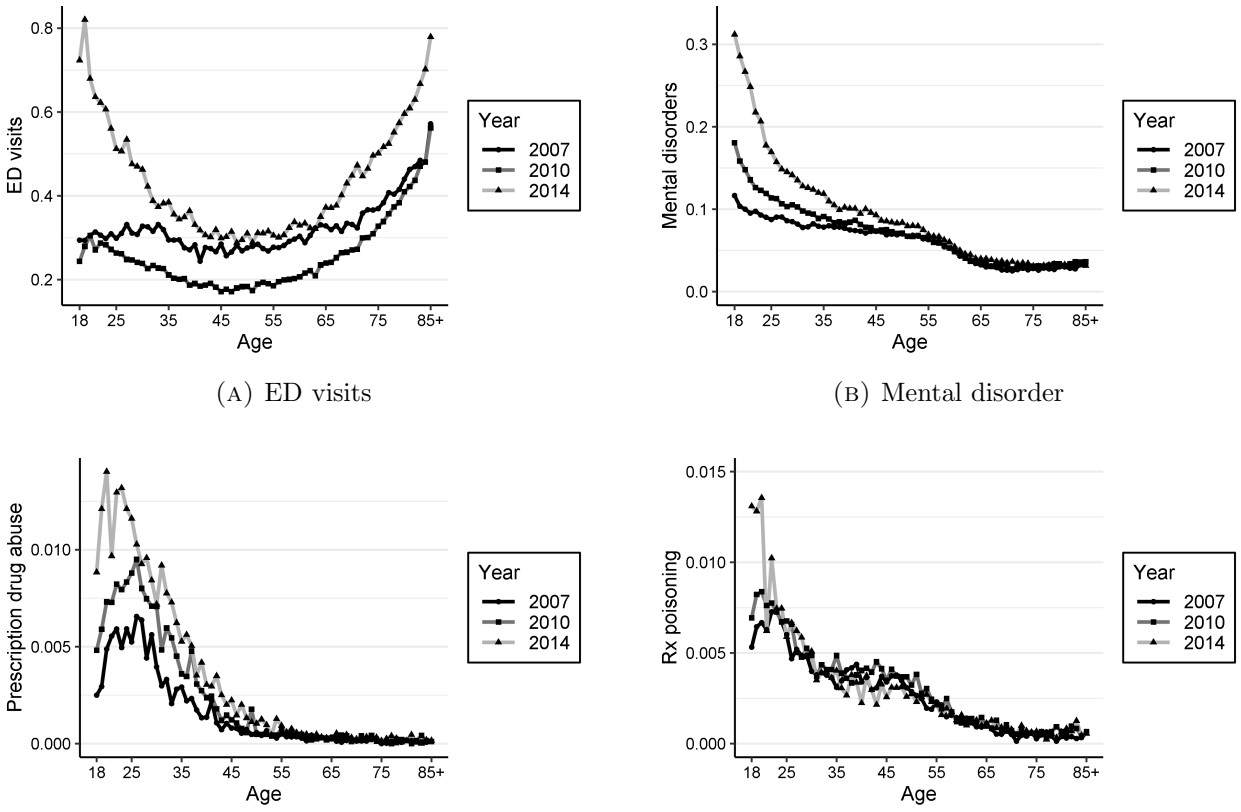


FIGURE 2: Yearly Benzodiazepine Use-Age Relationships at Intensive Margin: Number of Defined Daily Doses

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 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

We base our analysis on the staggered rollout of a nationwide e-prescribing system across municipalities over four years and on comprehensive administrative data. We use quasi-experimental variation created by the staggered rollout to estimate the effects of e-prescribing technology on benzodiazepine use and related health outcomes, using a difference-in-differences (DiD) strategy and individual biannual-level data.[22] Because e-prescribing was adopted at different times in different municipalities, and all municipalities eventually adopted the technology, patients in later-treated units (municipalities) are used as controls for patients in early-treated units in estimating the average treatment effects.

Baseline Specification.—We estimate DiD models using the following two-way fixed effects (TWFE) specification:

$$y_{imt} = \rho \mathbb{1}[t - E_m \geq 0] + X_{it}^{'}\beta + \alpha_m + \gamma_t + \epsilon_{imt}, \tag{1}$$

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). E_m denotes the time period of adopting e-prescribing in the patient's municipality of residence m and $t - E_m$ denotes the half-year periods relative to the adoption time. Municipality fixed effects α_m control for time-invariant differences between municipalities, time fixed effects γ_t control for the common time-varying trend that stems, for example, from the general changes in prescribing behavior. X_{it} includes patient controls: age and age squared.[23] We cluster the standard errors at the municipality level ($N = 304$) to account for within-municipality correlation in ϵ_{imt} over time.[24]

The take-up of e-prescriptions by patients and physicians was voluntary during the observation period. Hence, our approach identifies the ITT (intention-to-treat) 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 e-prescribing rollout, patient outcomes would have evolved under

[22] We follow individuals from the relevant population over time after, starting after they turn 18 years until they die, making the data 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. For the extensive margin outcomes, we use all Finnish adults as the relevant population (Section 3).

[23] As a robustness check, we also show the results using a specification in which we replace municipality fixed effects, α_m, with individual or patient fixed effects, η_i. This specification uses within-individual variation in identification and controls for unobserved, time-invariant heterogeneity across individuals or patients.

[24] We follow Buchmueller and Carey (2018), who cluster their standard errors at the state level in the U.S. context (the policy adoption occurred at this level in their study). The standard errors remain similar if we cluster them at the hospital district level.

parallel trends in municipalities adopting the technology at different times. We address various concerns that could otherwise impair our ability to interpret our estimates as causal effects.

Parallel Trends Assumption and Dynamic Patterns.—One might worry about the plausibility of the parallel trends assumption in our setting, as patient outcomes might have evolved differently across municipalities depending on their adoption time. In Section 2.3, we showed descriptive and institutional evidence that the adoption time is unrelated to pre-existing, time-varying patient outcomes at the municipality level. To conduct further visual inspections of potential pre-trends and dynamic effects of e-prescribing, we also estimate the following event study specification for patient i in municipality m in period t:

$$y_{imt} = \sum_{k} \delta_k \mathbb{1}[t - E_m = k] + X_{it}^{'}\beta + \alpha_m + \gamma_t + \epsilon_{imt}, \tag{2}$$

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 analyze the data up to five relative time periods prior to the adoption ($k = -5$) and three periods after the adoption ($k = 3$). 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. 2021). 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).[25]

Following Sun and Abraham (2021), we trim the event study graphs by balancing observations in relative (event) time between -5 and 3, since our data are unbalanced in relative time for some treatment units.[26] Following a fairly balanced set of municipalities over time around the adoption of e-prescribing mitigates changes in the composition of municipalities in distant periods and the

[25] Binning the endpoints in the event study is an alternative approach to dropping an additional pre-treatment indicator (Borusyak et al. 2021; Schmidheiny and Siegloch 2019).

[26] A commonly used alternative to trimming is binning the distant event-time indicators into the balanced range (Sun and Abraham 2021). While we show event study graphs based only on trimming, our results are not sensitive for the choice of approach.

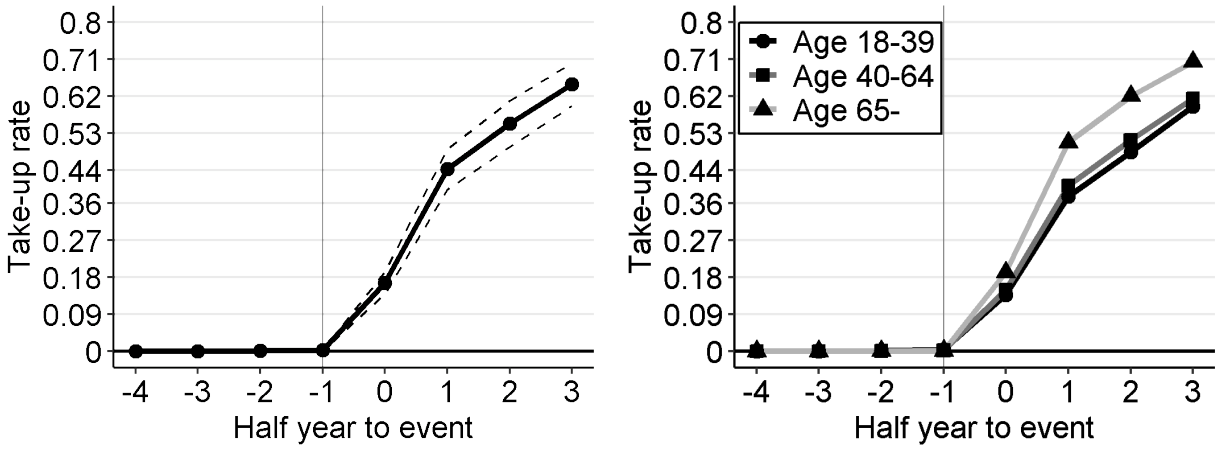
effect of individual municipalities (early- and late-treated municipalities) on event study coefficients. Trimming also implies that the post-treatment (the pre-treatment) periods are relatively short for the first (the last) treatment units.

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 staggered DiD settings, it is not guaranteed to provide consistent estimates without relatively strong assumption on treatment effect homogeneity (de Chaisemartin and D'Haultfœuille 2020; Borusyak et al. 2021; Callaway and Sant'Anna 2021). Importantly, Goodman-Bacon (2021) shows that the treatment effect estimated by the TWFE DiD estimator is the weighted average of all possible two-group, two-period treatment effects. 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 presenting robustness checks and conclude that negative weighting is not an issue in our application (Section 6.3).

We address the concerns about the reliability (and precision) of the TWFE estimator by also employing the efficient estimator proposed by Roth and Sant'Anna (2022). Similar to other recently developed DiD and event study estimators for staggered research designs, such as Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfœuille (2020), this estimator is based on comparisons between newly treated and not-yet or never-treated units. Thus, it can deliver consistent estimates even in the presence of heterogeneous treatment effects across time and treated units. Besides being efficient and robust for treatment effect heterogeneity, the estimator is implemented so that it is computationally feasible in our application based on large individual-level data sets containing millions of observations.

Take-up of E-prescriptions.—While our econometric approach is expected to provide an unbiased causal estimate of the policy or ITT effect (under the standard assumptions), it can provide an underestimate for the average treatment effect on treated (ATT) due to voluntary take-up of e-prescriptions. We take advantage of the prescription-level data to study take-up or compliance decisions made by individuals in using the e-prescribing technology.

Figure 4 shows the biannual take-up rate of e-prescriptions after the benzodiazepine patient's municipality of residence adopted e-prescribing (in primary care). The take-up rate by individual patients or their physicians increases sharply after the adoption on average (Panel A) and for all three age groups (Panel B) and continues to increase gradually over time. One year after adoption,



(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.

approximately 50% of benzodiazepine prescriptions are issued electronically, after which the number grows to around 60–70%. Panel B reveals that the take-up rate is notably similar in the three age groups with only a slightly higher take-up among the oldest patients. We conclude that take-up rate (compliance) is fairly high in all age groups and low take-up rates or differences in take-up rates across age groups are unlikely to explain our findings.

6 Results

We begin by presenting the baseline results on the effects of e-prescribing on the intensive and extensive margins of benzodiazepine use (Section 6.1) and then proceed to present the health outcomes (Section 6.2). Our primary interest is in estimating the average effects of the nationwide e-prescribing policy using the DiD approach, and we also study heterogeneity in the effects across different age groups (18-39, 40-64, 65 and older).[27] We present the DiD results from estimating the baseline TWFE specification in equation (1). For brevity, we show only the most relevant dynamic

[27]We have checked whether the age composition changed due to e-prescribing by regressing patient age on post-adoption indicator and municipality and time fixed effects. The coefficient estimate for the post-adoption indicator was equal to zero (-0.000) and statistically and economically insignificant (SE: 0.024, mean age: 56.654). We conclude that the adoption of e-prescribing did not change the age composition.

patterns using the event study plots from estimating equation (2) in the main text and include the remaining plots in Online Appendix.

6.1 Effects on Prescription Drug Use

Defined Daily Doses at the Intensive Margin.—Table 2 presents the estimated effects on the intensive margin of benzodiazepine use, as measured by the number of dispensed DDDs. As described in Section 3, the number of DDDs closely reflect the duration (or intensity) of taking benzodiazepines and thus, prescription renewals. It is thus, linked to the repeat use of benzodiazepines, and this is what easier renewal of prescriptions (e-prescribing) can facilitate.

Consistent with this hypothesis, we find that 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, we find an increase of approximately 2 DDDs on average, corresponding to 2 days of theoretical use. Figure 5 reveals that the increase in the use of benzodiazepines is gradual in response to e-prescribing, coinciding with the increasing take-up rate of e-prescribing over time (Figure 4). Importantly, the event study point estimates show no evidence of violations from the parallel trends assumption.[28]

Motivated by the large age-related differences in the use of benzodiazepines and the potential challenges in medication access and overuse among younger patients (Section 4), we also study the effects of e-prescribing across different age groups (18-39, 40-64, 65 and older). Panels B–D of Table 2 present the estimates and show age heterogeneity in the effects. For younger patients, the number of DDDs increases by 6% compared to the mean of 30 DDDs. The corresponding estimates for both of the older age groups (40–64, 65 and older) are markedly lower at 4% and 1% compared to the means of 58 and 69 DDDs, respectively. The event study plots in Figure 5 confirm the estimated effects on DDDs, albeit with some imprecision. The period-specific point estimates show a gradual increase in the use of benzodiazepines, especially for younger patients, who experienced an 8% increase in the long run, one year after the adoption.

Mechanism: Improved Access through Easier Renewal.—We next provide further evidence that easier renewal of prescriptions is the specific access mechanism that explains the estimated increases in benzodiazepine use or its duration at the intensive margin. Consistent with this mechanisms, we find that the increase in the number of DDDs on average results from repeat, as opposed

[28]The results are robust for using an alternative estimator proposed by Roth and Sant'Anna (2022), which is more efficient and robust for treatment effect heterogeneity, and also shows no significant evidence of pre-trends in the DDD outcome (Online Appendix Section F, Figure A15).

to new prescriptions (Columns 3-4 of Table 2 and Figure 6).[29] For younger patients aged 18-39 years, the increase in the number of renewed DDDs is substantial, approximately 7%. We also find similar point estimates for the older patient groups (aged 40-64 and over 65), but the estimated effects are quantitatively smaller (4% and 2%, respectively) compared to the younger patient group. Our results support the conclusion that easier renewal increases the use of benzodiazepines at the intensive margin.

Number of Prescriptions at the Intensive Margin.—We also study the effects of e-prescribing on the number of benzodiazepine prescriptions per patient and half-year period (Column 4 of Table 2 and Online Appendix Figure A5). We find that e-prescribing has only little effect on this outcome. For younger patients under 40 years of age, we can rule out effects larger than 2% based on the the 95% confidence intervals. For the elderly patients (over 65 years old), we find a statistically significant reduction of 2%, possibly because of an increase in their prescribing interval. The number of prescriptions is, however, a rather coarse measure because it does not capture changes in the duration or amount of benzodiazepine use per patient after e-prescribing. In contrast, our primary measure at the intensive margin, the number of DDDs, does capture these changes.

Prescription-level Analysis of Intensive Margin Adjustment, Long-term Use, and Prescribing Interval.—In Online Appendix Table A2, we present the results on the effects at the intensive margin adjustment using fine-grained prescription-level data. We confirm that the effects on the number of DDDs of all, renewed, and new prescriptions are similar to those obtained using the patient biannual-level panel data (Columns 1–3).

We also analyze additional prescription-level outcomes to get a more detailed understanding of the effects of e-prescribing on dispensed prescriptions at the intensive margin. We are particularly interested in the long-term prescriptions and use of benzodiazepines, which should be avoided according to the clinical treatment guidelines because of the increased risk of physical dependence (Section 2.4). Based on prior work (Kurko et al. 2015b,a) and the definition used by WHO (1996), we define long-term use as at least 180 dispensed DDDs and at least two separate drug purchases dispensed at a pharmacy, corresponding to at least six months' theoretical use. The definition relies on the clinical observation that 40% of patients have moderate to severe withdrawal symptoms after at least six months' use (Hood et al. 2014). Together with a high number of DDDs, multiple purchases per prescription indicate long-term use and the need for additional doses of benzodiazepines

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

despite the possible health harms.[30]

After the adoption of e-prescribing, the long-term use of benzodiazepines increases by 12% for younger patients aged 18-39 (Column 4). The effect is smaller, approximately 7%, on average and for the older patient groups.[31] Similar to the estimated effects on DDDs, the increase in long-term use of benzodiazepines results from renewed, rather than new prescriptions (Columns 5 and 6). For younger patients, prescribing became also more frequent as their prescribing interval decreased by 3%. In contrast, for the elderly patients, there is a 2% increase in the prescribing interval after e-prescribing (Column 7). We conclude that long-term use of benzodiazepines increased due to increased renewals, especially for younger patients, putting them at an elevated risk of experiencing physical dependence and even addiction.

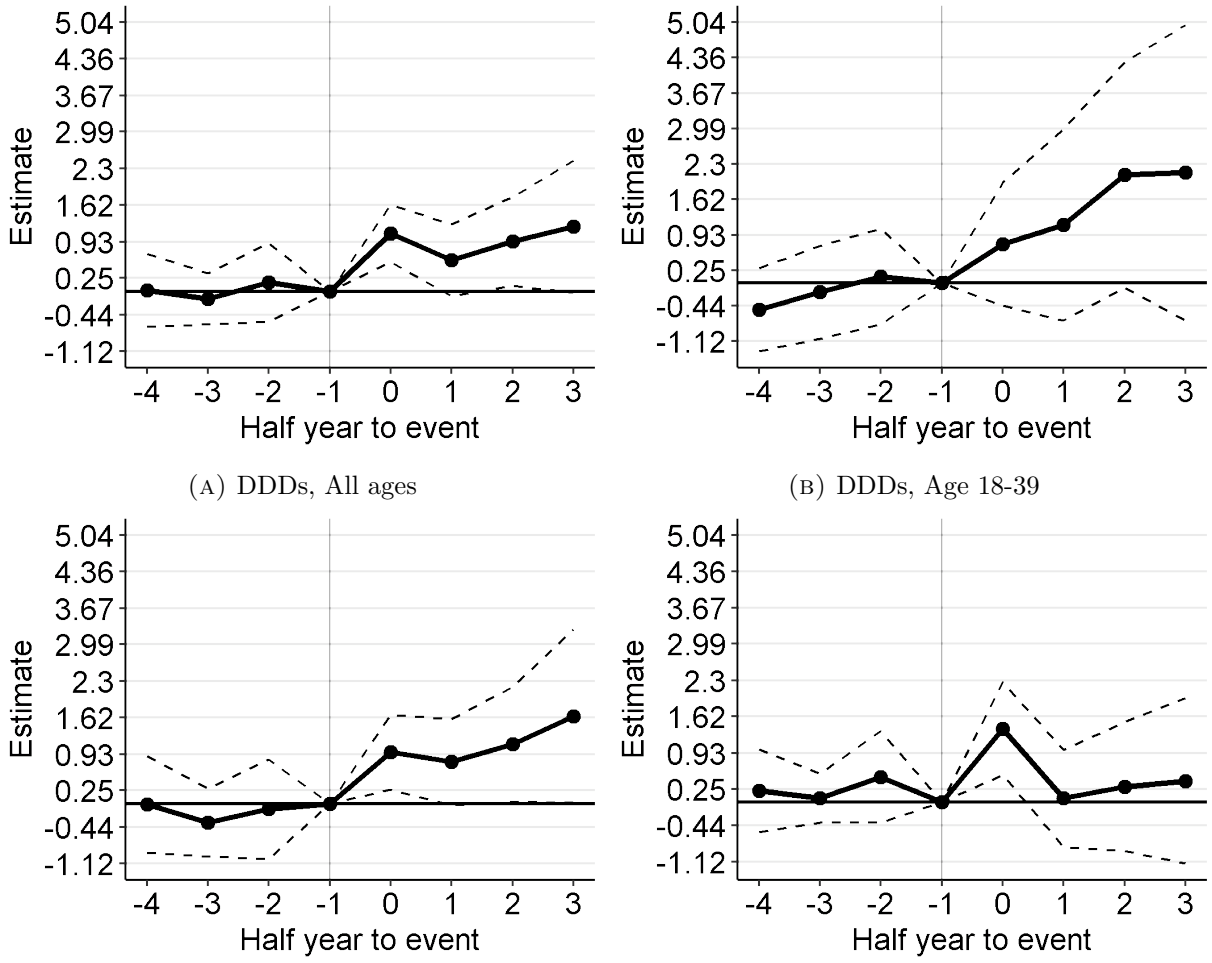
[30] According to the Finnish national treatment guidelines, a prescription of benzodiazepines should last for up to four weeks and be obtained from a Finnish pharmacy (FCCG 2022). Hence, to fill the full prescription, the patient may have to visit at a pharmacy multiple times.

[31] We also confirm that the effects on the long-term use of benzodiazepines are very similar to the effects using the patient biannual-level data, and both effects are 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	1.670***	1.655***	0.014	−0.006
	(0.382)	(0.428)	(0.119)	(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	1.847***	1.620***	0.227	0.002
	(0.643)	(0.574)	(0.165)	(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	2.134***	2.000**	0.133	−0.002
	(0.708)	(0.821)	(0.166)	(0.005)
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	1.016**	1.324***	−0.308**	−0.014***
	(0.409)	(0.374)	(0.152)	(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, municipality fixed effects, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.



(A) DDDs, All ages

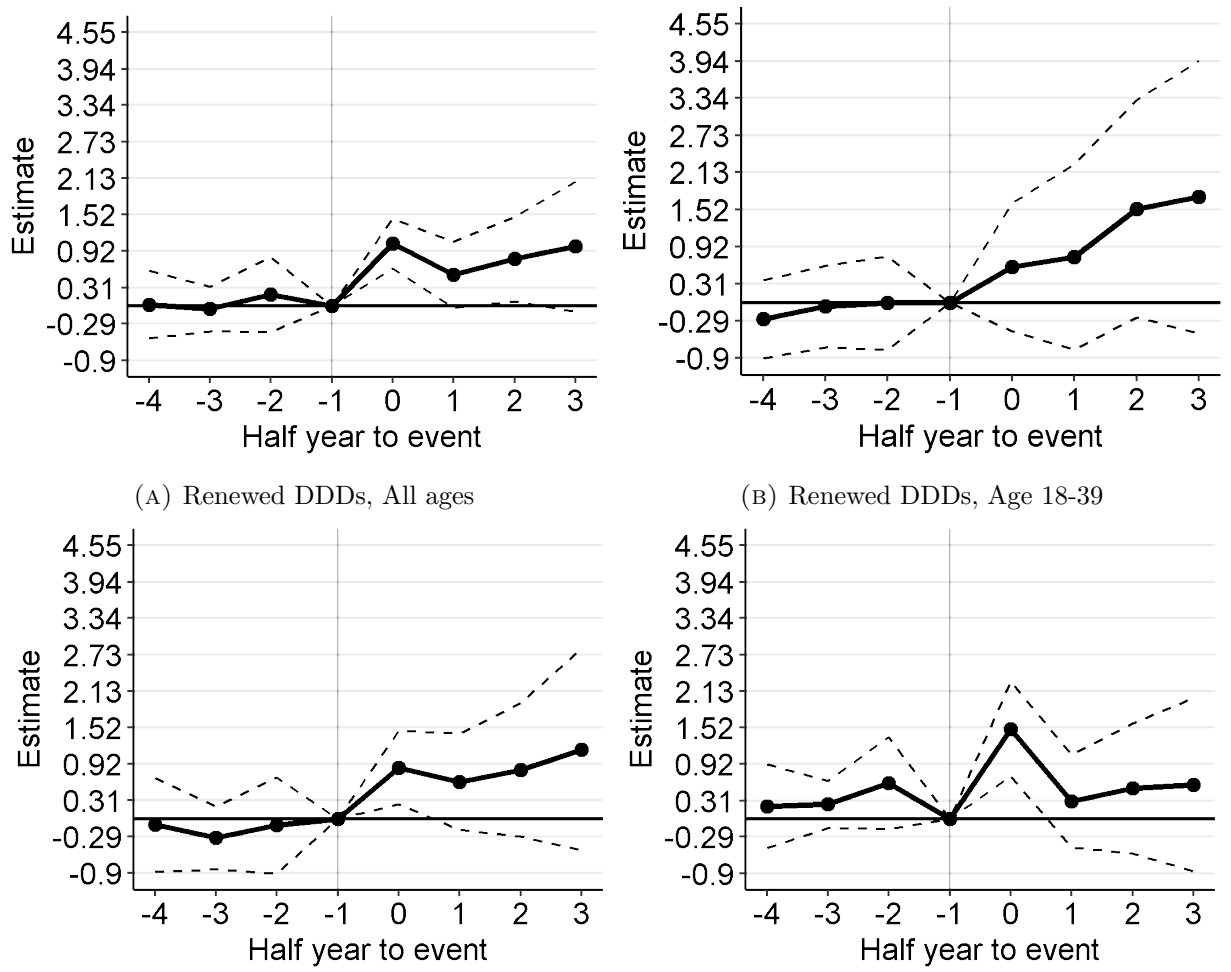
(B) DDDs, Age 18-39

(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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Renewed DDDs, All ages

(B) Renewed DDDs, Age 18-39

(C) Renewed DDDs, 40-64

(D) Renewed DDDs, Over 65

FIGURE 6: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

TABLE 3: Effects of E-Prescribing on Extensive Margin of Benzodiazepine Use (Scaled 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	−0.118***	−0.017***	−0.018	−0.006	−0.128***	−0.020**	−0.277***	−0.026*
	(0.017)	(0.006)	(0.018)	(0.010)	(0.026)	(0.010)	(0.045)	(0.013)
Mean outcome	7.362	0.859	2.735	0.716	7.404	0.88	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, municipality fixed effects and controls for individual age and age squared 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 cause adjustments at the extensive margin of benzodiazepine use through the information channel (Section 2.2); improved information on the patient's prescription history of *different drugs* such as selective serotonin reuptake inhibitors (SSRIs) can positively or negatively impact the physician's decision to initiate benzodiazepine treatment.[32] To study the potential effects of e-prescribing on benzodiazepine use and first-time use at the extensive margin, we combine the prescription data with the full Finnish adult population data using commonly coded individual identifiers. In this analysis, we study the adjustment of the non-benzodiazepine users who potentially become first-time users because of the e-prescribing technology adoption. This type of analysis complements our intensive margin results on benzodiazepine use and has rarely been conducted at the individual level in previously published studies due to data limitations.

Based on the results in Table 3 and Online Appendix Figures A6 and A7, we find that there is only a small (approximately 1–2%) decrease in benzodiazepine use and first-time use in the Finnish adult population on average and in the older age groups (40-64 and over 65) after e-prescribing adoption. However, there are no statistically significant effects at the extensive margin for the younger adults under 40 years of age.

Summary.—Overall, the estimated effects of e-prescribing at the extensive margin of benzodiazepine use are relatively small and of second-order importance when compared to the adjustment at the intensive margin. Consequently, economically significant effects can be detected only at

[32]This would imply that the composition of the patient population could also change, posing a potential threat for identification of the main effects on benzodiazepine use per patient. For example, if healthier patients were using benzodiazepines after e-prescribing and improved access (i.e., easier renewal), the coefficients of interest could partially reflect the change in the patient composition rather than the effects of e-prescribing on patients using the new technology.

the intensive margin: after e-prescribing, the long-term use and the duration or amount of benzodiazepine use per patient increased significantly, especially in the younger adult population. Our results also highlight that easier renewal is the key mechanism behind this observed increase in benzodiazepine use at the intensive margin. Based on these results, the new technology was effective in removing some of the pre-existing barriers in medication access by making renewal easier.

6.2 Effects on Health Outcomes

If e-prescribing increased the appropriate use of benzodiazepines sufficiently, we would expect patients' observed health outcomes to improve. On the other hand, if e-prescribing increased the overuse of benzodiazepines with fewer health benefits than harms through adverse drug effects, then we would expect patients' health outcomes to deteriorate. Lastly, as we found that e-prescribing caused the largest increase in benzodiazepine use among younger patients under 40 years of age, we would also expect to detect the largest impacts in their downstream health outcomes.

General and Mental Health Outcomes.—Columns 1-4 of Table 4 show the effects of e-prescribing on the general and mental health outcomes of benzodiazepine patients. Online Appendix Figures A8–A11 show the corresponding event study estimates and reveal very little evidence for pre-trends in these outcomes. Column 1 shows the results for mortality, which is a commonly used measure of patient health in the literature and does not suffer from measurement error. The point estimates on the probability of death are close to zero. The results are to be expected because death is a rare and quite extreme outcome especially for the younger people. For this reason, we also analyze the changes in other general outcomes. For the number of emergency department visits, we find no statistically significant effects (Column 2). The number of hospital visits seems to decrease for the age groups 18-39 and 40-64 (Column 3), but the effects are only short-term and the confidence intervals are quite large in Figure A10. It is thus difficult to make strong conclusions on the effects for hospital visits. Moreover, we find no statistically significant effects on the probability of a diagnosis of mental and behavioral health disorders (Column 4), similar to the results on most of the general health outcomes (see also Figure A11).[33]

Health Harms from Adverse Drug Effects.—Next, we evaluate the effects on primary indicators of medication misuse and serious adverse effects of benzodiazepines, that is, hospital diagnoses of prescription drug abuse and prescription drug poisonings. Health harms related to these adverse

[33]Using the hospital discharge data, we also explored the effects on more detailed health outcomes of anxiety, panic disorder, and sleeping disorders. These outcomes yield results similar to those for mental and behavioral disorders and, for brevity, are not reported in the paper.

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

	Death	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All ages							
Post-adoption	−0.019	−0.251	−6.625**	−0.269	0.011	0.011	−0.004
	(0.014)	(2.172)	(2.885)	(0.334)	(0.010)	(0.008)	(0.056)
Mean outcome	1.046	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	15,167,056
Panel B. Age 18-39							
Post-adoption	0.013	1.129	−15.869***	−0.621	0.074	0.050**	0.020
	(0.012)	(3.181)	(5.540)	(0.775)	(0.049)	(0.022)	(0.023)
Mean outcome	0.118	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	3,084,187
Panel C. Age 40-64							
Post-adoption	−0.007	0.011	−5.630**	−0.293	−0.003	−0.004	0.005
	(0.014)	(2.058)	(2.782)	(0.352)	(0.007)	(0.011)	(0.030)
Mean outcome	0.429	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	6,742,280
Panel C. Age over 65							
Post-adoption	−0.046	−1.217	−2.922	−0.058	−0.005*	0.007	−0.018
	(0.032)	(2.010)	(2.290)	(0.084)	(0.003)	(0.007)	(0.114)
Mean outcome	2.361	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	5,340,589

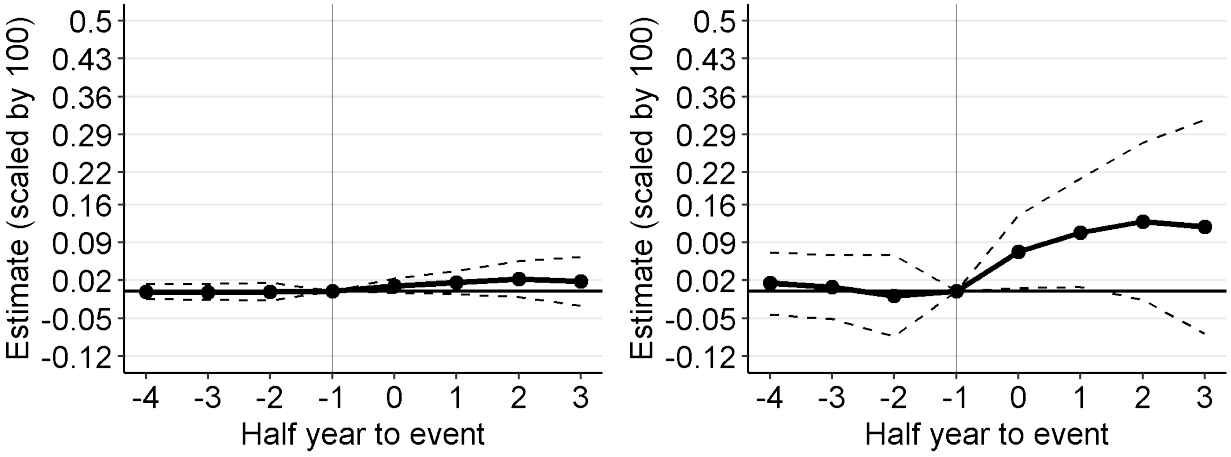
Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Panel A shows the results for all ages, Panel B for the age group under 18-39, Panel C for the age group 40-64, and Panel D for the age group 65 and older. Each regression controls for calendar time (half-year) fixed effects, municipality fixed effects, patient age and age squared. 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 effects are only prevalent in the younger patient population, and among this population, these effects have been increasing over time (Figure 3).

For younger patients, we find that e-prescribing gradually increased the probability of prescription drug abuse (Figure 7), despite the imprecisely estimated effect of the DiD specification (Column 5 of Table 4). Consistent with the increase in the probability of prescription drug abuse, e-prescribing also increased the probability of prescription drug poisonings by approximately 9% in the younger population (Column 5), although the event study estimates are imprecisely estimated (Figure 8). Online Appendix Table A4 decomposes the DiD effects to short- and long-run effects (one year and at least one year after the adoption, respectively), and confirms statistically and economically significant effects on prescription drug abuse disorders and poisonings in the long run (23% and 18%) in the younger population. In contrast, there are no statistically significant effects for older patients and the estimates are also relatively small in magnitude. Notably, Figures 7 and 8 do not show evidence for pre-trends for either of these outcomes.

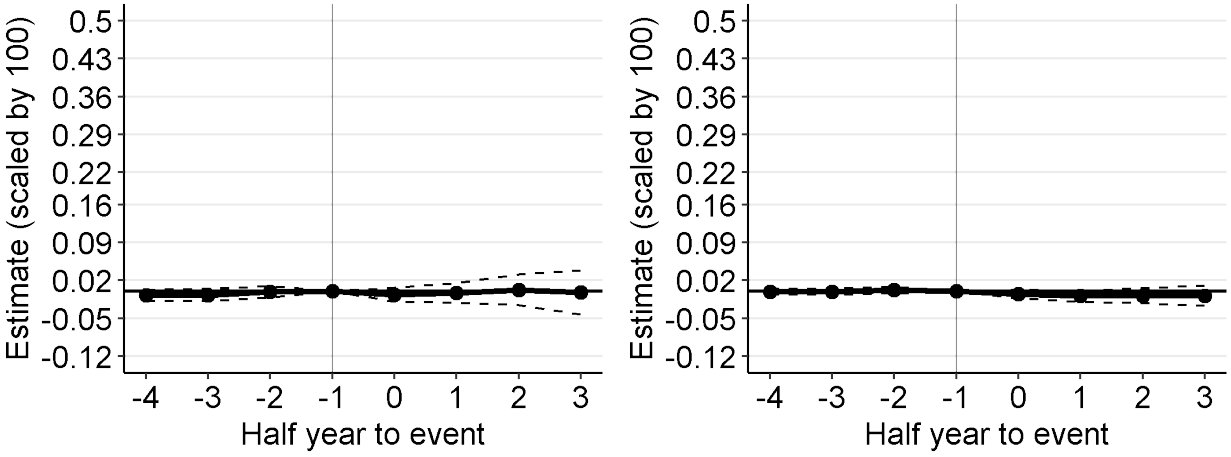
In addition to addiction, benzodiazepines may cause other side effects such as sedation and a decline in cognitive functions; health harms related to these other side effects are prevalent only among older patients (Section 4). Column 7 of Table 4 and Online Appendix Figure A12 reveal no statistically significant effect on the probability of a diagnosis related to any of these other side effects on average for all patients or for the three age groups (18–39, 40–64, over 65) separately.

Summary.—Overall, our results show that the adoption of e-prescribing (in primary care) has little effect on the general and mental health outcomes of benzodiazepine patients such as emergency department visits. In contrast, we find that e-prescribing led to significant adverse health effects for younger patients (aged 18-39), coinciding with substantial increases in their benzodiazepine use and long-term use.



(A) PDA diagnosis, All ages

(B) PDA diagnosis, Age 18-39

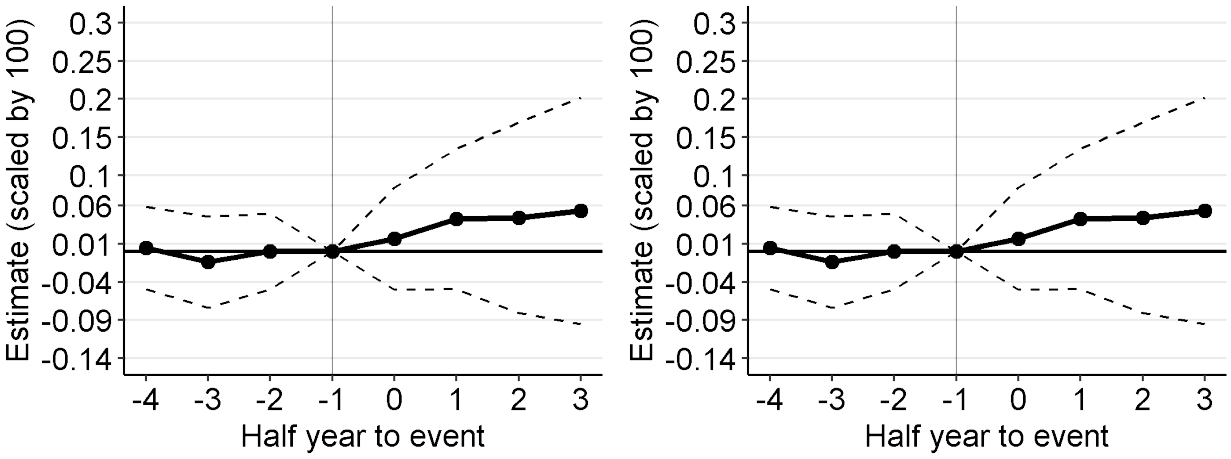


(C) PDA diagnosis, 40-64

(D) PDA diagnosis, Over 65

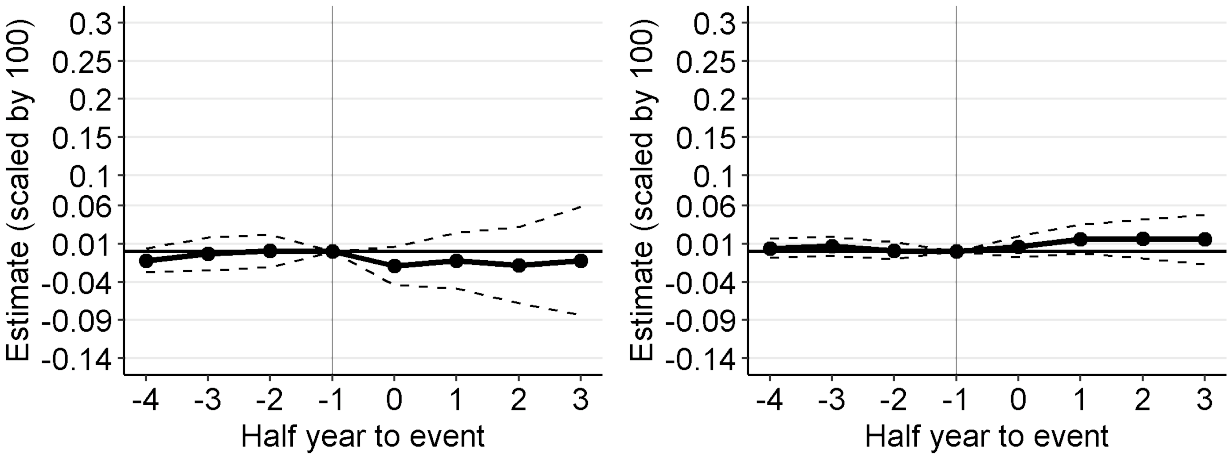
FIGURE 7: Prescription Drug Abuse Diagnosis

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, municipality fixed effects, patient age and age squared. 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 8: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

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

In this section, we first explore additional age heterogeneity of the estimated effects. Then, we conduct various robustness checks for our baseline models and use alternative estimators and tests based on recent advances in the staggered DiD literature. We also study improved diagnosing and changes in the use of other medications as alternative explanations for the observed health effects of e-prescribing. Finally, we implement a placebo regression test. We summarize the key results in the main text while presenting the full set of results, including regression estimates and event study graphs, in the Online Appendix.

Additional Age Heterogeneity.—Table A5 shows that the effects of e-prescribing on benzodiazepine use and adverse health outcomes for patients under 40 years of age are mostly driven by those aged 26-39. The only exception is the diagnosis of prescription drug poisoning, where the effect is driven by young adults aged 18-25 (note also the positive but statistically insignificant point estimate for the age group 26-39). Importantly, the differential responses to e-prescribing between these two age groups are not driven by differences in the take-up rate of e-prescriptions (Figure A4).

Robustness Checks and Alternative Specifications.–Our baseline results for benzodiazepine use and health outcomes are robust for the following changes in specifications, samples, and measurement. We use patient fixed effects instead of municipality fixed effects to show robustness for unobserved heterogeneity across patients (specifications in Tables A6 and A7). We also limit the data to those periods when the last-treated municipalities have not yet adopted e-prescribing. This is to confirm robustness for including the last-treated municipalities in the control group (as clean controls) and having only early-treated municipalities in the treatment group (specifications in Tables A8 and A9).[34] Tables A8 and A9 also show the results from specifications estimated without municipalities that adopted the national EMR system at the end of our observation period, starting in 2014. We are not aware of any other significant changes or policy reforms that could potentially confound our estimates or violate the parallel trends assumption.

We also conduct a robustness check and cluster standard errors at the hospital district level to account for possible correlation in standard errors due to geographical clustering of the policy

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

adoption within hospital districts (Section 2.3); and exclude patients (the movers) who switched municipalities during the observation period from our estimation sample (specifications in Tables A10 and A11). If patients switched from physicians in non-treated to treated municipalities or *vice versa* due to e-prescribing, this could potentially lead to the contamination of the treatment and control groups.

We also conduct a robustness check regarding the measurement of the main outcome variables related to benzodiazepine use. When calculating the number of renewed and new DDDs, we use an alternative definition of new versus renewed prescription without the 16-month cutoff to make sure that the effects are not driven by the change in the classification from "renewed" to "new" after 16 months (Table A12, Figures A13 and A14). To summarize, our results remain intact when using any of these alternative specifications.

Potential Biases in TWFE models and Robustness for Treatment Effect Heterogeneity.—We evaluate potential biases and assumptions in the TWFE models in three ways (Online Appendix Section F). First, if the treatment effect varies over time and municipalities, negative weights could arise for later-treated units, potentially biasing the treatment effect estimate (Section 5). Using the decomposition method of Goodman-Bacon (2021), we show that negative weighting is not a concern in our setting and that the DiD estimates are similar for the groups of early- and late-treated units (municipalities).

Second, we use the efficient DiD estimator proposed by Roth and Sant'Anna (2022) to evaluate the robustness of our DiD and event study estimates to treatment effect heterogeneity over municipalities and time.[35] We find that the estimated effects are similar or somewhat larger and more precise than those obtained using the baseline TWFE specifications (Tables A15 and A16 and Figures A15–A18). We conclude that our results for benzodiazepine use and health outcomes do not depend on the specific DiD estimator used.

Third, TWFE is primarily based on the parallel trends assumption. Even though event study point estimates provide support for the parallel trends assumption, we evaluate this assumption further by estimating the DiD model by controlling for a municipality-specific linear trend using the approach proposed by Freyaldenhoven et al. (2022). Moreover, we evaluate potential low-power issues in pre-trend tests by applying the tools proposed by Roth (2022). Based on the results of

[35]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). Consequently, only one normalization is needed in this event study specification, as opposed to the baseline specification based on two normalizations (equation (2)).

these two approaches, we conclude that an undetected pre-trend due to low power is an unlikely explanation of our results.

Alternative Mechanisms: Potential Role of Improved Diagnosing.—A concern in research estimating the effects of information technology is that the technology adoption improves the diagnoses of medical conditions, causing potential bias in the health effects estimates. In particular, the better information on a patient's prescription history provided by the e-prescribing technology may improve the physician's diagnosis of mental health disorders and adverse drug effects such as prescription drug abuse and consequently, increase their prevalence. 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. Both of these mechanisms could cause upward bias in the health effect estimates.[36]

To address this concern, we estimate the health effects based on diagnoses that are less likely to originate from the prescribing physicians and thus be confounded by improvements in diagnosing.[37] Table A19 shows the results that exclude 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 based on these alternative outcomes are almost the same as our main results. Thus, we conclude that our results are not driven by potential improvements in the diagnosing of medical conditions.

Alternative Mechanisms: Use of Other Medications.—E-prescribing can also affect the use of other medications for benzodiazepine patients, which could affect their health outcomes. To study this, we use additional data on benzodiazepine patients' prescriptions for a group of widely used antidepressants SSRIs. 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 (Table A20). For the patients aged 18-39, there is a small statistically significant increase in the number of SSRI prescriptions but not in the number of DDDs. Overall, we find only little evidence that the health effects of

[36]On the other hand, as the patient can receive prescriptions more easily (from primary care and/or without face-to-face consultation), 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 mechanism is relevant for the interpretation of the estimates, our point estimate for mental health effects would likely be conservative and lower than the true effect.

[37]General outcomes related to emergency department and hospital visits are arguably much less susceptible to improvements in diagnosing compared, for example, to prescription drug abuse disorder diagnoses.

e-prescribing are explained by changes in the use of other medications, such as SSRIs, for benzodiazepine patients.

Placebo Regression Test.—In Table A21, we show the results from placebo regressions for a health outcome that should not have been affected by e-prescribing: diseases of the appendix, especially appendicitis. The condition is quite prevalent, especially among younger individuals, and it is not correlated with socioeconomic status, making it a good candidate for placebo regressions. In general, the estimates and confidence intervals show no statistically significant effect on this outcome and the point estimates also tend to be very close to zero. Only for the youngest patient group (aged 18-39), the point estimate is marginally statistically significant at the 10% level.

7 Conclusion

We analyze a large-scale public policy to improve medication access while limiting overuse, based on the staggered rollout of a nationwide e-prescribing system across all municipalities in Finland. We use comprehensive administrative data sets on hospital discharges and prescriptions for highly effective but addictive medications, benzodiazepines. Our empirical approach allows us to present evidence of the effectiveness of the new system in mitigating the access-overuse trade-off in medical care by making prescription renewal easier for patients while providing physicians with better prescription information.

Using the full population data, the intention-to-treat estimates of the e-prescribing policy show only little impact on the probability of benzodiazepine use at the extensive margin. In contrast, the duration or amount of benzodiazepine use per patient increases on average due to prescription renewals. Our heterogeneity analyses also reveal that the observed increase at the intensive margin of benzodiazepine use is much larger among younger patients (age 18-40). Importantly, we find little evidence of improvement in their general health outcomes but observe substantial increases in diagnoses of prescription drug abuse disorders and poisonings.

Our results are consistent with better access increasing the use of medication. Improved access and the reduction of the hassle costs of obtaining repeat medication predominantly affects younger patients, who have higher rates of mental and behavioral disorders. However, our results also show that medication misuse (abuse) increase in this vulnerable patient population. Thus, improving access to medication might be harmful for some patients and expose them to medication overuse.

The Finnish e-prescribing system is interoperable and fully standardized at the national level.

In terms of the external validity of our results, easier renewal, along with improved prescription information, are the core features of e-prescribing systems globally and are highly relevant for users of prescription drugs to treat mental illnesses and other chronic conditions. Making renewal easier improves persistence with medication treatment, but in some cases, further precautionary procedures might be needed for prescription renewals to prevent medication overuse or misuse.

Our findings based on benzodiazepines, a large drug class that is widely used in the population, are most directly relevant to other psychotropics because balancing the benefits and harms of medication (i.e., the access-overuse trade-off) remains particularly challenging. A potential limitation of our empirical approach is that we estimate reduced-form relationships with e-prescribing, which may not operate through benzodiazepine use only; the new technology can potentially impact the use of a large set of prescription drugs, which could also affect downstream health outcomes. Further research on other patient populations and prescription drugs is needed to complete the picture of the overall effects of e-prescribing. Moreover, the negative impact of e-prescribing on procurement costs for illicit benzodiazepines due to easier renewal could be an important unintended consequence of the system and a promising topic for further research.

Empirical research in economics has largely overlooked factors that influence joint physician-patient decisions particularly across health care providers. Our results highlight that the conditions under which joint decisions are taken may critically affect patient health outcomes. Information technology improves access and patient convenience but may impair face-to-face communication between physicians and patients. In addition to access, limited communication between decision-makers and the possibility of private information are potential drivers of medication overuse or misuse. Studies of other emerging technologies and markets from the perspective of optimal policy, along with studies focusing on physician prescribing behavior, are key areas for future research.

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

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

Table of Contents

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

Almost all of our health outcomes, except our mortality outcome, come from the hospital discharge data, which are based on hospital (specialized health care) visits.[38] Our mortality outcome comes from the prescription data. We list the ICD-10 codes and other details for the health outcome below.

- *Mortality* outcome is an indicator that equals one if the patient passed away in a given 6-month period.
- *Emergency department visit* is an indicator that equals one if the patient's discharge visit has one of the following category in their discharge record in a given 6-month period:
  - 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
- *Mental and behavioral disorder* is based on the fifth chapter of ICD10 "Mental and behavioral disorders" containing the ICD10 codes F00–F99.
- *Prescription drug poisoning* is identified using the ICD10 code T36.
- *Prescription drug abuse disorder diagnosis* is constructed by grouping multiple diagnoses measuring prescription drug abuse (such as abuse of benzodiazepines and opioids). We consider diagnoses with the following ICD10 codes:

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

  - Opioid-related disorders (F11)
  - Sedative-, hypnotic-, or anxiolytic-related disorders (F13)
  - 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 ICD10 classification contains codes that indicate that the patient is currently participating in controlled rehabilitation program, or uses a 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)

- *Other side effects* are measured based on diagnoses with the following ICD10 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 Additional Support for Exogeneity of the Adoption Time

The key identifying assumption in our empirical approach is that the timing of technology adoption across municipalities is unrelated to the trends in our outcomes.[39] To provide formal support for this assumption, we report the correlations between various municipality-level covariates from the pre-adoption years and the timing of the adoption of e-prescribing (Table A1). Specifically, the outcome is the log difference between the municipality's adoption date and the first adoption date, calculated in days. The municipality of Turku (located in Western Finland) was the first municipality to adopt e-prescribing on May 20, 2010. Supporting our assumption about the exogeneity of the adoption time, Table A1 reveals no evidence of correlation between the covariates and the timing of the adoption.

To further test the exogeneity assumption, we follow Bhuller et al. (2017) and estimate the following model:

$$T_{mt} = (\Gamma_t \times X_{m,2009})'\Psi + \gamma_t + \nu_{mt}, \tag{A1}$$

where Γ is a vector of biannual-level time dummies, X is a vector of municipality-level covariates for 2009, γ is time fixed effects, ν is an error term, and the outcome T_{mt} is a dummy variable equal to one if municipality m adopted e-prescribing in 6-month period t. For simplicity, we standardize the municipality-level covariates by dividing them by the corresponding standard deviations. Figure A1 plots the coefficients and the 95% confidence intervals from Ψ. As expected, the coefficients do not reveal any systematic correlation between the timing of the adoption and the covariates, further supporting the conclusion that the adoption of e-prescribing is not systematically related to observable differences in municipality-level covariates.

[39] Appendix B is based on Böckerman et al. (2023).

TABLE A1: Correlation Between the Timing of E-prescribing Adoption and Municipality-Level Covariates

	Covariate year		
	2008	2009	2010
Log(population)	−0.093	−0.088	−0.089
	(0.091)	(0.088)	(0.091)
Log(primary care costs)	0.126	0.141	0.091
	(0.115)	(0.140)	(0.086)
Percentage over 65 years	−0.009	−0.007	−0.006
	(0.013)	(0.011)	(0.010)
Percentage 15–64 years	−0.019	−0.016	−0.018
	(0.021)	(0.018)	(0.019)
Drug reimbursement index	0.008	0.006	0.006
	(0.007)	(0.006)	(0.007)
Morbidity index	−0.007	−0.006	−0.006
	(0.006)	(0.006)	(0.006)
Mortality index	−0.0004	0.001	0.001
	(0.001)	(0.001)	(0.001)
Log(outpatient visits in psychiatry)	−0.008	−0.013	−0.006
	(0.016)	(0.022)	(0.013)
Log(psychiatric inpatient periods of care)	0.086	0.015	0.013
	(0.074)	(0.027)	(0.026)
Semi-urban municipality	0.044	0.038	0.036
	(0.040)	(0.038)	(0.037)
Rural municipality	−0.056	−0.064	−0.069
	(0.087)	(0.096)	(0.098)
F statistic	31.24	35.983	35.983
Adjusted R^2	0.295	0.290	0.287
Observations	299	298	298
Hospital district FE	Yes	Yes	Yes

Notes: Each column shows parameter estimates from a separate regression using municipality-level data. Municipality covariates are for 2008, 2009, and 2010, in columns 1, 2, and 3, respectively. The outcome in each regression is the log of the difference in the time of e-prescribing adoption by the municipality relative to the earliest adoption time, calculated in days. The reference category for semi-urban and rural municipality indicators is urban municipalities. The variables are taken from the National Institute of Health and Welfare and from Statistics Finland. In each year, we exclude a few municipalities with missing observations in the covariates. Standard errors are clustered at the municipality level.
*p<0.1; **p<0.05; ***p<0.01

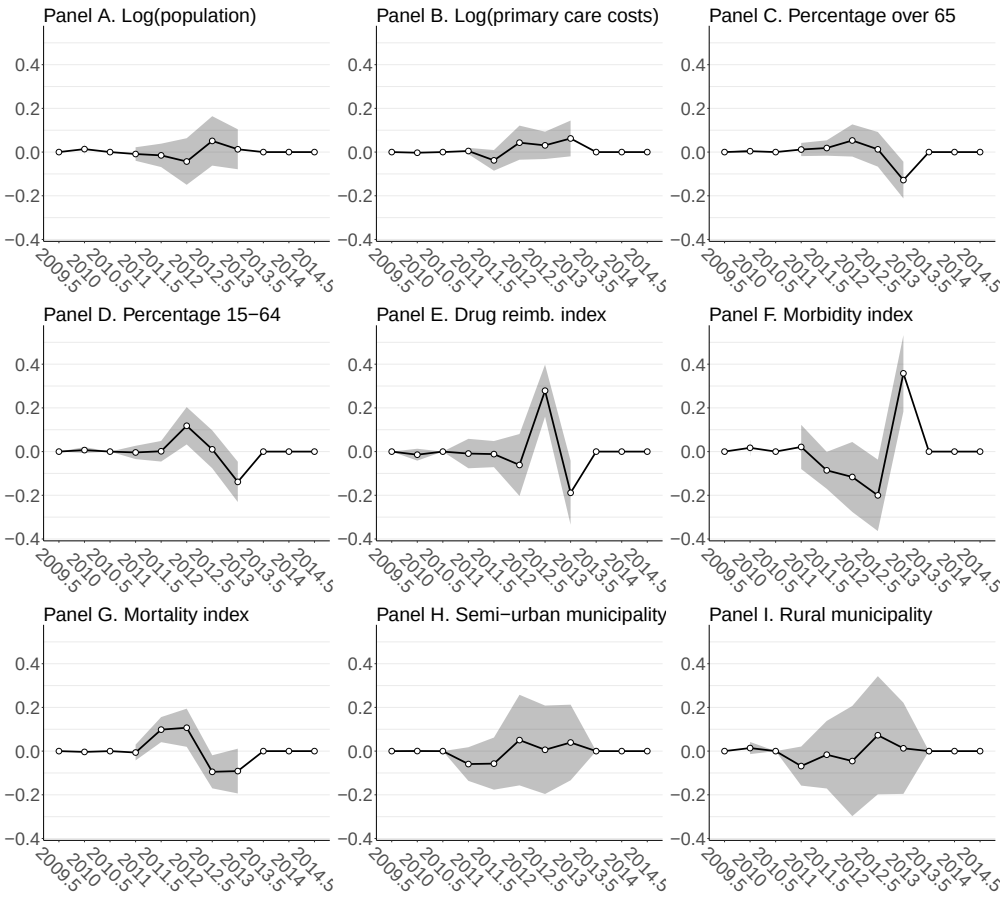


FIGURE A1: Adoption of E-Prescribing by Baseline Municipality Characteristics

Notes: Each panel plots coefficient estimates from a separate regression for interaction terms between a specific municipality covariate for the year 2009 and biannual dummies for the time of e-prescribing adoption by the municipality. Regressions are estimated using municipality-level data. The outcome is a dummy variable that equals one when the municipality adopted e-prescribing during the particular 6-month period. The coefficient estimates are standardized by dividing the covariates by their corresponding standard deviations. See Table A1 notes for data sources and equation A1 for details on the specifications.

C Illustration of E-prescribing Technology in Finland

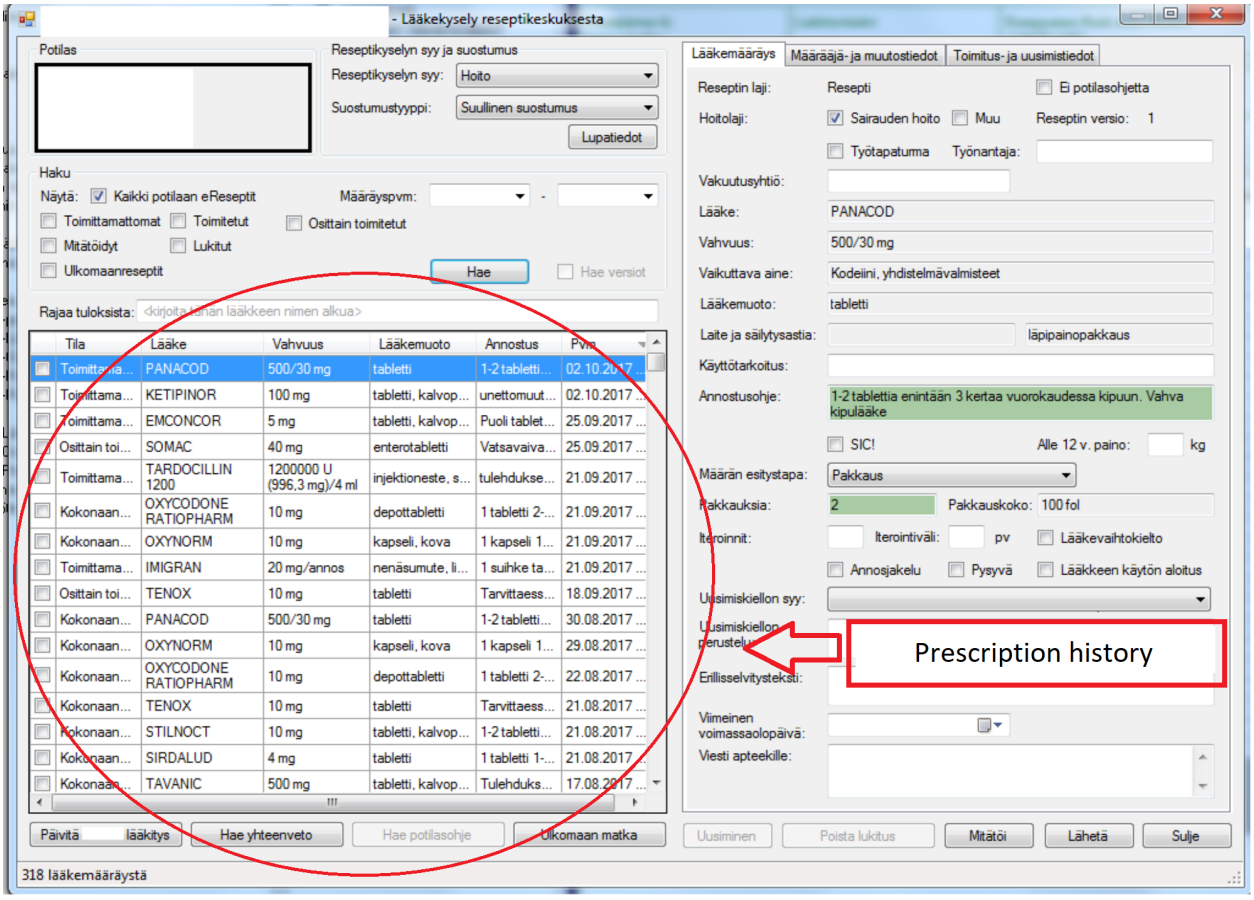


FIGURE A2: E-Prescribing Technology, Physician's View

Note: This figure is based on Böckerman et al. (2023).

D Tables and Figures of the Main Specification

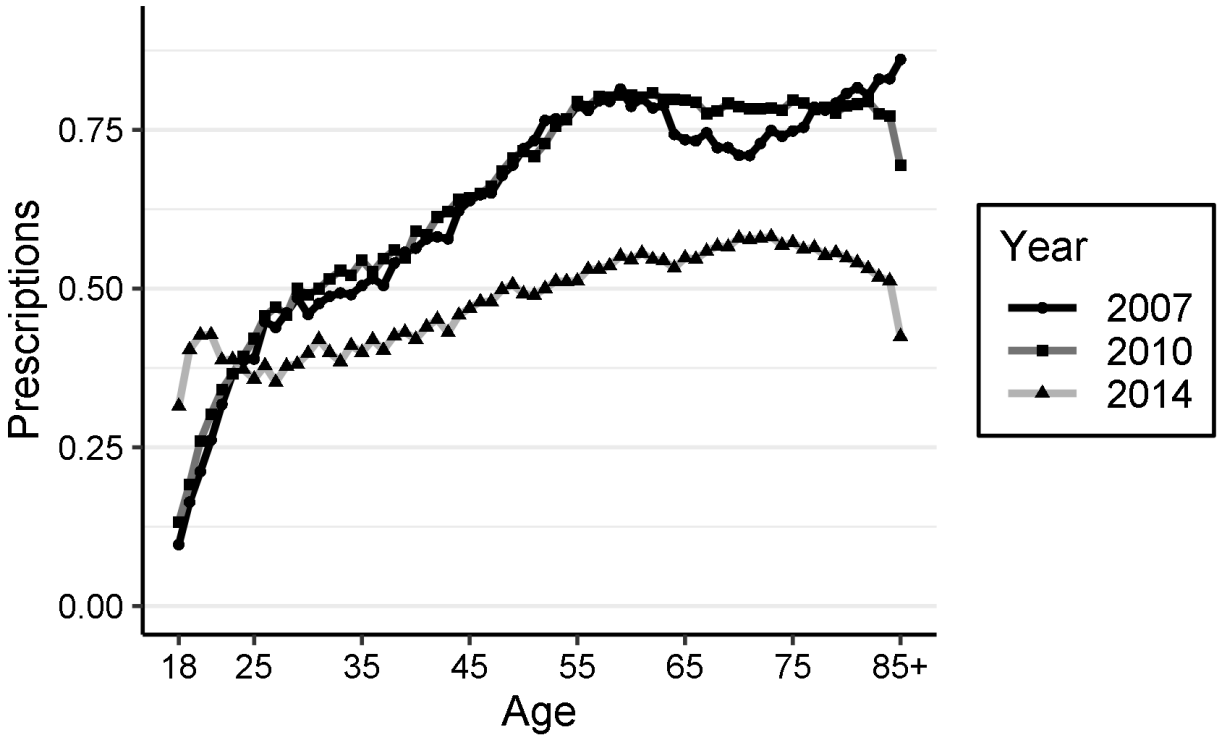


FIGURE A3: Yearly Benzodiazepine Use-Age Relationships at Intensive Margin: Number of All Prescriptions

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).

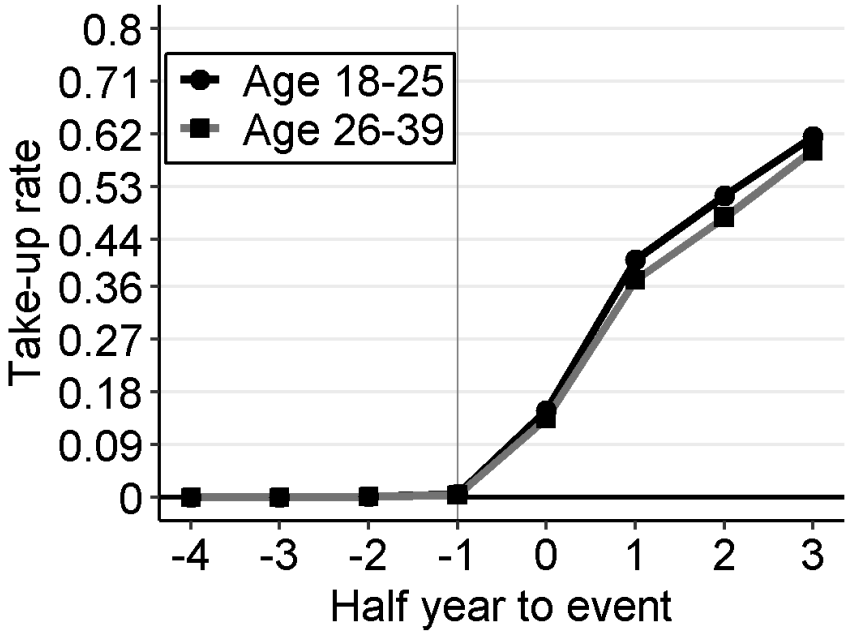
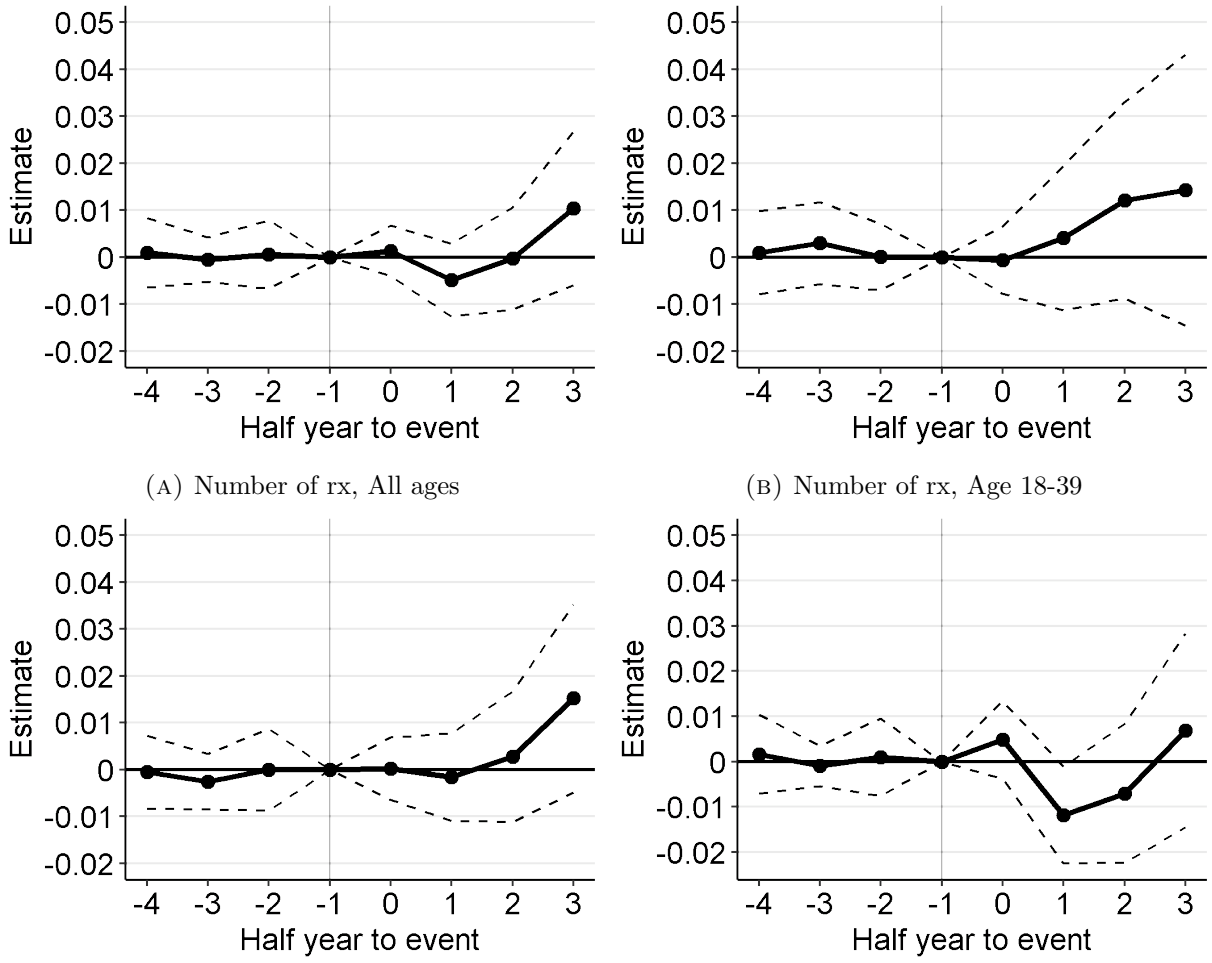


FIGURE A4: Conditional Take-up Rate of E-prescriptions, Ages 18–25 and 26–39

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.



(A) Number of rx, All ages

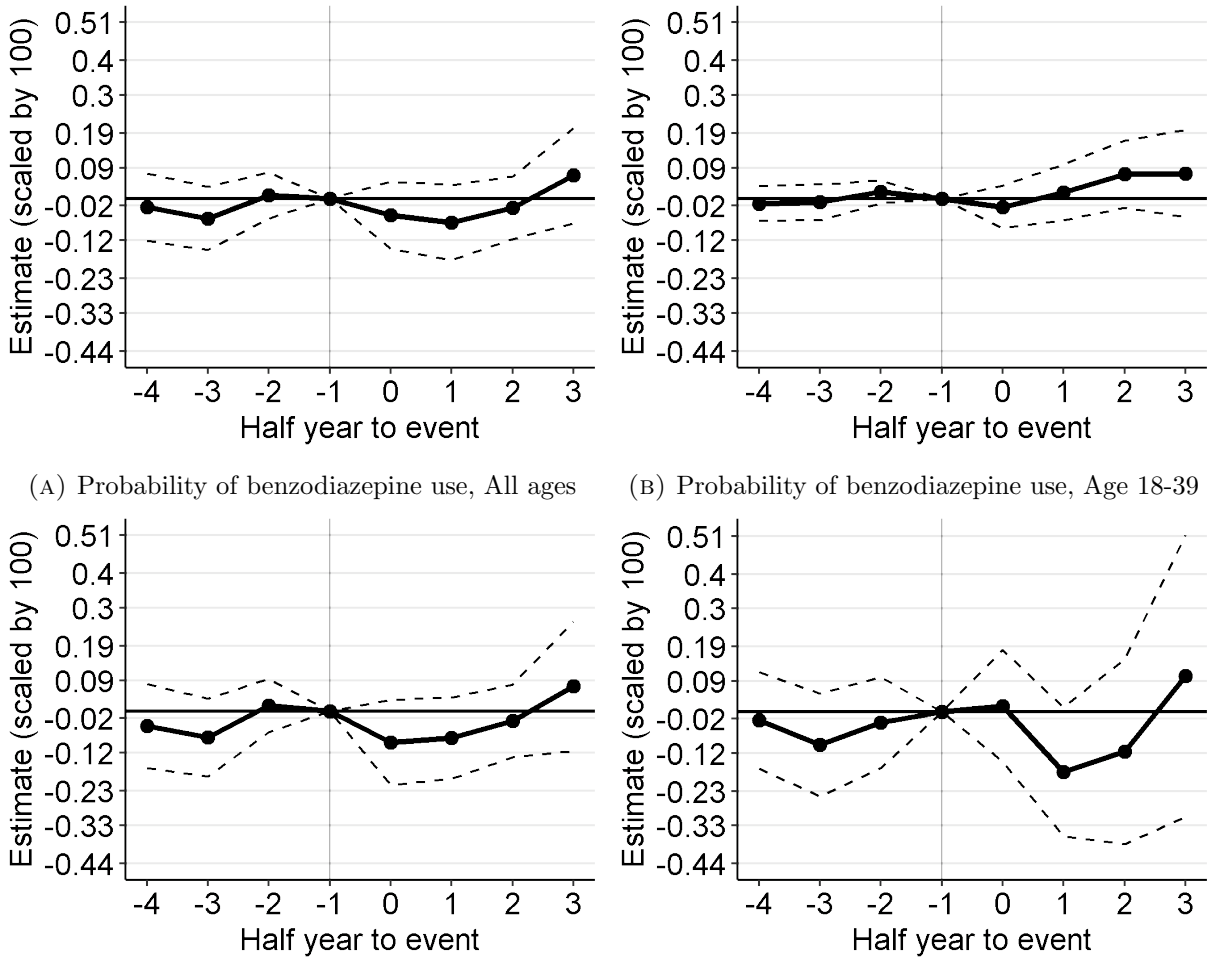
(B) Number of rx, Age 18-39

(C) Number of rx, 40-64

(D) Number of rx, Over 65

FIGURE A5: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Probability of benzodiazepine use, All ages

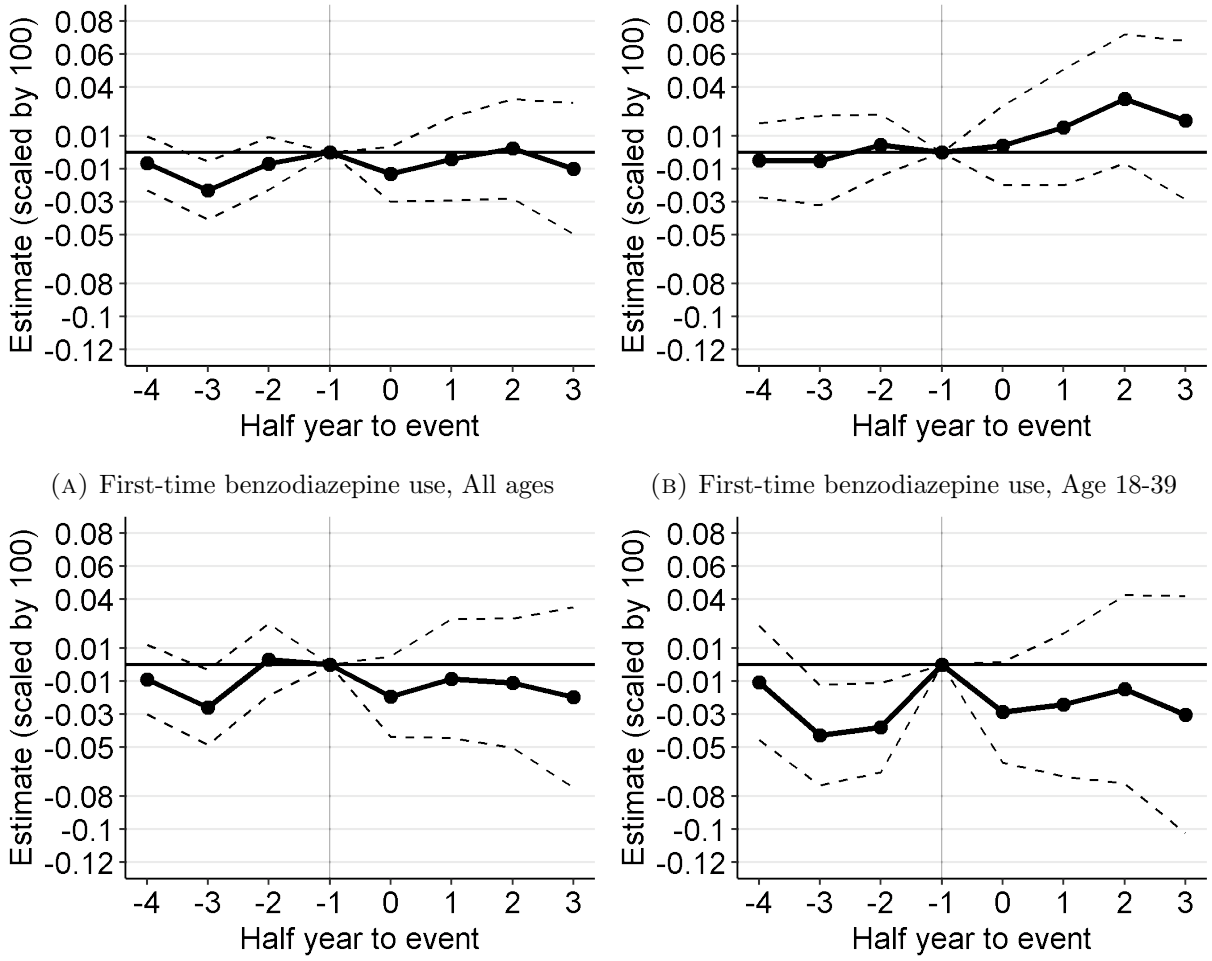
(B) Probability of benzodiazepine use, Age 18-39

(C) Probability of benzodiazepine use, 40-64

(D) Probability of benzodiazepine use, Over 65

FIGURE A6: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) First-time benzodiazepine use, All ages

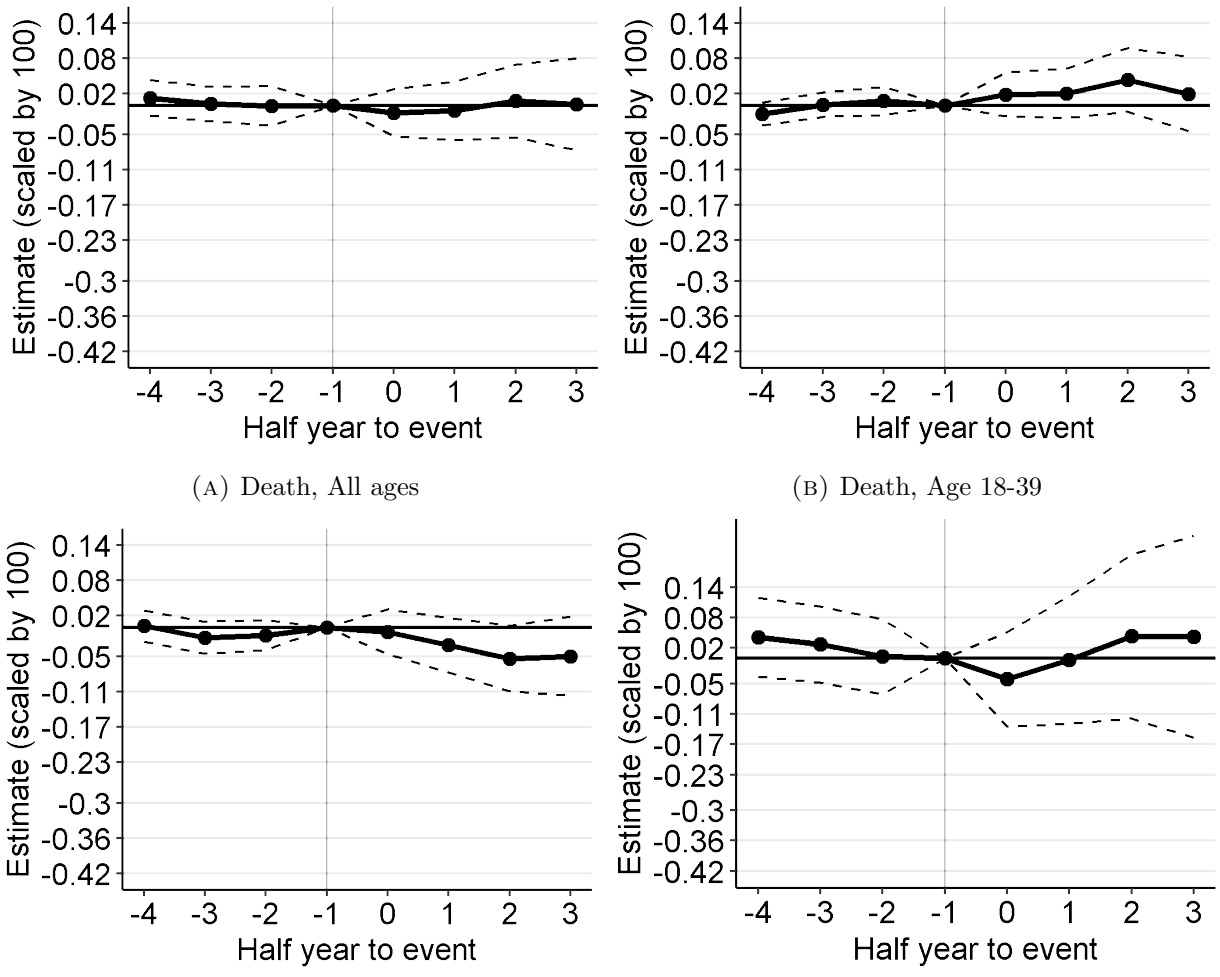
(B) First-time benzodiazepine use, Age 18-39

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

(D) First-time benzodiazepine use, Over 65

FIGURE A7: 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. Due to left censoring, the data used in the estimations are from 2008h2 to 2014h2. 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Death, All ages

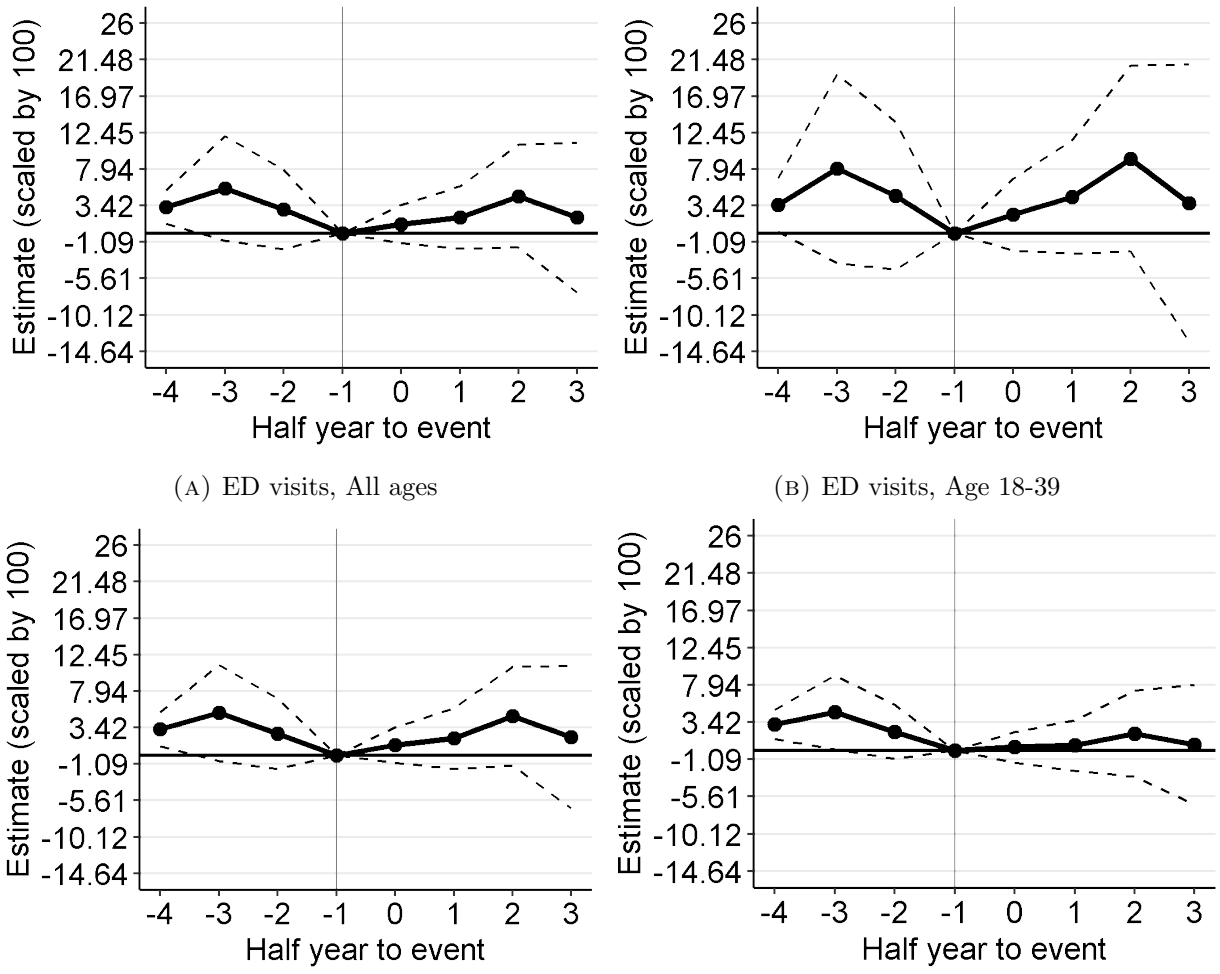
(B) Death, Age 18-39

(C) Death, 40-64

(D) Death, Over 65

FIGURE A8: Death

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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) ED visits, All ages

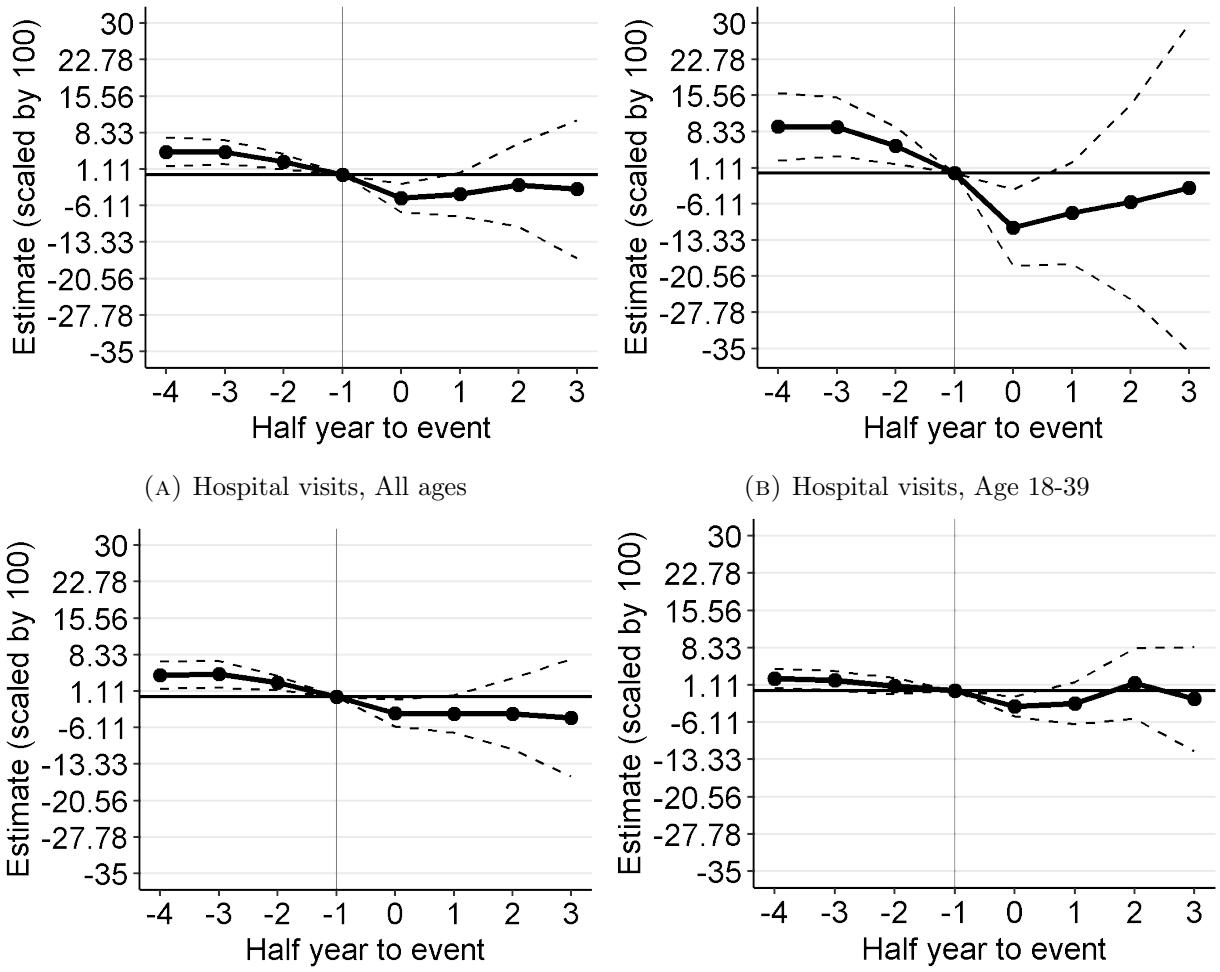
(B) ED visits, Age 18-39

(C) ED visits, 40-64

(D) ED visits, Over 65

FIGURE A9: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Hospital visits, All ages

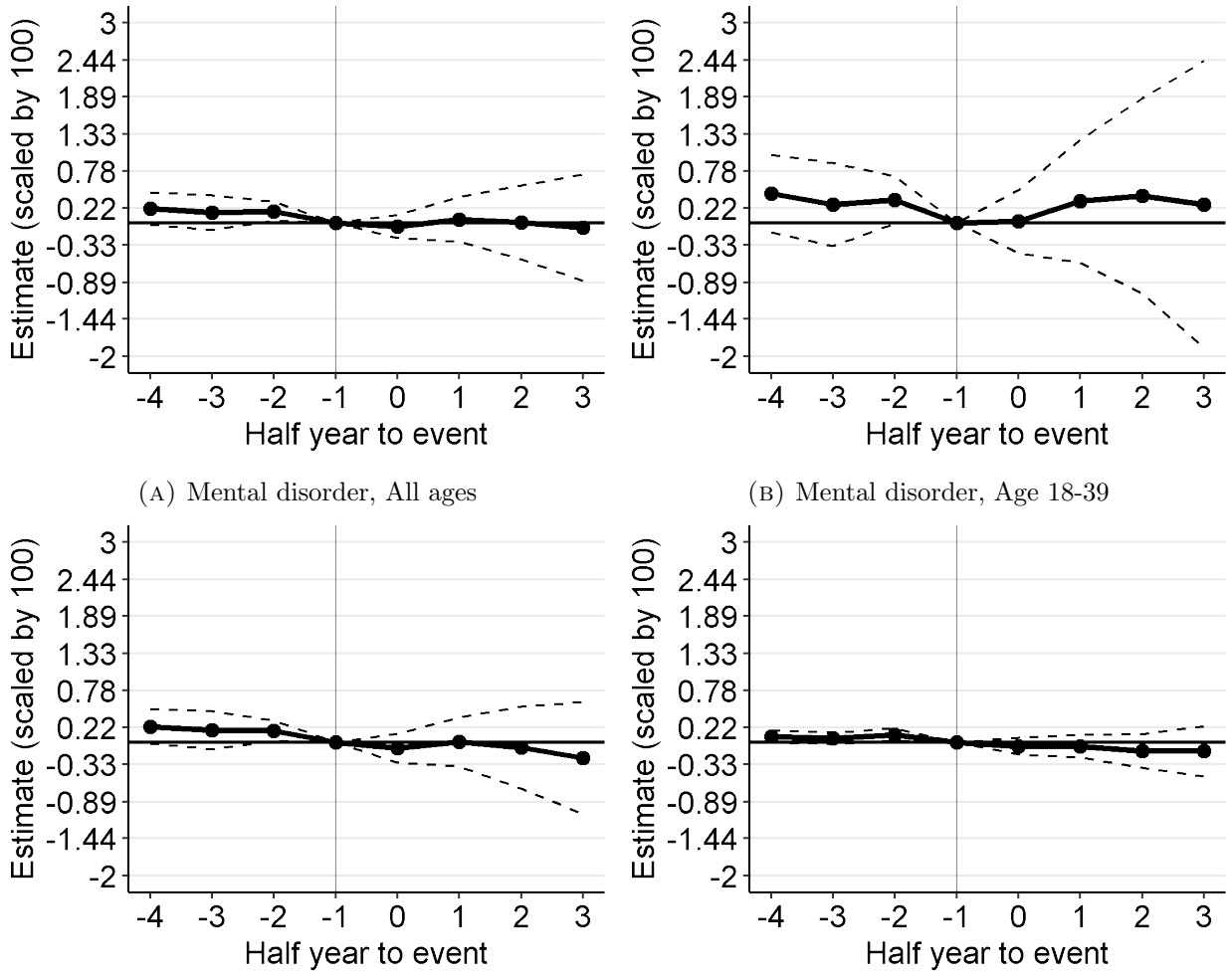
(B) Hospital visits, Age 18-39

(C) Hospital visits, 40-64

(D) Hospital visits, Over 65

FIGURE A10: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.



(A) Mental disorder, All ages

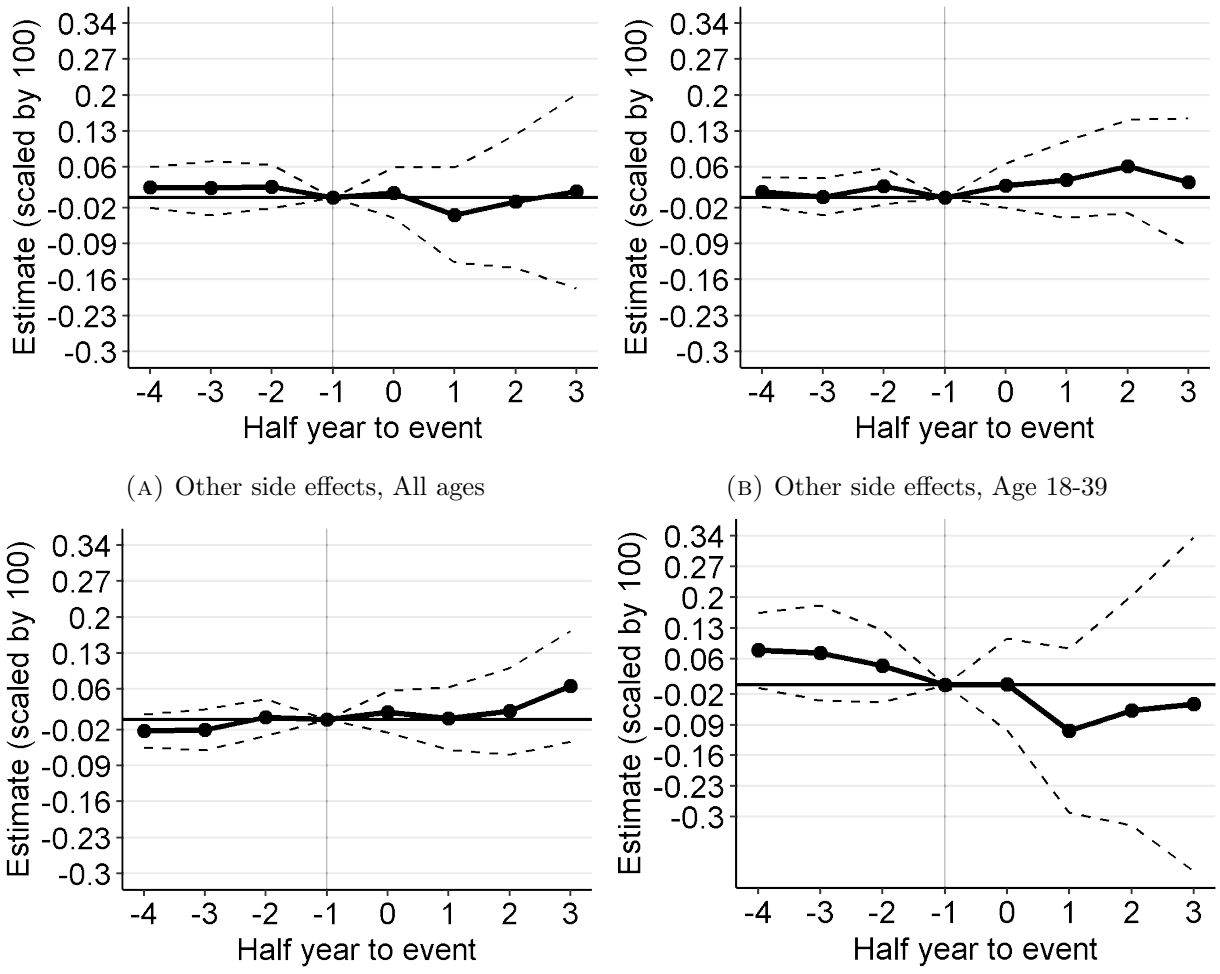
(B) Mental disorder, Age 18-39

(C) Mental disorder, 40-64

(D) Mental disorder, Over 65

FIGURE A11: 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, municipality fixed effects, patient age and age squared. 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 A12: 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

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	2.901***	2.836***	0.065	0.007***	0.008***	−0.001	1.779**
	(0.354)	(0.352)	(0.169)	(0.001)	(0.001)	(0.000)	(0.765)
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	3.052***	2.490***	0.562*	0.007**	0.006**	0.001	−3.346**
	(0.976)	(0.919)	(0.310)	(0.003)	(0.003)	(0.001)	(1.602)
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	2.841***	2.665***	0.176	0.006***	0.005***	0.000	1.415
	(0.523)	(0.601)	(0.202)	(0.001)	(0.001)	(0.000)	(1.131)
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	2.664***	3.203***	−0.539**	0.008***	0.010***	−0.002***	2.959***
	(0.402)	(0.424)	(0.231)	(0.002)	(0.002)	(0.001)	(0.796)
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 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, municipality fixed effects, patient age and age squared. 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***	0.002***	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, municipality fixed effects, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE A4: Short-run and Long-run Effects of E-Prescribing on Selected Benzodiazepine Use and Health Outcomes at Intensive Margin

	DDDs	Renewed DDDs	PDA diagnosis	Rx poisoning
	(1)	(2)	(3)	(4)
Panel A. All ages				
Short-run	1.634***	1.619***	0.011	0.010
	(0.358)	(0.393)	(0.011)	(0.009)
Long-run	2.330***	2.347***	0.029*	0.021
	(0.559)	(0.676)	(0.016)	(0.013)
Mean outcome	55.694	45.614	0.200	0.200
Observations	15,167,056	15,167,056	15,167,056	15,167,056
Panel B. Age 18-39				
Short-run	1.743***	1.516**	0.068	0.047**
	(0.659)	(0.598)	(0.055)	(0.022)
Long-run	3.011***	2.786***	0.140**	0.089***
	(1.036)	(0.889)	(0.065)	(0.027)
Mean outcome	30.342	23.307	0.600	0.500
Observations	3,084,187	3,084,187	3,084,187	3,084,187
Panel C. Age 40-64				
Short-run	2.079***	1.949***	−0.003	−0.004
	(0.626)	(0.729)	(0.007)	(0.011)
Long-run	3.296***	3.096**	0.006	0.005
	(0.984)	(1.316)	(0.012)	(0.019)
Mean outcome	57.504	47.085	0.100	0.200
Observations	6,742,280	6,742,280	6,742,280	6,742,280
Panel D. Age over 65				
Short-run	1.017**	1.316***	−0.006*	0.007
	(0.402)	(0.366)	(0.003)	(0.007)
Long-run	0.989	1.515**	−0.004	0.005
	(0.680)	(0.634)	(0.006)	(0.014)
Mean outcome	68.051	56.638	0.000	0.100
Observations	5,340,589	5,340,589	5,340,589	5,340,589
Scaled 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, municipality fixed effects, patient age and age squared. "Short-run" refers to the first year of e-prescribing adoption, and "Long-run" refers to periods at least one year after adoption. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, coefficients, standard errors and means in columns 3 and 4 have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

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

E.1 Additional Age Heterogeneity

TABLE A5: Effects of E-Prescribing on Selected Benzodiazepine use and Health Outcomes at Intensive Margin, Ages 18–25 and 26–39

	DDDs	Renewed DDDs	PDA diagnosis	Rx poisoning
	(1)	(2)	(3)	(4)
Panel A. Age 18-25				
Post-adoption	0.300	0.132	0.049	0.121**
	(0.776)	(0.648)	(0.077)	(0.054)
Mean outcome	17.994	12.541	0.800	0.800
Observations	752,758	752,758	752,758	752,758
Panel B. Age 26-39				
Post-adoption	2.273***	2.042***	0.081*	0.028
	(0.862)	(0.757)	(0.048)	(0.025)
Mean outcome	34.328	26.783	0.500	0.400
Observations	2,331,429	2,331,429	2,331,429	2,331,429
Scaled 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, municipality fixed effects, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, coefficients, standard errors and means in columns 3 and 4 have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

E.2 Specification with Patient Fixed Effects

TABLE A6: Robustness for Patient Fixed Effects: Effects of E-Prescribing on Intensive Margin of Benzodiazepine Use

	DDDs		Renewed DDDs		New DDDs		Number of rx	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All ages								
Post-adoption	1.670***	1.814***	1.655***	1.752***	0.014	0.062	−0.006	−0.005
	(0.382)	(0.445)	(0.428)	(0.474)	(0.119)	(0.112)	(0.004)	(0.004)
Mean outcome	55.694	55.694	45.614	45.614	10.081	10.081	0.644	0.644
Observations	15,167,056	15,167,056	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	1.847***	2.371***	1.620***	1.960***	0.227	0.411**	0.002	0.007
	(0.643)	(0.666)	(0.574)	(0.570)	(0.165)	(0.186)	(0.005)	(0.005)
Mean outcome	30.342	30.342	23.307	23.307	7.035	7.035	0.445	0.445
Observations	3,084,187	3,084,187	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	2.134***	2.099***	2.000**	1.936**	0.133	0.162	−0.002	−0.003
	(0.708)	(0.689)	(0.821)	(0.806)	(0.166)	(0.171)	(0.005)	(0.004)
Mean outcome	57.504	57.504	47.085	47.085	10.419	10.419	0.680	0.680
Observations	6,742,280	6,742,280	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	1.016**	1.001**	1.324***	1.254***	−0.308**	−0.253	−0.014***	−0.014***
	(0.409)	(0.416)	(0.374)	(0.376)	(0.152)	(0.158)	(0.005)	(0.005)
Mean outcome	68.051	68.051	56.638	56.638	11.414	11.414	0.714	0.714
Observations	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Municipality FE	✓		✓		✓		✓	
Patient FE		✓		✓		✓		✓

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. Controls for patient age and age squared are included in all models. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE A7: Robustness for Patient Fixed Effects: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes

	Death		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)	(13)	(14)
Panel A. All ages														
Post-adoption	−0.019	−0.018	−0.251	−0.497	−6.625**	−6.092**	−0.269	−0.328	0.011	0.010	0.011	0.015*	−0.004	−0.007
	(0.014)	(0.014)	(2.172)	(2.118)	(2.885)	(2.590)	(0.334)	(0.329)	(0.010)	(0.009)	(0.008)	(0.009)	(0.056)	(0.056)
Mean outcome	1.046	1.046	33.925	33.925	164.768	164.768	6.363	6.363	0.166	0.166	0.240	0.240	1.157	1.157
Observations	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056	15,167,056	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	0.013	0.017	1.129	1.053	−15.869***	−12.196***	−0.621	−0.841	0.074	0.066	0.050**	0.062***	0.020	0.012
	(0.012)	(0.013)	(3.181)	(2.965)	(5.540)	(4.080)	(0.775)	(0.747)	(0.049)	(0.045)	(0.022)	(0.024)	(0.023)	(0.023)
Mean outcome	0.118	0.118	32.984	32.984	182.878	182.878	11.174	11.174	0.603	0.603	0.529	0.529	0.299	0.299
Observations	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187	3,084,187	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	−0.007	−0.003	0.011	−0.134	−5.630**	−5.161*	−0.293	−0.311	−0.003	−0.004	−0.004	−0.000	0.005	0.002
	(0.014)	(0.016)	(2.058)	(1.976)	(2.782)	(2.661)	(0.352)	(0.353)	(0.007)	(0.006)	(0.011)	(0.012)	(0.030)	(0.031)
Mean outcome	0.429	0.429	26.297	26.297	151.715	151.715	6.615	6.615	0.082	0.082	0.245	0.245	0.583	0.583
Observations	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280	6,742,280
Panel C. Age over 65														
Post-adoption	−0.046	−0.048	−1.217	−1.697	−2.922	−3.479	−0.058	−0.064	−0.005*	−0.006*	0.007	0.006	−0.018	−0.025
	(0.032)	(0.032)	(2.010)	(1.944)	(2.290)	(2.266)	(0.084)	(0.084)	(0.003)	(0.003)	(0.007)	(0.008)	(0.114)	(0.115)
Mean outcome	2.361	2.361	44.100	44.100	170.789	170.789	3.268	3.268	0.020	0.020	0.066	0.066	2.378	2.378
Observations	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589	5,340,589
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Municipality FE	✓		✓		✓		✓		✓		✓		✓	
Patient FE		✓		✓		✓		✓		✓		✓		✓

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. Controls for patient age and age squared are included in all models. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficient, standard errors and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

E.3 Exclusion of Last-Treated Municipalities and Municipalities that Adopted National EMR System

TABLE A8: Robustness of Effects on Benzodiazepine Use for Excluding Last-Treated Municipalities and Adopters of National EMR System

	DDDs		Renewed DDDs		New DDDs		Number of rx	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All ages								
Post-adoption	1.342***	1.658***	1.492***	1.647***	−0.150	0.011	−0.005	−0.006
	(0.372)	(0.381)	(0.421)	(0.427)	(0.218)	(0.121)	(0.005)	(0.004)
Mean outcome	59.993	56.099	48.355	45.917	11.638	10.182	0.681	0.647
Observations	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871
Panel B. Age 18-39								
Post-adoption	1.250	1.834***	1.273*	1.610***	−0.023	0.224	−0.001	0.002
	(0.843)	(0.645)	(0.701)	(0.577)	(0.248)	(0.165)	(0.006)	(0.005)
Mean outcome	31.607	30.476	24.033	23.406	7.573	7.071	0.456	0.446
Observations	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518
Panel C. Age 40-64								
Post-adoption	1.924***	2.123***	1.902**	1.992**	0.022	0.131	−0.000	−0.001
	(0.544)	(0.701)	(0.751)	(0.817)	(0.293)	(0.168)	(0.005)	(0.005)
Mean outcome	61.996	57.942	50.012	47.420	11.984	10.522	0.722	0.684
Observations	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978
Panel D. Age over 65								
Post-adoption	0.778	0.989**	1.295***	1.305***	−0.517**	−0.317**	−0.010	−0.013**
	(0.523)	(0.414)	(0.448)	(0.375)	(0.261)	(0.155)	(0.006)	(0.005)
Mean outcome	74.632	68.638	60.975	57.081	13.657	11.557	0.764	0.717
Observations	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375
Exclude last-treated municipalities	✓		✓		✓		✓	
National EMR excluded		✓		✓		✓		✓

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

TABLE A9: Robustness of Effects on Health Outcomes for Excluding Last-Treated Municipalities and Adopters of National EMR System (Scaled by 100)

	Death		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)	(13)	(14)
Panel A. All ages														
Post-adoption	−0.022	−0.019	0.816	−0.246	−5.768	−6.655**	−0.048	−0.275	0.020*	0.011	0.012	0.011	0.024	−0.003
	(0.017)	(0.014)	(2.749)	(2.166)	(4.043)	(2.890)	(0.309)	(0.333)	(0.010)	(0.010)	(0.012)	(0.009)	(0.065)	(0.056)
Mean outcome	0.947	1.040	31.905	33.820	159.372	164.421	6.180	6.349	0.156	0.166	0.245	0.240	1.123	1.156
Observations	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871	11,604,223	14,930,871
Panel B. Age 18-39														
Post-adoption	0.010	0.013	1.637	1.081	−15.482**	−15.902***	−0.208	−0.624	0.109**	0.073	0.057**	0.051**	0.032	0.020
	(0.013)	(0.012)	(3.904)	(3.167)	(7.342)	(5.601)	(0.702)	(0.777)	(0.050)	(0.049)	(0.026)	(0.022)	(0.028)	(0.023)
Mean outcome	0.112	0.118	30.760	32.872	172.916	181.987	10.489	11.113	0.559	0.600	0.528	0.529	0.276	0.298
Observations	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518	2,423,853	3,045,518
Panel C. Age 40-64														
Post-adoption	−0.009	−0.007	0.730	−0.004	−5.167	−5.679**	−0.053	−0.303	0.000	−0.003	−0.004	−0.004	0.028	0.005
	(0.015)	(0.014)	(2.688)	(2.060)	(3.917)	(2.796)	(0.331)	(0.353)	(0.007)	(0.007)	(0.015)	(0.011)	(0.032)	(0.030)
Mean outcome	0.417	0.429	25.212	26.248	148.537	151.474	6.448	6.599	0.074	0.082	0.252	0.246	0.576	0.583
Observations	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978	5,190,270	6,637,978
Panel D. Age over 65														
Post-adoption	−0.054	−0.048	0.663	−1.159	−1.299	−2.975	−0.027	−0.060	−0.004	−0.005	0.007	0.007	0.034	−0.016
	(0.034)	(0.032)	(2.357)	(1.997)	(3.239)	(2.258)	(0.112)	(0.084)	(0.004)	(0.003)	(0.008)	(0.007)	(0.132)	(0.114)
Mean outcome	2.144	2.347	41.307	43.948	165.238	170.603	3.214	3.266	0.018	0.020	0.064	0.066	2.350	2.380
Observations	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375	3,990,100	5,247,375
Exclude last-treated municipalities	✓		✓		✓		✓		✓		✓		✓	
National EMR excluded		✓		✓		✓		✓		✓		✓		✓

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

E.4 Clustering Standard Errors at Hospital District Level and Excluding Patients Who Switch Municipalities

TABLE A10: 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	1.670***	1.659***	1.655***	1.691***	0.014	−0.033	−0.006	−0.007
	(0.422)	(0.424)	(0.490)	(0.484)	(0.153)	(0.127)	(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	1.847***	2.418***	1.620**	2.149***	0.227*	0.268	0.002	0.005
	(0.604)	(0.679)	(0.573)	(0.616)	(0.132)	(0.181)	(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	2.134**	1.959***	2.000**	1.845**	0.133	0.114	−0.002	−0.002
	(0.777)	(0.712)	(0.926)	(0.840)	(0.211)	(0.181)	(0.005)	(0.005)
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	1.016**	1.017**	1.324***	1.345***	−0.308*	−0.328**	−0.014**	−0.015***
	(0.419)	(0.415)	(0.431)	(0.380)	(0.166)	(0.163)	(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, municipality fixed effects, patient age and age squared. *p<0.1; **p<0.05; ***p<0.01.

TABLE A11: Robustness of Effects on Health Outcomes for Standard Errors Clustering at Hospital District Level and Excluding Patients With Multiple Municipalities

	Death		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)	(13)	(14)
Panel A. All ages														
Post-adoption	−0.019**	−0.024	−0.251	−0.306	−6.625**	−5.333**	−0.269	−0.227	0.011	0.008	0.011	0.009	−0.004	−0.005
	(0.009)	(0.016)	(3.243)	(2.124)	(3.053)	(2.614)	(0.374)	(0.287)	(0.010)	(0.007)	(0.010)	(0.008)	(0.060)	(0.061)
Mean outcome	1.046	1.157	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	15,167,056	13,242,972
Panel B. Age 18-39														
Post-adoption	0.013	0.013	1.129	1.010	−15.869***	−12.829**	−0.621	−0.582	0.074*	0.076*	0.050**	0.055**	0.020	0.009
	(0.011)	(0.015)	(4.285)	(3.198)	(5.187)	(5.246)	(0.816)	(0.718)	(0.044)	(0.039)	(0.023)	(0.023)	(0.023)	(0.024)
Mean outcome	0.118	0.133	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	3,084,187	2,165,200
Panel C. Age 40-64														
Post-adoption	−0.007	−0.011	0.011	0.153	−5.630*	−4.646*	−0.293	−0.268	−0.003	−0.004	−0.004	−0.006	0.005	0.013
	(0.012)	(0.017)	(3.101)	(2.049)	(3.094)	(2.652)	(0.398)	(0.330)	(0.006)	(0.005)	(0.013)	(0.011)	(0.035)	(0.030)
Mean outcome	0.429	0.452	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	6,742,280	5,980,332
Panel D. Age over 65														
Post-adoption	−0.046*	−0.050	−1.217	−1.242	−2.922	−3.201	−0.058	−0.043	−0.005*	−0.004	0.007	0.008	−0.018	−0.022
	(0.027)	(0.032)	(3.081)	(2.032)	(2.658)	(2.301)	(0.109)	(0.084)	(0.003)	(0.004)	(0.009)	(0.008)	(0.121)	(0.116)
Mean outcome	2.361	2.419	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	5,340,589	5,097,440
Hospital district level clustering	✓		✓		✓		✓		✓		✓		✓	
Patients with multiple municipalities excluded		✓		✓		✓		✓		✓		✓		✓

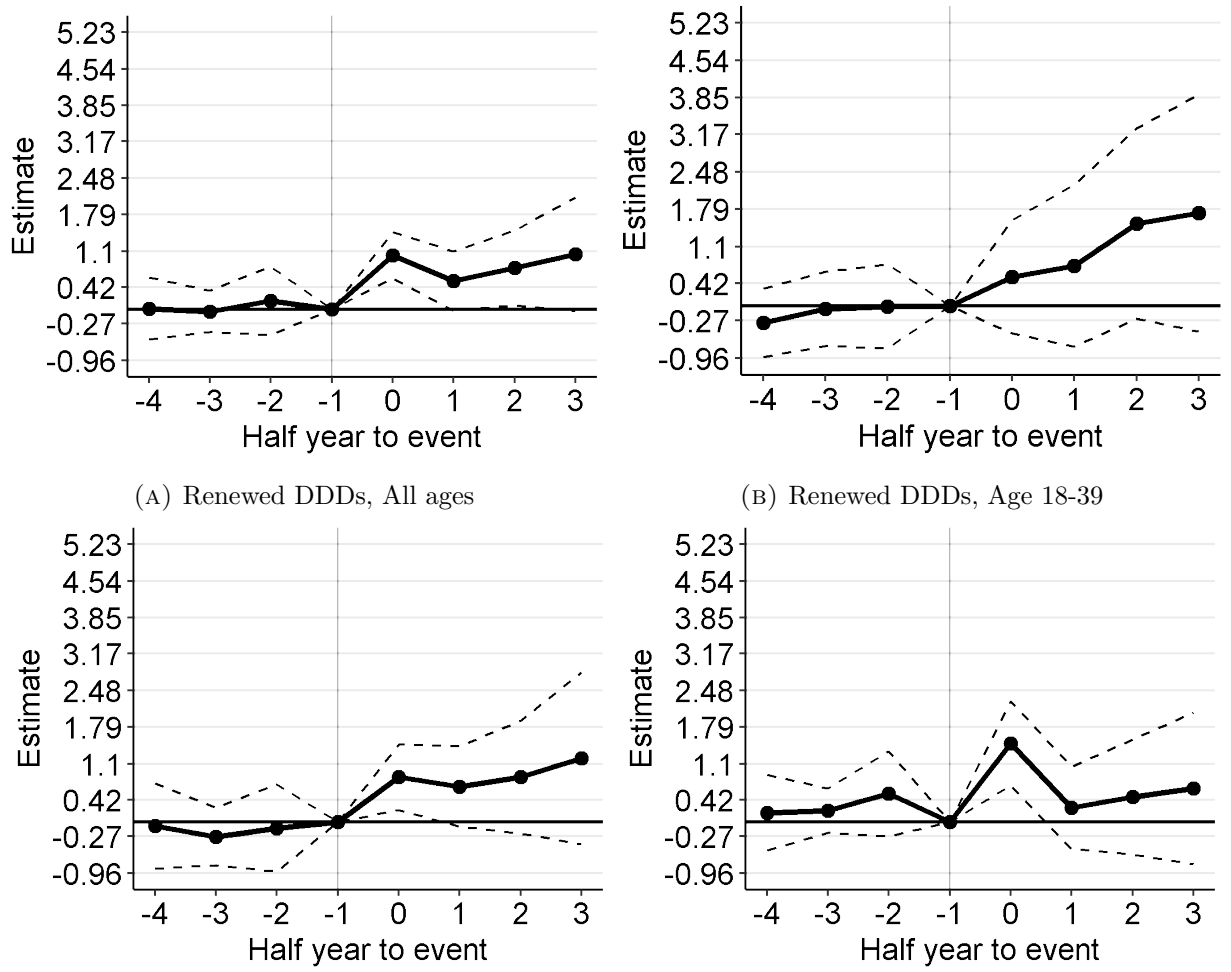
Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Columns 1, 3, 5, 7, 9, 11 and 13 cluster standard errors at the hospital district level and show them in parentheses. Columns 2, 4, 6, 8, 10, 12 and 14 exclude patients with multiple municipalities and show standard errors clustered at the municipality level in parentheses. Each regression controls for calendar time (half-year) fixed effects, municipality fixed effects, patient age and age squared. For scaling purposes, all coefficient, standard errors and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.

E.5 Alternative Definition of Renewed versus New Prescriptions

TABLE A12: 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	1.708***	−0.037	1.651***	0.202	2.049**	0.085	1.393***	−0.377**
	(0.439)	(0.129)	(0.563)	(0.167)	(0.823)	(0.164)	(0.384)	(0.183)
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 have used 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, municipality fixed effects, patient age and age squared. 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

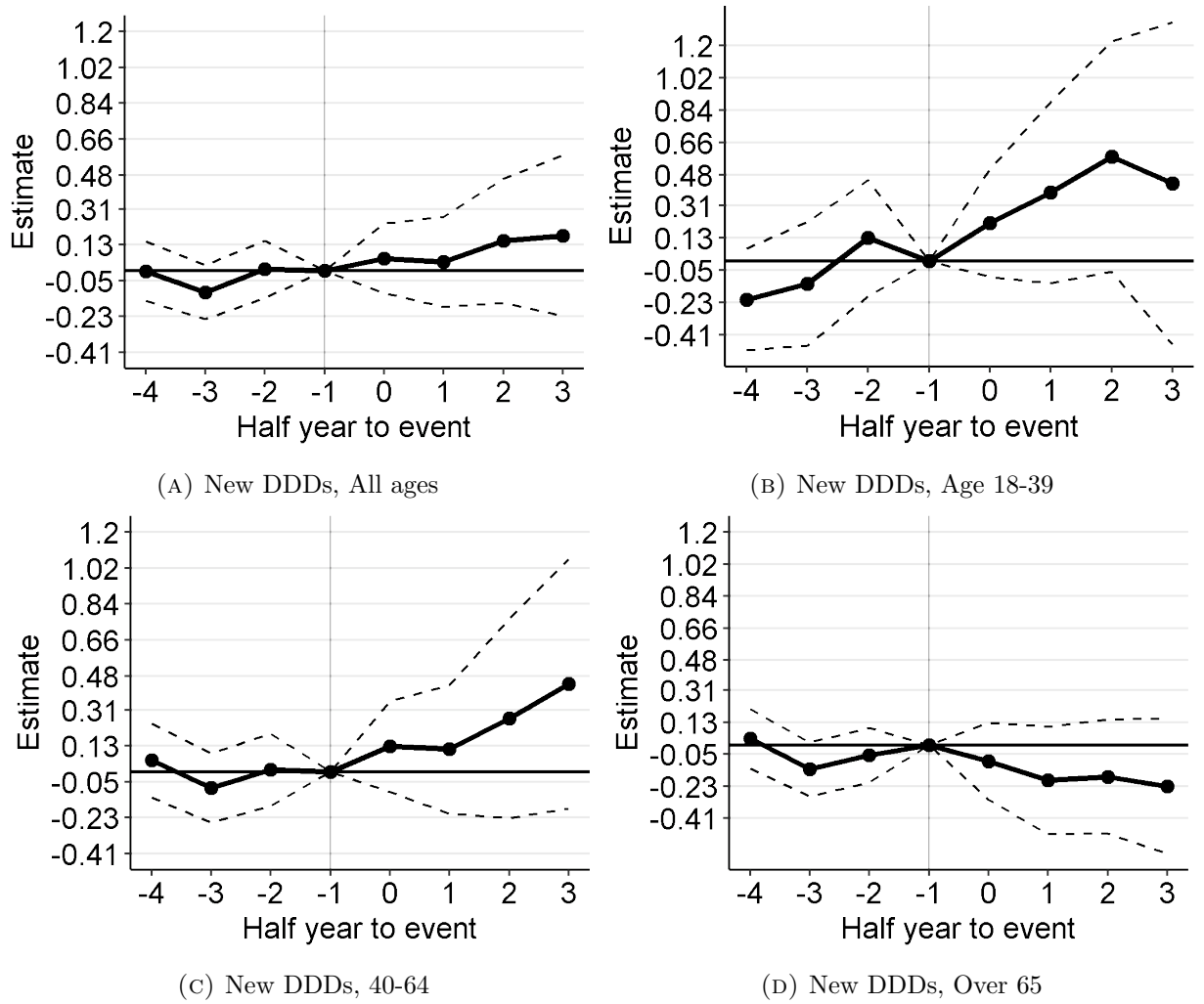
(B) Renewed DDDs, Age 18-39

(C) Renewed DDDs, 40-64

(D) Renewed DDDs, Over 65

FIGURE A13: 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 have used 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, municipality fixed effects, patient age and age squared. 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 A14: 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 have used 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, municipality fixed effects, patient age and age squared. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

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

Two-way fixed effects (TWFE) regressions are widely employed for difference-in-differences designs, but in staggered settings they are guaranteed to provide consistent estimates if it assumed that the treatment effects are homogeneous. We next evaluate the sensitivity of our baseline results for heterogeneity-robust estimation and implement relevant approaches and test statistics to investigate 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 for the estimation of treatment effects for later-treated municipalities in the case of time-varying treatment effect. The 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 the benzodiazepine use and related 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-run effects (Callaway and Sant'Anna 2021). This approach can increase the imprecision of the long-run estimates and bias them towards zero. Based on our event study graphs, the estimated effects for prescription and health outcomes tend to be larger in the long run (Figures 5, 6, 7, and 8). This was indeed shown in Online Appendix Tables A8 and A9 (Section E.3); that is, the point estimates were slightly smaller for most of the outcomes. However, the conclusions remained the same with our baseline specification.

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 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] 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. As the current software package for the actual empirical implementation of Goodman-Bacon (2021) does not allow for population weights in the regressions when doing 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.

Tables A13 and A14 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 vs. later are very similar to later vs. earlier for most outcomes and samples. This is especially the case for outcomes on benzodiazepine use (DDDs, renewed DDDs, new DDDs, number of prescriptions) and health (death, mental disorder, PDA diagnosis, other side effects). Thus, albeit 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 baseline estimates using patient biannual-level data.

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

TABLE A13: 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 from 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 A14: Goodman-Bacon Decomposition of Equally Weighted TWFE Estimates of Benzodiazepine Patients' Health Outcomes

	Death		ED visits		Hospital visits		Mental disorder		PDA diagnosis		Rx poisoning		Other side effects	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.
Panel A. All ages														
Earlier vs Later Treated	0.683	0.01	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	0.017	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	1.336	1.336	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	4,864	4,864
Panel B. Age 18-39														
Earlier vs Later Treated	0.683	0	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	0.011	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	0.140	0.140	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	4,864	4,864
Panel A. Age 40-64														
Earlier vs Later Treated	0.683	-0.043	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	-0.031	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	0.479	0.479	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	4,864	4,864
Panel A. Age over 65														
Earlier vs Later Treated	0.683	0.069	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	0.06	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	2.532	2.532	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	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.

Roth and Sant'Anna (2022) Efficient Estimator—We use the efficient DiD estimator proposed by Roth and Sant'Anna (2022), since 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 the other DiD-based methods. Third, its algorithm is computationally feasible in our application using large individual-level data sets with millions of observations.

The efficient estimator by Roth and Sant'Anna (2022) also also 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. Fourth, using Roth and Sant'Anna (2022) we cannot include municipality fixed effects to the empirical specifications, because the R algorithm only allows for fixed effects for units that have one observation per time period. Thus, we have to use patient fixed effects as opposed to municipality fixed effects.

Tables A15 and A16 show the point estimates using the efficient estimator by Roth and Sant'Anna (2022). 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 11% and this increase is driven by renewed prescriptions (Table A15, Figures A15 and A16).[41] There is only little improvement in their general health outcomes but significant increases in adverse effects related to prescription drug abuse and poisonings (Table A16, Figures A17 and A18).

Replication of the Results at the Municipality Level—We have confirmed that the results are not sensitive for the choice of the level of aggregation (patient- versus municipality-level). To this end, we have confirmed that the results using the individual-level data were generally consistent with those obtained based on the municipality biannual-level data, municipality fixed effects, and econometric approaches presented by Roth and Sant'Anna (2022) and de Chaisemartin and D'Haultfœuille (2020). In the latter case, the current software package for the actual implementation of the estimation algorithm allowed for the clustering of standard errors at the municipality level. (For the sake of brevity and because the estimators are closely related, we do not present the results in the paper, but they can be requested from the authors.)

[41] We estimate the event study coefficients using Roth and Sant'Anna (2022) 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 A15: Roth and Sant'Anna (2022) Approach for Estimating Effects of E-Prescribing on Intensive Margin of Benzodiazepine Use

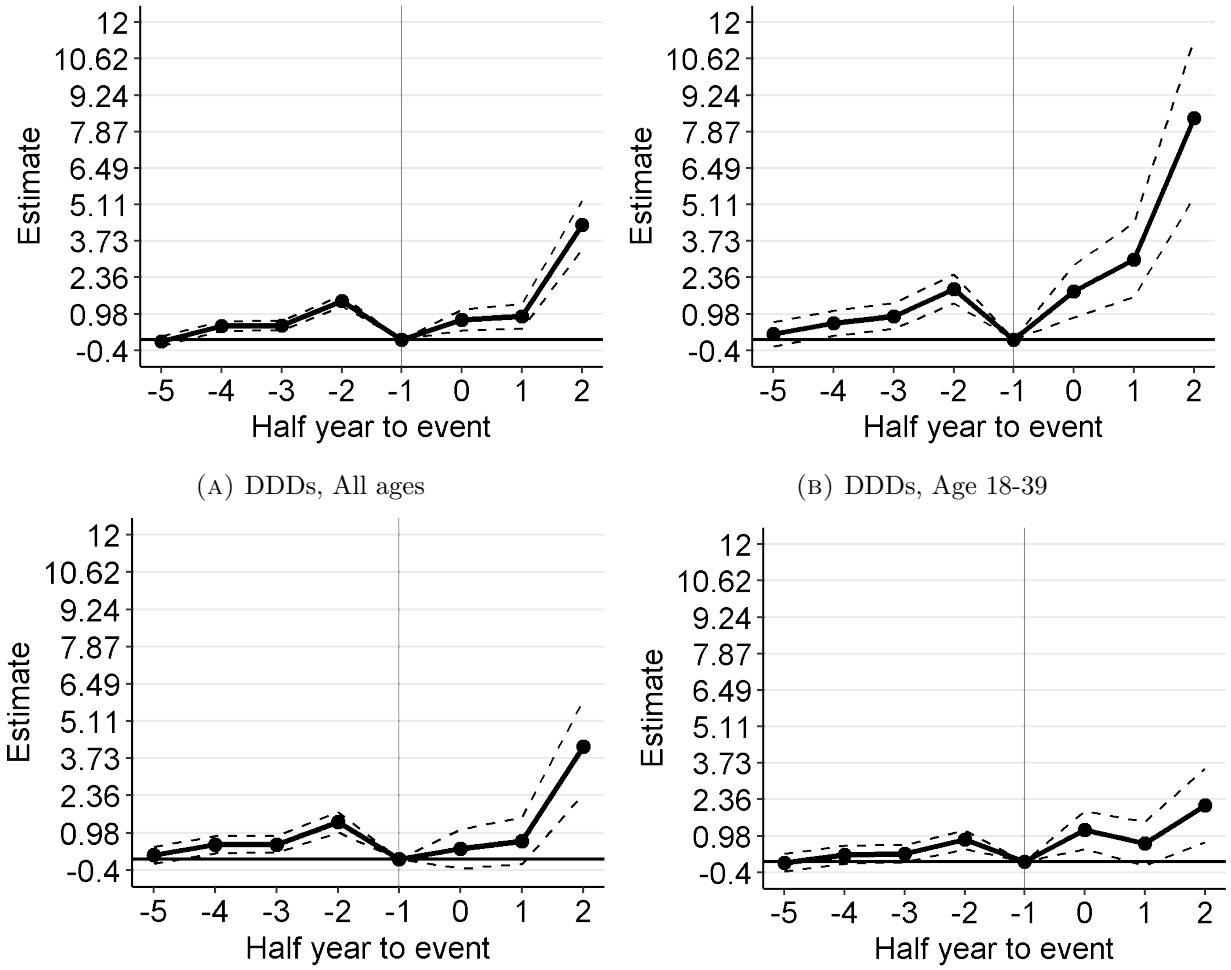
	DDDs (1)	Renewed DDDs (2)	New DDDs (3)	Number of rx (4)
Panel A. All ages				
Post-adoption	1.656	1.419	0.42	-0.012
	(0.203)	(0.186)	(0.075)	(0.002)
Mean outcome	56.548	46.391	10.158	0.644
Observations	13,242,972	13,242,972	13,242,972	13,242,972
Panel B. Age 18-39				
Post-adoption	3.458	2.643	1.096	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 (2022). 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 and it only allows for fixed effects for units that have one observation per time period. Hence, patient fixed effects are used instead of municipality fixed effects. Standard errors are shown in parentheses.

TABLE A16: Roth and Sant'Anna (2022) Approach for Estimating Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes (Scaled 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 (2022). 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 and it only allows for fixed effects for units that have one observation per time period. Hence, patient fixed effects are used instead of municipality fixed effects. Standard errors are shown in parentheses.



(A) DDDs, All ages

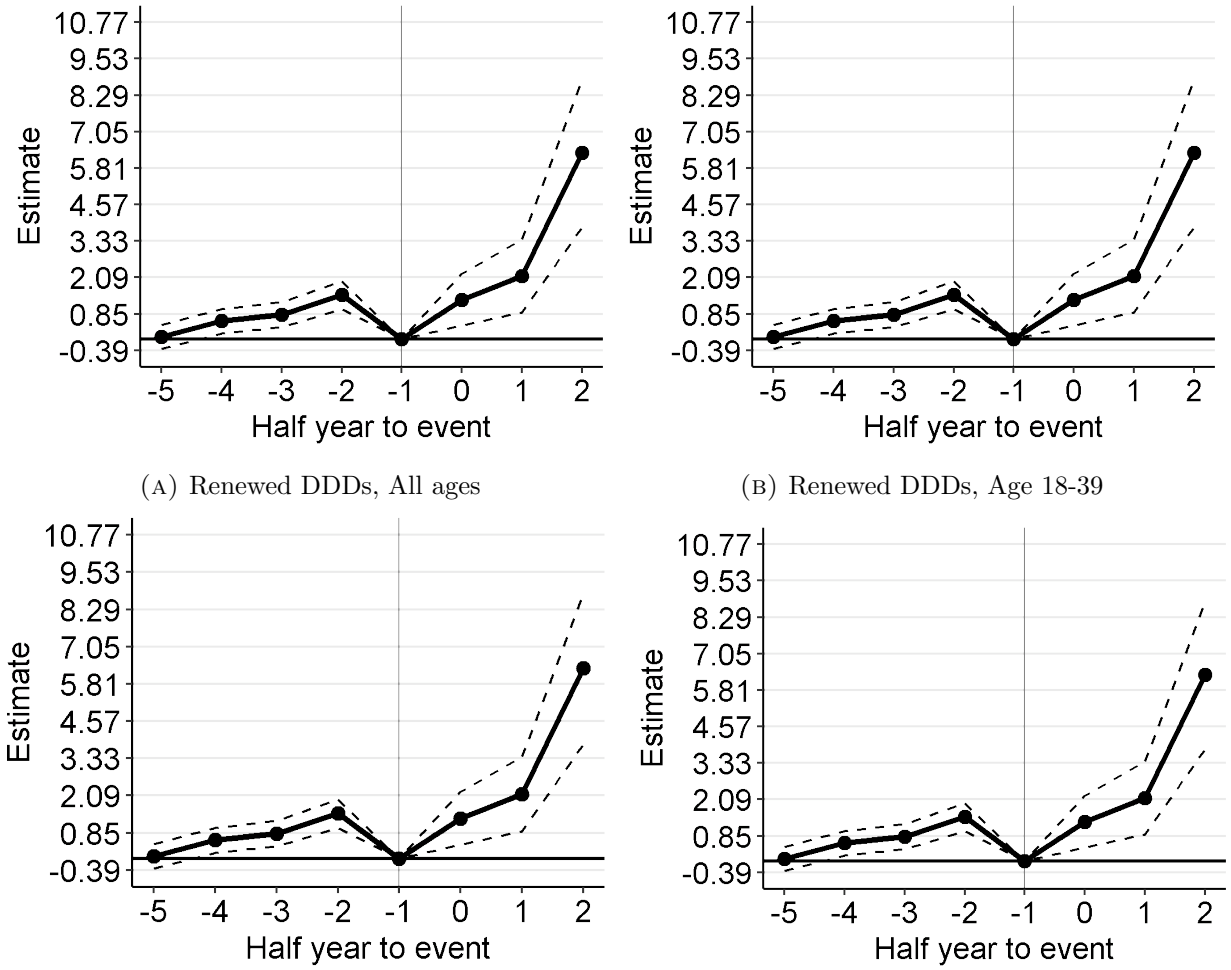
(B) DDDs, Age 18-39

(C) DDDs, Age 40-64

(D) DDDs, Age over 65

FIGURE A15: Robustness to Treatment Effect Heterogeneity at Intensive Margin: Number of Defined Daily Doses

Note: The figures plot the efficient Roth and Sant'Anna (2022) 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 and it only allows for fixed effects for units that have one observation per time period. Hence, patient fixed effects are used instead of municipality fixed effects.



(A) Renewed DDDs, All ages

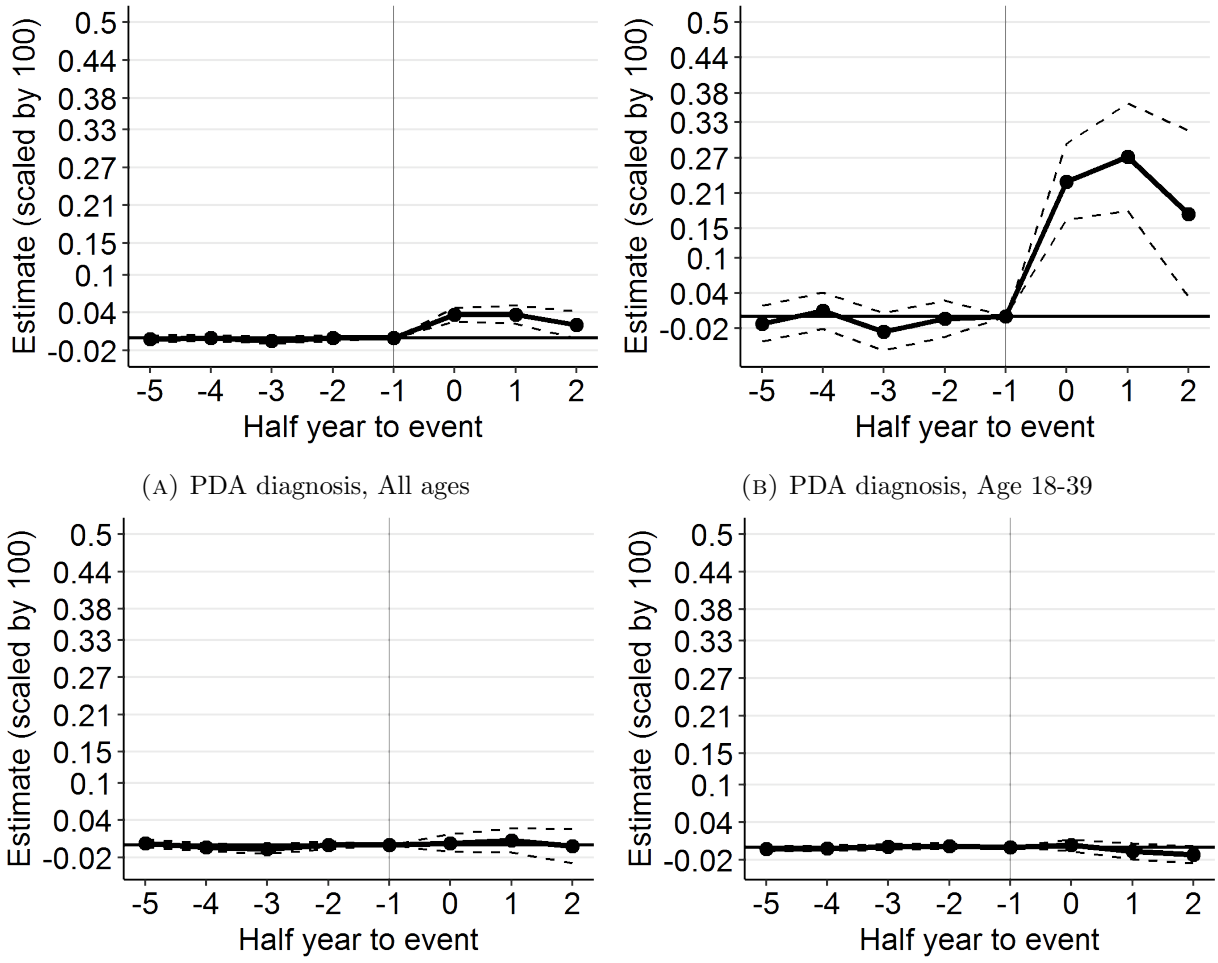
(B) Renewed DDDs, Age 18-39

(C) Renewed DDDs, Age 40-64

(D) Renewed DDDs, Age over 65

FIGURE A16: Robustness to Treatment Effect Heterogeneity at Intensive Margin: Number of Renewed Defined Daily Doses

Note: The figures plot the efficient Roth and Sant'Anna (2022) 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 and it only allows for fixed effects for units that have one observation per time period. Hence, patient fixed effects are used instead of municipality fixed effects.



(A) PDA diagnosis, All ages

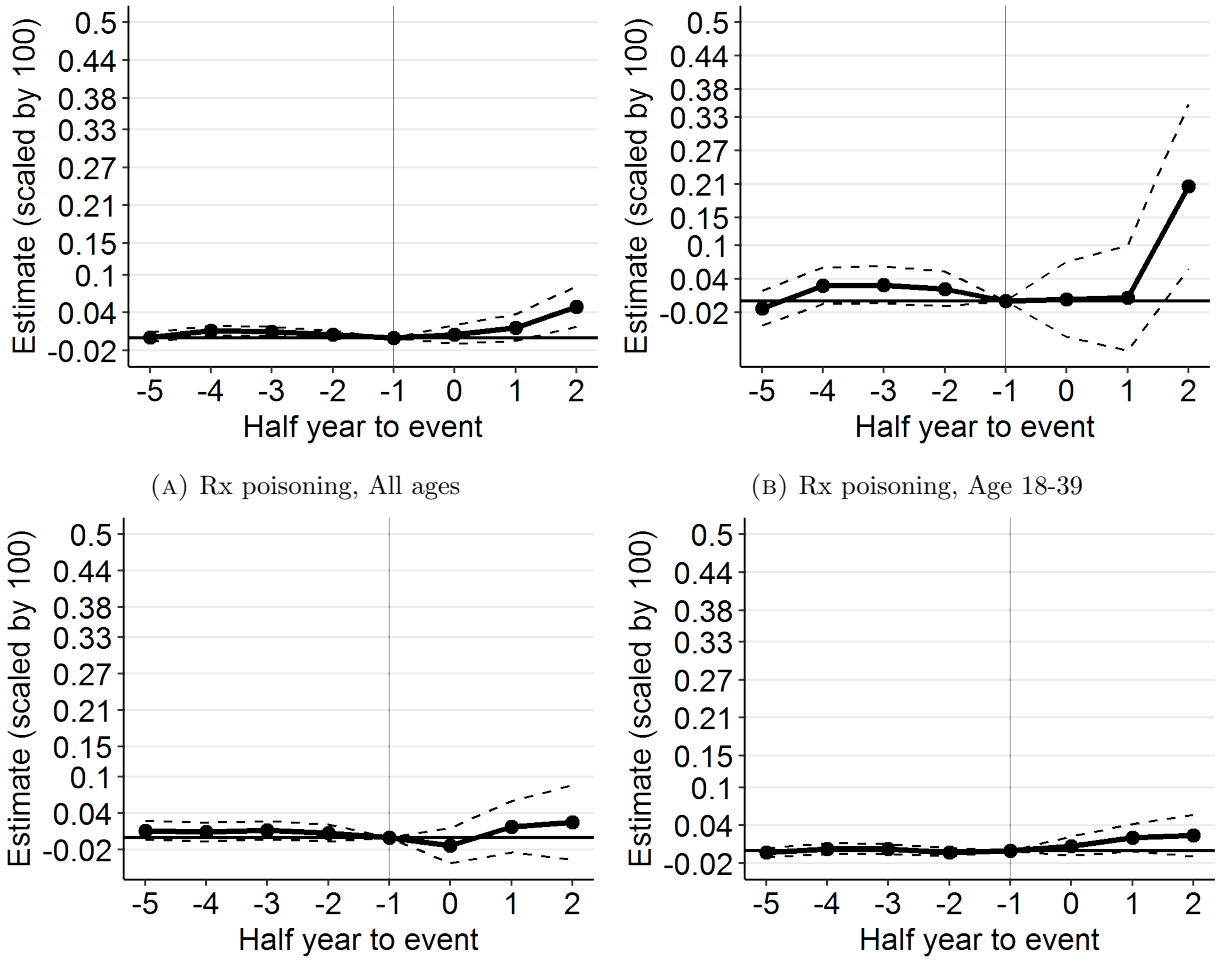
(B) PDA diagnosis, Age 18-39

(C) PDA diagnosis, Age 40-64

(D) PDA diagnosis, Age over 65

FIGURE A17: Robustness to Treatment Effect Heterogeneity: Prescription Drug Abuse (PDA) Diagnosis (Scaled by 100)

Note: The figures plot the efficient Roth and Sant'Anna (2022) 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 and it only allows for fixed effects for units that have one observation per time period. Hence, patient fixed effects are used instead of municipality fixed effects.



(A) Rx poisoning, All ages

(B) Rx poisoning, Age 18-39

(C) Rx poisoning, Age 40-64

(D) Rx poisoning, Age over 65

FIGURE A18: Robustness to Treatment Effect Heterogeneity: Prescription Drug Poisoning (Scaled by 100)

Note: The figures plot the efficient Roth and Sant'Anna (2022) 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 and it only allows for fixed effects for units that have one observation per time period. Hence, patient fixed effects are used instead of municipality fixed effects.

Addressing Limitations of Pre-trends Testing— The econometric literature has recently 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 have notable limitations. For example, it is possible that the pre-trend tests (visual or statistical) fail to reject differences in trends due to low statistical power (Freyaldenhoven et al. 2022; Roth 2022). For this reason, we implement the following two procedures to address the potential limitations of standard pre-trends testing.

First, following Jacobson et al. (1993) and Freyaldenhoven et al. (2022), we estimate the DiD parameters by further controlling for a municipality-specific linear trend, ω_{it}. Specifically, we estimate the following TWFE DiD specification:

$$y_{imt} = \rho \mathbb{1}[t - E_m \geq 0] + X_{it}^{'}\beta + \alpha_m + \gamma_t + \omega_{it} + \epsilon_{imt}. \tag{A2}$$

The estimated specification (A2) is otherwise the same to our baseline TWFE specification (1) with the time and municipality fixed effects (α_m and γ_t), but the model now also includes the municipality-specific linear time trends which have been added as an interaction between municipality fixed effects and calendar time as a continuous variable (ω_{it}). Because this covariate in specification (A2) allows for arbitrary permanent heterogeneity between municipalities in both 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. We estimate these models by using OLS.

The results in Tables A17 and A18 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 A17: Robustness for Controlling Municipality-Specific Linear Time Trend: Effects of E-Prescribing on Intensive Margin of Benzodiazepine Use

	DDDs	Renewed DDDs	New DDDs	Number of rx
	(1)	(2)	(3)	(4)
Panel A. All ages				
Post-adoption	1.673***	1.64***	0.033	-0.007
	(0.409)	(0.393)	(0.086)	(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	1.856***	1.547***	0.309**	0.002
	(0.588)	(0.501)	(0.153)	(0.004)
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	2.077**	1.964**	0.113	−0.004
	(0.837)	(0.86)	(0.116)	(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	1.116***	1.32***	−0.203	−0.014***
	(0.351)	(0.321)	(0.132)	(0.004)
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, municipality fixed effects, municipality-specific linear trend, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

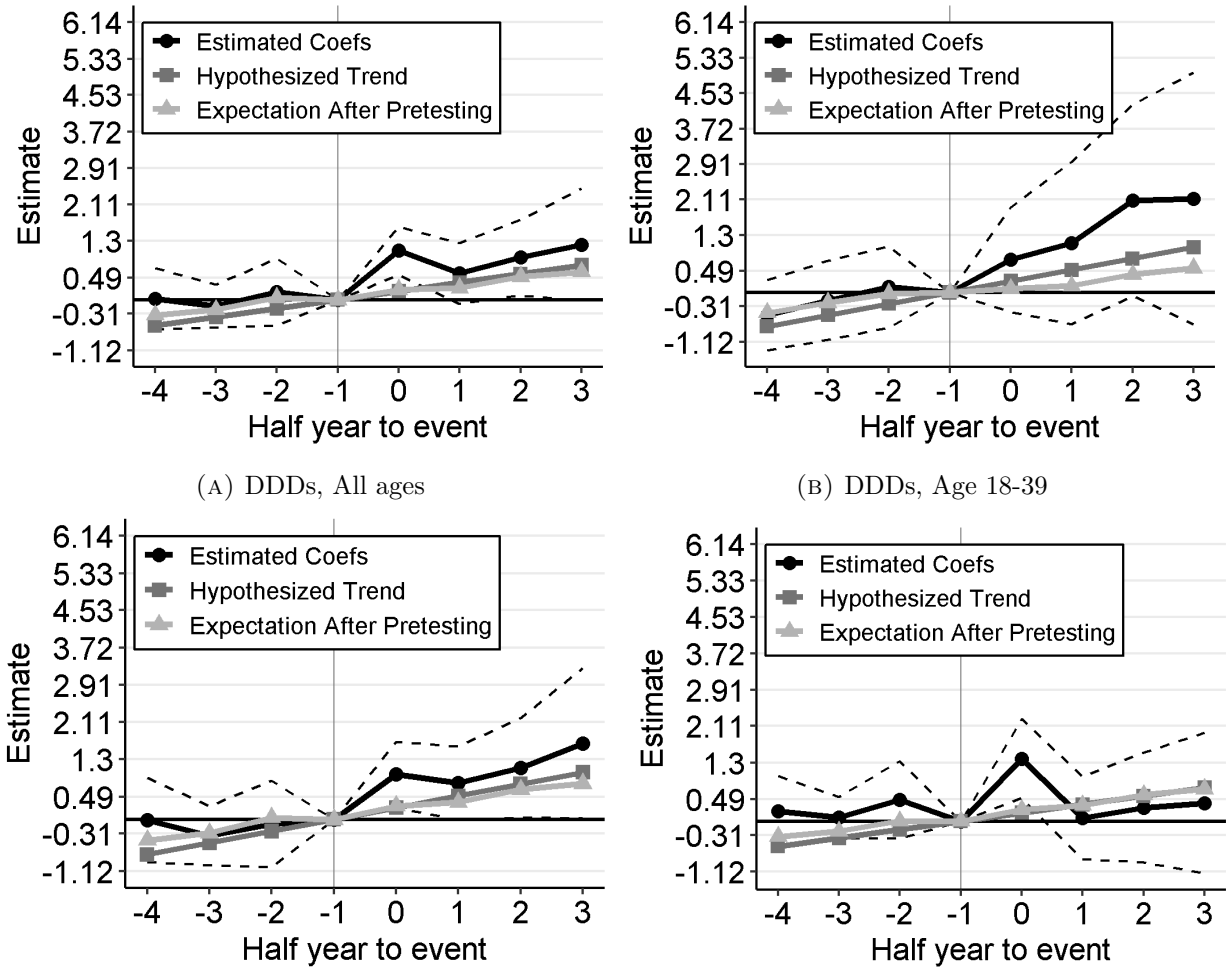
TABLE A18: Robustness for Controlling Municipality-Specific Linear Time Trend: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes (Scaled by 100)

	Death	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All ages							
Post-adoption	-0.015	-0.35	-7.309***	-0.333	0.004	0.003	-0.027
	(0.013)	(1.848)	(2.645)	(0.349)	(0.01)	(0.008)	(0.043)
Mean outcome	1.046	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	15,167,056
Panel B. Age 18-39							
Post-adoption	0.014	1.491	-15.988***	-0.829	0.038	0.028	0.006
	(0.012)	(2.962)	(5.908)	(0.84)	(0.046)	(0.023)	(0.017)
Mean outcome	0.118	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	3,084,187
Panel C. Age 40-64							
Post-adoption	−0.007	0.309	−5.952***	−0.376	−0.006	−0.009	−0.006
	(0.015)	(1.73)	(2.258)	(0.381)	(0.008)	(0.011)	(0.024)
Mean outcome	0.404	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	6,311,289
Panel C. Age over 65							
Post-adoption	−0.041	−1.926	−4.186**	−0.047	−0.007**	0.006	−0.059
	(0.033)	(1.722)	(1.757)	(0.078)	(0.003)	(0.007)	(0.089)
Mean outcome	2.361	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	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, municipality fixed effects, municipality-specific linear trend, patient age and age squared. 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 researcher-hypothesized violations of parallel trends. To empirically implement the 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). Figures A19-A22 visualize the hypothesized linear trends in dark grey. 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 grey). The 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. 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

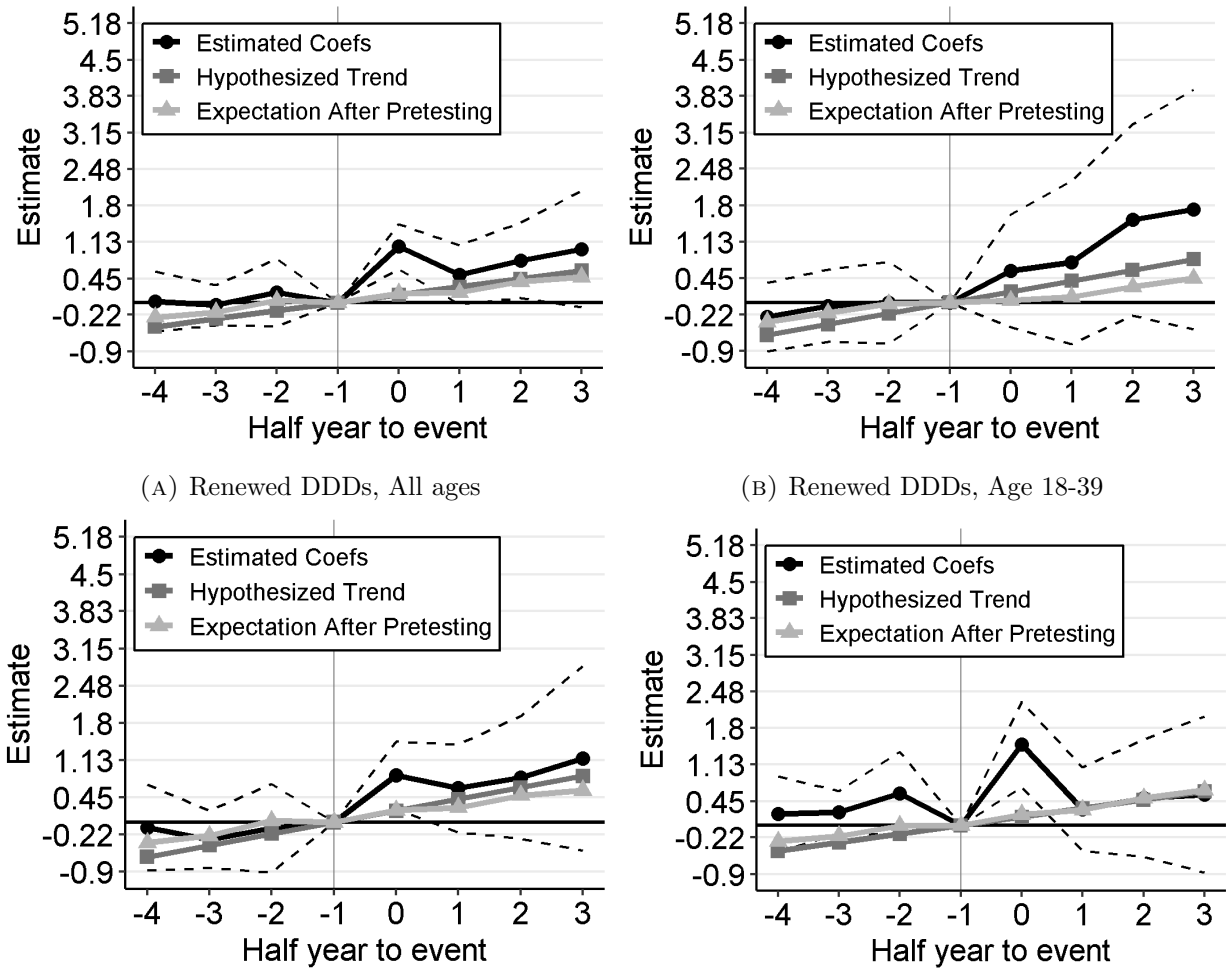
(B) DDDs, Age 18-39

(C) DDDs, Age 40-64

(D) DDDs, Age over 65

FIGURE A19: 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) Renewed DDDs, All ages

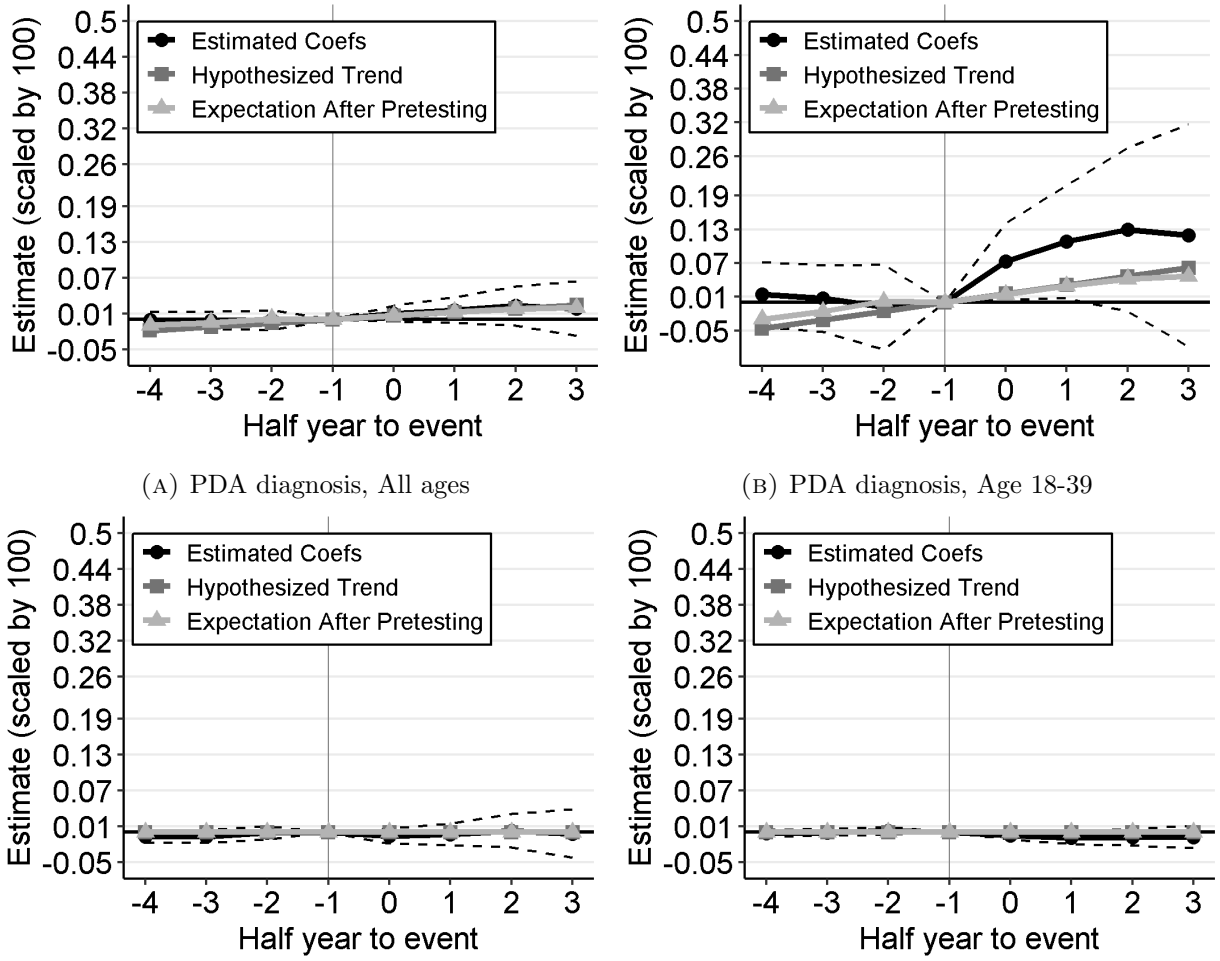
(B) Renewed DDDs, Age 18-39

(C) Renewed DDDs, Age 40-64

(D) Renewed DDDs, Age over 65

FIGURE A20: Baseline TWFE Estimates and Hypothesized Trend: Number of Renewed 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) PDA diagnosis, All ages

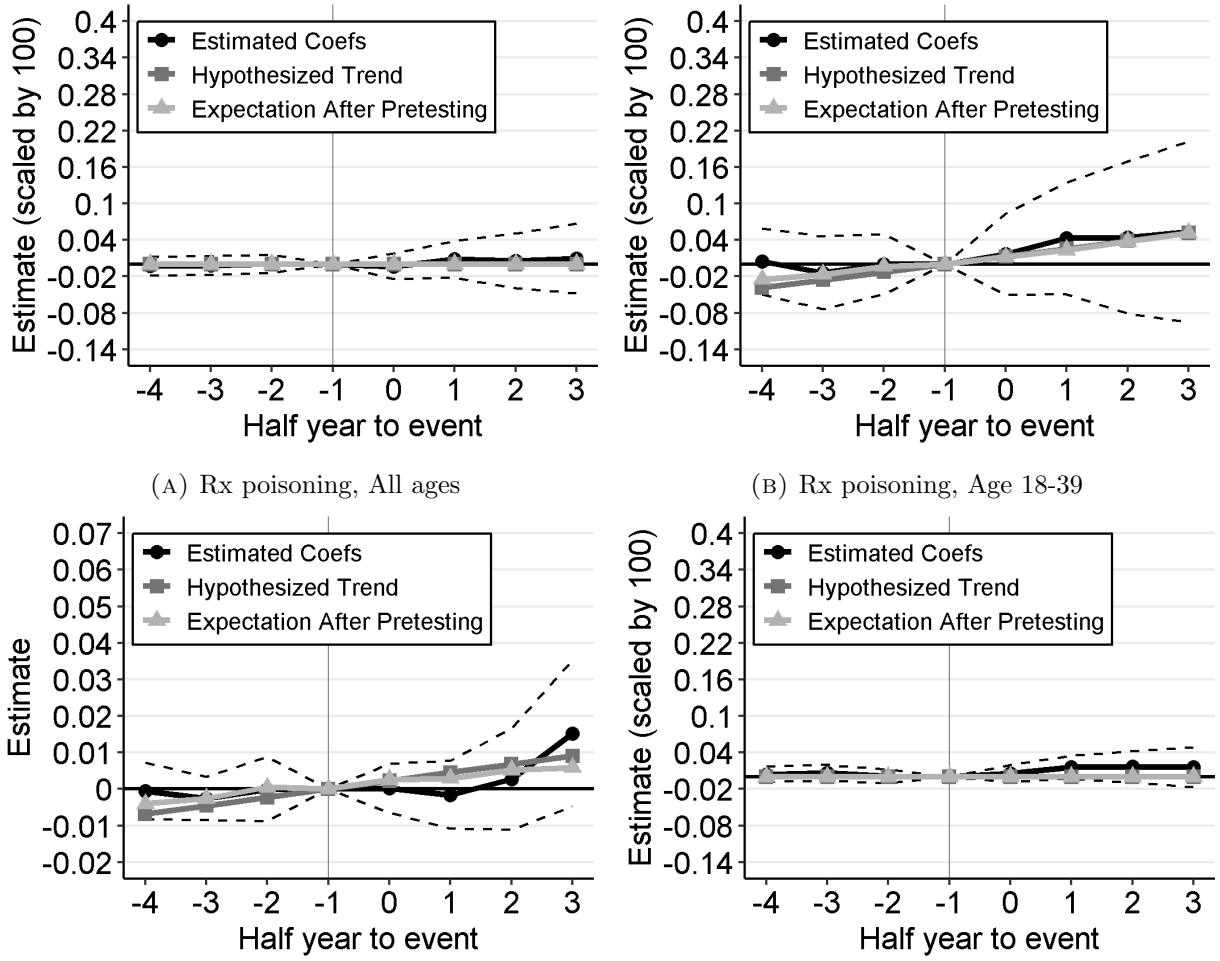
(B) PDA diagnosis, Age 18-39

(C) PDA diagnosis, Age 40-64

(D) PDA diagnosis, Age over 65

FIGURE A21: Baseline TWFE Estimates and Hypothesized Trend: Prescription Drug Abuse (PDA) Diagnosis (Scaled 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 A22: Baseline TWFE Estimates and Hypothesized Trend: Prescription Drug Poisoning (Scaled 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).

G Alternative Mechanisms

G.1 The Role of Improved Diagnosing

TABLE A19: 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

	Mental disorder (1)	Prescription drug abuse (2)	Rx poisoning (3)	Other side effects (4)
Panel A. All ages				
Post-adoption	−0.274	0.011	0.011	−0.004
	(0.332)	(0.010)	(0.008)	(0.056)
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	−0.634	0.071	0.050**	0.021
	(0.770)	(0.048)	(0.022)	(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	−0.296	−0.003	−0.003	0.004
	(0.351)	(0.007)	(0.011)	(0.029)
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	−0.060	−0.005	0.007	−0.020
	(0.083)	(0.003)	(0.007)	(0.113)
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, municipality fixed effects, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

G.2 The Use of Other Medications

TABLE A20: Effects of E-Prescribing on Benzodiazepine Patients' SSRI Use

	All ages		Age 18-39		Age 40-64		Age over 65	
	DDDs	Number of rx	DDDs	Number of rx	DDDs	Number of rx	DDDs	Number of rx
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-adoption	0.206	0.001	0.335	0.004**	0.127	−0.001	0.212	0.000
	(0.158)	(0.001)	(0.365)	(0.002)	(0.263)	(0.001)	(0.156)	(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, municipality fixed effects, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

H Placebo Regression

TABLE A21: Placebo Regressions: Effects of E-Prescribing on Benzodiazepine Patients' Appendix Disease Diagnosis (Scaled by 100)

	All ages	Ages 18-39	Age 40-64	Age over 65
	(1)	(2)	(3)	(4)
Post-adoption	0.005	0.018*	0.003	−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, municipality fixed effects, patient age and age squared. Standard errors are clustered at the municipality level and shown in parentheses. For scaling purposes, all coefficient, standard errors and means have been multiplied by 100. *p<0.1; **p<0.05; ***p<0.01.