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. Our empirical design uses the staggered rollout of a nationwide electronic prescribing system in Finland, and employs both a standard difference-in-differences approach and methods based on recent advances in staggered designs to estimate the effects. We use comprehensive administrative data from patients treated with benzodiazepines, which are globally popular and effective, but addictive medications. 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 find substantial increases in prescription drug abuse disorders and poisonings. We show robust evidence that easier access increases medication overuse.

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

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1 Introduction

Access to essential medications is a fundamental policy goal of health care (UN Human Rights 2019). Policy measures to improve access include lower out-of-pocket costs for medications and non-price mechanisms such as longer-term prescriptions and online pharmacies to distribute medications more easily. These policies can be socially beneficial: barriers to access are a major reason for patients stopping taking their medications or not taking them as recommended, which causes up to 70 percent of medication-related hospitalizations and an estimated $100 billion in preventable costs annually in the U.S. alone (Osterberg and Blaschke 2005). However, access-improving policies can also expose some patients to medication overuse, for which there are fewer health benefits than health harms. Overuse of medications is a significant problem worldwide (Brownlee et al. 2017), creating wasteful spending and health harms in society. Hence, providing ready access to essential medications while limiting overuse is a challenging but important trade-off to strike.

We examine a large-scale public policy designed to improve access to medication while simultaneously limiting overuse: the introduction of a nationwide, fully centralized electronic prescribing (e-prescribing) system to digitize all paper prescriptions and renewal requests in Finland. E-prescribing improves medication access by reducing patients' time and hassle costs in obtaining repeat prescriptions without necessarily having to visit a physician face-to-face.[1] By helping patients to continue using medication, e-prescribing can increase medication demand among appropriate users with high health returns, but also among those who overuse medication. In addition to improving access, e-prescription systems provide physicians with more comprehensive information on a patient's prescription history, which can help them to limit medication overuse.

We provide evidence on the access-overuse trade-off in technology adoption for patients treated with benzodiazepines, which are commonly prescribed but addictive mental health and insomnia medications. We estimate the effects of e-prescribing on benzodiazepine use and related health outcomes using the plausibly exogenous rollout of the new technology across all municipalities and over four years in 2010–2013. We use comprehensive administrative data on repeat and new benzodiazepine prescriptions in 2007–2014. For benzodiazepine patients' health outcomes, we use administrative discharge data containing their general health outcomes such as mortality and emergency department visits, but also more specific diagnosis-based measures of health to capture potential health benefits from appropriate use and harms from potential medication overuse.

[1] Repeat prescriptions are commonly issued to patients and account for as much as 80 percent of prescription drug use (Avery 2011; Duncan et al. 2014).

Benzodiazepines have several characteristics that make them relevant for studying the trade-off between access and overuse. First, benzodiazepines, included in the World Health Organization's 2017 Model List of Essential Medicines, are among the most widely used psychotropics in developed countries (Olfson et al. 2015) and repeat use of them is also common.[2] Second, benzodiazepines provide both benefits if used appropriately and health harms if overused. When appropriately used, benzodiazepines are effective treatments for common and often disabling disorders, such as anxiety, panic disorder, and insomnia. Overuse of benzodiazepines, however, is harmful because it can cause adverse health effects such as dependence and abuse. Benzodiazepine abuse is a pressing problem in developed countries, reaching an epidemic level in the U.S. (UNODC 2017). Long-term use of benzodiazepines leads to these health harms, as highlighted recently by the U.S. Food and Drug Administration (FDA) (Hirschtritt et al. 2021), and this is exactly what easier access and repeat prescriptions can facilitate.

In the light of the barriers to medication access and increasing health harms due to overuse of medications, policy makers have stressed the adoption of new digital solutions such as e-prescribing to improve health care provision. Despite the widespread adoption of e-prescribing, for example, in the U.S., Europe, Canada, and Australia, there is only little credible causal evidence on its effects on medication use and health outcomes.[3] In addition, previous research on e-prescribing has not evaluated its effect on medication overuse. More broadly, while medication overuse is widely documented in the medical literature (Brownlee et al. 2017), there is still scarce evidence on policies and mechanisms that can cause overuse in health care (Einav et al. 2022).

Using a standard difference-in-differences (DiD) approach based on the staggered rollout of e-prescribing across all Finnish municipalities and administrative data, we find that e-prescribing led to a 5 percent increase in benzodiazepine use per patient on average due to increased prescription renewals. In contrast to this adjustment along the intensive margin, we find no significant adjustment along the extensive margin – the probability of becoming a benzodiazepine user. Overall, our findings are robust to using alternative or more general model specifications, subsamples and recent advances in staggered DiD designs (Goodman-Bacon 2021; de Chaisemartin and D'Haultfœuille 2020).

[2] In our prescription-level data, approximately 80 percent of a patient's benzodiazepine use results from repeat prescriptions on average.

[3] In the U.S., e-prescribing has expanded rapidly, with approximately 70 percent of physicians using e-prescribing by 2014 (Gabriel and Swain 2014) and almost 85 percent of prescriptions sent electronically in 2018 (Surescripts 2019). Policy initiatives affecting e-prescribing include the Medicare Improvements for Patients and Providers Act in 2008 and the Medicare and the Medicaid Electronic Health Record Incentive Programs in 2011.

Our large patient-level data also allow us to examine heterogeneous effects in different parts of the age distribution, with large differences in prescription drug use and health outcomes. Younger adults are more likely to have higher non-financial barriers to health care access (Kullgren et al. 2012).[4] They also use benzodiazepines less than adults in older age groups, but have higher rates of mental health admissions (Kessler et al. 2010; Olfson et al. 2017). On the other hand, the risk of prescription drug abuse is largest in the younger patient population (NIDA 2016). Thus, in addition to access, younger patients are expected to be a salient target for the e-prescribing policy in limiting medication overuse.

We find that the quantitative magnitude of the increase at the intensive margin of benzodiazepine use is much larger among younger patients (age under 40). Their benzodiazepine use increases by approximately 15 percent compared to the mean, which results from repeat prescriptions in higher daily doses. The corresponding estimate for older patients is much lower at 4 percent. Despite the larger increase in benzodiazepine use among younger patients, we find little evidence of an improvement in their general health outcomes such as mortality or emergency department visits in the long run (one year after adoption). By contrast, prescription drug abuse disorders and poisonings increase by nearly 20 percent in the younger population. In effect, e-prescribing improves access to medication but may lead to medication overuse among younger patients, who are more vulnerable to mental health problems and prescription drug abuse.

Our results reveal some unintended consequences of increasingly popular information technology. Reducing patients' hassle costs or "ordeals" in obtaining repeat medication through digitization of prescriptions can worsen medication overuse by redirecting health care spending to patients with lower marginal utility. Digitization (and easier renewal without face-to-face consultation) may weaken physician-patient interaction and joint decision-making in treatment decisions, in addition to prescription drug monitoring, which are essential for screening and preventing potential overuse. We provide new insights into e-prescribing controlled, addictive substances. Our results also have broader relevance for policy makers in deciding how to improve access to medications that have potential health harms.

Our paper contributes to the literature on welfare and health care program design, access, and targeting. Previous literature on health care access mostly focused on the effects of prices, information, and changes in the availability of health care and treatment options (Cohen et al. 2015; Alpert et al. 2018; Hamilton et al. 2018). Unlike our paper, these studies do not investigate infor-

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

mation technology or the hassle costs of the prescribing process, a prominent non-price mechanism affecting access and targeting.

We also contribute to the literature on self-selection or ordeal mechanisms in welfare program design. The literature on ordeal mechanisms investigates how imposing differential transaction costs on participants helps with program targeting (Nichols and Zeckhauser 1982; Zeckhauser 2021), recently studied in the context of the Supplemental Nutrition Assistance Program (SNAP) (Finkelstein and Notowidigdo 2019) and pediatric health care (Iizuka and Shigeoka 2022). Our result of weakened targeting due to reduced hassle costs of prescribing is consistent with the findings of the ordeal mechanisms in other settings.

By studying the effects of e-prescribing on the access-overuse trade-off based on a large-scale policy change, we further contribute to the health information technology literature and complement recent descriptive studies on e-prescribing (Samadbeik et al. 2017; Del Giorno et al. 2019). Previous quasi-experimental literature on health information technology has focused on 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). This literature has not focused on the prescribing process, apart from PDMP studies that have mainly analyzed overuse (or abuse) of opioids. Importantly, e-prescribing differs from EMRs and PDMPs in two ways. First, EMRs and PDMPs are information-improving technologies, whereas e-prescribing directly affects both information and medication access. Second, the information transmission between different providers is limited in EMRs and PDMS due to a lack of interoperability. In contrast, the national technology that we study is fully standardized and interoperable, providing all providers access to the centralized prescription information.

2 Setting

2.1 E-prescribing and Mechanisms

E-prescribing systems generate digital prescriptions and electronically transfer prescriptions as well as renewal (or refill) requests between physicians, pharmacies, and patients.[5] In the following we describe the main mechanisms through which the effects on the use of prescription drugs arise.

[5]In many health care settings, the terms prescription "renewal" (repeat) and "refill" are used interchangeably. Prescription 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, as opposed to refill, prescriptions.

E-prescribing and Access.—E-prescribing improves medication access by making it easier for patients to order additional medication without a face-to-face physician consultation. Before e-prescribing, a patient had to drop off an existing paper prescription at a health care unit or pharmacy for renewal, and prescriptions were transferred between physicians and pharmacies, for example, by fax or mail.

After e-prescribing, a patient makes a request for a repeat prescription by contacting a health care unit by phone. The request can be also made via a pharmacy, which automatically transmits it to the health care unit through a computer interface.[6] After physician approval, the digital prescription is readily available for the patient to be filled at the pharmacy. E-prescribing therefore considerably reduces the time and hassle costs of prescription renewal, in addition to eliminating or reducing other costs, such as those related to lost (paper) prescriptions. Easier renewal should have an impact primarily at the intensive margin of adjustment, that is the use of medication per patient. Because e-prescriptions (improved information) can increase the chance of becoming a medication user, we also estimate the effects at the extensive margin.

E-prescribing systems generally permit repeat prescriptions or refills for psychotropics and some controlled substances such as benzodiazepines—the prescription drugs that we study and could be overused—without physician consultation. In the U.S., Schedule IV controlled substances may be refilled but only up to five times within six months after the date the prescription was issued (U.S. Department of Justice 2006). Previous research has also shown that issuing prescriptions without physician consultation is most common for psychotropics in comparison to many other groups of prescription drugs in primary care (Saastamoinen et al. 2008).

E-prescribing and Information.—E-prescribing also improves prescription information. Before e-prescribing, physicians did not have access to a patient's full prescription history, especially if the patient had obtained prescriptions from different health care providers. With e-prescribing (and a patient's permission), each physician has access to the full history, as illustrated in online Appendix Figure A2.[7] The e-prescribing system contains records of a patient's all filled and unfilled e-prescriptions, but not paper prescriptions. However, the system might make it difficult to acquire relevant information on prescriptions, especially if there are many of them.

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

[7]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 according to the law of November 1, 2015 onward, which is outside of our observation period.

Net Effects of E-prescribing.—The net effects on medication use and patient health are ambiguous. Easier access to medication can increase appropriate use of medication that improves patient health. Easier access can, however, also increase medication overuse for some patients who have low and possibly negative health returns from medication overuse. More comprehensive information on a patient's prescription history can limit medication overuse.

2.2 Adoption of Nationwide E-prescribing System

Finland has a decentralized, tax-financed single-payer health care system, in which all residents are entitled to public health care services.[8] Over 300 municipalities (local authorities) are responsible by law for the provision of health care services for their residents. Municipalities fund and organize the provision of primary care, and belong to one of 20 hospital districts that fund and provide hospital care. Because of this decentralization of the responsibility of care provision, the health care system, including the information technologies used by the providers, is highly fragmented. In 1995, the Finnish government set a policy goal of digitization of the health care service (Hyppönen et al. 2015). A fully integrated e-prescribing system was a central element of this policy.

We evaluate a large-scale public policy change: the adoption of a nationwide e-prescribing system in Finland. The e-prescribing system was designed to be highly standardized and interoperable, recording all e-prescriptions and their dispensing records at pharmacies. The information is stored in a centralized system accessible by all physicians operating in the country. The system enables prescription renewal via any pharmacy or (public or private) provider.

There is substantial and plausibly exogenous regional heterogeneity in the adoption time of the e-prescribing system. The introduction of the nationwide system required massive investments in information technology systems, software, and a skilled workforce. Consequently, the system was introduced gradually across providers and over time. According to the national deadlines, public health care providers had to adopt the system by 2014, and private providers had to adopt the system by 2015. Practitioners argue that the adoption time was determined by technical reasons related to the difficulties in the integration of the e-prescribing system into existing information technology systems in health care units and pharmacies, as opposed to factors related to the trends in prescribing and health outcomes.

[8]The Finnish health care system is largely based on public provision, and there is also a small private sector. In 2014, public primary and specialized (hospital) health care accounted for approximately 50 percent of health care costs. In contrast, private health care covered by the National Health Insurance Scheme accounted for 5 percent of the costs and occupational health care provided by the private sector accounted for 3 percent of the costs. (THL 2021)

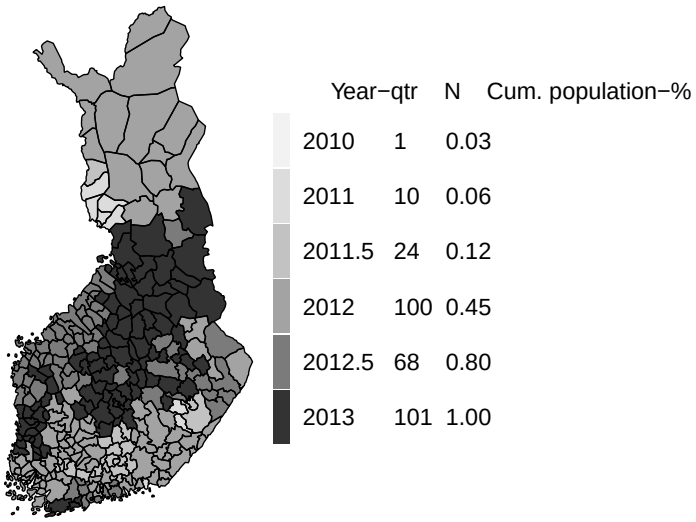


FIGURE 1: E-prescribing Adoption Half-Year in Municipalities

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

Technology Adoption by Municipalities.—We focus on the adoption of e-prescribing by municipalities in primary care for two 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). Studies also show that primary care physicians write most of the prescriptions, especially for benzodiazepines (Cascade and Kalali 2008). Second, we validate our approach in Section 5 by showing a sharp increase in the take-up rate of e-prescriptions for benzodiazepines after the patients' municipality adopted e-prescribing.

2.3 BENZODIAZEPINE MARKET

We study patients treated with mental health and insomnia medications called benzodiazepines. The top five active ingredients of benzodiazepines in Finland are diazepam (international brand name Valium), oxazepam (e.g. Serax), temazepam (e.g. Restoril), midazolam (e.g. Versed), and zopiclone (e.g. Imovane). These ingredients represented approximately 77 percent of total sales of benzodiazepines in 2017 (Fimea 2018).

Benzodiazepines are one of the most widely used psychotropics in developed countries (Olfson et al. 2015). In Finland, the wholesale value of benzodiazepines was 11.5 million euros in 2017, with a market share of approximately 16 percent of the wholesale value of all psycholeptics (Fimea

2018). For comparison, in the U.S., 13.5 million adults filled a benzodiazepine prescription in 2013, an increase of 67 percent from 1996 (Bachhuber et al. 2016).

Benzodiazepines are effective medications for treating disorders such as anxiety, panic attacks, insomnia or sleeping problems, as well as depression, for example when anxiety is involved.[9] Appropriate use of benzodiazepines improves patient health for example, it can result in fewer emergency department admissions related to severe anxiety symptoms.

Health harms through adverse drug effects are indicators of medication overuse. Benzodiazepine use may cause sedation, poor coordination, a decline in cognitive functions, and delirium, as well as increased risk of accidental falls and hip fractures (Lader 2011). Prolonged use of benzodiazepines may lead to physical dependence, abuse, and overdose, with increased tolerance, and strong withdrawal symptoms such as worsened anxiety and depression (Lader 2011). In addition, long-term use of benzodiazepines is linked to an elevated risk of drug poisoning and suicide (Ajdacic-Gross et al. 2008; Dodds 2017). Consequently, treatment guidelines generally recommend benzodiazepines to be used for no more than 2–4 weeks, and harmful medications should be withdrawn. Despite these guidelines and health harms, long-term benzodiazepine use is fairly common (Olfson et al. 2015).

Benzodiazepines are also relevant for public policy because mental and behavioral health disorders are on the rise globally. Thus, increasing benzodiazepine use may be valid from a clinical perspective, but there is also an urgent need for medication oversight. Benzodiazepines are commonly involved in deaths and emergency department visits related to nonmedical use of prescription drugs (Jones and McAninch 2015), especially when combined with alcohol and opioids. Recent research on prescription drug abuse has mostly focused on the opioid epidemic in the U.S. and less focus has been put on other important addictive psychotropics such as benzodiazepines.[10]

3 Administrative Datasets

We use comprehensive administrative data from the national health insurer, the Social Insurance Institution of Finland, to identify all individual benzodiazepine patients and all their new and repeat prescriptions in Finland. We define benzodiazepine patients as those who have at least one

[9] In treating, for example, anxiety related to depression, benzodiazepines are commonly prescribed in combination with antidepressants. Benzodiazepines are also used to treat other conditions and disorders such as epilepsy, alcohol withdrawal, and chronic pain.

[10] Global consumption of opioids is heavily concentrated in the U.S. (PPSG 2015; Bosetti et al. 2019). In Finland, for example, opioids are considered only as a last-line treatment for severe pain.

benzodiazepine prescription in the years 2007–2014.[11] We also use the Discharge Data from the Finnish Institute for Health and Welfare to identify patients' health outcomes. Next we provide an overview of the datasets and describe the main variables, while leaving details (e.g. diagnosis codes) to the online Appendix.

The Prescription Data.—Our Prescription Data contain all benzodiazepine prescription claims dispensed at Finnish pharmacies and covered by the National Health Insurance (NHI) scheme from 2007 through 2014. We identify individual prescriptions based on the coded patient and physician identifiers, the Anatomical Therapeutic Chemical (ATC) code (active ingredient), and the date of prescribing. For each patient, the data record the date of birth and death, and the municipality of residence based on the 2014 municipality classification.

For each prescription, the data record the strength of the drug, the route of administration, and the number of defined daily doses (DDD) dispensed. Repeat and new prescriptions are identified based on the characteristics of the prescriptions. We define a prescription as renewed or repeated 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, and the renewal is made within 16 months (renewal of an electronic prescription for benzodiazepines must be requested within this time interval).[12] Notably, a repeat prescription can be from a different physician than the previous prescriptions because the patient cannot influence which doctor the renewal request is passed to in a health care unit. If a prescription is not renewed, we define it as new.

We construct two sets of outcomes for prescription drug use. The first set contains the intensive margin outcomes for the sample of benzodiazepine patients, where we expect to detect the largest effects; easier renewal implies an increased amount of medication per patient, hence an increase at the intensive margin. Our primary measure is the biannual number of defined daily doses of benzodiazepine prescriptions per patient.[13] The WHO's defined daily dose is a widely used international metric, defined as the assumed average maintenance dose per day for a drug used

[11] We use this rather loose definition of 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 (8 percent of patients fill only a single prescription in the data and the average number of prescriptions is 10).

[12] Our renewal measure captures typical patterns of obtaining repeat prescriptions: for example, a patient first obtains a prescription of A and then of B, after which she obtains a repeat of A, and then of B. Our results are robust to defining a renewal based on the previous prescription or three previous prescribing events within a 16-month interval and robust to the exclusion of the 16-month interval rule.

[13] We consider a period of 6 months to find a balance between the accuracy of the adoption time of e-prescribing (observed at the daily level) and short-term idiosyncratic variation in benzodiazepine use and patient health outcomes. Our 6-month period is also motivated by general benzodiazepine prescribing patterns: the time difference between two subsequent benzodiazepine prescriptions is 136 days on average in the data.

for its main indication in adults. It provides a fixed unit of measurement independent of package size, strength and drug form, enabling us to assess changes in drug consumption across different benzodiazepine products. Our alternative intensive margin outcome is the biannual number of prescriptions per patient. This general measure, however, does not account for important aspects of prescriptions such as the number and strength of the tablets. We additionally calculate these two outcomes separately for repeat and new prescriptions.

The second set of outcomes contains the extensive margin outcomes of benzodiazepine use. We calculate the share of persons who have any benzodiazepine prescriptions at all during a half-year period. As we do not have full Finnish population data at the individual level, we calculate the municipality average of the outcome, and weight each observation by the number of individuals contributing to the average in the estimation (Section 5). Specifically, the average outcome is the biannual number of persons with a benzodiazepine prescription per municipality divided by the municipality population size obtained from Statistics Finland. Similarly, we calculate the share of first-time benzodiazepine users in a municipality over a half-year period. We define a first-time user as a person 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 period for this variable is the second half of 2008.

Following Buchmueller and Carey (2018), we also construct various patient outcomes for the sample of prescription drug users (here, 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 6-month period.

The Discharge Data.—Our Discharge Data identify all Finnish inpatient and outpatient discharges in hospitals for benzodiazepine patients from 2007 through 2014. The deidentified data record 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, as described in Table 2. Even based on our rich data, it is challenging to comprehensively measure and distinguish health effects from appropriate use or overuse of benzodiazepines.[14] 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

[14] As stated in the 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 cured and thus the focus of the treatment is on management of the disorder (Maclean 2019).

mortality indicator, as general measures of patient health. These outcomes are widely used in the literature and they are especially relevant for mental health patients. The use of mortality as an outcome is useful in our context because it does not suffer from measurement error in diagnosis. Emergency department and hospital visits are less extreme outcomes than mortality and may be more sensitive to health problems caused, for example, by mental illness or overuse of benzodiazepines.

We then construct health outcomes based on a patient's hospital discharge(s) for particular health conditions within a period of 6 months. We consider diagnoses of a broad class of mental and behavioral disorders (fifth chapter of ICD10). We also consider detailed diagnoses of prescription drug abuse disorders, which indicate rather strong abuse, as well as diagnoses related to the other side effects of benzodiazepines such as sedation, poor coordination, and decline in cognitive functions. We additionally calculate a biannual indicator of prescription drug poisoning. Drug poisoning (overdose) is a common method in suicides, especially in the Nordic countries (Ajdacic-Gross et al. 2008). Thus, this outcome reflects both mental health issues as well as prescription drug abuse and suicide attempts.

Data on Technology Adoption.—The information on the dates of the adoption of e-prescribing by municipalities is based on data from the Finnish Institute for Health and Welfare. We link these dates to our analysis data by the patient's municipality of residence, and consider the adoption of e-prescribing within a period of 6 months.[15]

4 Descriptive Statistics

Table 1 shows that almost 20 percent of the Finnish population had at least one benzodiazepine drug prescription during the observation period. Mortality is substantial (15 percent on average) among benzodiazepine patients, although mortality is also quite high (3 percent) when the number of patients who died is compared to the size of the general Finnish population in Column 2.

There are also several notable differences in the use of benzodiazepines (and the related health outcomes) in different parts of the age distribution. Motivated by the general access barriers and higher rates of mental and behavioral disorders among younger adults (Kessler et al. 2010; Kullgren et al. 2012;NIDA 2016), we separately consider two age groups: under and over 40 years old. Table 1 shows that the use of benzodiazepines is much lower among younger individuals

[15] A patient typically chooses a public health care unit in his/her municipality of residence. For this reason, the municipality of residence also serves as a good proxy for the location of the prescribing physician.

(adults). When compared to the size of the general population, the share of individuals having at least one benzodiazepine prescription was 10 percent for individuals aged under 40 and nearly 30 percent for older individuals during the observation period.

Panel A of Table 2 reports additional summary statistics on benzodiazepine use per patient on average and by age group over the years 2007–2014. The average number of defined daily doses is 490 for younger patients and almost twice as large (937) among patients aged over 40. Approximately 80 percent of the defined daily doses and of the number of prescriptions are driven by repeat prescriptions. Using detailed biannual patient-level data, Figure 2 confirms that both overall and repeat use of benzodiazepines increase considerably with age.

Patients' health outcomes are also substantially different for the two age groups. Younger patients have a much lower mortality rate (only 1.5 percent) than older patients (18 percent) (Table 1), but there is only very little difference in the number of emergency department visits between the two age groups, as shown in Panel B of Table 2. In addition, younger patients experience much higher rates of visits related to mental and behavioral disorders (32 percent) at any time than older patients (22 percent). Younger patients also have much higher rates of prescription drug abuse disorders (3 percent). In contrast, our measure for the other side effects of benzodiazepines is much higher for older patients. Figure 3 highlights that biannual health outcomes are notably different among patients under 40 years old compared to older patients. The cut-offs at the age of around 40 are clearest for prescription drug abuse (Panel C of Figure 3) and prescription drug poisonings (Panel D of Figure 3).

In brief, younger age is a strong predictor of the potential need for benzodiazepines and poor health outcomes. Younger patients use benzodiazepines less, but have higher rates of discharges related to mental and behavioral health and a strikingly higher probability of prescription drug abuse. They may underuse medications more frequently, which could worsen their mental health outcomes. On the other hand, medication overuse can cause significant health harms among younger patients because they are at much higher risk of prescription drug abuse.

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

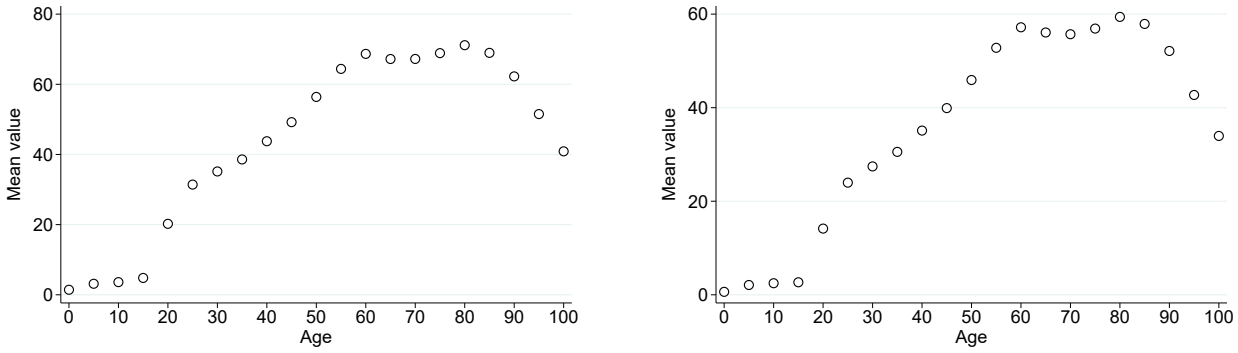
	Benzodiazepine patients (1)	All individuals (2)
Panel A. All ages		
Share taking benzodiazepines	1.000	0.189
Share of patients who die	0.154	0.029
Number of persons	1,030,383	5,442,837
Panel B. Age under 40		
Share taking benzodiazepines	1.000	0.100
Share of patients who die	0.015	0.001
Number of persons	258,136	2,571,623
Panel C. Age over 40		
Share taking benzodiazepines	1.000	0.299
Share of patients who die	0.180	0.054
Number of persons	858,995	2,871,214

Notes: "Benzodiazepine patients" means patients who fill at least one benzodiazepine prescription. Note that 8 percent of patients fill only a single prescription in the data (the average number of prescriptions is 10). "All individuals" means all Finnish residents. The values depict the overall values during the observation period (years 2007-2014). The only exception is the number of persons or population size for the Finnish residents in Column (2), which is calculated from the municipality-level data for the year 2014 based on information provided by Statistics Finland.

TABLE 2: Summary Statistics: Overall Outcomes Among Benzodiazepine Patients

	All ages		Ages < 40		Ages ≥ 40	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A. Intensive margin of overall benzodiazepine use						
Number of defined daily doses	825.248	1691.770	489.665	1713.486	937.422	1669.475
Number of renewed defined daily doses	675.730	1461.137	384.087	1447.052	773.216	1452.818
Number of new defined daily doses	149.518	360.348	105.578	375.462	164.205	353.938
Number of prescriptions	9.514	14.387	6.912	14.124	10.384	14.369
Number of renewed prescriptions	7.338	12.787	4.766	12.124	8.198	12.887
Number of new prescriptions	2.176	2.691	2.146	2.870	2.186	2.628
Panel B. Overall health outcomes						
Number of hospital visits	25.729	50.726	29.120	63.813	24.596	45.463
Number of emergency department visits	5.623	10.839	5.404	11.752	5.696	10.516
Share with mental and behavioral health disorder	0.256		0.323		0.221	
Share with prescription drug abuse diagnosis	0.012		0.032		0.005	
Share with prescription drug poisoning	0.024		0.043		0.017	
Share with other side effects	0.114		0.029		0.129	

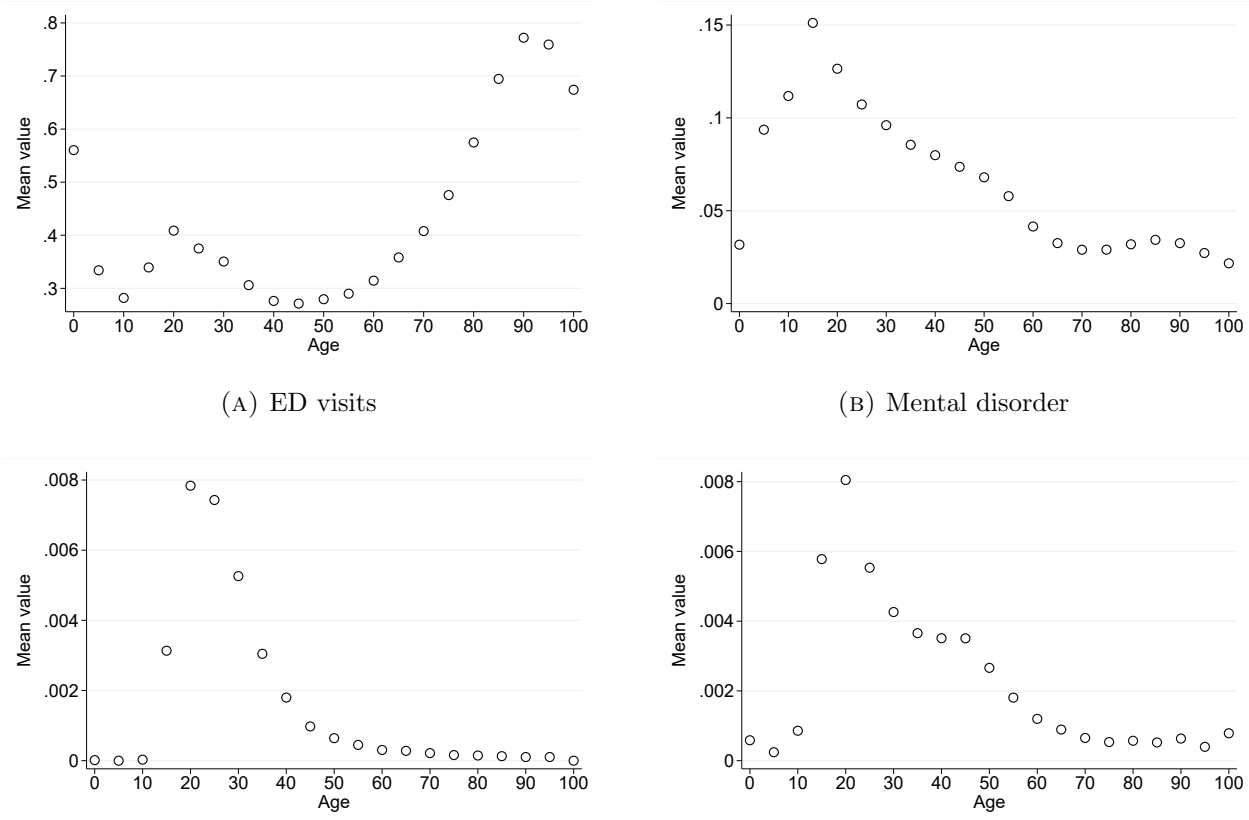
Notes: Unit of observation is a patient. The values depict the overall values for benzodiazepine patients during the observation period (years 2007–2014).



(A) DDDs (B) Renewed DDDs

FIGURE 2: Biannual Benzodiazepine Use-Age Relationships at Intensive Margin: Number of All and Renewed Defined Daily Doses

Notes: The figures are based on patient biannual-level balanced data. The age on the x-axis is grouped into 5-year bins, after which the mean total number of defined daily doses (Panel A) and the mean number of renewed defined daily doses (Panel B) are calculated for each bin.



(A) ED visits

(B) Mental disorder

(C) Prescription drug abuse

(D) Rx poisoning

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

Notes: The figures are based on patient biannual-level balanced data. The age on the x-axis is grouped into 5-year bins, after which the mean number of hospital visits (Panel A) and the probability of a diagnosis (Panels B–D) are calculated for each bin. "Mental disorder" refers to the diagnosis of mental and behavioral disorders. See online Appendix Section A.2 for the definitions of the diagnoses.

5 Econometric Approach and Identification

We base our analysis on the staggered rollout of a nationwide e-prescribing system across municipalities over four years, as well as on the patient-level data combined with the municipal-level population data. We evaluate the effects on municipality-half-year aggregates (means) of benzodiazepine use and health outcomes on average and by age group, using the relevant population size as a weight in the estimation. Our aggregated data approach closely follows Buchmueller and Carey (2018), and it is particularly useful for analyzing extensive margin outcomes that are only observed at the aggregate level (Angrist and Pischke 2009).[16]

To identify the effects of e-prescribing, we estimate a difference-in-differences (DiD) regression model using the following two-way fixed effects (TWFE) specification:

$$y_{mt} = \rho_1 \mathbb{1}[t - E_i \in \{0, 1\}] + \rho_2 \mathbb{1}[t - E_i \geq 2] + \alpha_m + \gamma_t + \epsilon_{mt}, \tag{1}$$

where y_{mt} is a benzodiazepine-related outcome averaged over municipality m and half-year period t. For all intensive margin and health outcomes, we use the number of individuals with at least one benzodiazepine prescription as the denominator.[17] For our two extensive margin outcomes, the biannual share of individuals using benzodiazepines and the biannual share of first-time users, we use the number of individuals in a given municipality and half-year as the denominator. We also use the number of individuals represented in the denominator as weights in the regressions.

E_i denotes the time period of adopting e-prescribing in municipality m and $t - E_i$ denotes the half-year periods relative to the adoption time. The short-run estimate, ρ_1, captures the effect of e-prescribing in the first year after adoption (indicated by $t - E_i \in \{0, 1\}$). The long-run estimate, ρ_2, captures the effect after the first year (indicated by $t - E_i \geq 2$). Municipality fixed effects α_m control for time-invariant differences between municipalities and calendar time fixed effects γ_t control for the common time-varying trend. We cluster the standard errors at the municipality level (N=304) to account for within-municipality correlation in ϵ_{mt}.[18]

[16] Another key reason for using this approach is that plausibly exogenous variation in technology adoption occurs at the municipality level, not at the individual level. In addition, estimating the model at the individual level yields the same coefficients as estimating the model based on municipality means using population sizes at the municipality level as analytic weights.

[17] When calculating the number of benzodiazepine patients (the denominator of the municipality-biannual level outcomes), we do not take into account patients who died in the previous period or were not yet born, which is an unlikely situation in our data.

[18] The standard errors that we report are more conservative than heteroskedasticity-robust standard errors. We

The identification of the parameters of interest (ρ_1 and ρ_2) is based on the variation in the timing of the adoption of e-prescribing between municipalities. The key identification assumption underlying our DiD strategy is that the technology adoption time is unrelated to trends in patient outcomes across municipalities. In online Appendix Table A1, we show that observable municipality-level characteristics are uncorrelated with the adoption time. We additionally show the event study results graphically to detect any pre-existing trends in the outcomes in municipalities that adopted early versus late and to evaluate potential dynamic effects. To accomplish this, we estimate the following TWFE event study model:

$$y_{mt} = \sum_k \delta_k \mathbb{1}[t - E_i = k] + \alpha_m + \gamma_t + \epsilon_{mt}. \tag{2}$$

Here, 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 capture a possible pre-existing trend in the outcome variable, while the coefficients δ_k for the post-adoption periods capture the effect of e-prescribing in periods $k \geq 0$. We follow standard practice by normalizing the coefficient for the indicator "one period before adoption" to zero, $\delta_{-1} = 0$. As noted in Borusyak et al. (2021), when there are no never-treated units in the sample, two relative time coefficients need to be normalized to avoid multicollinearity between t and E_i. Hence, in addition to $\delta_{-1} = 0$, we normalize the coefficient for the most negative (minimum) relative time indicator to zero, $\delta_{-12} = 0$, so that 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 -12) prior to the treatment (Baker et al. 2022).[19]

Because the technology adoption occurs at different times in different municipalities, the later-treated units use already-treated units as controls in estimating the treatment effects. Goodman-Bacon (2021) shows that the treatment effect estimated by the TWFE DiD estimator (the so-called pooled DiD estimator) is the weighted average of all possible two-group, two-period treatment effects. If the treatment effect varies over time, negative weights could arise for later-treated units, potentially biasing the treatment effect estimate downwards or upwards (Baker et al. 2022). We

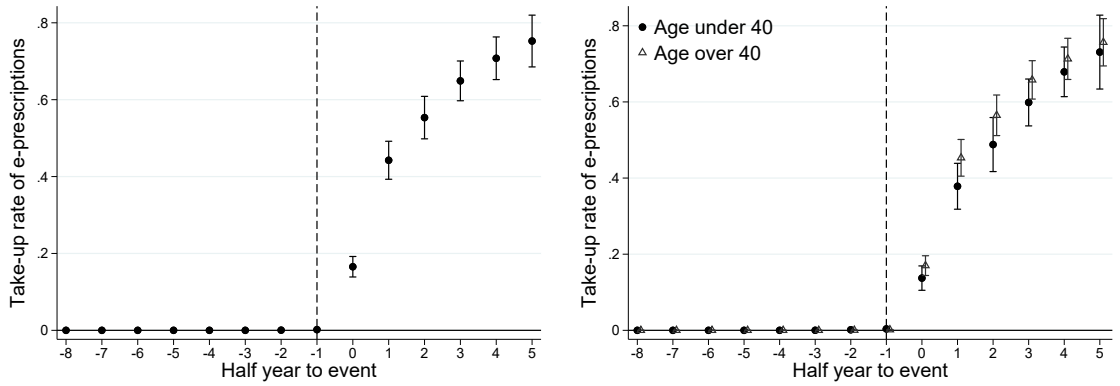
follow Buchmueller and Carey (2018), who cluster their standard errors at the state level in the U.S. context (the policy adoption occurred at this level in their study). The standard errors remain similar if we cluster them at the hospital district level.

[19] 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).

present robustness checks to address these concerns in online Appendix Section A.5 and conclude that negative weighting is not an issue in our setting (see also Section 6.3). In the same section, we also establish the robustness of our baseline results using an event study approach by de Chaisemartin and D'Haultfœuille (2020) that allows for treatment effect heterogeneity and compares treated municipalities to "clean controls" that have not yet adopted e-prescribing technology.

The take-up of e-prescriptions by patients (and physicians) was voluntary during the observation period. This implies that the parameters of interest are intention-to-treat (ITT) estimates on the average effects of the e-prescribing policy. Several prior studies have found the benefits of health information technology to be, at best, fairly small or limited to specific circumstances (Agha 2014; McCullough et al. 2016). However, many earlier studies fail to identify the actual take-up rates at the individual level.

Using the prescription-level data and its information on the e-prescribing status, we plot the biannual take-up rate of e-prescriptions for benzodiazepines around the municipality's technology adoption in Figure 4. The take-up rate by patients (or their physicians) increases sharply in the adoption period and continues to increase gradually over time. One year after adoption approximately 60 to 70 percent of benzodiazepine prescriptions are issued electronically. The figure also reveals that the take-up rate is very similar in the two age groups. Therefore, low take-up rates or differences in take-up rates across age groups are very unlikely to explain our results.



(A) All patients (B) By age group

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

Notes: The figures plot the coefficient estimates from 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 −12. The regressions include only event dummies and do not use any additional controls. Standard errors are clustered at the municipality level.

6 RESULTS

6.1 EFFECTS ON PRESCRIPTION DRUG USE

We start our analyses by estimating the effect of e-prescribing on benzodiazepine use both on average and by age group. We have two broad age groups in our baseline estimations: those younger than 40 and those older than 40. In online Appendix Table A2, we also report the main results using specifications based on finer age groups and find no considerable heterogeneity in the estimated effects within the older group. The only exception is that we observe a small increase in benzodiazepine use for patients aged 40-64. As a further motivation for our heterogeneity analysis, we document meaningful age-related differences in the use of benzodiazepines (and related adverse health outcomes) in Section 4.

We focus on the DiD results and present only the most interesting patterns using event study plots in the main text (the remaining plots are presented in the Online appendix). The estimated effects of e-prescribing on benzodiazepine use both in the short run (i.e. during the first year of e-prescribing adoption) and in the long run (i.e. periods at least one year after adoption) are summarized in Table 3. Columns 1-4 examine the effects at the intensive margin (for benzodiazepine patients), while Columns 5-6 focus on the effects at the extensive margin of adjustment (for the general population).

Intensive Margin Adjustment.—We find that there is an increase in the use of benzodiazepines on average due to e-prescribing (see Column 1), as measured by the number of defined daily doses (DDDs). The average effect is highly significant both in the short and the long run. Two additional patterns are notable. First, the effect is much larger in the long run (i.e. in the periods at least one year after adoption), approximately 5 percent compared to the mean. Second, the increase in benzodiazepine use is substantially larger among younger adults (aged less than 40) compared to older adults (older than 40). Importantly, e-prescribing considerably increases the number of DDDs of benzodiazepines for younger adults in the long run, coinciding with the increase in the take-up of e-prescription technology shown in Figure 4. According to the long-run point estimates in Panel B of Table 3, e-prescribing increases the number of DDDs by approximately 5 DDDs for younger adults. This translates into an increase of DDDs by approximately 15 percent compared to the mean. The corresponding estimate for older adults is much lower at 4 percent.

To graphically illustrate the effects on benzodiazepine use at the intensive margin, Figure 5 plots the baseline event study coefficients δ_k and their confidence intervals from estimating Equation (2) and using the number of DDDs as an outcome. The event study estimates generally show no evidence of differential pre-trends, providing support for our research design. The figures confirm the parameter estimates in Table 3. We find a statistically significant effect on the number of DDDs on average and much larger effects for younger patients. The imprecision of the estimates increases over time, especially after the second year post-adoption. This increase in imprecision most likely happens because we do not observe these last periods for a substantial number of municipalities ($N = 101$) that adopted e-prescribing in 2013.

Mechanisms.—Next we study the mechanisms through which e-prescribing affects overall benzodiazepine use at the intensive margin. By making prescription renewal easier (the access mechanism), e-prescribing is likely to increase repeat, as opposed to new benzodiazepine use. We thus estimate the effects on the number of defined daily doses separately for repeat and new prescriptions (Columns 2-3 of Table 3). Consistent with improved access to medication for younger patients, e-prescribing increases their number of renewed DDDs substantially in the long run. According to the long-run point estimates in Panel B, e-prescribing increases renewed DDDs by approximately 18 percent for younger patients compared to the mean. In contrast, we find no significant increase in younger patients' new benzodiazepine use.[20] Overall, our results show that easier renewal is the

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

driving mechanism increasing younger patients' benzodiazepine use. We also find similar effects for older patients, but the estimated effects are quantitatively much smaller compared to younger patients. For example, the long-run point estimate of renewed DDDs for older patients is approximately 5 percent compared to the mean. Online Appendix Figure A3 confirms graphically the importance of the renewal mechanism as the driver of overall changes in benzodiazepine use at the intensive margin, consistent with the parameter estimates reported in Table 3.

Alternative Outcome.—Our alternative outcome of medication use, the biannual number of benzodiazepine prescriptions per patient, shows no significant increase due to e-prescribing (Columnn 4). For younger patients, we find a statistically insignificant increase of 3 percent. This coarse outcome of medication use does not, however, capture potential changes in the total amount or dose (i.e. items and the amount of drug per item) of prescriptions, unlike the number of defined daily doses.

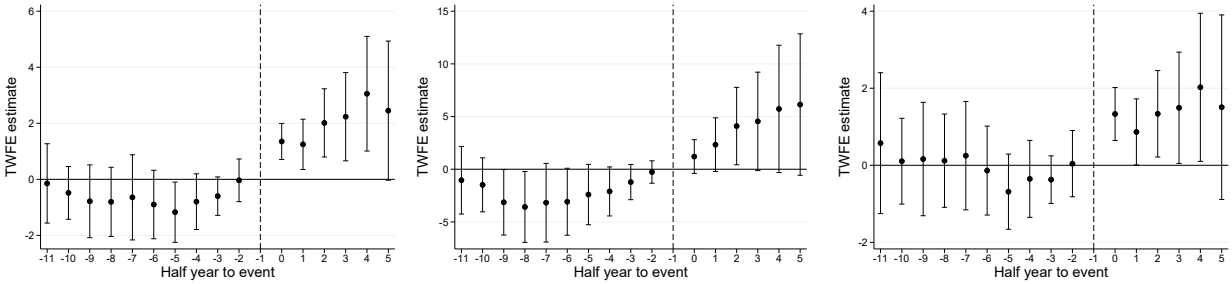
Extensive Margin Adjustment.—We analyze the potential effects at the extensive margin of adjustment in the general population on average and by age group. E-prescribing (improved information) may affect the probability of using benzodiazepines and, more specifically, the probability of first-time use.[21] We do not find consistently significant impacts on these extensive margin outcomes in Columns 5–6 of Table 3. The quantitative size of the point estimates also tends to be very small. The only exception is the statistically significant long-run increase (7 percent) in the younger population (see Figure 6), although their probability of benzodiazepine use does not change much based on the corresponding point estimate (0.2 percent) and online Appendix Figure A4. We conclude that the extensive margin adjustments are relatively small and often insignificant and the clear significant effects can be detected only at the intensive margin in the amount of benzodiazepines used per patient.

[21] Therefore, 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 true effects of e-prescribing.

TABLE 3: Effects of E-Prescribing on Benzodiazepine Use

	Intensive margin				Extensive margin	
	DDDs	Renewed DDDs	New DDDs	Number of rx	Benzo use	First-time use
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All ages						
Short run	1.7204***	1.6902***	0.0302	-0.0059	-0.0003	0.0002
	(0.3751)	(0.3969)	(0.1146)	(0.0039)	(0.0007)	(0.0002)
Long run	2.7418***	2.6846***	0.0572	-0.0051	-0.0004	0.0004
	(0.6024)	(0.6863)	(0.2792)	(0.0062)	(0.0012)	(0.0004)
Mean outcome	55.0838	45.1037	9.9800	0.6350	0.1143	0.0191
Panel B. Age under 40						
Short run	2.1278***	1.8881***	0.2397	0.0034	0.0003	0.0003
	(0.8011)	(0.6904)	(0.1949)	(0.0045)	(0.0004)	(0.0002)
Long run	4.5261***	4.0586***	0.4675	0.0120	0.0001	0.0006**
	(1.5430)	(1.2469)	(0.3988)	(0.0084)	(0.0008)	(0.0003)
Mean outcome	29.0834	22.3343	6.7491	0.4184	0.0351	0.0087
Panel C. Age over 40						
Short run	1.6199***	1.6720***	-0.0521	-0.0077*	-0.0011	0.0001
	(0.4174)	(0.4848)	(0.1469)	(0.0042)	(0.0011)	(0.0003)
Long run	2.3310***	2.4337***	-0.1027	-0.0077	-0.0005	0.0002
	(0.6493)	(0.8450)	(0.3516)	(0.0071)	(0.0020)	(0.0006)
Mean outcome	62.3001	51.4233	10.8768	0.6952	0.1858	0.0285
Observations	4,864	4,864	4,864	4,864	4,864	3,952

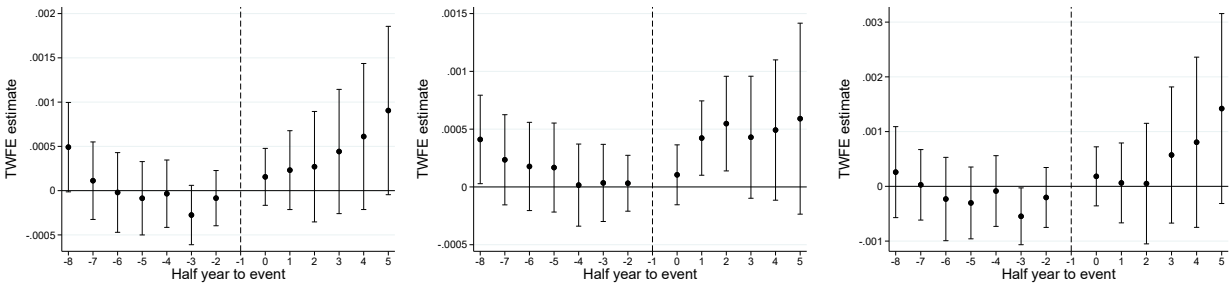
Notes: Each column shows parameter estimates from a separate regression using aggregated municipality biannual-level balanced data. Panel A shows the results for all ages, Panel B for the age group under 40 and Panel C for the age group 40 and older. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of individuals represented (benzodiazepine patients for the intensive margin outcomes and municipality population size for the extensive margin outcomes). Fixed effects for municipalities and half-years are included in all models. The effect on the probability of first-time benzodiazepine use is estimated for 2008h2 to 2014h2 (due to left censoring), and the other effects are estimated for 2007h1 to 2014h2. 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, Ages < 40 (C) DDDs, Ages ≥ 40

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 based on aggregated municipality biannual-level balanced data. 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 -12) prior to the treatment. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.



(A) First-time use, All ages (B) First-time use, Ages < 40 (C) First-time use, Ages ≥ 40

FIGURE 6: Extensive Margin Adjustment: First-Time Benzodiazepine Use

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions based on aggregated municipality biannual-level balanced data. The effects are estimated for 2008h2 to 2014h2 (due to left censoring in the outcome of first-time benzodiazepine use). 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 -9) prior to the treatment. Each observation is weighted by the municipality population. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.

6.2 Effects on Health Outcomes

If e-prescribing substantially increased the appropriate use of benzodiazepines in the younger population, the health outcomes of those individuals would be expected to improve. E-prescribing might have also increased the overuse of benzodiazepines by these patients, with fewer health benefits than harms, due to e.g. adverse drug effects. Instead, e-prescribing had a smaller effect on benzodiazepine use for older patients aged over 40, and thus we do not expect to detect large impacts in their downstream health outcomes. As earlier, we report the results using finer age groups in online Appendix Table A2, and find no heterogeneity in the estimated effects within the older age group.

General Health Outcomes.—We begin by estimating the effects of e-prescribing on the general health outcomes of benzodiazepine patients in Columns 1-3 of Table 4. We find no consistent effect on the probability of death (see also Figure 7). Mortality is a commonly used measure of patient health in prior work and does not suffer from measurement error. Mortality is, however, quite an extreme outcome, especially in the younger population. For this reason, we also analyze the changes in the number of emergency department visits in Column 2 and in the number of hospital care visits in Column 3. We find no significant effects on emergency department visits. There is a statistically significant reduction in the number of hospital visits, but the effect prevails only in the short run for younger patients (see Panel B of online Appendix Figure A5). Based on the short-run effects on hospital visits, it is difficult to make any strong conclusions on the health effects in general.

Mental and Adverse Health Outcomes.—Similar to most of the general health outcomes, we find no significant effects on the probability of a diagnosis of mental or behavioral disorders (Column 4).[22] In contrast, for younger patients, we find substantial effects on increasingly important indicators of medication overuse and serious side effects of benzodiazepines: prescription drug abuse disorders and poisonings (Columns 5-6 of Table 4 and Figure 8). According to the long-run point estimates in Panel B of Table 4, e-prescribing increases the probability of prescription drug abuse disorders and poisonings by approximately 17 and 16 percent in the younger population, respectively. However, there are no statistically significant effects for older patients and the estimates are also small in magnitude.

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

[22] Using the 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.

among older patients (Section 4). Column 7 of Table 4 (and Panels G–I of online Appendix Figure A5) reveals no statistically significant effect on the probability of a diagnosis related to any of these other side effects on average or for the two age groups separately.

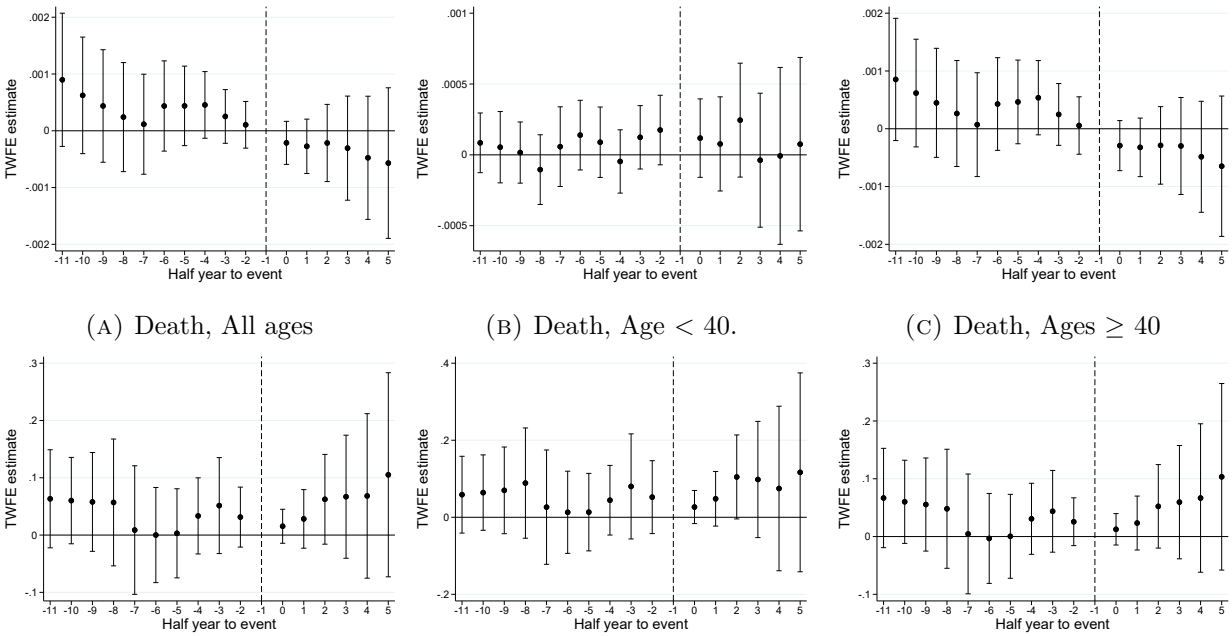
TABLE 4: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes

	Death	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All ages							
Short run	-0.0002	-0.0000	-0.0668**	-0.0026	0.0001	0.0001	-0.0001
	(0.0001)	(0.0254)	(0.0334)	(0.0034)	(0.0001)	(0.0001)	(0.0005)
Long run	-0.0001	0.0377	-0.0241	0.0009	0.0002	0.0002	0.0003
	(0.0003)	(0.0466)	(0.0734)	(0.0042)	(0.0001)	(0.0001)	(0.0009)
Mean outcome	0.0103	0.3753	1.7174	0.0604	0.0015	0.0023	0.0108
Panel B. Ages < 40							
Short run	0.0001	0.0117	-0.1490***	-0.0063	0.0005	0.0004*	0.0001
	(0.0001)	(0.0326)	(0.0552)	(0.0080)	(0.0005)	(0.0002)	(0.0002)
Long run	0.0001	0.0697	-0.1067	0.0015	0.0009*	0.0008***	0.0001
	(0.0002)	(0.0640)	(0.1139)	(0.0092)	(0.0005)	(0.0003)	(0.0004)
Mean outcome	0.0011	0.3564	1.8915	0.1033	0.0052	0.0049	0.0028
Panel C. Ages ≥ 40							
Short run	-0.0003*	-0.0030	-0.0440	-0.0016	-0.0000	-0.0000	-0.0002
	(0.0002)	(0.0238)	(0.0290)	(0.0022)	(0.0000)	(0.0001)	(0.0006)
Long run	-0.0002	0.0295	0.0016	0.0007	0.0000	0.0001	0.0004
	(0.0003)	(0.0430)	(0.0654)	(0.0031)	(0.0001)	(0.0002)	(0.0011)
Mean outcome	0.0128	0.3806	1.6691	0.0485	0.0005	0.0016	0.0130
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864

[1] *Notes:* Each column shows parameter estimates from a separate regression using aggregated municipality biannual-level balanced data. Panel A shows the results for all ages, Panel B for the age group under 40 and Panel C for the age group 40 and older. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of individuals represented (benzodiazepine patients). Fixed effects for municipalities and half-years are always included. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

6.3 Robustness Checks, Alternative Mechanisms, and Placebo Regression Test

Additional Specifications.— To confirm the robustness of our main results for benzodiazepine use and health outcomes, we implement various sensitivity checks and additional estimations as well as using alternative estimators and tests, based on the recent advances in the difference-in-differences

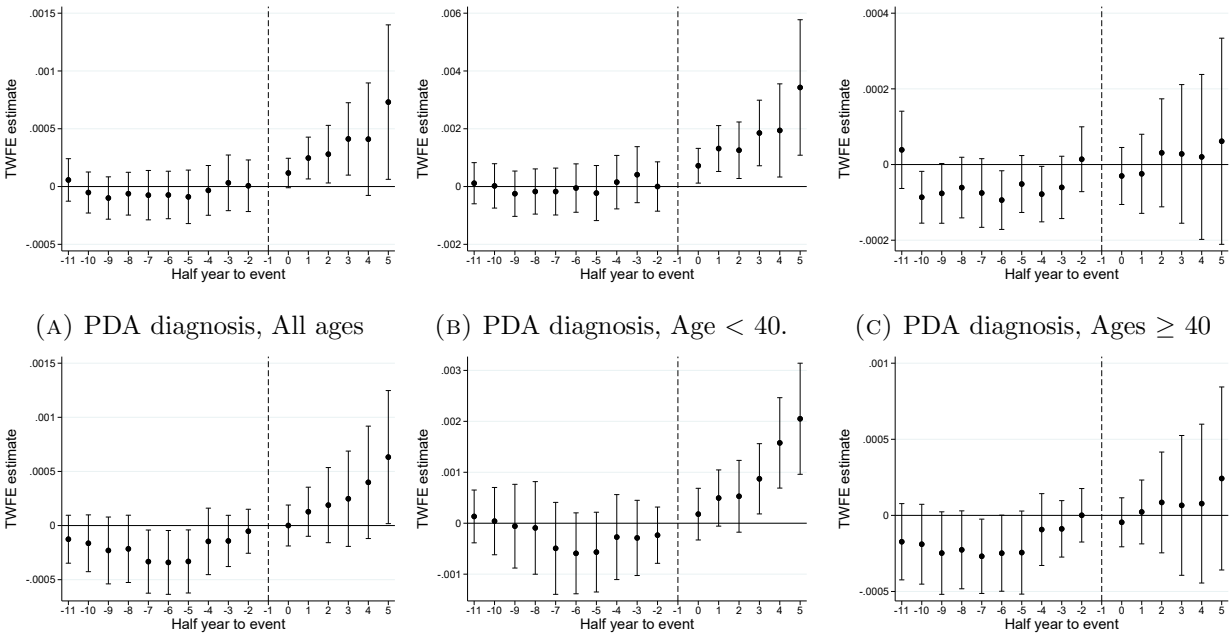


(A) Death, All ages (B) Death, Age < 40. (C) Death, Ages ≥ 40

(D) ED visits, All ages (E) ED visits, Age < 40. (F) ED visits, Ages ≥ 40

FIGURE 7: Selected General Health Outcomes

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions based on aggregated municipality biannual-level balanced data. 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 -12) prior to the treatment. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.



(A) PDA diagnosis, All ages (B) PDA diagnosis, Age < 40. (C) PDA diagnosis, Ages ≥ 40

(D) Rx poisoning, All ages (E) Rx poisoning, Age < 40. (F) Rx poisoning, Ages ≥ 40

FIGURE 8: Selected Adverse Health Outcomes

Notes: The figures plot the coefficient estimates from two-way fixed effects (TWFE) event study regressions based on aggregated municipality biannual-level balanced data. 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 -12) prior to the treatment. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.

literature. For brevity, we summarize the results and conclusions from these additional specifications and models in this section, while all the estimation results, including regression coefficients and event study graphs, are presented in detail in the online Appendix material.

To test the sensitivity of our main results, we use different specifications that are based on alternative assumptions or use different data. In the first specification, we allow for differential time trends, depending on the municipality type (urban, semi-urban, and rural). Second, we exclude municipalities that adopted the national EMR system at the end of our observation period, starting in 2014. We are not aware of any other reforms or significant changes taking place in physician practices in 2007–2014 that could potentially confound our results. Third, we only use data from periods when the last-treated municipalities have not yet adopted e-prescribing.[23] By excluding the last periods from the estimation sample, we test whether the results are sensitive to including the last-treated municipalities in the control group (as "clean controls") and having only early-treated municipalities in the treatment group.

The results based on these three additional specifications are presented for benzodiazepine use and health outcomes in Tables A4 and A5, correspondingly. Generally, the estimates are very similar in the alternative specifications compared to the baseline results. For the third specification, the estimates are a bit smaller and more imprecisely estimated, but still significant. This is not surprising, as for most municipalities we concentrate on short-term effects, even though the long-term effects are larger. Overall, for all specifications, we find that the conclusions from our main analysis remain intact.

Goodman-Bacon Decomposition and Alternative Estimator.—The literature has proposed alternative estimators for staggered DiD analysis that are based on slightly different identification assumptions and normalization procedures. These methods tackle the potential challenge related to negative weights in the identification of the average effects using DiD models. Goodman-Bacon (2021) shows that in the empirical setting of a staggered adoption such as ours, the TWFE DiD estimator is a weighted average of all possible individual two-period/two-group DiD estimators in the data. Moreover, especially in the setting in which all units get treatment at some point (i.e. there are no never-treated units), some weights can be negative and TWFE may produce a biased estimate for the average treament effect and even a wrong sign. Using the decomposition method of Goodman-Bacon (2021), we show that negative weighting is not a concern in our setting and that

[23]The downside of this approach 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.

our results are similar for the treatment groups of early- and late-treated units (online Appendix Section A.5).

We also use the DiD estimator proposed by de Chaisemartin and D'Haultfœuille (2020) to evaluate the robustness of our results to treatment effect heterogeneity over municipalities and time.[24] We report the event study coefficients in Figures A6-9. While the estimates based on their approach are a bit smaller and somewhat more imprecisely estimated compared to TWFE, again the conclusions regarding the effects on medication use and health outcomes do not depend on the specific estimator used.

Alternative Mechanisms: Use of Other Medications.—E-prescribing can also affect the use of other medications for benzodiazepine patients, which could have implications on their health outcomes. To study this, we use additional data on benzodiazepine patients' prescriptions for a group of antidepressants called selective serotonin reuptake inhibitors (SSRIs), which are considered non-addictive and can be either substitutes or complements for benzodiazepines in treating conditions such as anxiety. SSRI use decreases and benzodiazepine use increases if physicians substitute SSRIs for benzodiazepines in treating anxiety or panic disorder. Both SSRI and benzodiazepine use can increase if these two drugs are used as complements.

Table A6 shows there are no significant effects for all patients. For younger patients, we find an increase in the use of SSRIs both in the short and long run, but this effect can only be detected using the number of SSRIs as the outcome. In contrast, for older patients we find a reduction in DDDs in the long run. However, the quantitative magnitude of the estimate is small. According to the long-run point estimates, e-prescribing reduces DDDs by approximately 2 percent for older patients compared to the mean. Overall, the magnitudes of the estimates are so small that they are unlikely to explain the changes in health outcomes.

Alternative Mechanisms: The Potential Role of Improved Diagnosing.—A well-known concern in research estimating the effects of health information technology on patient health outcomes is that the technology may improve diagnoses of medical conditions. This mechanism could cause upward bias in some of our health effect estimates, especially if the diagnoses (health outcomes) originate from the prescribing physician. Because e-prescribing increases the repeat use of benzodiazepines, the related diagnoses of mental and behavioral health disorders might also increase. For example, anxiety may justify a repeat prescription and could be diagnosed by the prescribing physician (some

[24] In this case, not yet treated municipalities act as "clean controls", and we only use 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, in contrast to the baseline specification based on two normalizations (equation (2)).

of the prescriptions are renewed at the physician's office). Information on a patient's e-prescription history may also improve the physician's diagnosis of conditions such as prescription drug abuse disorders, poisoning or other side effects, thereby increasing their prevalence.[25]

To address this concern, we estimate the health effects based on diagnoses that are less likely to originate from the prescribing physicians and thus to be confounded by the improvements in diagnosing. Table A7 shows the 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 percent of all diagnoses). The results based on these alternative outcomes are virtually identical to the main results and thus our results do not seem to be driven by potential improvements in the diagnosing of medical conditions.

Placebo Regression Test.—In Table A8, 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. The estimates and confidence intervals show no significant effect on this outcome and the point estimates are also very close to zero.

7 Conclusion

We estimate the effects of a nationwide e-prescribing system designed to improve medication access while limiting overuse. We find that e-prescribing has a statistically and economically significant effect on benzodiazepine use per patient on average due to increased prescription renewals. The observed effect is much larger among younger adults (aged under 40). In the long run, there is little evidence of an improvement in younger patients' general health outcomes, but we find substantial increases in prescription drug abuse disorders and poisonings.

Improved access through easier renewal requests, along with improved prescription information, are the core features of e-prescribing systems globally and are highly relevant for users of prescription drugs. Making renewal requests easier for the patient can be an important factor in improving medication compliance and persistence, especially for younger patients, who have the lowest utilization of repeat medication and the highest barriers to access (Kullgren et al. 2012; Duncan et al. 2014). Younger patients also have a higher prevalence of mental and behavior disor-

[25] However, our emergency department and hospital visit outcomes are arguably much less susceptible to improvements in diagnosing compared, for example, to prescription drug abuse disorders.

ders, and therefore they can benefit from potential improvements in the use of medication owing to e-prescribing.

Our evidence shows that easier prescription renewal increased the use of repeat prescriptions especially in the younger patient population. However, our evidence on the increase in adverse health outcomes reveals that medication overuse may also increase in this vulnerable patient population. A potential limitation of our analysis 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. Because our analysis focuses on benzodiazepine patients and their specific health outcomes, further research on other patient populations and prescription drugs is obviously needed to provide a more complete picture of the overall effects of e-prescribing.

Our evidence on the unintended consequences of health information technology nonetheless suggests that further precautionary procedures might be needed for renewals of prescriptions for potentially harmful medications. Consistent with several prior studies on PDMPs (Buchmueller and Carey 2018; Grecu et al. 2019; Kim 2021), we show that providing better information on a patient's prescription history may not be fully effective in limiting medication overuse, especially with voluntary physician access to this information. However, in contrast to previous findings, we demonstrate that regardless of improved information, medication overuse can even increase with easier access.

In terms of generalizability to other institutional contexts, the Finnish e-prescribing system was designed to reduce hassle costs by making renewals or refills easier, although the actual take-up of e-prescriptions was voluntary for physicians during the observation period. Mandatory e-prescribing could impose hassle costs on physicians by forcing them to use a system they otherwise would not. The effects of e-prescribing might especially depend on how refills are treated in the e-prescribing regulation and in general (i.e. whether or not a visit to a physician's office is required for a refill of any controlled substance). Our results highlight that in some cases decreasing hassle costs and related frictions might be even harmful for patients.

Empirical research in economics has largely overlooked the factors that influence joint physician-patient decisions in health care. Our results suggest 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 direct 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. Studies of other emerging technologies and markets from the perspective of correct policy, in addition to research focusing on physician prescribing behavior, are key areas for future research.

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A Online Appendix

For online publication only.

A.1 Determination of Benzodiazepine Prescriptions

We use the ATC classification codes to identify benzodiazepine and benzodiazepine-related (referred to as benzodiazepines) prescription drugs from the Prescription Data. Benzodiazepines in the Prescription Data include the pharmacological subgroup codes N05BA, N05CD and N05CF and the following chemical substance levels:

- N05BA01, N05BA02, N05BA04, N05BA06, N05BA09, N05BA12
- N05CD02, N05CD07, N05CD08
- N05CF01, N05CF02, N05CF03

For SSRI prescriptions, the ATC classification codes in the Prescription Data are as follows:

- N06AB03, N06AB04, N06AB05, N06AB06, N06AB08, N06AB10.

A.2 Health Outcomes

Almost all of our health outcomes come from the Discharge Data, which are based on hospital (specialized health care) visits. Our mortality outcome comes from the Prescription Data.

We classify a discharge visit as an emergency department visit if the patient has one of the following category in their discharge record:

- Type of admission: emergency duty
- Referral type: the patient arrived at care without a referral, e.g. 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

We construct our health outcomes using the primary diagnoses in the Discharge Data because they are recorded accurately and because the quality of recording secondary diagnoses has raised some concerns in validation studies (Sund 2012).

Our general class of mental and behavioral disorder outcome 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.

We construct our prescription drug abuse disorder diagnosis outcome by grouping multiple diagnoses measuring prescription drug abuse (such as abuse of benzodiazepines and opioids). This grouping is natural because many abusers are polydrug users, and a prescription drug abuse diagnosis in our data is an indication of rather strong abuse, which further suggests polydrug use. Specifically, we consider diagnoses with the following ICD10 codes:

- 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 abuse. The ICD10 classification contains codes that indicate that the patient has already been weaned off the abused prescription drug, is in a controlled rehabilitation program, or uses a drug withdrawal medication. 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 common side effects of benzodiazepines include sedation, poor coordination, decline in cognitive functions, such as learning and memory impairment, and delirium, as well as increased risk of falls and hip fractures (Lader 2011). We measure these other side effects 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)

A.3 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. 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 was the first municipality to adopt e-prescribing on May 20, 2010. Supporting our assumption, Table A1 shows 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:

$$T_{mt} = (\Gamma_t \times X_{m,2009})'\Psi + \gamma_t + \nu_{mt}, \tag{1}$$

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 percent 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 technology adoption is not systematically related to differences in municipality characteristics.

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

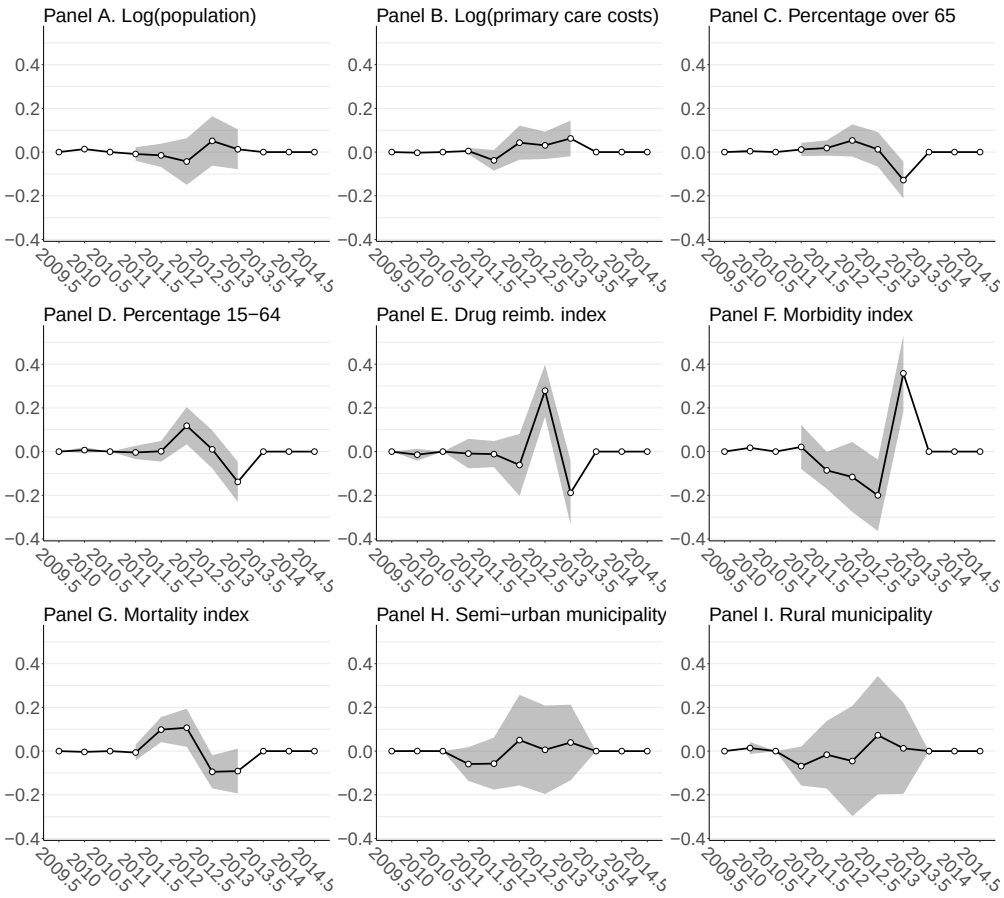


FIGURE A1: Adoption of E-Prescribing by Baseline Municipality Characteristics

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 1 for details on the specifications.

A.4 Additional Figures and Tables

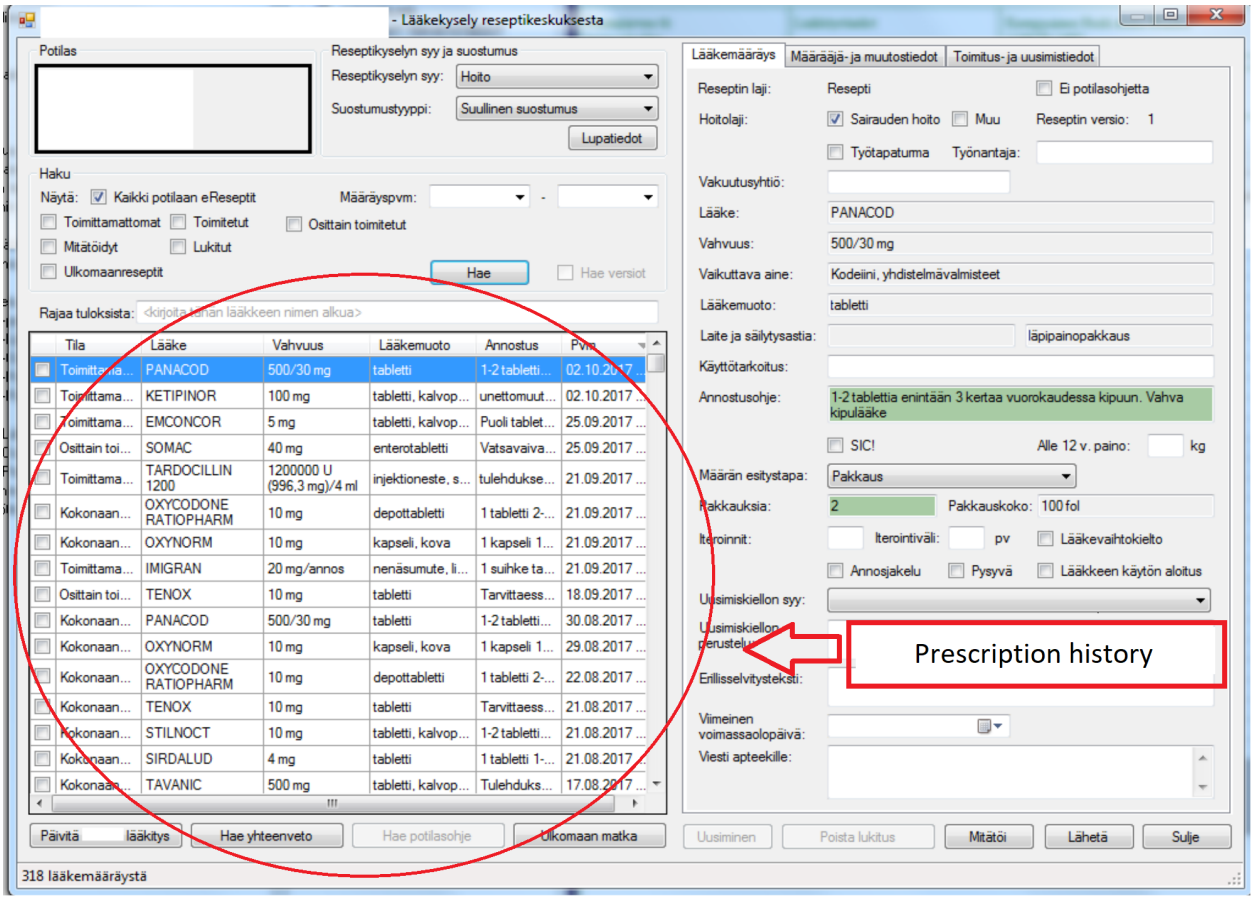
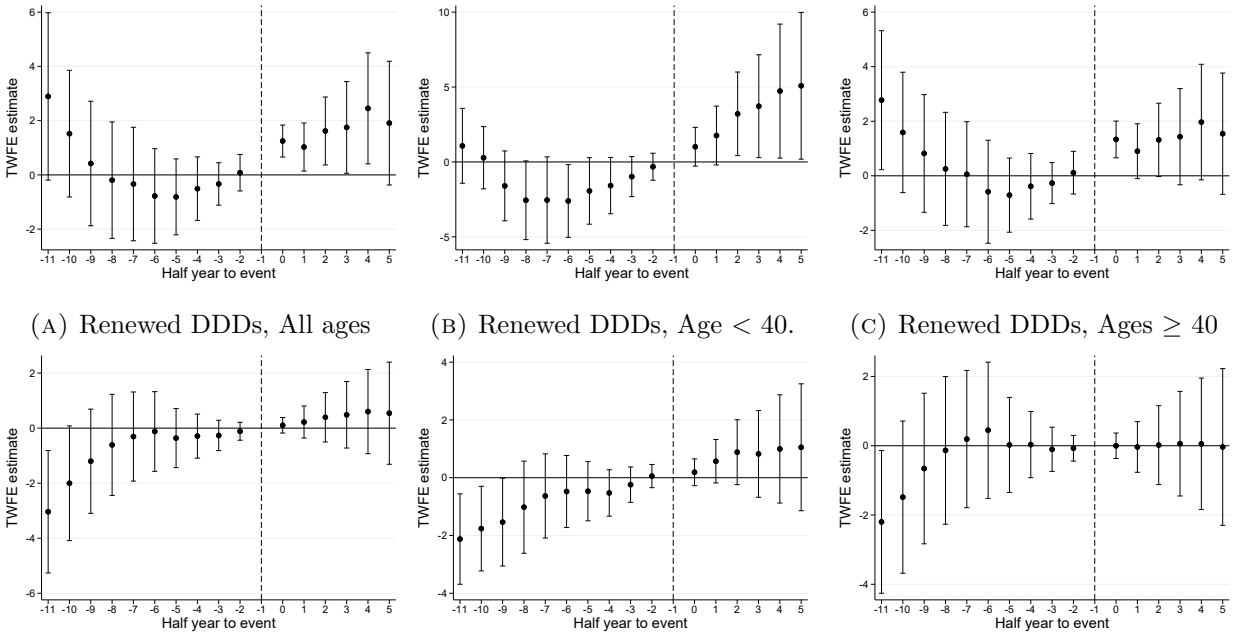


Figure A2: E-Prescribing Technology, Physician's View

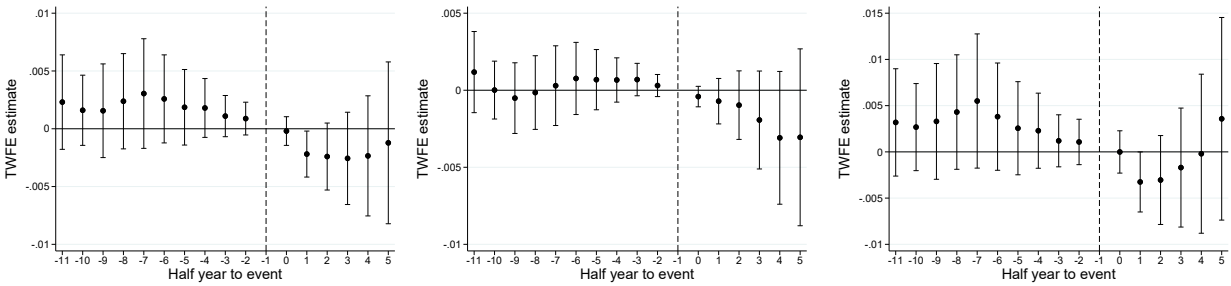


(A) Renewed DDDs, All ages (B) Renewed DDDs, Age < 40. (C) Renewed DDDs, Ages ≥ 40

(D) New DDDs, All ages (E) New DDDs, Age < 40. (F) New DDDs, Ages ≥ 40

FIGURE A3: Decomposition of Intensive Margin Adjustment: Number of Renewed and New Defined Daily Doses

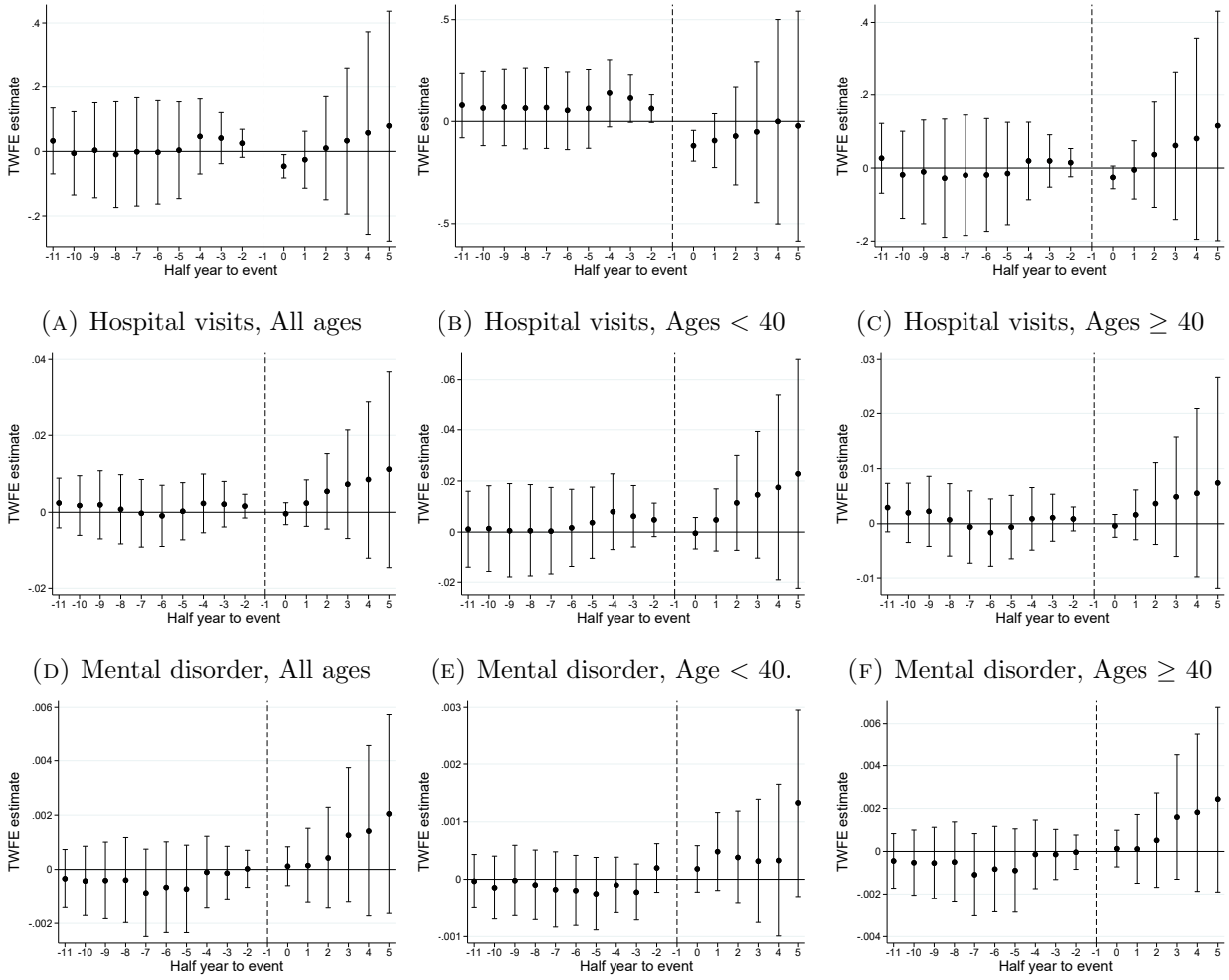
Note: The figures plot the coefficient estimates from event study regressions using aggregated municipality biannual-level balanced data. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (-1 and -12) prior to the treatment. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.



(A) Benzo use, All ages (B) Benzo use, Ages < 40 (C) Benzo use, Ages ≥ 40

FIGURE A4: Extensive Margin Adjustment: Benzodiazepine Use

Notes: The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions based on aggregated municipality biannual-level balanced data. 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 -9) prior to the treatment. Each observation is weighted by the municipality population. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.



(A) Hospital visits, All ages (B) Hospital visits, Ages < 40 (C) Hospital visits, Ages ≥ 40

(D) Mental disorder, All ages (E) Mental disorder, Age < 40. (F) Mental disorder, Ages ≥ 40

(G) Other side effects, All ages (H) Other side effects, Age < 40. (I) Other side effects, Ages ≥ 40

FIGURE A5: Additional Health Outcomes

Note: The figures plot the coefficient estimates from event study regressions using aggregated municipality biannual-level balanced data. 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 -12) prior to the treatment. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.

TABLE A2: Effects of E-Prescribing on Benzodiazepine Use, Finer Age Groups

	Intensive margin		Extensive margin
	DDDs	Number of rx	Benzo use
	(1)	(2)	(3)
Panel A. Age 18-39			
Short run	2.1645***	0.0023	0.0005
	(0.8240)	(0.0044)	(0.0007)
Long run	4.5977***	0.0097	-0.0000
	(1.5592)	(0.0082)	(0.0013)
Mean outcome	31.3940	0.4460	0.0597
Panel B. Age 40-64			
Short run	2.0384***	-0.0028	0.0001
	(0.6384)	(0.0044)	(0.0011)
Long run	3.3685***	0.0025	0.0015
	(0.9621)	(0.0074)	(0.0018)
Mean outcome	57.7312	0.6806	0.1524
Panel C. Age $\geq$ 65			
Short run	1.0185**	-0.0134***	-0.0037**
	(0.4011)	(0.0049)	(0.0015)
Long run	1.0112	-0.0190**	-0.0045
	(0.6809)	(0.0080)	(0.0030)
Mean outcome	68.0683	0.7135	0.2500
Observations	4,864	4,864	4,864

Notes: Each column shows parameter estimates from a separate regression using aggregated municipality biannual-level balanced data. Panel A shows the results for all ages, Panel B for age group under 40 and Panel C for age group 40 and older. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of individuals represented (benzodiazepine patients for the intensive margin outcomes and municipality population size for the extensive margin outcome). Fixed effects for municipalities and half-years 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 A3: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes, Finer Age Groups

	Death	ED visits	Hospital visits	Mental disorder	PDA diagnosis	Rx poisoning	Other side effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Ages 18-39							
Short run	0.0001	0.0125	-0.1620***	-0.0068	0.0006	0.0003	0.0001
	(0.0001)	(0.0332)	(0.0596)	(0.0084)	(0.0006)	(0.0002)	(0.0002)
Long run	0.0002	0.0712	-0.1238	0.0009	0.0009*	0.0008**	0.0001
	(0.0002)	(0.0652)	(0.1180)	(0.0097)	(0.0006)	(0.0003)	(0.0004)
Mean outcome	0.0012	0.3558	1.8820	0.1035	0.0056	0.0052	0.0028
Panel B. Ages 40-64							
Short run	-0.0001	0.0006	-0.0566*	-0.0027	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0225)	(0.0294)	(0.0036)	(0.0001)	(0.0001)	(0.0003)
Long run	-0.0003	0.0375	-0.0365	0.0011	0.0000	0.0001	0.0005
	(0.0002)	(0.0424)	(0.0683)	(0.0046)	(0.0001)	(0.0002)	(0.0005)
Mean outcome	0.0043	0.2884	1.5676	0.0624	0.0008	0.0024	0.0055
Panel C. Ages $\geq$ 65							
Short run	-0.0005	-0.0072	-0.0308	-0.0004	-0.0001*	0.0001	-0.0004
	(0.0003)	(0.0271)	(0.0313)	(0.0007)	(0.0000)	(0.0001)	(0.0011)
Long run	-0.0001	0.0200	0.0397	0.0001	-0.0001	0.0001	0.0004
	(0.0005)	(0.0460)	(0.0677)	(0.0016)	(0.0001)	(0.0001)	(0.0018)
Mean outcome	0.0236	0.4969	1.7972	0.0311	0.0002	0.0006	0.0224
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864

[1] *Notes:* Each column shows parameter estimates from a separate regression using aggregated municipality biannual-level balanced data. Panel A shows the results for all ages, Panel B for age group under 40 and Panel C for age group 40 and older. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of individuals represented (benzodiazepine patients). Fixed effects for municipalities and half-years are always included. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE A4: Robustness: Effects of E-Prescribing on Benzodiazepine Use

	Municipality type trend			National EMR excl.			Periods: H1:2007-H2:2012		
	All ages (1)	Ages < 40 (2)	Ages ≥ 40 (3)	All ages (4)	Ages < 40 (5)	Ages ≥ 40 (6)	All ages (7)	Ages < 40 (8)	Ages ≥ 40 (9)
Panel A. Outcome: DDDs (intensive margin)									
Short run	1.9515***	2.2183***	1.8987***	1.9258***	2.6197**	1.7565***	1.5432***	1.9841*	1.4114***
	(0.3753)	(0.7888)	(0.4257)	(0.4006)	(1.0246)	(0.4026)	(0.4006)	(1.0504)	(0.3817)
Long run	3.1220***	4.7564***	2.8808***	3.0299***	5.4564***	2.5337***	1.6117**	3.1207*	1.2655*
	(0.6055)	(1.5085)	(0.6727)	(0.6598)	(2.0589)	(0.6194)	(0.7064)	(1.8521)	(0.7628)
Mean outcome	55.0838	29.0834	62.3001	56.9122	30.1384	64.6648	59.2641	30.2499	67.6323
Panel B. Outcome: Number of rx (intensive margin)									
Short run	-0.0019	0.0047	-0.0029	-0.0041	0.0036	-0.0053	-0.0037	0.0034	-0.0044
	(0.0033)	(0.0044)	(0.0036)	(0.0043)	(0.0043)	(0.0049)	(0.0044)	(0.0055)	(0.0051)
Long run	-0.0003	0.0142*	-0.0011	-0.0035	0.0108	-0.0042	-0.0138	-0.0069	-0.0127
	(0.0060)	(0.0079)	(0.0070)	(0.0071)	(0.0084)	(0.0085)	(0.0089)	(0.0094)	(0.0091)
Mean outcome	0.6350	0.4184	0.6952	0.6407	0.4219	0.7041	0.6702	0.4263	0.7406
Panel C. Outcome: Benzo use (extensive margin)									
Short run	0.0004	0.0006	-0.0001	0.0000	0.0005	-0.0006	-0.0004	-0.0002	-0.0005
	(0.0007)	(0.0004)	(0.0011)	(0.0007)	(0.0004)	(0.0012)	(0.0009)	(0.0006)	(0.0014)
Long run	0.0007	0.0007	0.0012	-0.0002	0.0002	0.0002	-0.0051***	-0.0041***	-0.0044*
	(0.0010)	(0.0008)	(0.0020)	(0.0015)	(0.0012)	(0.0025)	(0.0017)	(0.0015)	(0.0025)
Mean outcome	0.1143	0.0351	0.1858	0.1172	0.0370	0.1902	0.1238	0.0378	0.2017
Observations	4,864	4,864	4,864	3,015	3,015	3,015	3,648	3,648	3,648

Notes: Each column shows parameter estimates from a separate regression using municipality biannual-level balanced data for benzodiazepine patients. Columns 1-3 include controls for separate time trends for urban, semi-urban, and rural municipalities. Columns 4-6 exclude municipalities that implemented the national EMR system. Columns 7-9 use data from periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of individuals represented (benzodiazepine patients for the intensive margin outcomes and municipality population size for the extensive margin outcome). Fixed effects for municipalities and half-years 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 A5: Robustness: Effects of E-Prescribing on Benzodiazepine Patients' Health Outcomes

	Municipality type trend			National EMR excl.			Periods: H1:2007-H2:2012		
	All ages	Ages < 40	Ages ≥ 40	All ages	Ages < 40	Ages ≥ 40	All ages	Ages < 40	Ages ≥ 40
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Outcome: Death									
Short run	-0.0001	0.0001	-0.0002	-0.0001	0.0001	-0.0002	-0.0002	0.0001	-0.0003*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Long run	0.0002	0.0001	0.0001	0.0001	0.0000	0.0001	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0004)
Mean outcome	0.0103	0.0011	0.0128	0.0100	0.0011	0.0126	0.0093	0.0011	0.0117
Panel B. Outcome: ED visits									
Short run	0.0029	0.0134	0.0002	0.0208	0.0336	0.0177	0.0183	0.0279	0.0166
	(0.0265)	(0.0344)	(0.0247)	(0.0277)	(0.0318)	(0.0271)	(0.0292)	(0.0391)	(0.0268)
Long run	0.0441	0.0763	0.0359	0.0669	0.0965	0.0598	0.0195	0.0207	0.0200
	(0.0490)	(0.0667)	(0.0454)	(0.0508)	(0.0612)	(0.0489)	(0.0506)	(0.0671)	(0.0472)
Mean outcome	0.3753	0.3564	0.3806	0.3684	0.3419	0.3761	0.3614	0.3381	0.3681
Observations	4,864	4,864	4,864	3,015	3,015	3,015	3,648	3,648	3,648
Panel C. Outcome: Hospital visits									
Short run	-0.0712**	-0.1550***	-0.0460	-0.0794*	-0.1798***	-0.0485	-0.0472	-0.1281*	-0.0237
	(0.0344)	(0.0571)	(0.0301)	(0.0442)	(0.0681)	(0.0397)	(0.0429)	(0.0683)	(0.0378)
Long run	-0.0312	-0.1143	-0.0005	-0.0207	-0.1123	0.0136	-0.0398	-0.1730**	0.0090
	(0.0787)	(0.1192)	(0.0702)	(0.1064)	(0.1560)	(0.0961)	(0.0466)	(0.0823)	(0.0428)
Mean outcome	1.7174	1.8915	1.6691	1.7020	1.8220	1.6673	1.6727	1.8012	1.6356
Panel D. Outcome: Mental disorder									
Short run	-0.0031	-0.0069	-0.0020	-0.0048	-0.0103	-0.0033	-0.0014	-0.0037	-0.0008
	(0.0034)	(0.0080)	(0.0022)	(0.0039)	(0.0088)	(0.0026)	(0.0034)	(0.0077)	(0.0023)
Long run	-0.0001	0.0004	0.0001	-0.0004	-0.0014	-0.0002	0.0075	0.0095	0.0063
	(0.0044)	(0.0097)	(0.0032)	(0.0056)	(0.0113)	(0.0041)	(0.0056)	(0.0074)	(0.0048)
Mean outcome	0.0604	0.1033	0.0485	0.0591	0.0978	0.0479	0.0589	0.0974	0.0477
Panel E. Outcome: PDA diagnosis									
Short run	0.0000	0.0005	-0.0000	0.0001	0.0007	-0.0001	0.0001	0.0008	-0.0000
	(0.0001)	(0.0005)	(0.0000)	(0.0001)	(0.0006)	(0.0000)	(0.0001)	(0.0005)	(0.0000)
Long run	0.0001	0.0008	-0.0000	0.0002	0.0012*	-0.0000	0.0003**	0.0013**	-0.0001
	(0.0001)	(0.0006)	(0.0001)	(0.0002)	(0.0006)	(0.0001)	(0.0001)	(0.0005)	(0.0000)
Mean outcome	0.0015	0.0052	0.0005	0.0016	0.0052	0.0005	0.0014	0.0048	0.0005
Panel F. Outcome: Rx poisoning									
Short run	0.0001	0.0004*	-0.0000	0.0001	0.0006**	-0.0000	0.0001	0.0004	0.0000
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)
Long run	0.0002	0.0008***	0.0001	0.0002	0.0009***	0.0000	-0.0000	0.0010***	-0.0003
	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Mean outcome	0.0023	0.0049	0.0016	0.0024	0.0050	0.0017	0.0024	0.0049	0.0017
Panel G. Outcome: Other side effects									
Short run	-0.0001	0.0001	-0.0002	-0.0001	0.0002	-0.0001	0.0001	0.0002	0.0002
	(0.0006)	(0.0002)	(0.0007)	(0.0007)	(0.0003)	(0.0009)	(0.0006)	(0.0003)	(0.0008)
Long run	0.0003	0.0001	0.0003	0.0004	0.0004	0.0005	0.0003	0.0003	0.0004
	(0.0010)	(0.0004)	(0.0011)	(0.0013)	(0.0005)	(0.0015)	(0.0008)	(0.0003)	(0.0009)
Mean outcome	0.0108	0.0028	0.0130	0.0107	0.0026	0.0130	0.0104	0.0026	0.0127
Observations	4,864	4,864	4,864	3,015	3,015	3,015	3,648	3,648	3,648

Notes: Each column shows parameter estimates from a separate regression using municipality biannual-level balanced data for benzodiazepine patients. Columns 1-3 include controls for separate time trends for urban, semi-urban, and rural municipalities. Columns 4-6 exclude municipalities that implemented the national EMR system. Columns 7-9 use data for periods when the last-treated municipalities have not yet adopter e-prescribing (H1:2007-H2:2012). "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years 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 A6: Effects of E-Prescribing on Benzodiazepine Patients' SSRI Use

	All Ages			Ages < 40			Age ≥ 40		
	DDDs (1)	Number of rx (2)	SSRI use (3)	DDDs (4)	Number of rx (5)	SSRI use (6)	DDDs (7)	Number of rx (8)	SSRI use (9)
Short run	0.2286	0.0008	0.0002	0.4188	0.0041**	-0.0000	0.1636	-0.0002	0.0003
	(0.1457)	(0.0008)	(0.0002)	(0.3110)	(0.0019)	(0.0003)	(0.1506)	(0.0007)	(0.0002)
Long run	-0.3472	0.0003	0.0001	0.3736	0.0065*	-0.0009	-0.5643**	-0.0013	0.0008*
	(0.2851)	(0.0015)	(0.0007)	(0.6694)	(0.0035)	(0.0010)	(0.2647)	(0.0014)	(0.0004)
Mean outcome	24.5428	0.1425	0.1800	30.3936	0.2046	0.0824	22.9189	0.1252	0.2681
Observations	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864	4,864

Notes: Each column shows parameter estimates from a separate regression using aggregated municipality biannual-level balanced data. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. The number of defined daily doses of SSRI prescriptions ("DDDs") and the number of SSRI prescriptions ("Number of rx") are intensive margin outcomes and the indicator of the patient's SSRI use ("SSRI use") is an extensive margin outcome. Each observation is weighted by the number of individuals represented (benzodiazepine patients for the intensive margin outcomes and municipality population size for the extensive margin outcome). Fixed effects for municipalities and half-years 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 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				
Short run	-0.0032	0.0001	0.0001	-0.0002
	(0.0034)	(0.0001)	(0.0001)	(0.0005)
Long run	-0.0002	0.0001	0.0002	0.0003
	(0.0044)	(0.0001)	(0.0001)	(0.0010)
Mean outcome	0.0601	0.0015	0.0023	0.0107
Panel B. Ages < 40				
Short run	-0.0070	0.0005	0.0004*	0.0001
	(0.0079)	(0.0005)	(0.0002)	(0.0002)
Long run	0.0001	0.0008	0.0008***	0.0001
	(0.0096)	(0.0005)	(0.0003)	(0.0004)
Mean outcome	0.1027	0.0051	0.0049	0.0028
Panel C. Ages ≥ 40				
Short run	-0.0020	-0.0000	0.0000	-0.0002
	(0.0022)	(0.0000)	(0.0001)	(0.0007)
Long run	-0.0000	-0.0000	0.0001	0.0003
	(0.0032)	(0.0001)	(0.0002)	(0.0011)
Mean outcome	0.0483	0.0005	0.0016	0.0129
Observations	4,864	4,864	4,864	4,864

Notes: Each column shows parameter estimates from a separate regression using municipality biannual-level balanced data for benzodiazepine patients. Each outcome is the share of patients with a specific diagnosis depicted in the column title during a half-year period. Additionally, 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."Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years 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 A8: Placebo Regressions: Effects of E-Prescribing on Benzodiazepine Patients' Appendix Disease Diagnosis

	All Ages (1)	Ages < 40 (2)	Age ≥ 40 (3)
Short run	0.0000	0.0001	0.0000
	(0.0000)	(0.0001)	(0.0000)
Long run	0.0001	0.0001	0.0000
	(0.0001)	(0.0002)	(0.0001)
Mean outcome	0.0007	0.0012	0.0006
Observations	4,864	4,864	4,864

Notes: Each column shows parameter estimates from a separate regression using aggregated municipality biannual-level balanced data. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years 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.

A.5 Potential Bias in Staggered Adoption: Goodman-Bacon Decomposition and Alternative Estimators

Goodman-Bacon (2021) shows that, in the case of a staggered adoption where the treatment occurs at different times across units, the two-way fixed effects (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 control groups *before* the treatment for patients in early-treated municipalities, and patients in early-treated municipalities *after* the treatment are used as control groups for later-treated municipalities. This is potentially worrisome for the estimation of treatment effects for later-treated municipalities in the case of varying treatment effect. The feature could induce negative weights for later-treated groups as these units are compared to already-treated units, potentially biasing the DiD estimates away from the true sign of the estimates. To mitigate these concerns, we conduct two additional robustness checks.

First, as described in the main text, we estimate the DiD regressions for the main 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 to mitigate potential bias in the DiD estimates as some of the later versus early comparisons are dropped. The downside of this approach 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. In our case, as the effects are larger in the long run, this approach is likely to increase the imprecision of the long-run estimates and bias them towards zero. As expected and shown in Appendix Tables A4 and A5, the point estimates are slightly smaller for most of the outcomes. However, the conclusions remain the same as in our baseline analysis.

Second, we follow Goodman-Bacon (2021) and perform an explicit decomposition of the summed weights and average DiD estimates for early- versus later-treated groups and later- versus early-treated groups.[26] This way we can see how much bias is accounted for in the overall DiD estimate for the later-treated group. The shortcoming of this approach is that as such it does not allow us to separate the treatment effect to the short- and long-run effects as in our main analysis. Also, the approach does not allow for weights within the regressions when doing the full decomposition. Thus, the estimates are not fully comparable to our baseline estimates obtained using population weights and municipal biannual-level data, but the results should give an idea of whether using

[26] To accomplish this in practice, we use the *bacondecomp* package available in R and Stata.

early-treated units as a control group is worrisome in our setting.

The results for the municipality-level DiD estimates and the decompositions underlying them are shown in Tables A9, and A10. Based on these decompositions, we conclude that negative weighting is not an issue, as the estimates for earlier vs. later are very similar to later vs. earlier for most outcomes. This is especially the case for our main outcomes on medication (DDDs) and health (death, hospital visits, PDA diagnosis). Thus, albeit not fully comparable, our conclusions about the effects of e-prescribing based on these alternative treatment groups and aggregated data remain fairly similar to those drawn from our baseline estimates using population weights and municipal biannual-level data.

We also use the DiD estimator proposed by de Chaisemartin and D'Haultfœuille (2020) to evaluate the robustness of our baseline results to treatment effect heterogeneity over municipalities and time in the case of a staggered adoption. In this alternative approach, late-treated municipalities act as "clean controls" and we only use data for periods before the last-treated municipalities adopted e-prescribing (H1:2007-H2:2012). We use data before the last municipality becomes treated (in 2013) and also exclude the last periods for the first adopter (the municipality of Turku). Thus, only one normalization is needed for this event study specification in contrast to the baseline specification based on two normalizations. The event study coefficients based on the de Chaisemartin and D'Haultfœuille (2020) estimator are reported in Figures A6-9 below. For comparability, we also report in these figures our baseline two-way fixed effects (TWFE) estimates using the same time period.

Figure A6 shows that at the intensive margin there is an increase in the use of benzodiazepines both on average and for younger patients based on both estimators, although the effects are somewhat more imprecisely estimated using the de Chaisemartin and D'Haultfœuille (2020) estimator. At the extensive margin, the estimates are very similar for the two approaches, although small in quantitative magnitude and mostly insignificant (see Figure A7). For the general health outcomes reported in Figure A8, the estimates are mostly insignificant and again very similar for the two approaches. Finally, for the selected adverse health outcomes reported in Figure A9, the estimates obtained using TWFE and the de Chaisemartin and D'Haultfœuille (2020) estimator are again almost identical. Note that we do not find significant impact for prescription drug poisonings in the short run using the de Chaisemartin and D'Haultfœuille (2020) estimator, but this finding also prevails when based on the TWFE estimator.

TABLE A9: Goodman-Bacon Decomposition of Equally Weighted TWFE Estimates of Benzodiazepine Use

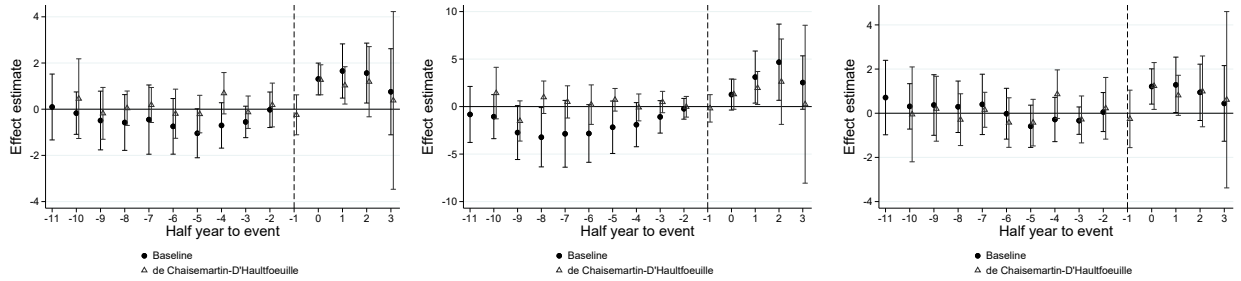
	Intensive margin				Extensive margin	
	DDDs (1)		Number of rx (2)		Benzo use (3)	
	Est.	Weight	Est.	Weight	Est.	Weight
Panel A. All ages						
Earlier vs later	1.5063	0.6830	-0.0146	0.6830	-0.0018	0.6830
Later vs earlier	1.6862	0.3170	-0.0137	0.3170	-0.0017	0.3170
Average TWFE	1.5633		-0.0143		-0.0018	
Mean outcome	57.9907		0.6703		0.1155	
Panel B. Age < 40						
Earlier vs later	2.9421	0.6830	0.0159	0.6830	-0.0001	0.6830
Later vs earlier	3.4982	0.3170	0.0190	0.3170	0.0016	0.3170
Average TWFE	3.1183		0.0169		0.0004	
Mean outcome	26.4007		0.3844		0.0253	
Panel B. Age ≥ 40						
Earlier vs later	1.3217	0.6830	-0.0176	0.6830	-0.0030	0.6830
Later vs earlier	1.5350	0.3170	-0.0182	0.3170	-0.0043	0.3170
Average TWFE	1.3893		-0.0178		-0.0034	
Mean outcome	63.6324		0.7206		0.1789	
Observations	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). Panel A shows the results for all ages, Panel B for age group under 40 and Panel C for age group 40 and older. Fixed effects for municipalities and half-years 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 A10: 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)	
height	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight	Est.	Weight
Panel A. All ages														
Earlier vs later	0.0001	0.6830	-0.0192	0.6830	-0.0544	0.6830	-0.0010	0.6830	0.0001	0.6830	0.0001	0.6830	-0.0000	0.6830
Later vs earlier	0.0001	0.3170	-0.0121	0.3170	-0.0460	0.3170	-0.0009	0.3170	0.0000	0.3170	-0.0001	0.3170	-0.0011	0.3170
Average TWFE	0.0001		-0.0170		-0.0517		-0.0010		0.0000		0.0000		-0.0004	
Mean outcome	0.0131		0.3841		1.6421		0.0542		0.0009		0.0019		0.0123	
Panel B. Age < 40														
Earlier vs later	0.0000	0.6830	-0.0273	0.6830	-0.0864	0.6830	0.0029	0.6830	0.0004	0.6830	0.0000	0.6830	-0.0001	0.6830
Later vs earlier	0.0001	0.3170	0.0236	0.3170	-0.0294	0.3170	-0.0016	0.3170	0.0003	0.3170	0.0001	0.3170	-0.0007	0.3170
Average TWFE	0.0001		-0.0112		-0.0684		0.0014		0.0004		0.0001		-0.0003	
Mean outcome	0.0013		0.3560		1.8208		0.1002		0.0037		0.0045		0.0032	
Panel B. Age ≥ 40														
Earlier vs later	0.0001	0.6830	-0.0178	0.6830	-0.0500	0.6830	-0.0016	0.6830	-0.0000	0.6830	0.0001	0.6830	-0.0000	0.6830
Later vs earlier	0.0002	0.3170	-0.0174	0.3170	-0.0437	0.3170	-0.0008	0.3170	-0.0000	0.3170	-0.0001	0.3170	-0.0012	0.3170
Average TWFE	0.0001		-0.0176		-0.0480		-0.0013		-0.0000		0.0000		-0.0004	
Mean outcome	0.0151	0.3886	1.6105	0.0459	0.0003	0.0014	0.0139							
Observations	4,864	4,864	4,864		4,864	4,864	4,864	4,864						

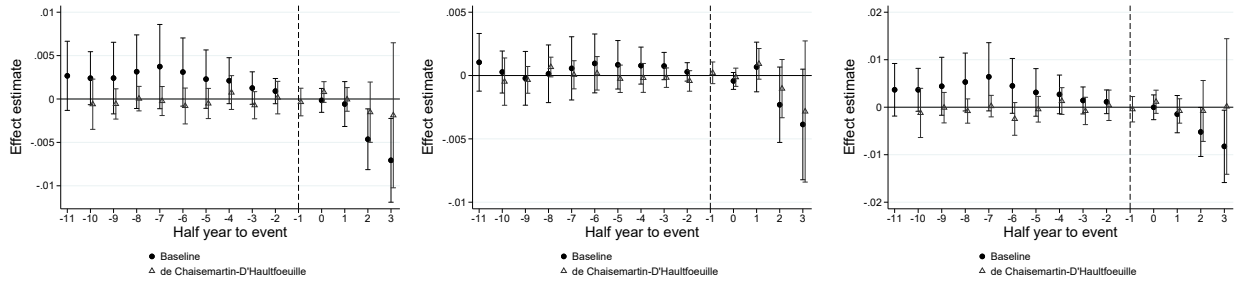
Notes: Each model shows a Goodman-Bacon decomposition of two-way fixed effects (TWFE) estimates from a separate regression using aggregated municipality biannual-level balanced data. In TWFE, each observation is weighted equally (currently, the method does not allow for population weighting). Panel A shows the results for all ages, Panel B for age group under 40 and Panel C for age group 40 and older. Fixed effects for municipalities and half-years 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.



(A) DDDs, All ages (B) DDDs, Age < 40. (C) DDDs, Ages ≥ 40

FIGURE A6: Robustness to Treatment Effect Heterogeneity at Intensive Margin: Number of Defined Daily Doses

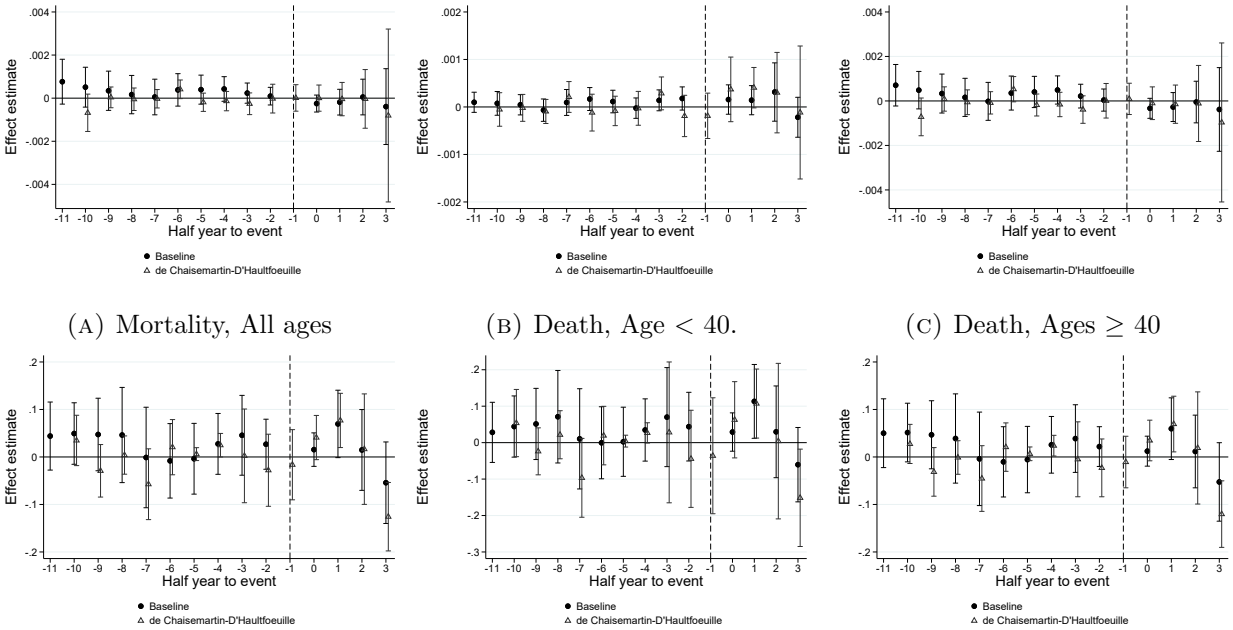
Note: The figures plot the baseline two-way fixed effects (TWFE) and de Chaisemartin and D'Haultfœuille (2020) estimates from event study regressions using aggregated municipality biannual-level balanced data for periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). We normalize TWFE coefficients for the two relative time periods to zero (-1 and -12), corresponding to the baseline specification in the main text. In the de Chaisemartin and D'Haultfœuille (2020) specification, we only normalize coefficients for one relative time period to zero (-1). Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.



(A) Benzo use, All ages (B) Benzo use, Age < 40 (C) Benzo use, Ages ≥ 40

FIGURE A7: Robustness to Treatment Effect Heterogeneity at Extensive Margin: Benzodiazepine Use

Note: The figures plot the baseline two-way fixed effects (TWFE) and de Chaisemartin and D'Haultfœuille (2020) estimates from event study regressions using aggregated municipality biannual-level balanced data for periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). We normalize TWFE coefficients for the two relative time periods to zero (-1 and -12), corresponding to the baseline specification in the main text. In the de Chaisemartin and D'Haultfœuille (2020) specification, we only normalize coefficients for one relative time period to zero (-1). Each observation is weighted by the municipality population. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.

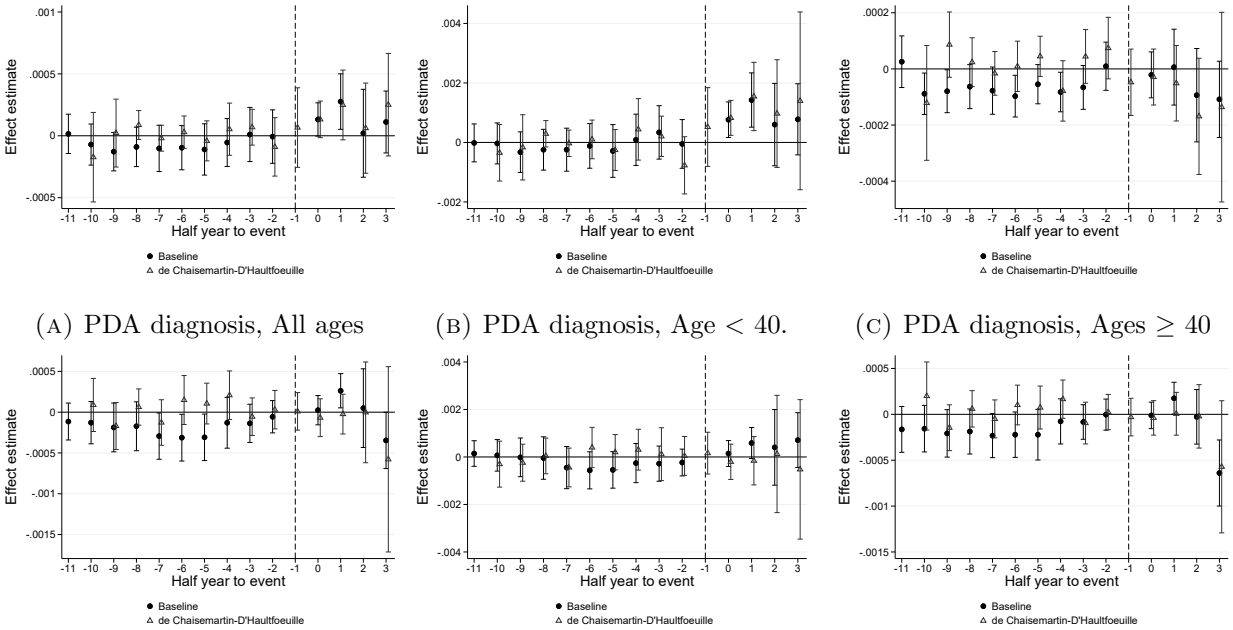


(A) Mortality, All ages (B) Death, Age < 40. (C) Death, Ages ≥ 40

(D) Emergency, All ages (E) ED visits, Age < 40. (F) ED visits, Ages ≥ 40

FIGURE A8: Robustness to Treatment Effect Heterogeneity: General Health Outcomes

Note: The figures plot the baseline two-way fixed effects (TWFE) and de Chaisemartin and D'Haultfœuille (2020) estimates from event study regressions using aggregated municipality biannual-level balanced data for periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). We normalize TWFE coefficients for the two relative time periods to zero (-1 and -12), corresponding to the baseline specification in the main text. In the de Chaisemartin and D'Haultfœuille (2020) specification, we only normalize coefficients for one relative time period to zero (-1). Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.



(A) PDA diagnosis, All ages (B) PDA diagnosis, Age < 40. (C) PDA diagnosis, Ages ≥ 40

(D) Rx poisoning, All ages (E) Rx poisoning, Age < 40. (F) Rx poisoning, Ages ≥ 40

FIGURE A9: Robustness to Treatment Effect Heterogeneity: Selected Adverse Health Outcomes

Notes: The figures plot the baseline two-way fixed effects (TWFE) and de Chaisemartin and D'Haultfœuille (2020) estimates from event study regressions using aggregated municipality biannual-level balanced data for periods when the last-treated municipalities have not yet adopted e-prescribing (H1:2007-H2:2012). We normalize TWFE coefficients for the two relative time periods to zero (-1 and -12), corresponding to the baseline specification in the main text. In the de Chaisemartin and D'Haultfœuille (2020) specification, we only normalize coefficients for one relative time period to zero (-1). Each observation is weighted by the number of benzodiazepine patients. Fixed effects for municipalities and half-years are included in all models. Standard errors are clustered at the municipality level.