# INFORMATION TECHNOLOGY, IMPROVED ACCESS, AND USE OF PRESCRIPTION DRUGS

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**Abstract**
We estimate the effects of health information technology designed to improve access to medication while limiting overuse through easier prescription renewal and improved information provision. We focus on benzodiazepines, a commonly prescribed class of mental health and insomnia medications, which are highly effective but potentially addictive. We study the staggered rollout of a nationwide electronic prescribing system over four years in Finland and use population-wide, individual-level administrative data sets. We find that e-prescribing increases average benzodiazepine use due to increased prescription renewals. The increase is most pronounced for younger patients. E-prescribing can improve the health of elderly patients and may help to balance the access-overuse trade-off. Without additional monitoring for addiction in place, it may, however, also have unintended health consequences for younger patients, who are more likely to develop mental and behavioral health disorders. (JEL: H51, H75, I12, I18)

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## 1. Introduction

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

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

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

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

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during 2007–2014. Using a difference-in-differences (DiD) strategy, we estimate the effects of the access-improving technology on benzodiazepine use and downstream health outcomes.

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

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

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

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

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

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

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

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

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

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

## 2. Institutional Background

### *2.1. Finnish Health Care System*

Finland has a decentralized, tax-financed health care system, in which the National Health Insurance Scheme (NHI) covers all Finnish residents. The public

sector overwhelmingly dominates the provision of health care services.[4] By law, municipalities ($N = 304$ in 2014) are responsible for organizing primary care for their residents at the local level. Each municipality also belongs to one of the 20 hospital districts that organize specialized (hospital) health care. The resources for public sector health care services are rationed and waiting times are typically long (Keskimäki et al. 2019).

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

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

### *2.2. Mechanisms Related to E-prescribing*

E-prescribing is widely used but understudied health information technology that digitizes prescriptions and transfers information between physicians and pharmacies and allows them to electronically request prescription renewals.[5] Below, we describe the key mechanisms through which interoperable nationwide e-prescribing systems can affect prescription drug use and downstream health outcomes.

*2.2.1. E-prescribing and Access.* E-prescribing systems can improve medication access by making it easier for patients to renew their existing prescriptions. Before

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

5. A renewal is the generation of a new prescription based on a previous prescription. Prescriptions can be renewed without an in-person physician visit and e-prescribing made this much easier. In some countries, patients can also electronically request prescription refills. This means that they can order a new supply of medication without an in-person physician visit for an existing prescription. When a prescription has expired or has no medication or refills left, it has to be renewed. In Finland, patients can renew, but not refill, prescriptions.

e-prescribing, a patient had to deliver an existing paper prescription at a health care unit or pharmacy for prescription renewals and renewed prescriptions were transferred between physicians and pharmacies, for example, by fax or mail.

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

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

*2.2.2. E-prescribing and Information.* Interoperable nationwide e-prescribing systems also improve the exchange of prescription information both within and across provider organizations. In contrast to providers' pre-existing incompatible and incomplete health information (such as EMR) systems, the nationwide e-prescribing system provides physicians with access to a patient's complete e-prescription history.[7] Thus, the system reduces the likelihood of a physician not knowing about the patient's previous prescriptions. The benefit of improved information can, however, be relatively small in the first year after the adoption of the e-prescribing system, because the system

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

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

only includes information on the e-prescription history and it takes time for the e-prescription data to accumulate in the system.

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

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

### *2.3. Staggered Adoption of Nationwide E-prescribing System*

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

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

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

9. The Finnish law enacted on April 2014 made it possible for physicians to access information on prescriptions for central nervous system drugs without a patient's permission. In practice, physicians were obligated to act in accordance with the law from November 1, 2015 onward, which is outside of our observation period.

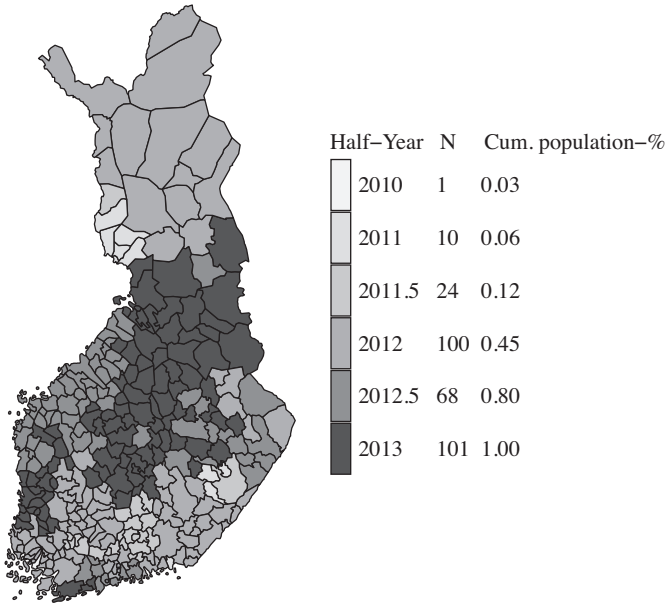



FIGURE 1. E-prescribing adoption half-year in municipalities. The figure plots the half-year when e-prescribing was adopted by a municipality in the primary care setting. The figure also shows the number of municipalities and the cumulative population share by adoption half-year. Source: Finnish Institute for Health and Welfare, and Statistics Finland: Population Statistics.

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

According to our government expert interviews, the regional variation in the adoption time was driven mainly by difficulties in integrating the e-prescribing system with the pre-existing information technology systems in local health care units, not by regional differences in patient outcomes. The adoption was gradual across municipalities, because the implementation of a national and fully standardized system required substantial investments in information technology infrastructure, tailoring

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

software, and a skilled workforce in each municipality. To support the findings from the government expert interviews and the credibility of our research design, Böckerman et al. (2023) show that the adoption time is unrelated to municipality-level covariates such as measures of prescription drug use and morbidity in the pre-adoption period.

### *2.4. Benzodiazepine Market*

Benzodiazepines are one of the most widely used psychotropics in high-income countries (Olfson, King, and Schoenbaum 2015). They are commonly used in the adult population to treat mental health disorders and insomnia. In Finland, the top five active ingredients (benzodiazepine drugs) based on 2014 sales measured in euros were alprazolam (e.g. Xanax), diazepam (e.g. international brand name Valium), oxazepam (e.g. Serax), temazepam (e.g. Restoril), and zopiclone (e.g. Imovane) (Fimea 2015).[11] Notably, nearly 10% of all Finnish adults had used benzodiazepines in 2014 (Kurko et al. 2018). For comparison, the prevalence of benzodiazepine use within a year has reached 20% in France (Airagnes et al. 2019), approximately 10% in Norway (Holm et al. 2012), and 5% for U.S. adults (Olfson, King, and Schoenbaum 2015).

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

Health harms through adverse drug effects indicate medication overuse. Benzodiazepines may cause sedation, a decline in cognitive functions and delirium (Lader 2011). Benzodiazepine poisoning is characterized by excessive sedation for example, and may result after an overdose and the use of medication in large amounts. Moreover, long-term use of benzodiazepines may lead to physical dependence and abuse, with strong withdrawal symptoms and increased tolerance over time (Lader 2011; Votaw et al. 2019). Clinical treatment guidelines generally recommend not using benzodiazepines for more than 2–4 weeks (FCCG 2020). Despite these guidelines and health harms, long-term use of benzodiazepines is common in Finland (Kurko et al. 2018) and generally in Europe (Huerta et al. 2016).

Because mental and behavioral health disorders are on the rise globally, benzodiazepines are a relevant drug class for studying how a public policy of health information technology adoption succeeds in balancing the access-overuse trade-off in medical services. Misuse of benzodiazepines is prevalent in Europe and the U.S., and these medications are commonly involved in poisonings, overdose deaths, and emergency department visits related to non-medical misuse of prescription drugs

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

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

(Jones and McAninch 2015), especially when combined with alcohol and opioids.[13] However, research on medication misuse has mostly focused on the opioid epidemic in the U.S. and policies such as the adoption of information technologies aimed at curbing it (Buchmueller and Carey 2018; Ellyson, Grooms, and Ortega 2022; Maclean et al. 2022).

Notably, global consumption of opioids is concentrated in the U.S. (Organisation for Economic Cooperation and Development (OECD) (2019). In Finland, opioid prescribing is heavily regulated and opioid consumption is much smaller compared with benzodiazepines (Fimea 2015). More generally, less focus has been placed on other important potentially addictive psychotropics such as benzodiazepines, their impact in countries other than the U.S., and the role of access-improving policies in causing the overuse or misuse of these medications.

## 3. Data

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

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

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

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

### *3.1. Measures for Benzodiazepine Use*

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

We identify individual prescriptions based on the unique patient and physician identifiers, the ATC code (active ingredient), and the prescription date. We define a prescription as renewed if the prescribed drug is essentially the same as the two previous prescriptions with the same ATC code, strength, and adminstrative route, and the renewal is made within 16 months (renewal of an electronic prescription for benzodiazepines must be requested within this time period in Finland). If a prescription is not renewed, we define it as new. Our results are robust to the exclusion of the 16-month interval rule (Section 6.3).[17]

We measure the effects of e-prescribing at the intensive margin of benzodiazepine use, that is, the total amount (duration) of medication use per patient. However, this measurement is challenging because the amount of a medication needed to produce a given effect varies across benzodiazepine drugs. For example, 15 mg of diazepam is approximately equivalent to 3 mg of lorazepam, according to the national treatment guidelines (FCCG 2020). To address this challenge, we use the WHO's DDD measure. DDD is defined as the assumed average maintenance dose per day of a drug used for its main indication in adults, providing us with a standardized unit of measurement for different types of benzodiazepines. We calculate the number of dispensed DDDs of benzodiazepine prescriptions, which is our primary measure of benzodiazepine use at the intensive margin.

We also calculate the number of dispensed prescriptions. In contrast to the number of dispensed DDDs, this measure is rather coarse because it does not capture changes in an important aspect of medication use at the intensive margin: the total amount of medication use.[18] We calculate these two measures separately for renewed and new prescriptions. To better understand the adjustment at the intensive margin, we also

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

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

18. For example, assume that a patient fills one prescription at a pharmacy (the number of prescriptions is one). If the prescription contains one tablet of 5 mg diazepam to be taken three times a day for 5 days, the actual daily dose is 15 mg (3 is multiplied by 5 mg). As the theoretical DDD of the drug per day is 10 mg, then each day we have 1.5 DDDs per day (= 15 mg/10 mg). In total, the number of DDDs dispensed is

use additional outcomes such as those related to the long-term use of benzodiazepines (Section 6.1).

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

### *3.2. Measures for Patient Health Outcomes*

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

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

In addition to these general and mental health outcomes, we construct proxies for health harms from adverse drug effects and medication overuse. We calculate the indicators of the diagnoses of prescription drug abuse (PDA) disorder and prescription

7.5 DDDs (5 days multiplied by 1.5 DDDs), corresponding to 7.5 days of *theoretical* use (10 mg per day). The number of DDDs also reflects the *actual* duration of medication use (5 days) as well as its relative amount (daily dose intensity of medical therapy), that is, the ratio of actual to theoretical daily dose (15 mg/10 mg).

drug poisoning for hospitalizations. Prescription drug poisoning may result from an unintentional or intentional overdose. Prescription drug abuse is more specifically related to physical dependence and can be prevented by investigating patients' prescription histories (NIDA 2023). Although hospitalizations for prescription drug poisonings and abuse might not be exclusively attributed to benzodiazepine use,[19] both are positively correlated with the number of DDDs of benzodiazepine prescriptions (Online Appendix Figure B.1). We supplement these two measures with an indicator of hospitalization with a diagnosis of other possible side effects of benzodiazepines, such as sedation, poor coordination, and cognitive function decline.

## 4. Evidence on Prescribing and Health Patterns

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

Panel C shows benzodiazepine patients' health patterns. Patient mortality is 16% on average. As expected, mortality is much higher for older patients (Online Appendix Table B.1), which is likely most directly related to pain treatment in palliative care as opposed to mental health care. Moreover, 26% of benzodiazepine patients receive hospital diagnoses of mental disorders at least once during the observation period. Panel D shows that the average age of benzodiazepine patients is only a little higher (55 years) than the average age of the general Finnish adult population (49 years).[21]

*Age Heterogeneity.* We study differences in the use of benzodiazepines and downstream health outcomes in the different age groups. Figure 2 documents the

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

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

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

TABLE 1. Summary statistics for overall outcomes among benzodiazepine patients and all Finnish adults.

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

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

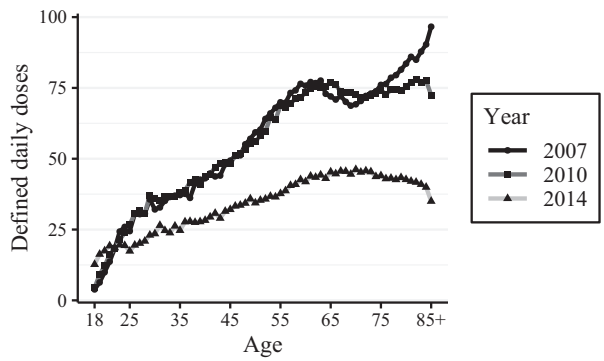



FIGURE 2. Yearly benzodiazepine use-age relationships at intensive margin: Number of defined daily doses. The figure is based on aggregated patient biannual-level panel data. The mean number of defined daily doses is calculated for each year (2007, 2010, and 2014).

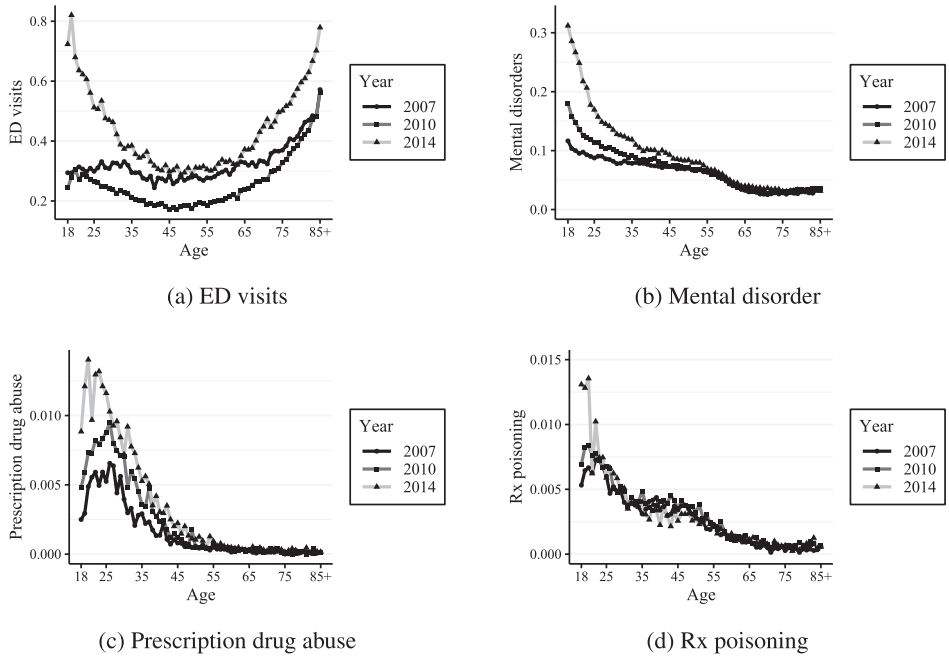



FIGURE 3. Yearly health outcome-age relationships among benzodiazepine patients. The figures are based on aggregated patient biannual-level panel data. The mean number of emergency department visits (panel a) and the probability of a hospital diagnosis (panels b–d) are calculated for each year (2007, 2010, and 2014). "Mental disorder" refers to the diagnosis of mental and behavioral disorders. "Rx poisoning" refers to prescription drug poisoning.

flexible age profiles for our main measure of benzodiazepine use at the intensive margin: the mean biannual number of dispensed DDDs per patient and by age for three years (2007, 2010, and 2014) to detect possible changes in consumption patterns over time before and after the e-prescribing rollout (Online Appendix Figure B.2 shows the profile for the number of prescriptions).

Figure 2 shows that the use of benzodiazepines, as measured by the number of DDDs, is more concentrated among older patients, consistent with earlier findings (Olfson, King, and Schoenbaum 2015). For patients above age 55, there also was a substantial decrease in the use of benzodiazepines between 2010 and 2014, the two years between which e-prescribing was rolled out. A decline in long–term benzodiazepine use has also been documented in previous research in Finland (Kurko et al. 2018). Prescribing behavior for benzodiazepines has evolved over time, and that could be because of changes to mental health prescribing practices. However, Figure 2 also shows that the decrease in benzodiazepine use was much smaller among younger patients. In fact, we find that for those aged under 20, the number of DDDs increased over time.

Figure 3 documents the age profiles for the selected adverse health outcomes and shows that younger patients have much higher rates of hospitalizations for mental and

behavioral disorders, PDA, and prescription drug poisoning than other age groups (panels B–D). Moreover, younger patients (under 40 years of age) also experienced a substantial increase in the prevalence of these adverse health outcomes and the number of emergency department visits from 2007 to 2014. Emergency department visits increased also for elderly patients (age over 65), but not as much as for younger adults.

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

## 5. Empirical Approach and Identification

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

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

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

where $y_{imt}$ is a benzodiazepine-related outcome such as the number of DDDs for individual $i$ in municipality $m$ at time $t$ (a period of 6 months). $t - E_m$ denotes the half-year periods relative to the time period of adopting e-prescribing in the individual's municipality of residence $m$, $E_m$, and $\mathbb{1}[t - E_m \geq 0]$ denotes the post-adoption indicator. We include individual and time fixed effects, $\alpha_i$ and $\gamma_t$, to control for individual- and time-specific factors such gender, age, and general trends in prescribing behavior.[23] We cluster the standard errors at the municipality level ($N = 304$).

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

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

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

where the negative values of $k$ indicate the pre-adoption periods and the positive values indicate the post-adoption periods. The coefficients $\delta_k$ for the pre-adoption periods $k < 0$ capture a possible pre-existing trend in the outcome variable, while the coefficients $\delta_k$ for the post-adoption periods $k \geq 0$ represent the period-specific dynamic effects of e-prescribing on the outcome. We normalize the coefficient for the indicator one period before adoption to zero, $\delta_{-1} = 0$. When there are no never-treated units in the sample, two relative time coefficients have to be normalized to avoid multicollinearity between $t$ and $E_i$ (Borusyak, Jaravel, and Spiess 2024). Hence, in addition to $\delta_{-1} = 0$, we normalize the coefficient for the most negative (minimum) relative time indicator to zero, $\delta_{-5} = 0$, so that the coefficients for the relative time indicators can be interpreted as the mean differences from the average values of the outcomes in two specific relative periods ($-1$ and $-5$) prior to the treatment (Baker, Larcker, and Wang 2022).[24]

Following Sun and Abraham (2021), we trim the event study graphs by analyzing the data up to five relative time periods prior to the adoption ($k = -5$) and three periods

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

24. Binning the endpoints in the event study is an alternative approach to dropping an additional pre-treatment indicator (Borusyak, Jaravel, and Spiess 2024; Schmidheiny and Siegloch 2024).

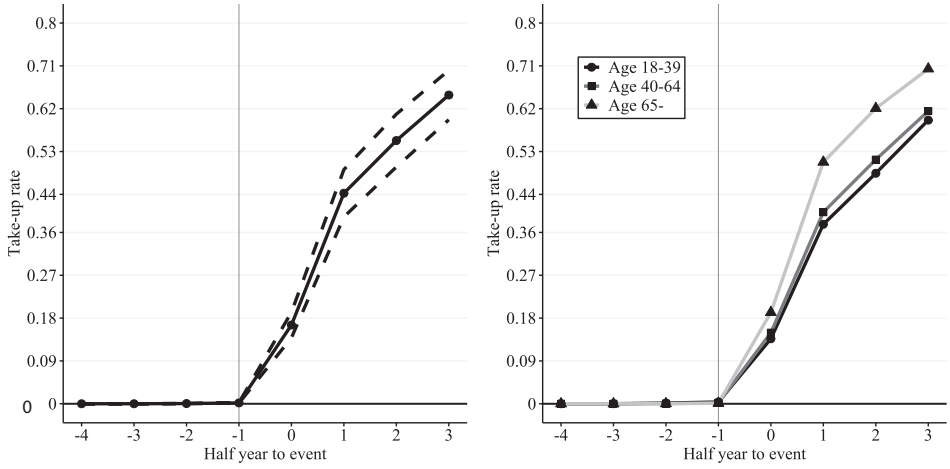
after the adoption ($k = 3$), since our data are unbalanced in relative time for some treatment units. Following a fairly balanced set of municipalities over time around the adoption mitigates changes in the composition of municipalities in distant periods and the effect of individual municipalities (early- and late-treated municipalities) on the event study coefficients.[25]

*Potential Biases in TWFE models and Robustness for Treatment Effect Heterogeneity.* Although the TWFE regression similar to the one in equation (1) is the workhorse model in the staggered DiD settings, it is not guaranteed to be a consistent estimator without a relatively strong assumption about the constant treatment effect (de Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024). Specifically, if the treatment effect varies over time, negative weights could arise for later-treated units, potentially biasing the average treatment effect estimate downward or upward (Goodman-Bacon 2021; Baker, Larcker, and Wang 2022). We address the concerns regarding potential negative weights by performing robustness checks and conclude that negative weighting is not an issue in our application (Section 6.3). We also address the concerns about the reliability (and precision) of the TWFE estimator by employing the efficient estimator proposed by Roth and Sant'Anna (2023). Besides being efficient and robust for treatment effect heterogeneity, the estimator is computationally less demanding than many other heterogeneity-robust estimators in our application based on large individual-level data sets containing millions of observations.[26]

*Take-up of E-prescriptions.* The estimated ITT effect of the e-prescribing policy may underestimate the average treatment effect on treated (ATT) because the take-up of the new technology by individuals was voluntary. Fortunately, we can use our prescription-level data to study the take-up rate of e-prescriptions by individual patients or their physicians after the patients' municipality of residence adopted e-prescribing in primary care. Figure 4 shows that the take-up rate increases sharply after adoption (panel a): 1 year after adoption, approximately 50% of benzodiazepine prescriptions are issued electronically, after which the number grows gradually to around 60%–70%. The take-up rate is also very similar in the three age groups, with only a slightly higher take-up among the elderly patients (panel b). We conclude that low take-up rates or differences in take-up rates across age groups are unlikely to explain our findings.

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

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




(a) All patients (b) By age group

FIGURE 4. Conditional take-up rate of e-prescriptions. The figures plot the coefficient estimates from different event study regressions using prescription-level data. Panel (a) shows the results for all ages and panel (b) by age group (18–39, 40–64, and at least 65 years old). The outcome is a binary variable equal to one if the benzodiazepine prescription is issued electronically. Event time is the biannual period relative to the period of e-prescribing adoption by the patient's municipality of residence. The omitted period is −1. The regressions include only event dummies and do not use any additional controls. The dashed lines (panel a) are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

## 6. Results

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

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

TABLE 2. Effects of e-prescribing on intensive margin of benzodiazepine use.

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

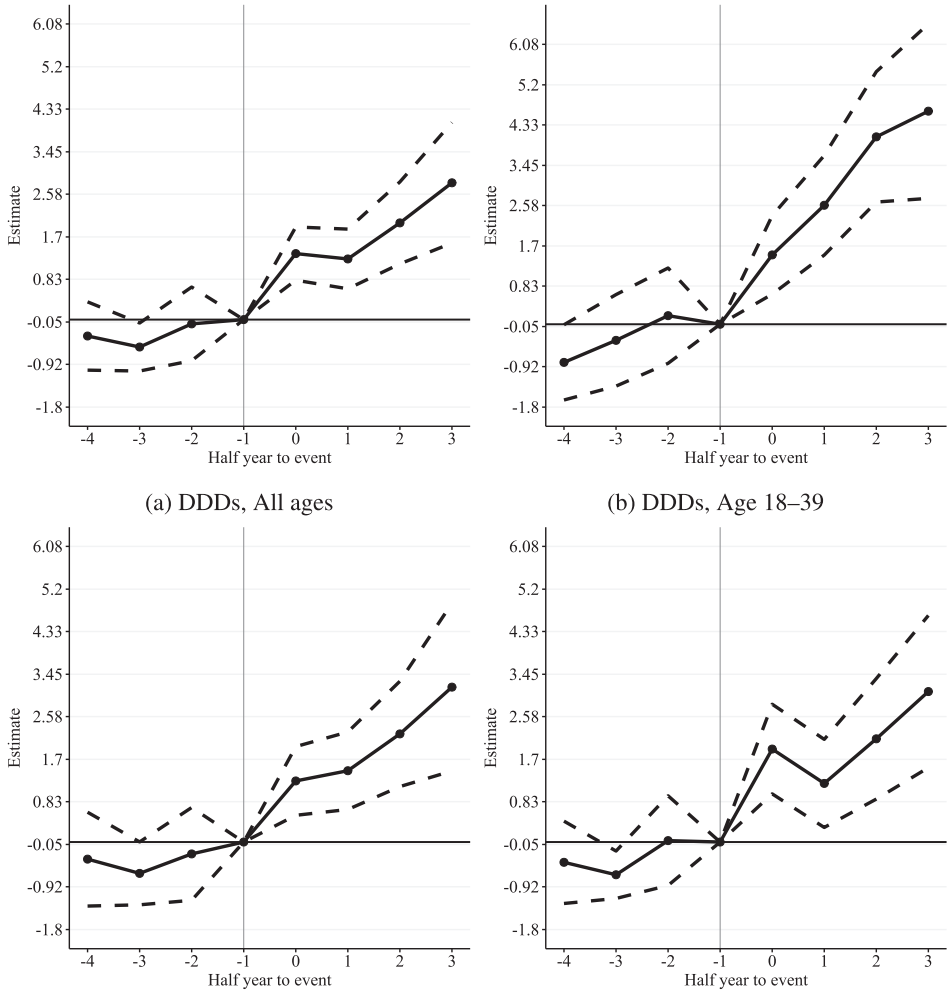
Notes: Each column shows parameter estimates from a separate regression using aggregated patient biannual-level panel data. Panel A shows the results for all ages, panel B for the age group under 18–39, panel C for the age group 40–64, and panel D for the age group 65 and older. Each regression controls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

### 6.1. *Effects on Prescription Drug Use*

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

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

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




(a) DDDs, All ages

(b) DDDs, Age 18–39

(c) DDDs, 40–64

(d) DDDs, Over 65

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

e-prescribing over time (Figure 4). Importantly, they show little evidence of deviations from the parallel trends assumption.

*6.1.2. Mechanism: Improved Access through Easier Renewal.* Consistent with e-prescribing improving access to medication through easier renewal, we find that the

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

*6.1.3. Number of Prescriptions at the Intensive Margin.* Next, we present the results on the alternative measure of benzodiazepine use at the intensive margin: the number of prescriptions per patient. We find that the number of prescriptions increases gradually over time for younger patients, with an increase of 4% 1 year after the adoption (Online Appendix Figure B.4). The corresponding DiD estimate is, however, statistically insignificant, ruling out an effect larger than 3% based on the 95% confidence intervals (column (4) of Table 2). For the elderly patients, the estimated effect is negative (2%) and statistically significant despite the increase in the number of DDDs. Next, we study changes in individual prescriptions to explain these patterns and to provide more comprehensive evidence of the effects of e-prescribing.

*6.1.4. Long-term Use and Prescribing Interval Using Prescription-level Data.* In Online Appendix Table B.2, we present additional results on the long-term use of benzodiazepines and prescribing interval, using raw prescription-level data. We follow Kurko et al. (2015) and the definition used by the WHO (1996) and define long-term use of benzodiazepines as at least 6 months' theoretical use (180 dispensed DDDs) and at least two separate drug purchases dispensed at a pharmacy per prescription. Along with a high number of DDDs, multiple purchases per prescription indicate long-term use and the need for additional doses of benzodiazepines, despite potential health harms.

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

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

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

*6.1.5. Extensive Margin Adjustment.* E-prescribing can also lead to adjustments at the extensive margin of benzodiazepine use through the information channel (Section 2.2); improved information on the patient's prescription history of other drugs than benzodiazepines might help the physician to learn about the potential harms (benefits) of benzodiazepines, and thus negatively (positively) impact the physician's decision to initiate benzodiazepine treatment. We combine our prescription data with the entire Finnish adult population data, including also all individuals who did not have a benzodiazepine prescription during the observation period, to study the potential effects on benzodiazepine use and first-time use at the extensive margin. This type of analysis, only rarely conducted at the individual level in the literature because of data limitations, complements our intensive margin results by using comprehensive individual-level data on benzodiazepine users and non-users who potentially become first-time users.

We find that benzodiazepine use increases by 2% in the younger Finnish adult population; however, the point estimate for first-time use is statistically insignificant. For the elderly, the extensive margin point estimates are negative, statistically insignificant and are small in magnitude (decreases of less than 1%). (Table 3 and Online Appendix Figures B.5 and B.6.)

### *6.2. Effects on Health Outcomes*

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

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

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

TABLE 3. Effects of e-prescribing on extensive margin of benzodiazepine use (multiplied by 100).

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

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

TABLE 4. Effects of e-prescribing on benzodiazepine patients' health outcomes (multiplied by 100).

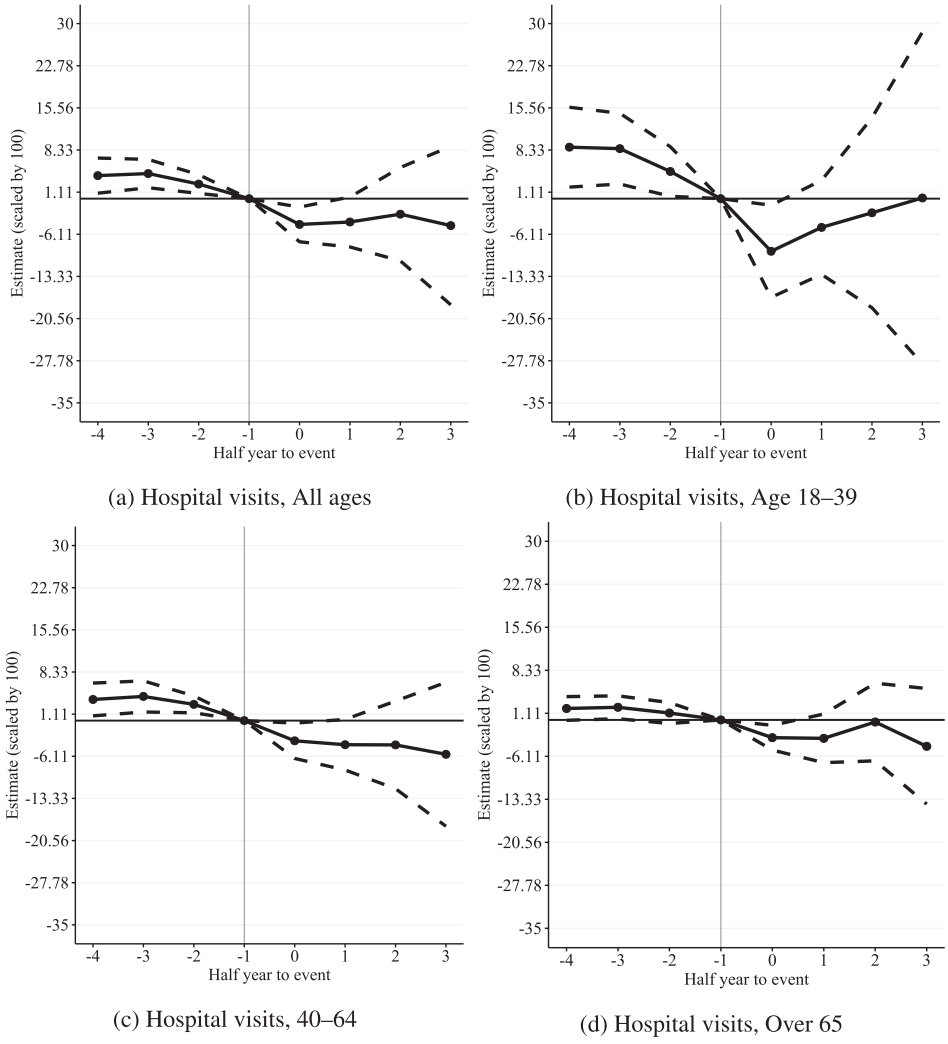
| | ED visits (1) | Hospital visits (2) | Mental disorder (3) | PDA diagnosis (4) | Rx poisoning (5) | Other side effects (6) |
|---|---|---|---|---|---|---|
| *Panel A. All ages* | | | | | | |
| Post-adoption | −0.517 | −6.103** | −0.327 | 0.010 | 0.015* | −0.008 |
| | (2.142) | (2.594) | (0.329) |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

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

insignificant (Online Appendix Figure B.8), similar to the results for most of the other general health outcomes.[32]

*6.2.2. Health Harms from Adverse Drug Effects.* We then focus our attention on proxy measures for health harms from adverse drug effects and medication overuse. We find that e-prescribing increases younger patients' probability of hospitalization for PDA and prescription drug poisoning by approximately 11%–12% compared with the mean, showing that e-prescribing had unintended health harms for younger patients

32. We also explored the effects on mortality and the effect estimates are statistically insignificant (column (1) of Online Appendix Table B.4). These results are as expected, given that death is an extreme outcome and quite rare in age groups other than the elderly. However, we also find statistically insignificant effects on more specific health outcomes of hospitalizations for anxiety, panic disorder, depression, and sleeping disorders (columns (2)–(5)). The only exception is a statistically significant 35% decrease in the probability of a hospitalization for panic disorders in the elderly population.




(a) Hospital visits, All ages

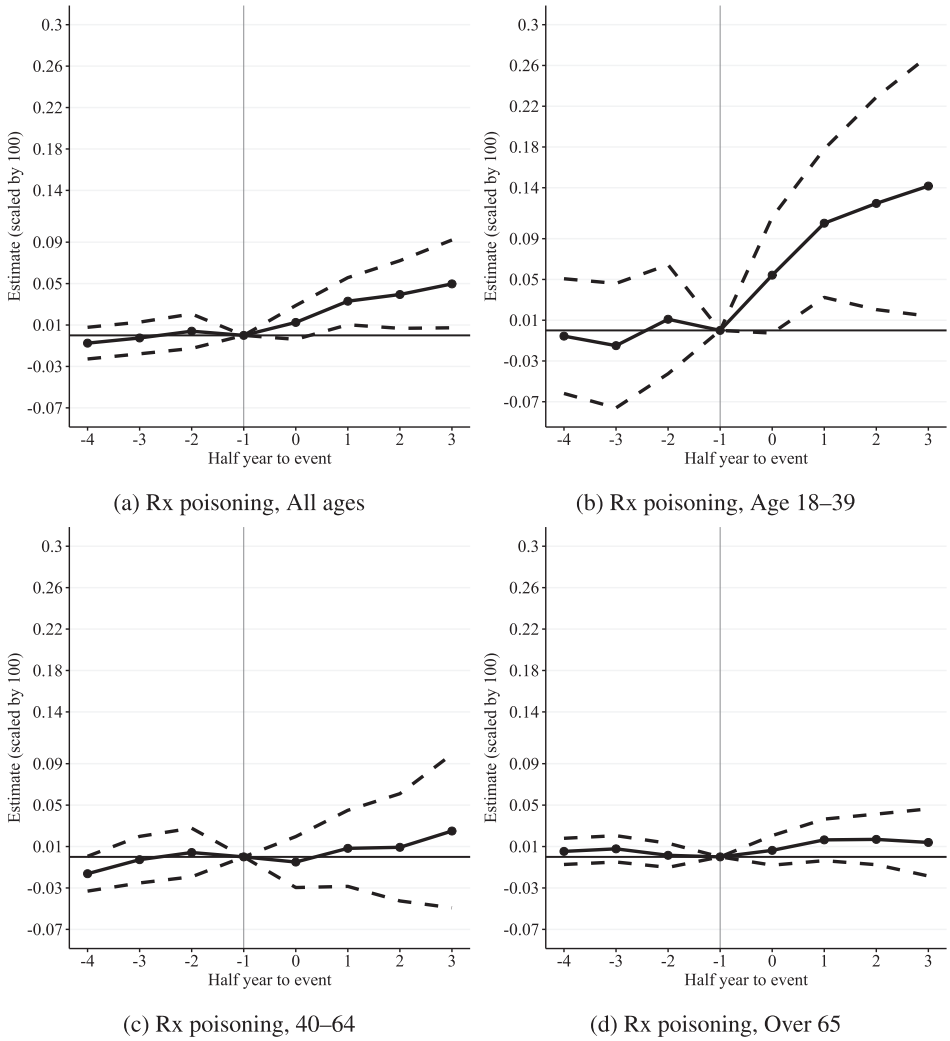
(b) Hospital visits, Age 18–39

(c) Hospital visits, 40–64

(d) Hospital visits, Over 65

FIGURE 6. Hospital visits. The figures plot the coefficient estimates using two-way fixed effects (TWFE) event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

(columns (4) and (5) in Table 4). The effects on PDA and poisonings are consistent with each other, but the latter effect is more precisely estimated. The increase in poisonings is also gradual and approximately twice as large after the first year of adoption based on the event study estimates (Figure 7).




(a) Rx poisoning, All ages

(b) Rx poisoning, Age 18–39

(c) Rx poisoning, 40–64

(d) Rx poisoning, Over 65

FIGURE 7. Prescription drug poisoning. The figures plot the coefficient estimates using TWFE event study regressions using aggregated patient biannual-level panel data trimmed between relative time periods −5 and 3. The coefficients for the relative time indicators can be interpreted as the mean differences from the average value of the outcomes in two specific relative periods (−1 and −5) prior to the treatment. Each regression controls for calendar time (half-year) fixed effects and patient fixed effects. The dashed lines are pointwise 95% confidence intervals based on standard errors clustered at the municipality level.

In contrast, for the elderly, we find that e-prescribing reduces the probability of PDA by 30% and the estimated effect is statistically significant at the 10% level (column (4) in Table 4 and Online Appendix Figure B.9). The point estimates for prescription drug poisonings are, however, positive and statistically insignificant for the elderly. The possible increase in prescription drug poisonings might reflect a

modest increase in the total amount of their benzodiazepine use after e-prescribing, whereas hospitalizations more specifically related to physical dependence and PDA appear to be more easily prevented with better prescription information. Although imprecisely estimated, our results on hospitalizations related to other side effects of benzodiazepines (e.g. sedation and a decline in cognitive functions) also suggest a gradual decrease in these relatively prevalent health harms for the elderly (Online Appendix Figure B.10). However, it is difficult to make strong conclusions based on the statistically insignificant estimates.

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

### *6.3. Robustness and Additional Mechanisms*

*6.3.1. Alternative Specifications.* We test the robustness of our results by using alternative specifications in both the estimations and samples. First, we exclude those who die during the observation period. Second, we restrict our data to periods when the last-treated municipalities had not yet adopted e-prescribing and thus act as "clean controls" for early-treated municipalities.[34] (Online Appendix Tables C.1 and C.2.) Third, we cluster standard errors at the hospital district, rather than at the municipality level (see Section 2.3). Fourth, we exclude patients who switched municipalities during the observation period and could cause contamination bias in the treatment effect estimates. (Online Appendix Tables C.3 and C.4.) Fifth, we estimate specifications using physician fixed effects as in Dubois and Tunçel (2021), based on our prescription-level data, to evaluate the role of unobserved heterogeneity across physicians in their prescribing decisions (Online Appendix Table C.5). Sixth, we use an alternative definition of new versus renewed prescription without the 16-month cutoff (Online Appendix Table C.6, Online Appendix Figures C.1 and C.2). Our results remain similar to our baseline results in all these alternative specifications.

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

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

*6.3.2. Potential Biases in TWFE models and Robustness for Treatment Effect Heterogeneity.* We evaluate potential biases and assumptions in the TWFE models (Online Appendix Section D). First, using the decomposition method of Goodman-Bacon (2021), we show that possible negative weighting does not bias the treatment effect estimates in our setting and that the DiD estimates are similar for the early- and late-treated units (Online Appendix Tables D.1 and D.2). Second, we use the efficient DiD estimator proposed by Roth and Sant'Anna (2023) to show the robustness of our results to treatment effect heterogeneity and to address low-power concerns in the baseline estimates (Online Appendix Tables D.3 and D.4 and Online Appendix Figures D.1–D.4). Our results are not sensitive to using alternative heterogeneity-robust DiD estimators.[35] Third, we establish the robustness regarding undetected parallel trends and noise by controlling for municipality-specific linear time trends in the TWFE model, following Freyaldenhoven et al. (2024) (Online Appendix Tables D.5 and D.6), and by applying the tools proposed by Roth (2022) (Online Appendix Figures D.5– D.8). We conclude that an undetected pre-trend due to low statistical power is an unlikely explanation of our results.

*6.3.3. Further Age-based Heterogeneity.* Online Appendix Table E.1 shows no major differential responses to e-prescribing when patients under 40 years of age are separated into two additional age groups (aged 18–25 and 26–39). Compared to the means, the increases in the number of DDDs and the probability of prescription drug poisoning are slightly larger for those aged 18–25 than for those aged 26–39 (increases of 11% versus 7% and 14% versus 9%, respectively). Moreover, there is a similar 7% decrease in patient hospitalizations in both age groups.[36]

*6.3.4. Additional Mechanism: Potential Role of Improved Diagnosing.* Improved information on a patient's prescription history after the adoption of e-prescribing in primary care may enhance the prescribing physician's ability to diagnose mental health disorders and identify adverse drug effects. Thus, referrals and hospitalizations for these conditions might also increase, which could cause upward bias in our health effect estimates.[37] Online Appendix Table F.1 shows the results excluding diagnoses for hospital visits where the referrals are obtained on the same day, and potentially from the same physicians, as the benzodiazepine prescriptions (less than 1% of all

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

36. Moreover, the take-up rate of e-prescriptions does not differ between the two age groups (Online Appendix Figure E.1).

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

diagnoses). The results remain intact and they are clearly not driven by potential improvements in the diagnosing of medical conditions.

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

*6.3.6. Placebo Regressions.* We estimate placebo regressions for a health outcome that should not have been affected by e-prescribing or improved diagnosing: diagnosis of diseases of the appendix. This condition is quite prevalent, especially among younger individuals, and not correlated with socioeconomic status, making it a good candidate for placebo regressions. We find that the effect estimates for these placebo regressions are not statistically significant and the point estimates are close to zero (Online Appendix Table G.1).

## 7. Conclusion

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

Our results are consistent with e-prescribing improving access to medication through easier renewal. We find that e-prescribing increases the total amount of benzodiazepine use per patient due to increased prescription renewals. The increase in benzodiazepine use is over twice as large for younger patients (aged 18–39) as for the elderly (age over 65). We provide further suggestive evidence that the information technology adoption can benefit the health of the elderly due to improved information provision, but it can also increase the risk of medication overuse and health harms for younger patients due to improved medication access. Thus, the ability of e-prescribing to balance the access-overuse trade-off depends on whether the improved access to

medication, characterized by easier renewals without an in-person physician visit, offsets the benefits of improved information provision for physicians.[38]

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

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

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

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

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## Supplementary Data

Supplementary data are available at *JEEA* online.

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