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IZA DP No. 12275

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ABSTRACT

Digital Waste? Unintended Consequences of Health Information Technology*

We exploit a large-scale natural experiment – the rollout of a nationwide electronic prescribing system in Finland – to study how digitization of prescriptions affects pharmaceutical use and health outcomes. We use comprehensive administrative data from patients treated with benzodiazepines, which are globally popular, effective but addictive psychotropic medications. We find no impact on benzodiazepine use on average, but among younger patients e-prescribing increases repeat prescription use. Younger patients' health outcomes do not improve but adverse outcomes, such as prescription drug abuse disorders and suicide attempts, increase dramatically. Improving access to medication through easier ordering may thus increase medication overuse.

JEL Classification: H51, H75, I12, I18

Keywords: health information technology, electronic prescribing, repeat prescriptions, ineciency, medication overuse

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1 Introduction

Access to essential medications is a fundamental policy goal of health care systems (UN Human Rights 2019). Policy measures to improve access include lower out-of-pocket costs for medications and nonprice mechanisms such as longer-term prescriptions to distribute medications more easily. These policies can be socially beneficial: barriers in access is a major reason for patients stopping to take their medications or not taking them as directed, 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; Cutler and Everett 2010; Marcum et al. 2013). However, access-improving policies can also expose some patients to medication overuse for which there are fewer health benefits than health harms. Overuse of some medications is already a significant problem worldwide (WHO 2011; Brownlee et al. 2017), creating wasteful spending and health harms in society. Hence, providing ready access to essential medications while simultaneously limiting overuse is a challenging but important trade-off to strike.

We analyze a popular but surprisingly understudied policy to improve access to medication while limiting overuse: digitization of prescriptions. Specifically, we estimate the effects of electronic prescribing (e-prescribing) on prescription drug use and health outcomes in the Finnish market for benzodiazepines—globally popular but addictive mental health and insomnia medications. Our identification approach is based on a large-scale natural experiment. We use the plausibly exogenous rollout of a national e-prescribing system in primary care, where a substantial fraction of benzodiazepines are prescribed (Cascade and Kalali 2008; Kjosavik et al. 2009). We use two nationwide administrative datasets for benzodiazepine patients of all ages during 2007–2014, including nearly 20 percent of the Finnish population. The Prescription Data identify the patients' benzodiazepine use throughout the period. From the Discharge Data, we identify the patients' health outcomes based on diagnoses in specialized health care. Our detailed health outcomes include the health benefits from appropriate use of benzodiazepines and the health harms from their overuse.

E-prescribing——similar to online pharmacies and other electronic ordering platforms——improves medication access by reducing the time and hassle costs for patients to order additional medication without necessarily having to visit a physician.[1] By helping patients to get the repeat medication or refills they need, e-prescribing can increase appropriate use of medicines. When health returns from

[1]Repeat prescriptions are commonly issued to patients without having to visit a physician each time (Avery 2011; Price et al. 2017), accounting for as much as 80 percent of prescription drug use (Duncan et al. 2014).

medication are heterogeneous across patients, e-prescribing can also increase the overuse of medication by some patients; the demand can increase, especially among those for whom the marginal health returns from medication are low and possibly negative. In addition to improving access, e-prescription systems also provide physicians with more comprehensive information on a patient's prescription history, which can help them limit medication overuse.

Our research is motivated by the fact that rising health harms due to overuse of medications such as benzodiazepines (e.g., Valium and Xanax) coincide with the adoption of e-prescribing worldwide. In the U.S. the use of e-prescriptions has expanded in response to the Medicare and Medicaid programs, with almost 60 percent of prescriptions sent electronically in 2013 and approximately 70 percent of physicians using e-prescribing by 2014 (Gabriel and Swain 2014). Nationwide e-prescribing initiatives are increasing in several European countries, and e-prescribing is an integral element of digital health strategies in other countries, including Australia, New Zealand, and Canada. Despite the widespread adoption of e-prescribing, there is a lack of credible evidence on its effects. More broadly, there is a growing consensus about the importance of medication overuse (Brownlee et al. 2017), but few studies provide evidence of exact mechanisms or policies behind overuse in health care (Abaluck et al. 2016; Einav et al. 2018a).

Benzodiazepines have several characteristics that make them relevant for studying the effects of e-prescribing. First, benzodiazepines are among the most widely used psychotropic medications in developed countries, and their repeat use is common (Cunningham et al. 2010; Olfson et al. 2015). Second, benzodiazepines provide benefits from appropriate use and health harms as a result of overuse. Benzodiazepines are considered effective treatments for common and often disabling conditions, such as anxiety, panic disorder, and insomnia (Bambauer et al. 2005).[2] Benzodiazepines can reduce the risk of hospitalization and admissions for mental illnesses when used appropriately. Overuse of benzodiazepines is, however, harmful because it can cause adverse health effects such as dependence, abuse, and elevated risk of suicide. Long-term use of benzodiazepines promotes these health risks, and this is exactly what easier ordering through e-prescribing can facilitate. Consequently, benzodiazepine abuse is a growing public health problem in developed countries, even reaching an epidemic level in the U.S. (Novak et al. 2016; NIDA 2017; UNODC 2017).

Even though improving medication access while limiting overuse through e-prescribing is important for all patients, it can be especially essential for younger patients. Younger patients are more likely to have higher barriers to access (Kullgren et al. 2012), with higher rates of mental

[2]Benzodiazepines are included in the World Health Organization's 2017 Model List of Essential Medicines.

health admissions but fewer prescriptions for benzodiazepines (Kessler et al. 2010; Cunningham et al. 2010; Olfson et al. 2017). Younger patients, in fact, more often fail to take medications correctly or even stop taking them, especially in mental health care (Julius et al. 2009; Thompson and McCabe 2012; Feehan et al. 2017; Lauffenburger and Choudhry 2018). Improving access might thus encourage younger patients to continue taking medication, potentially improving their health outcomes. On the other hand, this improved access might also increase medication overuse in the younger population. The most notable health harms from overuse in this population are related to prescription drug abuse. Actually consistent with our data, younger adults are the largest abusers of anti-anxiety drugs such as benzodiazepines in the U.S. (NIDA 2016). Another health harm closely linked to overuse are suicides, one of the leading causes of death among younger people (NIMH 2018). Thus, in addition to access, younger patients are a salient target for the e-prescribing policy to limit medication overuse.

Using the rollout of e-prescribing and administrative data on all patients, we begin by showing that e-prescribing has no impact on the use of benzodiazepines on average. This result is driven by older patients (aged over 40). In contrast, among younger patients, e-prescribing increases overall benzodiazepine use by approximately 5 percent. This increase results from repeat prescriptions, especially in higher doses.

Despite the increase in benzodiazepine use among younger patients, we find no evidence of an improvement in the health of these patients. We do not observe any effect on the prevalence of diagnoses in specialized health care (such as hospitals) related to anxiety, panic disorder or insomnia or on overall visits to emergency departments. By contrast, e-prescribing increases health harms in the younger population. Remarkably, both prescription drug abuse and suicide attempt diagnoses increase by approximately 20 percent, and these adverse outcomes are already more prevalent among younger benzodiazepine patients. Overall, our results suggest that e-prescribing is effective at improving access but leads to medication overuse among those who are more vulnerable to mental health problems and abuse.

Our results reveal unintended consequences of health information technology and are therefore of direct relevance to public policy. Costly information technologies, such as e-prescribing systems, are motivated in policy discussion by their promise to improve access to and use of medications. If these technologies were effective at achieving these goals, the health gains could be far greater than those associated with many other improvements in health care. However, we find evidence of an access-overuse trade-off in the digitization of prescriptions for benzodiazepine patients. Digitization

contributes to overuse by reducing transaction costs to order medication, thereby redirecting health care spending to patients with lower marginal utility.[3] Digitization (easier ordering without face-to-face consultation) may also weaken physician-patient interactions and monitoring that are essential for screening and preventing potential overuse. Our results provide lessons for e-prescribing of controlled, addictive substances in the U.S. and Europe. These results also have broader relevance for policy makers deciding how to improve access to medications that have potential for health harms.

We provide causal evidence of how health information technology affects the trade-off between access and targeting of medical treatments. Previous work related to trade-offs in health care access has focused on prices, information, and changes in the availability of treatment options (Cohen et al. 2015; Sautmann et al. 2016; Alpert et al. 2018; Hamilton et al. 2018). Unlike our paper, these studies do not investigate the repeat prescribing process or health information technology, a prominent nonprice mechanism designed to improve access and information.

By studying the access-overuse trade-off in digitization of prescriptions, e-prescribing, we also contribute to the health information technology literature. Prior literature has focused on electronic medical records (EMRs) (Miller and Tucker 2011; Lee et al. 2013; Agha 2014; Dranove et al. 2014; McCullough et al. 2016; Atasoy et al. 2017, 2019) and prescription drug monitoring programs (PDMPs) (Ali et al. 2017; Buchmueller and Carey 2018; Grecu et al. 2019).[4] The technology that we consider differs from EMRs and PDMPs in several crucial ways. Most importantly, EMRs and PDMPs are information-improving technologies but e-prescribing directly affects both access and information. The unique feature of e-prescribing is that it may lead to overuse in health care, resulting from improved access and suboptimal monitoring of patients. Additionally, previous work has analyzed fragmented EMR and PDMP systems, but the nationwide technology that we examine is highly standardized for all health care providers. Using a large policy change to investigate the effects of e-prescribing, we also complement the descriptive literature on this technology (Grossman et al. 2007; Ammenwerth et al. 2008; Cooke et al. 2010; Samadbeik et al. 2017).

Our paper also complements the prior literature on inefficiency and overuse in health care (Chandra and Skinner 2012; Chandra and Staiger 2016; Das et al. 2016; Glied and Sacarny 2018; Lopez et al. 2018), often referring to health care spending that is not associated with improved health outcomes. Previous research has documented inefficiency of providers or medical treatments,

[3] See Finkelstein and Notowidigdo (2018) for related arguments on take-up of social safety net programs.

[4] This literature has not focused on the prescribing process, apart from the PDMP studies that have mainly analyzed overuse (abuse) of opioids.

but only a few studies have identified specific sources of inefficiency (Abaluck et al. 2016; Einav et al. 2018a,b). Particularly, there is little evidence of public policies as drivers of overuse in pharmaceutical markets, and the prior studies are unrelated to health information technologies. We focus on e-prescribing technology in leading to medication overuse through easier and faster access, creating wasteful spending and limiting the potential for productivity gains.

The remainder of this paper is structured as follows. Section 2 provides background on the implementation of e-prescribing and the benzodiazepine market. Section 3 introduces the data and provides descriptive statistics. Section 4 lays out the econometric approach. Section 5 reports our results. The last section concludes.

2 Background

2.1 E-prescribing and Mechanisms

Our empirical analysis focuses on e-prescribing—a popular health information technology around the world. E-prescribing systems generate digital prescriptions and electronically transfer prescriptions as well as renewal and refill requests between physicians, pharmacies, and patients.[5] In this section, we describe e-prescribing technology and the key channels through which the effects on prescription drug use and patient health may arise.

E-prescribing and Access.—Compared to traditional paper prescriptions, e-prescribing improves medication access by making it easier for patients to order additional medication without necessarily having to visit a physician face-to-face. Ordering and refilling traditional paper prescriptions (without a physician visit) was much more difficult and time-consuming: patients had to drop off existing prescriptions to a health care unit or pharmacy for renewal or refill, and prescriptions and requests were transferred between physicians and pharmacies (or patients), for example, by fax or mail. With e-prescribing, patients do not have to make extra visits to a health care unit or pharmacy every time they need additional medication.

To make a renewal or refill request for an electronic prescription, a patient can simply contact a physician by phone. Alternatively, the patient can make the request via a pharmacy, who then sends the request to the health care unit through the computer interface.[6] After the physician has

[5] In many health care settings the terms prescription "renewal" (repeat) and "refill" are used interchangeably. A prescription contains refills and it 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.

[6] Some e-prescribing systems or online pharmacies permit patients themselves to make electronic renewal or refill

electronically approved the request, the repeat or refilled prescription is readily available for the patient at the pharmacy. Thus, e-prescribing considerably shortens the waiting period associated with repeating or refilling prescriptions. E-prescribing also eliminates or reduces other costs, such as those related to lost (paper) prescriptions that made filling and ordering prescriptions even more difficult and time consuming for patients.[7] Overall, e-prescribing substantially reduces the hassle and time costs of ordering additional medication.

Review studies note that improving access through repeating or refilling prescriptions is the core feature of many e-prescribing systems (Samadbeik et al. 2017). In Finland, e-prescribing makes it easier to order repeat prescriptions as opposed to refills (Kauppinen et al. 2017; Kanta 2018), although the prescription renewal guidelines and practices might differ across health care units or physicians. In the Finnish system, ordering is also easier because patients will receive a text message to inform them about the approval of the renewal requests.

E-prescribing systems also generally permit prescription repeats or refills for psychotropic medications and some controlled substances such as benzodiazepines—prescription drugs that we study—without physician consultation.[8] Previous research has further shown that issuing prescriptions without physician consultation is, in fact, 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 provides better prescription information across different health care providers, with a potential of limiting medication overuse. Before e-prescribing, physicians did not typically have access to a patient's full prescription history, especially if the patient had obtained prescriptions from several physicians using different EMR systems. This lack of prescribing information made it more difficult for physicians to detect medication overuse.

With e-prescribing, each physician has access to the patient's complete e-prescription history, as illustrated in online Appendix Figure A2 from the Finnish health care provider setting. Physician access, however, often requires a patient's permission, except when addictive medications or other central nervous system drugs are prescribed (in our setting). Even with a patient's permission, the e-prescribing system may not enable physicians to efficiently acquire information on relevant

requests. For example, in Finland, electronic renewal requests were introduced to the e-prescribing system in 2015, outside of our observation period.

[7]These other costs also include mistakes in handwritten paper prescriptions.

[8]For example, in the UK, repeat prescriptions for Schedule IV controlled substances, such as most benzodiazepines, are legally valid within the normal periods of validity of the repeat prescription after the first dispensing (PSNC 2019). In Finland, prescriptions for central nervous system and narcotic medications can be renewed within 16 months from the issue date (Kanta 2018). 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).

prescriptions for possibly overused medications and to cope with potential information overload.[9]

Net Effects of E-prescribing.—The net effects of e-prescribing on pharmaceutical use and patient health are ambiguous. Improving access through easier ordering encourages patients to order additional medication, which increases pharmaceutical use. By improving access, e-prescribing can increase appropriate medication use and related health outcomes may improve. On the other hand, e-prescribing can also increase medication overuse. Importantly, improving access arguably affects the incentives for patients at the margin of ordering additional medication, with low and possibly negative health returns. Easier ordering without face-to-face consultation may also decrease patient monitoring, hindering the potential to screen and prevent overuse. Overall, if patients consumed too much (too little) of a drug, improving access will move prescription drug use away from (to) the welfare maximizing optimum.

In addition to improving access, another goal of e-prescribing is to limit overuse and health harms by providing more comprehensive information on prescription histories.[10] However, improving information on prescription histories might also increase physician reliance on other physicians' treatment decisions and thus encourage physicians to renew prescriptions. This channel also improves access, possibly affecting appropriate use and overuse and having ambiguous effects on patient health.

2.2 Implementation of the National E-prescribing System in Finland

We analyze the impacts of e-prescribing in the unique institutional setting in Finland. Our setting is beneficial for studying the effects of digitization of prescriptions for two reasons. First, we evaluate an exceptionally large-scale public policy: the implementation of a national e-prescribing system. The e-prescribing system includes all e-prescriptions and their dispensing records at pharmacies, and it covers all public and private health care providers both in primary and specialized health care in the country. The system is highly standardized, and the common standards guarantee that patients can make renewal requests to health care units via any pharmacy. The e-prescribing law is also uniform across the country.

Second, there is substantial and plausibly exogenous regional heterogeneity in the adoption time of the e-prescribing system. The introduction of the national system required massive in-

[9]The system shows all the previous e-prescriptions (both filled and unfilled prescriptions) on the physician's computer screen, potentially hindering the search of relevant prescriptions.

[10]Information may also help physicians to prevent overuse and health harms caused by so-called doctor-shopping—the practice of acquiring multiple prescriptions for addictive drugs from several physicians.

vestments in information technology systems, software, and a skilled workforce. Consequently, the e-prescribing system was introduced gradually across providers and over time. According to the national deadlines, public health care units had to adopt the system by 2014, and private health care units had to adopt the system by 2015.[11] Government experts and local practitioners argue that the adoption time was largely determined by technical reasons related to the difficulties in the integration of the e-prescribing system to existing information technology systems in health care units and pharmacies, as opposed to factors related to the trends in prescribing and health outcomes. This is a crucial issue for the identification of the effects, as discussed below in Section 4.

Figure 1 illustrates the year of technology adoption by municipalities (N=304) in public primary care. The figure, however, masks considerable within-year variation in the regional adoption time that we also use in estimations. E-prescribing was first introduced by a municipality in Southwest Finland in May 2010. By the end of 2014, all the municipalities had adopted the new system.

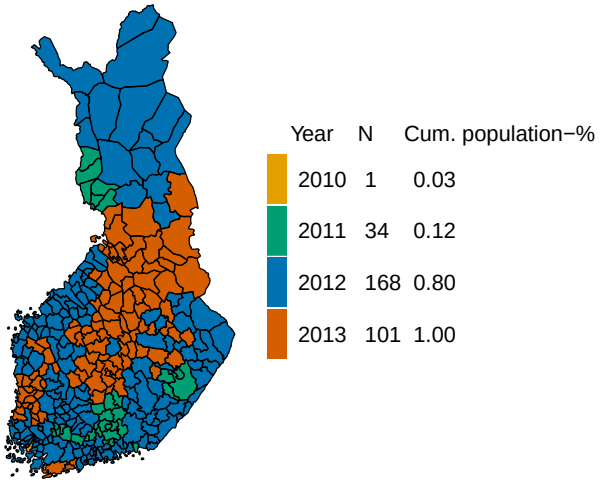

FIGURE 1: E-prescribing Adoption Year in Municipalities

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

[11] Very small private units, issuing less than 5,000 prescriptions annually, had the exception to adopt the system by 2017.

2.3 Benzodiazepine Market

Our analysis focuses on benzodiazepines—a class of pharmaceuticals used to treat conditions such as anxiety, panic attacks, insomnia or sleeping problems, and depression, for example, when anxiety is involved (Cunningham et al. 2010; Olfson et al. 2015; Varma 2016; Bushnell et al. 2017).[12] The top five active ingredients of benzodiazepines are diazepam (international brand name Valium), oxazepam (Opamox, Oxamin, and Serax, among others), temazepam (Restoril and Normison, among others), midazolam (Versed, among others), and zopiclone (Zimovane and Imovane). These ingredients represented approximately 77 percent of the total sales of benzodiazepines in Finland in 2017 (Finnish Medicines Agency 2018).

Benzodiazepines are a particularly interesting drug group for studying the effects of e-prescribing for three reasons. First, benzodiazepines are one of the most prescribed and popular groups of psychotropic medications in developed countries (Cunningham et al. 2010; Olfson et al. 2015), including also Finland and the U.S. In Finland, the wholesale value of benzodiazepines was 11.5 million euros in 2017, with a market share of approximately 16 percent from the wholesale value of all psycholeptics (Finnish Medicines Agency 2018). In the U.S., the number of adults who filled a benzodiazepine prescription was 13.5 million in 2013, an increase of 67 percent from 1996 (Bachhuber et al. 2016).

Second, improving access while limiting overuse through e-prescribing is challenging in the benzodiazepine market because these drugs have both health benefits from appropriate use and harms from overuse. Benzodiazepines are clinically proven, highly effective and tolerable medications (Andersch et al. 1991; Bambauer et al. 2005). Benzodiazepines are prescribed for symptomatic control and care when the medical condition is severe or disabling, or subjecting the patient to extreme distress, or is causing problems in social functioning (Fava et al. 2015). In treating anxiety, for example, the advantage of using benzodiazepines is that they alleviate symptoms much faster than other drugs such as antidepressants. Appropriate use of benzodiazepines can improve health outcomes, for example, by resulting in fewer admissions to specialized health care.

Overuse of benzodiazepines causes health harms through adverse drug effects. The potential adverse effects of the short-term use of benzodiazepines include dizziness, drowsiness, lightheadedness, ataxia, amnesia, and gastrointestinal symptoms (Morin and Benca 2012). Prolonged use of

[12] In treating anxiety related to depression, benzodiazepines are commonly prescribed in combination with antidepressants (Olfson et al. 2015; Bushnell et al. 2017). Benzodiazepines are also used to treat other conditions such as epilepsy, alcohol withdrawal, chronic pain, drug-associated agitation, nausea, and vomiting, and to achieve general anesthesia and muscle relaxation.

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 suicide (Neutel and Patten 1997; Carlsten et al. 2003; Tiihonen et al. 2012). Consequently, national guidelines and field experts generally do not recommend benzodiazepines for long-term use (Valvira 2013; US Food & Drug Administration 2016; Finnish Current Care Guidelines 2017).

Third, benzodiazepines are relevant for public health policy because mental health disorders are on the rise globally. Thus, increasing benzodiazepine use may be valid from the clinical perspective, but there is also a high demand for medication oversight. Benzodiazepines are in fact commonly involved in prescription drug overdose deaths and emergency department admissions related to nonmedical use of prescription drugs, especially when combined with alcohol and opioids (Jones and McAninch 2015). Recent research studying the effects of policies and institutions on prescription drug abuse has focused on the opioid epidemic in the U.S. and has largely ignored other addictive psychotropic medications and their potential health benefits. Global consumption of opioids is, however, heavily concentrated in the U.S. (PPSG 2015; Bosetti et al. 2019). The differences in pain management strategies may partly explain why the use of opioids is less common in other countries. For example, in Finland, opioids are mostly prescribed by specialists or pain clinics and are more tightly regulated and monitored than in the U.S. Thus, opioids are considered only as the last-line treatment for severe pain. By investigating both potential health benefits and harms of understudied but globally important psychotropic medications, we provide much-needed evidence on the effects of digitization of prescriptions.

3 Data

Our population of interest consists of patients who have filled a benzodiazepine prescription under the National Health Insurance (NHI) scheme in Finland during an eight-year period, 2007-2014. This population is highly representative of the target population of all benzodiazepine patients because the vast majority of prescriptions are covered by the NHI scheme.[13] The additional benefit of the Finnish setting is that the NHI scheme (high prescription drug coverage), and more broadly,

[13]Benzodiazepine prescriptions issued under the NHI scheme cover approximately 88 percent in 2010 and 73 percent in 2013 of the total amount of benzodiazepines sold by drug wholesalers to pharmacies in the respective years. We calculate these numbers using our Prescription Data (described below) and the annual drug consumption statistics provided by the Finnish Medicines Agency. The lower number in 2013 results from the withdrawal of some benzodiazepines from the scheme.

the universal public health care should significantly reduce potential sample selection bias where individuals with low income are systematically excluded from health care data.

We use two comprehensive administrative health care datasets: the Prescription Data, and the Care Register for Health Care (hereafter, the Discharge Data). The former identifies benzodiazepine prescriptions and the latter identifies the health outcomes for our study population over the years 2007–2014. Additionally, we use detailed data on the time of e-prescribing adoption in municipalities.

In Section 3.1, we briefly describe the two administrative datasets, as well as the variable and data construction, and leave further details to online Appendix A.1. In Section 3.2, we describe our data on the health information technology adoption. Section 3.3 presents summary statistics.

3.1 Administrative Data, Outcomes, and Data Construction

The Prescription Data.—The Prescription Data from the Social Insurance Institution of Finland contain all benzodiazepine and benzodiazepine-related (referred to as benzodiazepines) prescriptions dispensed at Finnish pharmacies and covered by the NHI scheme from 2007 through 2014. The data record patient and physician identifiers, the patient's date of birth and municipality of residence, the Anatomical Therapeutic Chemical (ATC) code of the prescription, the date of prescribing, the e-prescribing status, the strength of the prescribed drug, the route of administration, and the dispensed number of defined daily doses.[14] The defined daily dose by the WHO is an international metric that is widely used in pharmaceutical research. The metric is defined as the assumed average maintenance dose per day for a drug used for its main indication in adults.

We calculate the number of defined daily doses filled (i.e., purchased) by the patient per prescription from our data. We also calculate the number of defined daily doses separately for repeat (renewed) and new prescriptions. We define a prescription as renewed if the prescribed drug is essentially the same (as measured by the ATC code, strength, and route of administration) as in any of the two previous prescriptions, and the renewal is made within 16 months (renewal requests for electronic central nervous system drug prescriptions must be done within this time interval).[15]

[14] The data do not, however, identify patient gender.

[15] For many patients in our Prescription Data, we observe prescription sequences including multiple benzodiazepines. For example, a patient first obtains prescription A and then obtains prescription B, after which she obtains a repeat prescription (renewal) of A, and then of B. Our renewal measure captures this typical repeat pattern of obtaining repeat prescriptions. The results do not change (and the share of renewed benzodiazepine prescriptions from all benzodiazepine prescriptions is almost identical) if we instead compare the prescription to the prescriptions in the previous three prescribing events within the 16-month interval. Additionally, our results are robust to restricting the comparison only to the first previous prescribing event and/or to the exclusion of the 16-month interval rule.

Otherwise we define a prescription as new.

The Discharge Data.—The Discharge Data are from the National Institute for Health and Welfare. The data identify all Finnish inpatient and outpatient discharges in public specialized health care for our population from 2007 through 2014.[16] The data record patient identifiers, the diagnosis (ICD10 code), the date of discharge, and the patient's municipality of residence. Validation studies have documented that the Discharge Data are of high quality (Sund 2012). The limitation of our data is that they do not identify diagnoses from and visits to primary care. However, focusing on specialized health care is essential because the use of specialized health care disproportionately contributes to health care costs.

Data Aggregation and Outcome Variables.—We separately aggregate the two administrative datasets into the patient-time period observations to construct our main analysis data. The aggregated data are in a balanced-panel form meaning that each patient has an observation in each time period. Such data form is crucial for our analysis because we are studying changes in the use of new and repeat prescriptions and in patient health as a result of e-prescribing. In addition, in defining the time period, there is a trade-off between the accuracy of the implementation time of e-prescribing and short-term idiosyncratic variation in benzodiazepine use and patient health outcomes. As a compromise, we define the time as a period of 6 months.

From the Prescription Data, we construct measures of the patient's biannual benzodiazepine use. Our primary measure of overall drug use is the total number of defined daily doses filled by the patient biannually. Defined daily doses provide 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 measure is the total number of prescriptions. We only use this as a broad measure of drug use because it conceals important aspects of prescriptions such as the number of items and the strength of the tablets. We also calculate the number of defined daily doses and the number of prescriptions separately for renewed and new prescriptions filled by the patient biannually. In addition, we calculate the patient's age based on his/her birth date.

From the Discharge Data, we construct multiple measures of health outcomes by patient and half of a year. We construct the health outcomes based on diagnoses from treatment admissions to specialized health care (e.g., hospital).[17] Our main health outcomes measure the prevalence

[16]The private health care sector is relatively small especially in specialized health care because of the comprehensive universal public health care in Finland.

[17]Specifically, we use the primary diagnosis when constructing our outcomes. The exception is suicide attempts that are identified by the external reason for a visit to specialized health care. The results (available upon request) are similar when we supplement the information on the primary diagnosis with the secondary diagnosis.

of diagnoses related to mental health disorders (e.g., anxiety and panic disorder), severe sleeping disorders, adverse health effects related to benzodiazepine use (e.g., prescription drug abuse), and suicide attempts. Specifically, we construct indicator variables for whether the patient has been diagnosed with particular health conditions in specialized health care within a period of 6 months. We also calculate the total number of specialized health care visits and the total number of emergency department visits. Table A2 lists the main health outcomes that we study (11 in total). A detailed description of the ICD10 codes and definitions used in the health outcomes are provided in online Appendix A.1.2.

Finally, we link the aggregated Prescription and Discharge datasets by patient and half a year. The resulting data that we analyze have 15,436,868 observations covering 1,030,383 unique patients, corresponding to almost 20 percent of the Finnish population.

3.2 Adoption of E-Prescribing in Municipalities

We use detailed data on the date of the adoption of e-prescribing by municipalities in public primary care (hereafter, municipalities). These data are obtained from the National Institute for Health and Welfare. We link the data on regional adoption dates to our aggregated analysis data by the patient's municipality of residence. As the aggregated data are at the patient half-year-level, we consider the adoption of e-prescribing within the period of 6 months.

We focus on the adoption of e-prescribing by municipalities for three reasons. First, public primary health care is organized by municipalities by the Finnish law. The density of physicians is also relatively high because of the strong political commitment to provide universal access to public health care services. To obtain prescriptions, among other primary care services, a patient typically chooses a public health care unit from his/her municipality of residence.[18] For this reason, municipality of residence also serves as a good proxy for the location of the prescribing physician. Second, municipalities' public providers had earlier legal deadlines for the adoption of e-prescribing than private providers, as explained in Section 2.2. Thus, the date of adoption by a municipality (in *public* primary care) also measures the earliest adoption time in primary care in the region.

Third, prescription renewal and preventable harms from repeat medications are highly relevant in primary care settings worldwide (Duncan et al. 2014; Price et al. 2017). Several studies

[18] All Finnish municipalities are mandated by the law to provide primary health care for their residents. However, very small municipalities tend to contract with nearby municipalities to provide services jointly. If a patient lives in a municipality that does not have its own unit, we identify the time of adoption in the municipality it has contracted with. We obtain the historical data on these municipality contracts from the municipality websites.

have further found that primary care physicians write most of the benzodiazepine prescriptions (Cascade and Kalali 2008; Kjosavik et al. 2009). These two findings also motivate our focus on technology adoption in primary care, although e-prescribing was also adopted in specialized health care. Importantly, we validate our approach in Section 4 by showing a sharp and large increase in the take-up rate of electronic benzodiazepine prescriptions after the patients' municipality adopted e-prescribing in primary care, with no prescriptions issued electronically in the pre-adoption period.

3.3 Descriptive Statistics

Table 1 reports summary statistics on benzodiazepine use for all patients and by patient age over the years 2007–2014. On average patients filled over 800 defined daily doses of benzodiazepines at pharmacies. A vast majority of the purchases (82 percent) originate from repeat (renewed), as opposed to new, prescriptions. On average, the total number of prescriptions per patient is 10, of which 77 percent are renewed. This evidence together shows that the long-term use of benzodiazepines through repeat supply of medications is common.

Table 1: Outcomes Measuring Patients' Benzodiazepine Use

	All ages		Ages < 40		Ages ≥ 40	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
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	1461.128	384.087	1447.045	773.217	1452.808
Number of new defined daily doses	149.517	360.394	105.578	375.488	164.205	353.992
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
Number of unique patients	1,030,383		258,136		858,995	

Notes: Unit of observation is a patient. The numbers depict the overall values during 2007–2014.

For age, we divide the data into two groups: those less than 40 and those older than 40. With the data split this way, there are clear and important differences in benzodiazepine use by age group, as shown by Table 1. Overall, younger patients are significantly less likely to use benzodiazepines and have fewer repeat prescriptions than older patients over the years 2007–2014.

For younger patients, the average number of defined daily doses is 490 (SD 1,713), of which 78 percent are renewed, and the average number of prescriptions is 7 (SD 14), of which 69 percent are renewed. For older patients, the average number of defined daily doses is almost twice as large, 937 (SD 1,669), of which a higher proportion, 82 percent, are renewed than for younger patients. The

average number of prescriptions is also larger, 10 (SD 14), of which 79 percent are renewed. The number of unique patients aged under 40 is 258,136, and the number of unique patients aged over 40 is 858,995.[19]

Table 2 shows the prevalence of health outcomes related to benzodiazepine use over the years 2007–2014. Anxiety disorder, followed by depression, appears to be the most common mental health diagnosis in specialized health care in the patient population over the years: 7 percent of patients are diagnosed with anxiety. The prevalence of severe sleeping disorders tends to be small, less than 1 percent. We also find that 1 percent of the patients are diagnosed with prescription drug abuse. The prevalence of other side effects such as hip fracture is much higher, 11 percent.

TABLE 2: Health Outcomes Related to Patients' Benzodiazepine Use

	All ages	Ages < 40	Ages ≥ 40
Anxiety	0.072	0.137	0.047
Panic disorder	0.010	0.023	0.005
Depression	0.102	0.158	0.079
Sleep disorder	0.010	0.013	0.008
Prescription drug abuse	0.012	0.032	0.005
Other side effects	0.114	0.029	0.129
Suicide attempt	0.022	0.040	0.014
Prescription drug poisoning	0.024	0.043	0.017

Notes: Unit of observation is a patient. The values depict the overall probability of obtaining a specific diagnosis in specialized health care during 2007–2014. See online Appendix A.1.2 for the definitions of the diagnoses.

Health outcomes related to benzodiazepines also vary significantly by age group. Younger patients are experiencing higher levels of anxiety, severe sleep disorders, and other benzodiazepine-related health diagnoses. For example, the prevalence of anxiety diagnosis is 14 percent for younger patients and only 5 percent for older patients over the years 2007–2014. In addition, younger patients have significantly higher rates of diagnoses related to prescription drug abuse and poisoning compared to older patients. The prevalence of a prescription drug abuse diagnosis is 3 percent for younger patients and only 0.5 percent for older patients. The prevalence of suicide attempts is also much higher (4 percent) among younger patients than among older patients (1 percent). In contrast, the prevalence of other side effects is almost 4 and a half times larger (13 percent) for older patients than for younger patients.

[19]The number of unique patients in the age groups of younger and older than 40 years does not sum up to the total number of unique patients. This is because some patients turn 40 during 2007–2014, and thus switch age groups at some point of time in our data. The estimation results for the two age groups are robust to defining the cutoff age (40 years) based on the patient's first period in the data. These alternative results are available upon request.

Figure 2 further illustrates the relationship between patient age and benzodiazepine use using our biannual patient-level data (see Appendix Table A2 for summary statistics of the data). Panels A and B plot the age-relationships for the total number of defined daily doses and the number of renewed daily doses, respectively. For brevity, we do not show essentially similar results for the number of prescriptions. The panels show that both the overall and repeat use of benzodiazepines increase sharply with age. Only for a very small group of patients aged over 90, does benzodiazepine use decrease as patients get older.

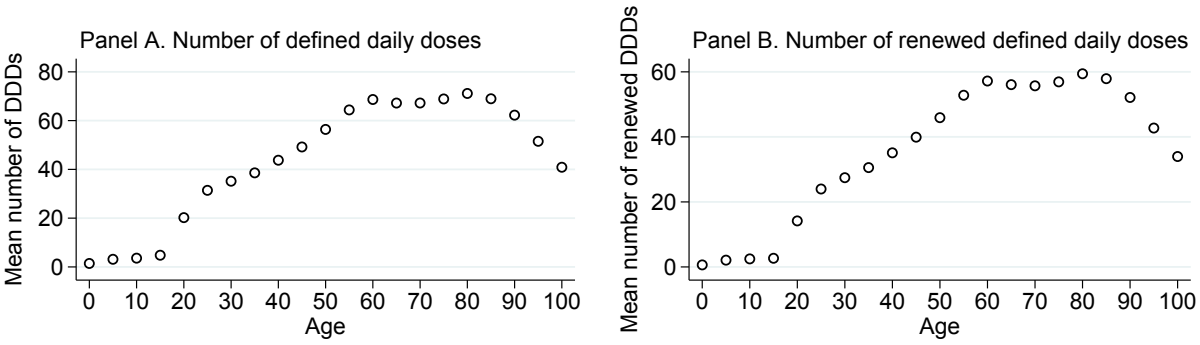

FIGURE 2: Biannual Benzodiazepine Use-Age Relationships

Notes: The figures use 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 within each bin.

Similarly, Figure 3 illustrates the age relationships for selected health outcomes. For brevity, we do not show the results for the other health outcomes. From Panels A and B we observe that the biannual probability of anxiety and sleeping disorders diagnoses, respectively, decreases with age. Panel C suggests that the probability of prescription drug abuse peaks at approximately 30 years of age, and decreases sharply after that, diminishing close to zero after the age of 40. On the other hand, other side effects diagnosed in specialized health care appear to increase only after age 40.

In summary, repeat prescriptions play a crucial role in the supply of benzodiazepines to patients, and approximately 80 percent of the prescriptions are renewed. Another fact is that younger age is a strong predictor of benzodiazepine use and health outcomes. Younger patients have fewer repeat prescriptions but strikingly higher rates of mental health admissions. It is possible that younger patients discontinue essential medications more frequently, which could worsen their health outcomes. On the other hand, younger patients also experience higher rates of severe adverse drug effects, such as prescription drug abuse and poisoning diagnoses, as well as suicide attempts.

Notably, our findings are consistent with previous evidence from other populations. The significant age-related differences in mental health outcomes, benzodiazepine use, and medication compliance are well documented in the medical literature (Julius et al. 2009; Kessler et al. 2010; Olfson et al. 2015; Feehan et al. 2017). Previous studies have also found a strong link between mental health problems and patients failing to take medications as prescribed or at all (Osterberg and Blaschke 2005; Bambauer et al. 2007), the lack of access potentially being a crucial barrier to taking medications. Overall, younger patients comprise a population of considerable interest for access-improving policies such as e-prescribing.

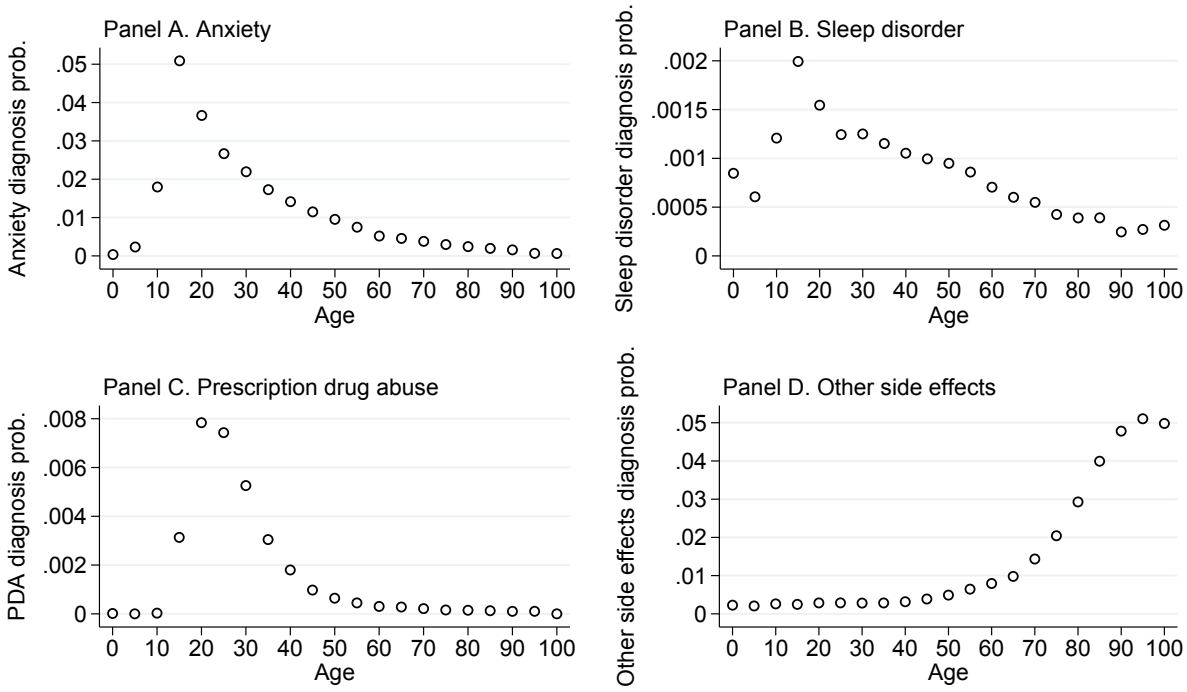

FIGURE 3: A Selection of Biannual Health Outcome-Age Relationships

Notes: The figures use patient biannual-level balanced data. The age on the x-axis is grouped into 5-year bins, after which the mean probability of a diagnosis (health outcome) are calculated within each bin. See online Appendix A.1.2 for the definitions of the diagnoses.

4 Econometric Approach and Identification

We analyze the effects of e-prescribing on prescription drug use and health outcomes on average, and by age group. Our identification strategy exploits the rollout of the technology across municipalities over the course of four years. We present graphical evidence based on an event study framework,

as well as regression results based on Difference-in-Differences (DiD) estimations.

We estimate the following event study specifications, using our biannual patient-level data:

$$y_{imt} = \sum_{\tau=-4}^{4} \delta_\tau D_{\tau,mt} + X_{imt}^{'}\beta + \alpha_m + \gamma_t + \epsilon_{imt}, \tag{1}$$

where y_{imt} is an outcome for individual i in municipality m at time t (a period of 6 months). For continuous outcome variables such as the number of defined daily doses filled, we use the logarithmic transformation $log(y+1)$. The binary variable, $D_{\tau,mt}$, indicates the period relative to the adoption period of e-prescribing in municipality m. The negative values of τ indicate the pre-adoption periods and the positive values indicate the post-adoption periods.[20] The coefficients δ_τ for the pre-adoption periods capture a possible pretrend in the outcome variable, while the coefficients δ_τ for the post-adoption periods capture the effect of e-prescribing in periods $\tau \geq 0$. Our main specification includes municipality fixed effects, α_m, that control for time-invariant differences between municipalities, and time fixed effects, γ_t, that control for the common time-varying trend. X_{imt} includes patient controls: age and age squared. We cluster the standard errors at the municipality level to capture correlation in ϵ_{imt} across patients in the same municipality.[21]

To further summarize the event study estimates δ_τ as short and long run point estimates, we estimate the following DiD model:

$$y_{imt} = \rho_1 Sr + \rho_2 Lr + X_{imt}^{'}\beta + \alpha_m + \gamma_t + \epsilon_{imt}. \tag{2}$$

The short run estimate, ρ_1, captures the effect of e-prescribing in the first year after the adoption ($\tau \in \{0, 1\}$ in the event study specification (1)). The long run estimate, ρ_2, captures the effect after the first year ($\tau \geq 2$). The advantage of estimating the long and short run effects separately is that it captures the dynamic impacts of e-prescribing as opposed to estimating only the average effect over the whole post-adoption period. We also show the results for a specification in which we replace municipality fixed effects, α_m, with patient fixed effects, η_i. This specification exploits within-patient variation in the identification, and controls for unobserved, time-invariant heterogeneity across patients such as their gender.

In both approaches, the identification of the parameters of interest (δ_τ in specification (1), and

[20] We estimate the same coefficient, δ_{-4}, for periods that took place two or more years before the adoption of e-prescribing ($\tau \leq -4$). Similarly, we estimate the same coefficient, δ_4, for periods that took place two or more years after the adoption of e-prescribing ($t \geq 4$).

[21] The number of clusters (municipalities) is 304.

ρ_1 and ρ_2 in specification (2)) are based on the differences in the outcomes of patients over time in municipalities that adopted e-prescribing early versus late. The key identification assumption is that the timing of the adoption of e-prescribing by municipalities is unrelated to unobserved or uncontrollable trends in prescription drug use and patient health across municipalities.

We develop four approaches to test this assumption in our setting. First, we show the event study results graphically with a sufficient amount of pretreatment periods to reveal any pretreatment trends in the outcomes of patients in municipalities that adopted early versus late. Second, we directly test whether observable municipality-level characteristics correlate with the adoption time, presented in Table A1. The results confirm the lack of correlation. Third, we also show the results from specifications that control for patient fixed effects. If any time-invariant patient-level characteristics are correlated with the adoption time, our results would vary across the specifications.

Fourth, we are not aware of any other policy changes in the years 2007–2014 that could potentially confound our results. The only exception is the introduction of a national EMR system. The system was integrated with the e-prescribing system, also providing information on a patient's diagnoses. The EMR system was adopted by municipalities at the end of our observation period, starting from 2014.[22] By the end of 2014, approximately 200 municipalities had adopted the system. In online Appendix A.5, we show that our results are not sensitive to the adoption of EMR by municipalities.

The take-up of e-prescriptions by patients (and physicians) was voluntary during the observation period.[23] This implies that the parameters of interest are intention-to-treat (ITT) estimates on the average effects of the e-prescribing policy. Interestingly, several prior studies have found the benefits of health information technology to be, at best, fairly small or limited to specific circumstances (Himmelstein et al. 2010; Lee et al. 2013; Agha 2014; McCullough et al. 2016). However, many earlier studies fail to identify the actual take-up rates at the individual level. Voluntary use and low take-up rates in treatment regions may explain why studies find that health information technologies have little or no benefits.

We take advantage of the prescription-level administrative data to explore the take-up rate of e-prescriptions for patients. Panel A of Figure 4 plots the biannual fraction of electronic benzo-

[22]We obtain the data on the adoption time of EMR for municipalities from the National Institute for Health and Welfare.

[23]The law on central nervous system drug prescribing was changed later and from October 2015 onward (outside of our observation period) all prescriptions for drugs in the class of benzodiazepines had to be issued electronically.

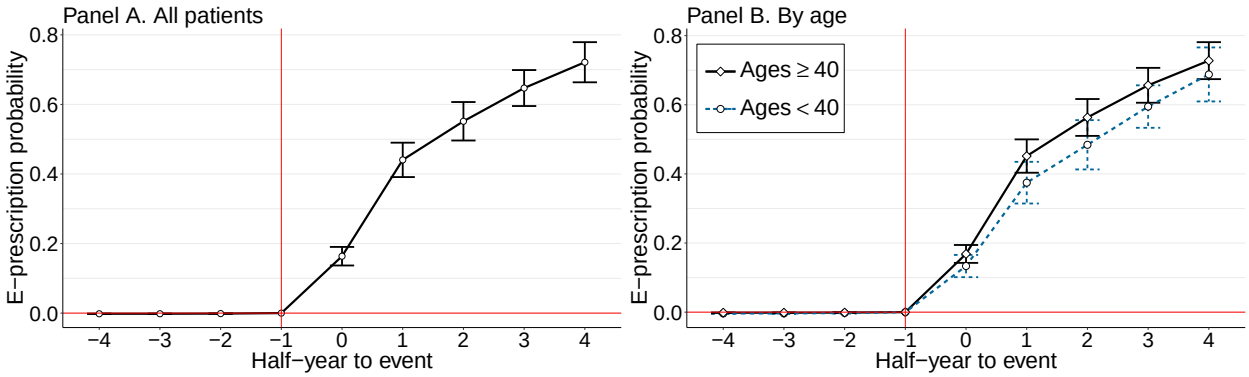

FIGURE 4: Conditional Take-up Rate of E-prescriptions, by Age Group

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

diazepine prescriptions around the implementation of e-prescribing in a municipality. Following the implementation, the take-up rate of e-prescriptions by patients (or their physicians) increases sharply in the adoption period and continues to increase gradually over time. One year after the adoption of e-prescribing approximately 60 to 70 percent of benzodiazepine prescriptions are issued electronically. This suggests that low take-up rates are unlikely to explain our results. Panel B in Figure 4 shows that the take-up rates do not differ significantly by age group. This pattern in turn suggests that the differences in the take-up rates by age groups are unlikely to drive the potentially heterogeneous impacts of e-prescribing that we analyze next.

5 Results

5.1 Benzodiazepine Use

We begin by estimating the effect of e-prescribing on benzodiazepine use on average, and by age group. We have two age groups in our baseline estimations: those younger than 40, and those older than 40. We motivate our heterogeneity analysis by large age-related differences in benzodiazepine use (and health outcomes), which we documented in Section 3.3. For example, we showed that younger patients have fewer repeat prescriptions for benzodiazepines. Improving access through e-prescribing might thus primarily encourage these patients to order repeat prescriptions. Further motivating our aggregated age groups, we find no apparent heterogeneity in the impacts of e-prescribing across patients in the older population using finer age grouping (aged 40–64 and over

65), as presented in online Appendix Table A6.

Figure 5 plots the baseline event study estimates of the effects of e-prescribing on the log number of defined daily doses of benzodiazepine prescriptions, which is our primary measure of overall benzodiazepine use. The figure reports the δ_τ coefficients and their confidence intervals from estimating Equation (1). We find that e-prescribing does not affect overall benzodiazepine use, as shown in Panel A. The corresponding baseline DiD estimates from Equation (2) are presented in column 1 of Table A3. In column 2, we report the estimates from the specification that exploits within-patient variation and replaces municipality fixed effects with patient fixed effects. This additional specification confirms the lack of a significant effect on average.

Next we examine whether e-prescribing has heterogeneous effects by age group. Panel B of Figure 5 shows the event study estimates for younger patients. Remarkably, we find that e-prescribing increases the number of defined daily doses for younger patients after the first year of adoption, coinciding with the gradual increase in the uptake of e-prescriptions by patients shown in Figure 4. The magnitude of the long run estimate is approximately 3–5 percent (columns 3 and 4 of Table A3). The event study estimates show no evidence of differential pretrends, providing evidence in support of our research design for this sub-population. Our alternative measure of overall use, the log number of benzodiazepine prescriptions, shows a similar, although somewhat smaller effect (approximately 1 percent increase) in the long run (Figure A3 and Table A5). However, as discussed, this coarse measure does not take into account the potential changes in the quantity or dose of prescriptions. The finding that daily doses increase more than the number of prescriptions suggests that the increase in overall use stems from larger doses.

By contrast, we do not find any significant increase in the number of defined daily doses for older patients (Figure 5 and Table A3). We also confirm this conclusion using the log number of prescriptions (Figure A3 and Table A5). Although there is no clear, statistically significant evidence of differential pretrends for daily doses, there appears to be some differences in the pretrends of the number of prescriptions across regions (that is, the early versus the late adopters). For this reason, our evidence for older patients should be taken with some caution.

We proceed to study a mechanism through which e-prescribing affects the use of benzodiazepines. E-prescribing improves medication access by making it easier for patients to order repeat medication. Thus, the access mechanism is likely to affect prescription renewal (repeat use), as opposed to new prescription drug use. We thus present the estimates for the log number of renewed defined daily doses in Panels A–C of Figure 6. Panels D–F show the corresponding estimates for the

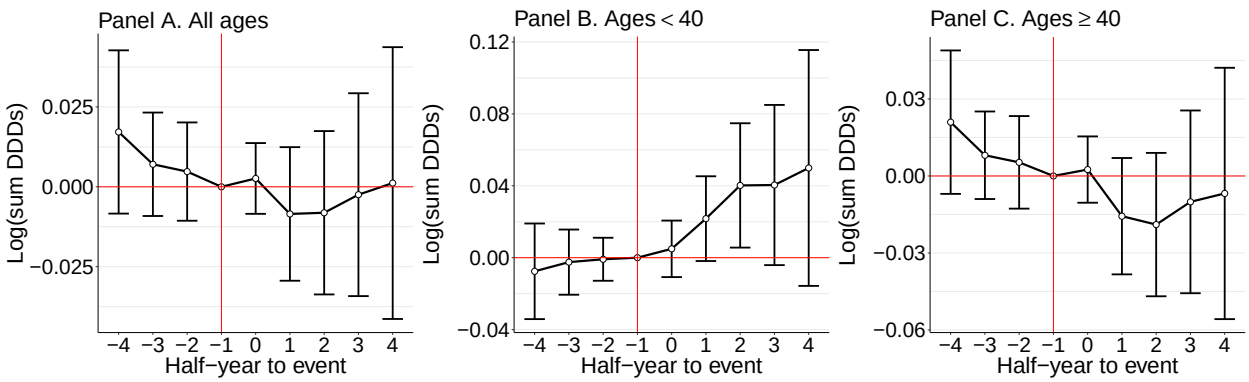

FIGURE 5: Number of Defined Daily Doses, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcome is the the log number of defined daily doses (DDDs) from benzodiazepine prescriptions filled by the patient during a biannual period. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

log number of defined daily doses of new prescriptions. Again, on average and for older patients, we find no evidence of an increase in the use of renewed or new benzodiazepine prescriptions. In contrast, consistent with improved access, e-prescribing primarily increases the number of renewed defined daily doses for younger patients but has a notably smaller effect on their use of new benzodiazepine prescriptions (Panel E).[24] The point estimates in columns 3 and 4 of Table A4 reveal that the increase in the number of renewed defined daily doses is 3–4 percent in the long run.[25] While column 4 shows that the point estimate for the new defined daily doses is statistically significant when estimated using patient fixed effects, it is also much smaller in magnitude than the point estimate for the renewed defined daily doses.[26]

We confirm the robustness of our main results using three different specifications in Table A14. First, we exclude municipalities that adopted the national EMR system. Second, we exclude benzodiazepine products that were removed from the NHI scheme during the observation period. Third, we allow for differential time trends depending on the municipality type (urban, semi-urban, and rural).

[24]E-prescribing can decrease or increase new prescription drug use. Improved information on prescription histories may prevent physicians from initiating unnecessary or harmful prescription drug therapy. However, improved prescription information may induce physicians to prescribe drugs in different strengths (e.g. in lower doses) and forms, increasing the use of new prescriptions.

[25]Because of the log transformation, the sum of the decomposed point estimates do not exactly equal the point estimates from the total effect. For example, $Log(sum\,DDDs) \neq Log(sum\,renewed\,DDDs) + Log(sum\,new\,DDDs)$ but $Log(sum\,DDDs) = Log(sum\,renewed\,DDDs + sum\,new\,DDDs)$.

[26]Online Appendix Table A5 Panels B and C show the results for the number of new and renewed prescriptions, leading to a similar conclusion.

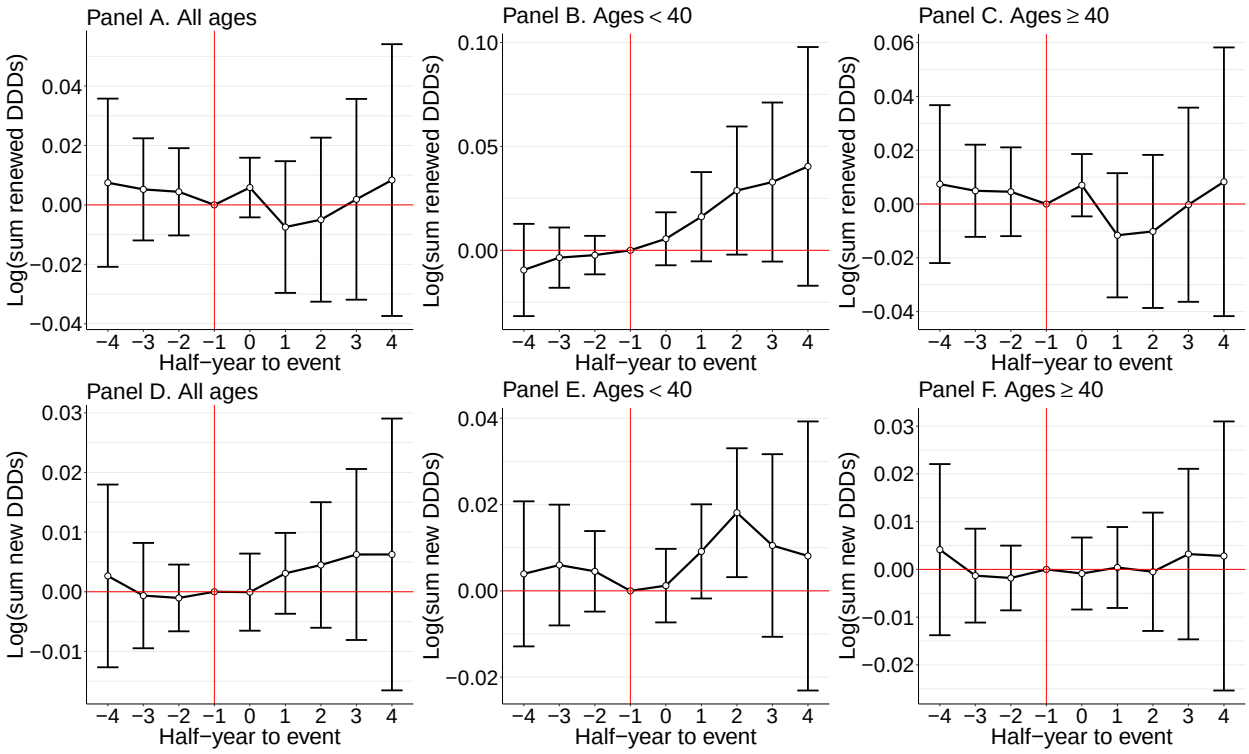

FIGURE 6: Number of Defined Daily Doses of Renewed and New Prescriptions, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcomes are the log number of defined daily doses (DDDs) of renewed benzodiazepine prescriptions (Panels A, B, and C) and the log number of defined daily doses of new benzodiazepine prescriptions (Panels D, E, and F) filled by the patient during a biannual period. See Section 3.1 for the definitions of renewed and new prescriptions. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

In summary, we find that e-prescribing does not affect benzodiazepine use on average, and this overall effect appears to be driven by older patients. Instead, for younger patients, we find an increase in repeat benzodiazepine use, especially in larger doses. This suggests that e-prescribing is effective at improving access to medications for younger patients—a population with fewer repeat prescriptions but strikingly higher rates of mental health admissions (Section 3.3). To shed light on whether e-prescribing increases appropriate use or overuse, we estimate the effects of e-prescribing on patient health in the following section.

5.2 Health Outcomes

E-prescribing and the resulting increase in benzodiazepine use for younger patients can improve their mental health outcomes and other conditions that are typically treated with benzodiazepines.

On the other hand, e-prescribing might have increased benzodiazepine overuse in the younger population. This is possible if the technology (easier ordering of prescriptions) primarily affected the incentives of younger patients at the margin of ordering repeat medication, with low and possibly negative health returns from benzodiazepines, for example, through adverse drug effects. Instead, e-prescribing had no effect on older patients' benzodiazepine use, and thus, we do not expect to see any change in their health outcomes.

We begin by estimating the impacts of e-prescribing on the probability of diagnoses related to mental health disorders in specialized health care on average, and by age group. We then proceed to other health outcomes that capture the potential health benefits of benzodiazepine use (Section 5.2.1). We also investigate whether e-prescribing had any adverse health effects which we measure by diagnoses related to prescription drug abuse and poisoning, as well as by suicide attempts (Section 5.2.2). Finally, we provide descriptive evidence in support of benzodiazepine use and repeat prescriptions as mechanisms driving the effects on patient health (Section 5.2.3).

5.2.1 Potential Health Benefits

Figure 7 plots the event study estimates for the probability of mental health disorders: anxiety (row 1), panic disorder (row 2), and depression (row 3) diagnoses on average (column 1), for those younger than 40 (column 2), and for those older than 40 (column 3).[27] The figure shows no evidence of differential pretrends, again confirming the credibility of our research design.

We find that e-prescribing has no impact on the mental health outcomes on average or for the two age groups. Not even younger patients, who experienced a substantial increase in their benzodiazepine use as a consequence of e-prescribing, have any improvements in their diagnosed health outcomes. The point estimates are very close to zero in magnitude and relatively precisely estimated right after the implementation of e-prescribing—however, their imprecision increases over time. The short and long run point estimates from the DiD estimations provide similar evidence on the anxiety, panic disorder, and depression diagnoses, as shown in Panels A, B, and C of Table A7, respectively.

In Figure 8, we report the event study estimates for the probability of a diagnosis related to severe sleep disorder, another common condition that is treated with benzodiazepines. The corresponding DiD estimates are documented in Panel D of Table A7. We find that e-prescribing has no apparent effect on a sleep disorder diagnosis, when using data of all patients or separately

[27] We report the results for the age groups 18–39, 40–64, and over 65 in Table A8.

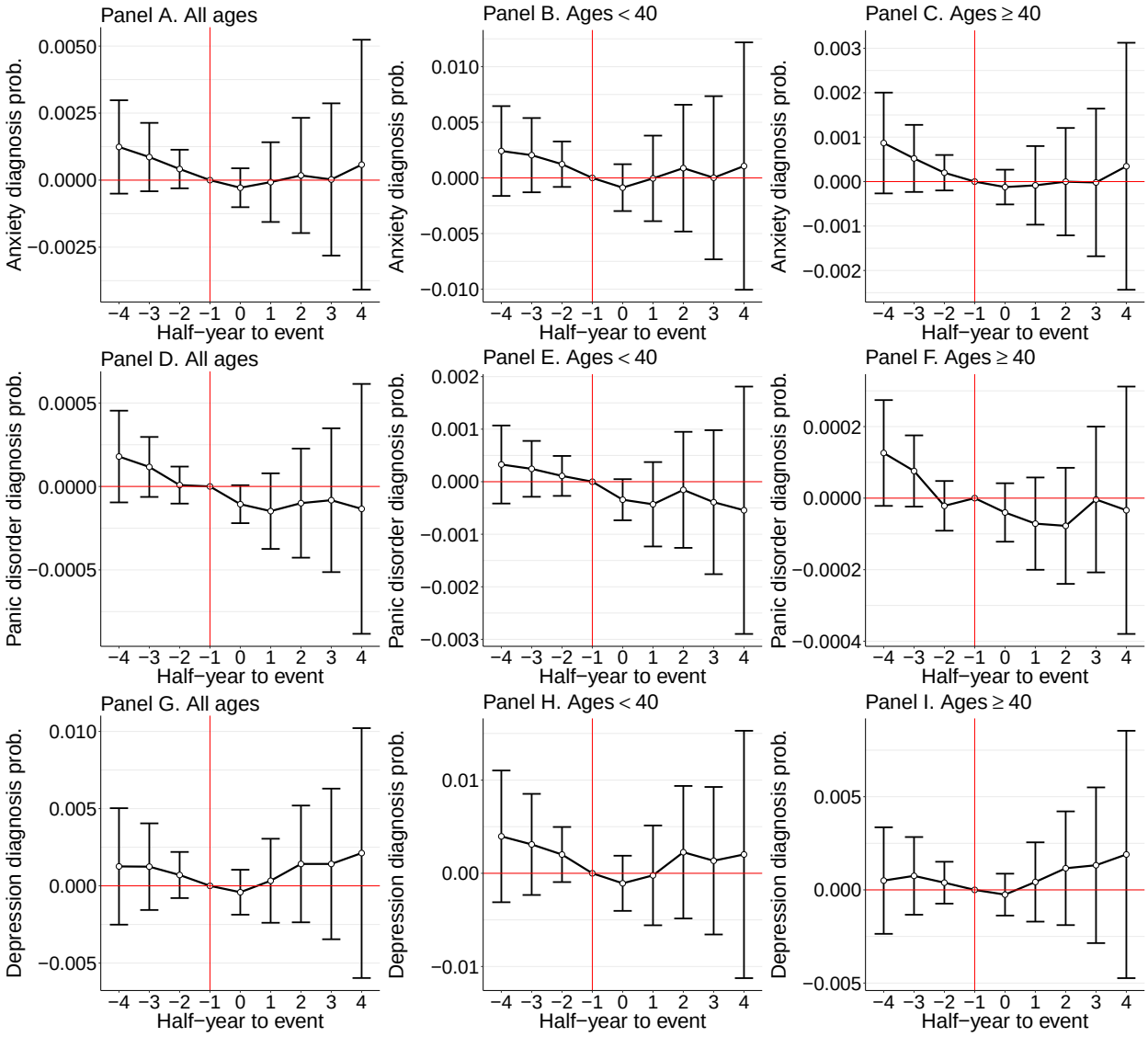

FIGURE 7: Mental Health Diagnoses, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnoses are anxiety (Panels A–C), panic disorder (Panels D–F), depression (Panels G–I). See online Appendix A.1.2 for the definitions of the diagnoses. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

studying the two age groups. We also obtain similar findings for our additional, but perhaps less clear-cut and coarser, health outcomes presented in Figure A5: the probability of an epilepsy diagnosis (row 1), and the total number of admissions to an emergency department (row 2) and to specialized health care (row 3).[28] The DiD estimates are presented in Table A9.

A potential concern regarding our analysis is that the insignificant health effects could result from e-prescribing mechanically affecting the diagnosis of medical conditions concurrently with prescription drug use. This would occur if a patient obtained a new diagnosis in specialized health care while (or after) renewing a prescription. Moreover, this would result in an underestimated effect if this mechanical effect occured simultaneously with improved health outcomes caused by the increased prescription drug use.[29] To address this concern, we explore the robustness of our results for not taking into account observations where a benzodiazepine is prescribed for a patient on the same day as he/she obtained a diagnosis in specialized health care (only 4 percent of diagnoses). In effect, we replace these observations with zeros when constructing our health outcomes. The results are presented in Table A12. Additionally, Table A13 shows the results from specifications where we do not take into account observations where the prescribing date is the same as the date of obtaining a referral to specialized health care (less than 1 percent of diagnoses). The results and outcome means based on these two sets of alternative specifications are virtually identical to those obtained from our main specifications. This suggests that the co-occurrence of prescribing and diagnosing and its potential changes that occur as a result of e-prescribing are not driving our results.

This finding is perhaps expected because our health outcomes are measured at a different level of the health care system (in specialized health care) than the adoption of e-prescribing (in primary care).[30] In addition, e-prescribing makes repeat ordering easier *without* having to see a physician, which might in fact worsen a physician's ability to diagnose medical conditions. Nevertheless, we explore the role of improved diagnoses also for adverse health outcomes in Sections 5.2.2 and 5.2.3.

We run the same robustness checks for the primary outcomes related to mental health and severe sleep disorder diagnoses as we did for the benzodiazepine use outcomes in Section 5.1. Table

[28] While benzodiazepines are not usually the first-line treatment choice to treat long-term epilepsy, physicians may still prescribe benzodiazepines for acute treatment of seizures and other symptoms of epilepsy.

[29] This concern is typical in research analyzing the impacts of health information technology. For example, EMRs might increase physicians' abilities to diagnose medical conditions and increase the prevalence of medical conditions. Any health effects measured with these outcomes are thus potentially underestimated.

[30] The increase in the use of repeat benzodiazepine prescriptions for younger patients is likely to come from primary as opposed to specialized care because our focus is on the adoption of e-prescribing in primary care. This in turn makes it less likely that additional diagnoses in specialized health care were obtained upon renewal of these additional benzodiazepine prescriptions.

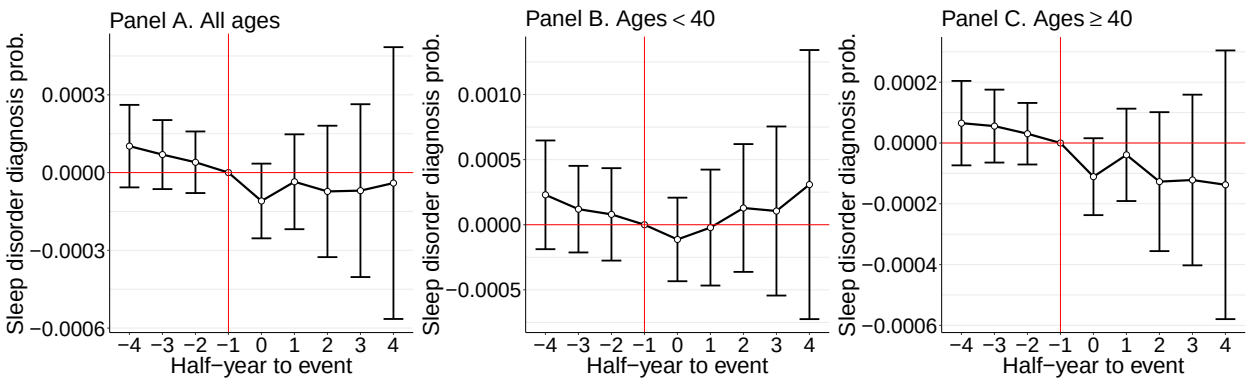

FIGURE 8: Sleep Disorder Diagnosis, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcome is a binary variable indicating if the patient has obtained a sleep disorder diagnosis in specialized health care during a biannual period. See online Appendix A.1.2 for the definition of the diagnosis. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

A15 reports the results. Our findings are robust to the alternative specifications.

To summarize, we do not find any compelling evidence of improvement in health outcomes on average or for different age groups. This finding is expected for older patients (whose benzodiazepine use did not change) but striking for younger patients. The result that the benzodiazepine use increases but the health outcomes do not improve in the younger population suggests that e-prescribing increases medication overuse. This could be driven by younger patients at the margin of ordering repeat prescriptions for benzodiazepines, with negligible health benefits. The result is also consistent with, though not directly comparable to the concerns raised on the limited benefits of benzodiazepines in long-term use (Lader 2011; NICE 2011; Moore et al. 2015), despite benzodiazepines' global popularity in treatment of mental health-related conditions. In the following section, we study whether e-prescribing resulted in adverse health effects related to benzodiazepine use.

5.2.2 Adverse Health Effects and Suicide Attempts

Figure 9 plots the event study estimates of the probability of a prescription drug abuse diagnosis. The results in Panel A show that the point estimates increase slightly as a result of e-prescribing on average, although the size of the effect is small. However, our estimates reveal that the impacts are highly heterogeneous across age groups. Notably, e-prescribing leads to a gradual statistically and quantitatively significant increase in the probability of a prescription drug abuse diagnosis for

younger patients. The increase is approximately 20 percent compared to the mean in the long run, although the impact becomes less precisely estimated with patient fixed effects compared to the baseline estimates (columns 3 and 4 of Panel A in Table A10). In contrast, we find no effect for older patients.

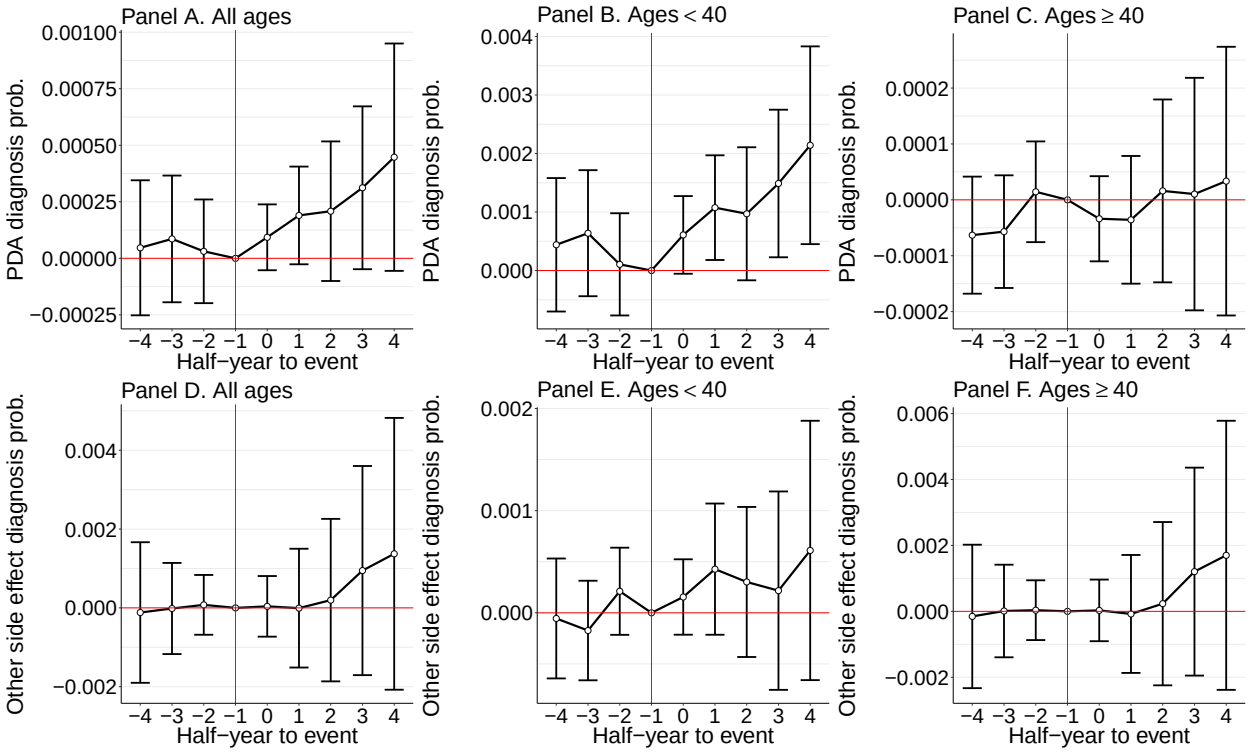

FIGURE 9: Diagnoses Related to Prescription Drug Abuse and Other Adverse Effects of Benzodiazepines, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnoses are prescription drug abuse (Panels A–C), and other common benzodiazepine-related side effects (Panels D–F). See online Appendix A.1.2 for the definitions of the diagnoses. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

In addition to possible addiction, benzodiazepines may have other side effects such as sedation, poor coordination, decline in cognitive functions, and delirium, as well as increased risk of accidental falls and hip fractures (Lader 2011). These are greater concerns for older patients as the prevalence of these side effects increases by age (see Section 3.3). The results in Panels A–F of Figure 9 and Panel B of Table A10 suggest that e-prescribing has no effects on the probability of a diagnosis related to any of these other side effects on average or for the two age groups.

Next, we examine whether the implementation of e-prescribing affects suicide attempts (Figure

10 and Panel B of Table A10). Suicide attempts are a particularly important outcome in our setting for three reasons. First, benzodiazepines are used to treat mental health problems such as anxiety and depression. Mental health problems in turn increase suicide risk, and thus suicide attempts can be used as a proxy of poor mental health status. Second, drug overdose is a fairly common method in suicide attempts (Ajdacic-Gross et al. 2008), making them closely related to prescription drug use and abuse. Third, benzodiazepine use is linked to the elevated risk of suicide, as discussed in Section 2.3.

We find that e-prescribing increases the probability of a suicide attempt on average. Interestingly, this effect is driven by younger patients, whose probability of a suicide attempt increased by 11 percent in the short run (column 3). The effect in the long run is somewhat larger (17 percent), though less precisely estimated. These effects become slightly larger in magnitude and more precisely estimated with patient fixed effects (column 4). These findings suggest that suicide attempts change concurrently with benzodiazepine use. This pattern is consistent with a positive association between benzodiazepine use and suicide risk documented in the medical literature (Neutel and Patten 1997; Carlsten et al. 2003; Tiihonen et al. 2012).[31]

We also explore the effect of e-prescribing on treatment admissions related to prescription drug poisoning (Figure 10 and Panel D of Table A10). We find that the probability of a prescription drug poisoning diagnosis increases significantly for younger patients, but we detect no impact for older patients. However, there is evidence of an increasing trend in prescription drug poisonings in the pre-adoption periods in early adopting municipalities. Therefore, our findings for this specific outcome have to be interpreted as suggestive, rather than conclusive.

We run the same robustness checks for the adverse health outcomes as we did in Section 5.1 and 5.2.1. The results in Table A16 indicate that our findings are robust to the alternative specifications. We also confirm that our results on the adverse effects of benzodiazepines are not explained by the improved diagnoses (see columns 6–7 of Table A12 and A13).[32]

Overall, our findings are similar for various measures of the adverse health effects of benzodiazepine use and for suicide attempts. Again, we do not find any evidence that e-prescribing affects older patients' health outcomes (or their benzodiazepine use, as documented earlier in Section 5.1).

[31] While benzodiazepines may mitigate mental distress symptoms of anxiety and insomnia and thus decrease the risk of suicide, increased use may also worsen withdrawal symptoms, aggressiveness and impulsiveness, leading to the elevated risk of suicide (Neutel and Patten 1997; Carlsten et al. 2003; Tiihonen et al. 2012). However, the causal link and exact underlying mechanisms remain unclear.

[32] For brevity, we omit suicide attempts and prescription drug poisonings from the set of outcomes because it is very unlikely that improved diagnosis would explain the observed changes in such extreme outcomes.

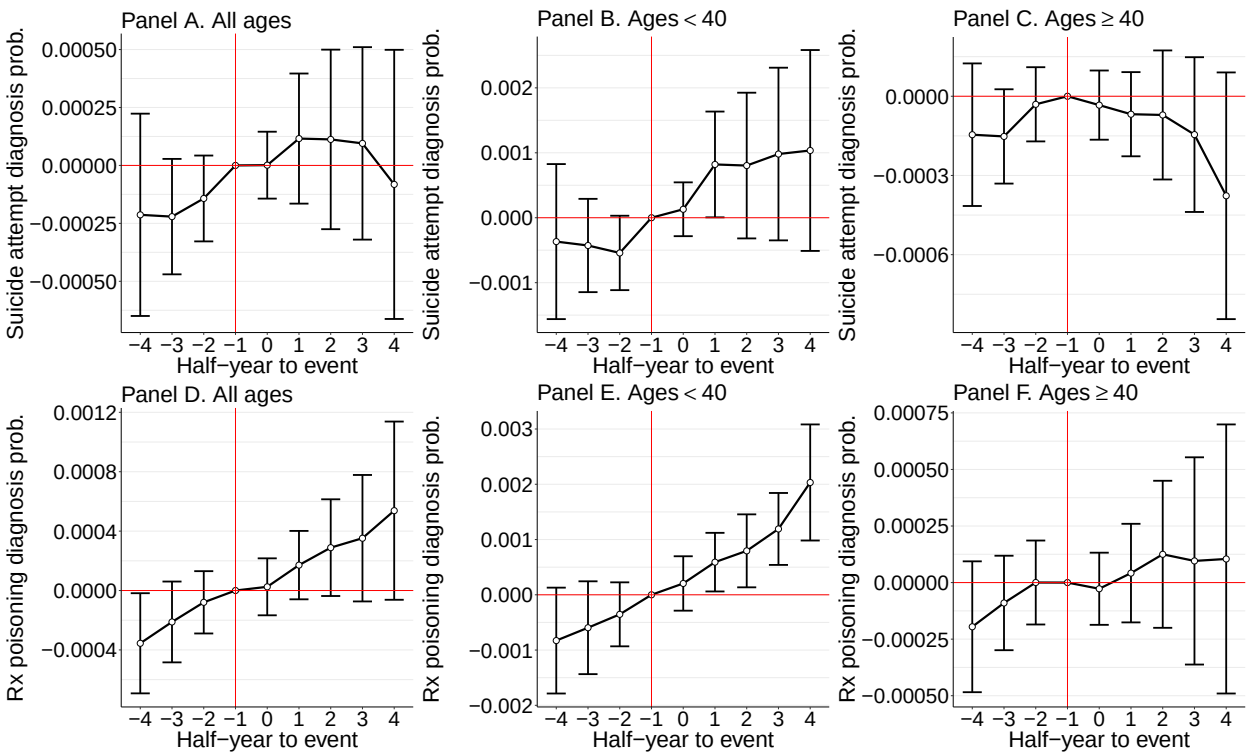

FIGURE 10: Diagnoses Related to Suicide Attempts and Prescription Drug Poisonings, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnoses are suicide attempt (Panels A–C), and prescription drug poisoning (Panels D–F). See online Appendix A.1.2 for the definitions of the diagnoses. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

In contrast, younger patients experience strikingly higher rates of diagnoses related to prescription drug abuse disorders, suicide attempts, and potentially also drug poisonings in specialized health care. These increases occur concurrently with the increase in benzodiazepine use. The finding that both the pharmaceutical use and patient harms increase suggests that e-prescribing is effective at improving access but leads to medication overuse for younger patients.

5.2.3 Link Between Benzodiazepine Use and Adverse Health Outcomes

Our results lead to the conclusion that the increase in repeat benzodiazepine use is contributing to adverse health outcomes for younger benzodiazepine patients, although e-prescribing may have also affected the concurrent use of multiple medications (so-called polypharmacy). In this section, we further explore the link between benzodiazepine use and prescription drug abuse—one of the

primary adverse health outcomes.

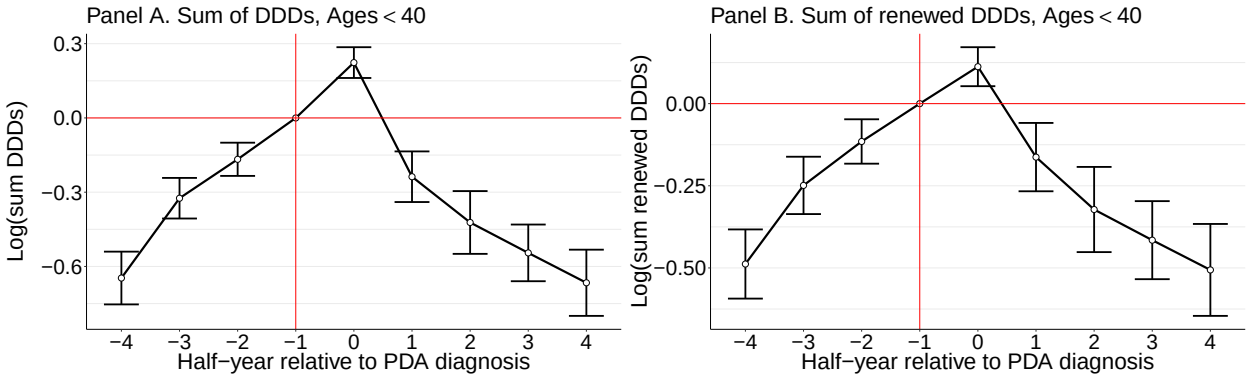

FIGURE 11: Benzodiazepine Use Around First Prescription Drug Abuse Diagnosis, Patients Aged Under 40

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data for those with at least one prescription drug abuse diagnosis in specialized health care during the period of 2009–2014. Event time is the biannual period relative to the patient's first prescription drug abuse diagnosis. Patients that have their first prescription drug abuse diagnosis before 2009 are excluded to account for left-censoring. In Panel A the outcome is the log number of defined daily doses (DDDs), and in Panel B the outcome is the log number of renewed defined daily doses. The omitted period is −1. The regressions control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

We investigate how benzodiazepine use changes around the period when a patient obtains his/her first prescription drug abuse diagnosis, as illustrated in Figure 11.[33] In Panel A, we measure benzodiazepine use by the number of defined daily doses, and in Panel B, by the number of renewed defined daily doses. Both panels show sharp changes in benzodiazepine use for younger patients in the periods around the first diagnosis, with a large increase (decrease) within two years before (after) the diagnosis. While only suggestive, these descriptive findings are consistent with the repeat use of benzodiazepines contributing to prescription drug abuse.

Another potential mechanism driving the observed increase in prescription drug abuse diagnosis could be that e-prescribing improved the diagnoses of medical conditions in specialized health care. In Sections 5.2.1 and 5.2.2 we provided evidence against this mechanism by exploring the co-occurrence of benzodiazepine prescribing and diagnosing. To investigate this further, we visually illustrate the effect of e-prescribing on the relationship between benzodiazepine use and prescription drug abuse diagnoses in specialized health care. If diagnosing improved as a result of e-prescribing, we would expect the probability of a prescription drug abuse diagnosis to be higher at a given level of benzodiazepine use. By contrast, this does not appear to be the case, as shown in Panel

[33]We exclude patients who have their first prescription drug abuse diagnosis before year 2009 to ensure that the event time is correctly defined relative to the first diagnosis.

A of Figure 12 for younger patients. The probability of a prescription drug abuse diagnosis is positively related to benzodiazepine use, and the associations are virtually identical before and after e-prescribing. We confirm the finding for older patients (Panel B), as well as for diagnoses related to the other adverse effects of benzodiazepines by age group (Panels C and D). Only Panel C shows some evidence of an increase in other side effects at higher levels of benzodiazepine use.[34]

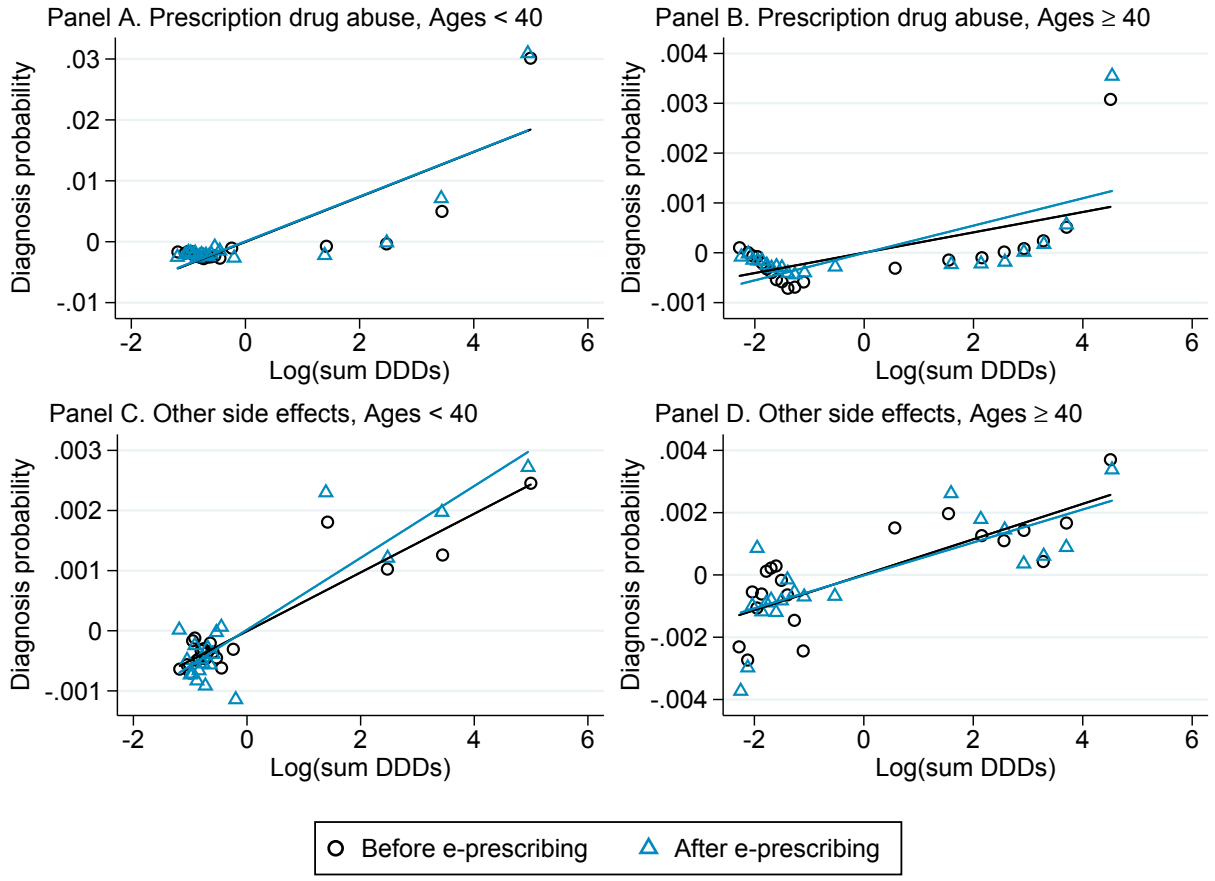

FIGURE 12: A Selection of Benzodiazepine Use and Adverse Health Outcome Relationships, by E-prescribing Adoption and Age Group

Notes: This figure plots the probability of prescription drug abuse (Panels A and B) and other side effects diagnosis (Panels C and D) for a given log number of defined daily doses (DDDs). The figures use patient biannual-level balanced data. See online Appendix A.1.2 for the definitions of the diagnoses. Both the x-axis and y-axis variables are residualized municipality fixed effects, common time trend, and patient's age and square of age. The residualization is done separately for the two age groups. After the residualization, the outcome variable is grouped into 20 equal-sized bins, and the mean probability of the diagnosis within each bin is plotted against the mean value of the log number of defined daily doses in the corresponding bin. The bins and the corresponding OLS line are plotted separately for the periods before the e-prescribing adoption (in blue) and after the e-prescribing adoption (in black).

[34]Additionally, in Table A16, we show that the results are not driven by potentially easier diagnosis after the adoption of the national EMR system in some municipalities.

6 Conclusion

We show that digitization of prescriptions improves medication access but causes overuse, with adverse health effects in vulnerable patient groups. We study how digitization of prescriptions affects pharmaceutical use and patient health outcomes, by using the rollout of a national e-prescribing system and comprehensive administrative data. The prescription drugs we are studying, benzodiazepines, are globally popular and effective but highly addictive mental health and insomnia medications.

We find that e-prescribing has no effect on benzodiazepine use and health outcomes on average. These results are driven by older patients. In contrast, for younger patients, e-prescribing increases repeat benzodiazepine use. There is no compelling evidence of an improvement in younger patients' health outcomes, but striking increases are observed in adverse health outcomes. For example, prescription drug abuse diagnoses and suicide attempts increase dramatically for younger patients who are already at much higher risk for such outcomes. Our findings suggest substantial welfare losses of increasing medication overuse, given that benzodiazepine abuse and suicide attempts alone cause large private and social costs in the younger population.

We make progress towards understanding the heterogeneous impacts of e-prescribing on patients across age groups that the average effects mask. Improving access has a smaller impact on older patients' incentives to order additional medication because repeat use is already common for them. For example, in the UK, the proportion of individuals on repeat medications is only 25 percent for children and young adults whereas for patients in their 60s and over 70s, respectively, it ranges from 75 percent to over 90 percent (Duncan et al. 2014). By reducing the hassle and time costs of ordering prescriptions, e-prescribing may increase repeat use especially among younger patients with low or negative health returns from medication. Medication benefits some (marginal) patients, but for others it can be harmful, in addition to being financially costly to society.

Our results inform the ongoing policy debate to improve medication access, for example, to longer repeat prescriptions, and online ordering of medications. We highlight that the efforts to improve access may lead to medication overuse, especially with suboptimal monitoring of patients. Our findings on e-prescribing also suggest that providing better information on prescription histories may not outweigh the risk of medication overuse, being an insufficient tool for targeting of medications only to patients with high health returns and low risks. Finally, our results raise fundamental questions about how much information technologies improve the repeat prescribing

process, and whether they impair face-to-face communication that is essential for optimal medical treatment. Studies of other emerging technologies and markets on the correct policy are key areas for future research.

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A Online Supplementary Appendix

A.1 Data

A.1.1 Identification of Benzodiazepine Prescriptions

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

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

During the observation period, 2007–2014, some prescription drug products/brands and product-strength combinations were discontinued from the NHI scheme (and hence, they exit the Prescription Data). In the main analysis, we include the discontinued products in the data, but the results are robust to exclusion of these products, as explained in the main text and presented in online Appendix A.5. The following list shows these products, the year of reimbursement discontinuation, and the ATC code in parenthesis:

- 2008: Normison (N05CD07)
- 2009: Alprazolam Merck NM (N05BA12); Zopiklon Merck NM (N05CF01)
- 2010: Zolpidem Sandoz (N05CF02); Zolpidem Stada (N05CF02)
- 2011: Risolid (N05BA02)
- 2013: Insomin (N05CD02); Tenox (N05CD07); Diapam 2mg/ml (N05BA01)

A.1.2 Identification of Health Outcomes

In this section, we describe the identification of our health outcomes from the Discharge Data. The outcomes are typically identified using detailed information on each patient's primary diagnoses in specialized health care. We use the primary diagnoses because they are recorded accurately and

because the quality of recording secondary diagnoses has raised some concerns in validation studies (Sund 2012). This section describes the diagnoses that we explore, and below in Section A.2, we provide further details of the Discharge Data and describe the construction of the health outcomes from the diagnoses at the patient biannual-level.

We identify the following disorders, as measured by the ICD10 classification:

- Anxiety (Neurotic, stress-related and somatoform disorders): F40–F48
- Panic disorder: F41.0
- Depression: F32–F33
- Sleep disorder: G47.0, G47.2, G47.8, G47.9, F51
- Epilepsy: G40
- Prescription drug poisoning: T36

The first five are disorders treated with benzodiazepines. The last disorder is one of the adverse effects of prescriptions drugs, most notably benzodiazepines.

To identify prescription drug abuse disorders we group together multiple diagnoses measuring from prescription drug abuse (e.g. abuse of benzodiazepines and opioids). This grouping is natural as many abusers are polydrug users, and a prescription drug abuse diagnosis in our data is an indication of rather strong abuse, which further hints towards 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 weaned off the prescription drug abuse, 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 the 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)

In contrast, suicide attempts are identified using a variable that measures an external cause for a visit (as opposed to primary diagnosis), with any of the following ICD10 codes: Intentional self-harm (X60–X84).

To identify emergency department visits, we take advantage of additional information on the patient's discharges in the data. If the patient's discharge is one of the following admissions, we classify the visit as an emergency department visit:

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

A.2 Data Description and Aggregation

To construct the final (patient biannual-level) analysis data used in the estimations, we aggregate the original administrative datasets in several steps. We begin by describing the Prescription Data and its aggregation, then proceed to describing the Discharge Data and its aggregation. Finally, we describe the merging procedure of the two aggregated datasets.

A.2.1 The Prescription Data and Its Aggregation

The Prescription Data for the years 2007–2014 are from the Social Insurance Institution of Finland. The data identify benzodiazepine prescriptions that are covered by the NHI scheme, the characteristics of prescriptions (described in Section 3), the patient's birth date and the patient's municipality of residence. As most of the prescriptions are covered by NHI, the data well represent the prescription drug purchases of the Finnish population. Notably, the observations are prescriptions filled by patients at pharmacies but not prescriptions that have never been filled. Thus, the observations should accurately measure the use of benzodiazepines. Initially, the Prescription Data are at the patient-purchase level, potentially containing multiple purchases for each individual prescription when the patient has not purchased all items of the prescription at once.

We begin with a sample size of 14,154,850 purchase events. First, we restrict the data to the period 2007–2014 by dropping rows where a prescription was prescribed in any of the years 2004, 2005, and 2006 (but purchased during 2007–2014). This excludes 212,613 observations.

Second, we drop observations where the patient's municipality of residence is in the province of Åland. Åland is a small, isolated and autonomous island with approximately 29,000 inhabitants, and its self-governance reaches out to almost all of its institutions and sectors, including health care. In addition, we drop observations with missing or foreign municipalities because we study the impacts of e-prescribing using information on the patient's municipality of residence in Finland, as described in Section 3.2. As a result, 50,302 observations are excluded.[35]

[35] We also remove one observation where the age is inputted as -1.

Third, we convert the yearly municipality classification to the classification in 2013. We use the 2013 classification because Finland has experienced a substantial number of municipal mergers throughout the years in the data (but not in 2014). Specifically, in 2009, 32 municipal mergers were carried out, which included 99 municipalities in total. In 2011, 6 municipal mergers took place, 10 in 2013, but no mergers were accomplished in 2014. To perform the conversion to the 2013 classification, we code the home municipalities of patients who lived in municipalities that have ceased to those that resulted from the merging process. The number of municipalities in our final data is 304.

Fourth, we exclude patients who have at least one observation with missing information on the number of defined daily doses, in total only 15,675 observations and 1,066 unique patients.[36] When the number of defined daily doses is missing, the number of purchased packages per prescription is also missing. Thus, we cannot calculate the number of defined daily doses per prescription. Our results remain similar if we include these patients in our analysis data with the assumption that the missing number of packages is equal to one purchased package. These alternative results are available upon request.

Fifth, we aggregate the data to the patient-prescription level. If the patient does not fill the whole prescription at once but instead fills the prescription in smaller packages (e.g. physicians might add restrictions to prescriptions that limit the amount that can be purchased at once), this creates duplicate observations per prescription in the data. To aggregate the data, we first identify single prescriptions as those that have the same patient identifier, physician identifier, the ATC code and the date of prescribing. In addition, we identify patient age based on birth date. Additionally, as the amount of defined daily doses is at the purchase level, in the aggregation process, we calculate the total number of defined daily doses per prescription. The sample size after this step is 9,803,090 patient prescription observations.

Sixth, we aggregate the patient prescription-level data to patient biannual-level. We thus construct a balanced panel sample, in which every patient has an observation during each of the 16 half-year periods (2007.1, 2007.2, 2008.1, ..., 2014.1, 2014.2). As patients do not necessarily have a prescription in each of these periods, we replace the missing values in the benzodiazepine use outcomes (i.e., the number of daily doses and the number of prescriptions per patient and 6-month period) with zeros. To address zeros, we use $\log(y + 1)$ for logarithmic outcomes (e.g. for log

[36] We also exclude one patient with an observation where the (purchased) number of defined daily doses is over 10,000—a plausible error in the original data.

number of defined daily doses). In addition, we calculate patient age per period.

A.2.2 The Discharge Data and Its Aggregation

The Discharge Data are provided by the National Institute for Health and Welfare. The data include comprehensive information on public inpatient and outpatient discharges in specialized health care in Finland over the years 2007–2014. The Discharge Data identify the patient's primary and secondary diagnoses (ICD10 code), external cause for the visit, and additional information on the discharge such as the type of admission, reason for admission, health care unit (provider) identifier, the date of discharge, procedures and interventions, as well as information on the patient's municipality of residence. We use these data to construct our patient biannual-level health outcomes based on diagnoses and other information (e.g. the type of admission) that we described earlier in Section A.1.2.

Our initial sample size is 42,548,868 which is then aggregated to patient biannual-level according to the following steps. First, we restrict the data to our study population, i.e. patients who have a benzodiazepine prescription in the observation period. We can perform the sample restriction because we have unique patient identifiers in both administrative datasets (the Discharge Data and the Prescription Data). After restricting the data, we have a sample size of 28,320,445 observations.

Second, we focus on discharges in the period 2007–2014.[37] We also remove all rows where the patient's municipality of residence is in the province of Åland, missing, or abroad, leaving a sample size of 28,064,530 observations.

Third, we aggregate the dataset to the patient episode-level because the patients may have multiple discharges per stay. An episode is defined by the patient identifier, care unit identifier, and the date of discharge. After aggregating the data, we have the sample size of 26,657,668 observations (episodes).

Fourth, we aggregate the patient episode-level Discharge Data to patient biannual-level, as defined by patient identifiers and the date of discharge. In the aggregated data, we construct binary health outcomes for each diagnosis (or admission) that is listed above in Section A.1.2. Specifically, the binary outcome for a given diagnosis (e.g., anxiety) is equal to one if the patient has the diagnosis in specialized health care in the 6-month period. In addition, we calculate the total number of health care visits and emergency visits per patient and time period. We replace missing observations, that is an observation without the corresponding diagnoses or admissions,

[37] Few observations were recorded outside of this period.

with zeros. In addition, we again use $\log(y+1)$ for logarithmic outcomes (e.g. for log number of specialized health care visits) to address zeros.

A.2.3 Construction of the Final Panel Data

We link the two aggregated panel datasets—one on benzodiazepine prescriptions (Section A.2.1) and the other one on the discharges in specialized health care (Section A.2.2)—by patient identifier and 6-month period.

Finally, we make two modifications to the data. First, we impute missing observations in the patient's municipality of residence. A municipality observation is missing when the patient is not in any of the two administrative data in the period.[38] We replace the missing observation by the nearest nonmissing observation from the patient's previous or subsequent periods. Second, we drop rows for periods where the patient has already died or was not yet born—an unlikely situation in our data. We identify the dates of birth and death from the Prescription Data. The final panel data that we analyze have 15,436,868 observations from 1,030,383 unique patients.

A.3 Exogeneity of the Adoption Time

The key identifying assumption of our empirical approach is that the timing of the technology adoption across municipalities is unrelated to the trends in our outcomes. Here we formally test this assumption. Table A1 reports the correlations between various municipality-level covariates from the pre-adoption years and the timing of the adoption of e-prescribing. Specifically, the outcome is the log difference between the municipality's adoption date and the first adoption date, calculated in days. The municipality of Turku (located in Western Finland) was the first municipality to adopt e-prescribing on the 20th of May 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:

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

where Γ is a vector of biannual-level time dummies, X is a vector of municipality-level covariates from 2009, γ is time fixed effects, ν is an error term, and the outcome T_{mt} is a dummy variable equal

[38] Municipality information is in both datasets.

to one if municipality m adopted e-prescribing in 6-month period t. For simplicity, we standardize the municipality-level covariates by dividing them with the corresponding standard deviations. Figure A1 plots the coefficients and their 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 the 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)	−0.219	−0.261	−0.227
	(0.197)	(0.242)	(0.237)
Log(primary care costs)	0.099	0.125	0.066
	(0.094)	(0.123)	(0.069)
Percentage over 65 years	−0.011	−0.011	−0.009
	(0.014)	(0.014)	(0.013)
Percentage 15–64 years	−0.018	−0.014	−0.016
	(0.019)	(0.015)	(0.017)
Drug reimbursement index	0.009	0.008	0.007
	(0.008)	(0.008)	(0.007)
Morbidity index	−0.008	−0.008	−0.007
	(0.007)	(0.007)	(0.006)
Mortality index	−0.0005	0.001	0.0001
	(0.002)	(0.001)	(0.001)
Log(outpatient visits in psychiatry)	−0.052	−0.043	−0.054
	(0.051)	(0.048)	(0.048)
Log(psychiatric inpatient periods of care)	0.110	0.013	0.026
	(0.095)	(0.030)	(0.031)
Log(number of anxiety diagnoses)	0.073	0.050	0.058
	(0.071)	(0.054)	(0.057)
Log(number of sleep disorder diagnoses)	0.005	0.009	0.045
	(0.016)	(0.014)	(0.036)
Log(number of prescription drug abuse diagnoses)	−0.016	−0.014	−0.021
	(0.019)	(0.023)	(0.025)
Log(number of other side effect diagnoses)	0.051	0.106	0.049
	(0.048)	(0.098)	(0.074)
Semi-urban municipality	0.030	0.007	0.025
	(0.040)	(0.047)	(0.041)
Rural municipality	−0.051	−0.097	−0.084
	(0.090)	(0.130)	(0.115)
Hospital district FE	Yes	Yes	Yes
Observations	299	298	298
F statistic	20.481***	24.082***	24.082***
Adjusted R^2	0.303	0.295	0.293

Notes: Each column shows parameter estimates from a separate regression using municipality-level data. Municipality covariates are from 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. Diagnoses related to sleep disorders, prescription drug abuse and other common benzodiazepine-related side effects are calculated from the Discharge Data. Other variables are from the National Institute of Health and Welfare, and Statistics Finland. In each year, we exclude 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

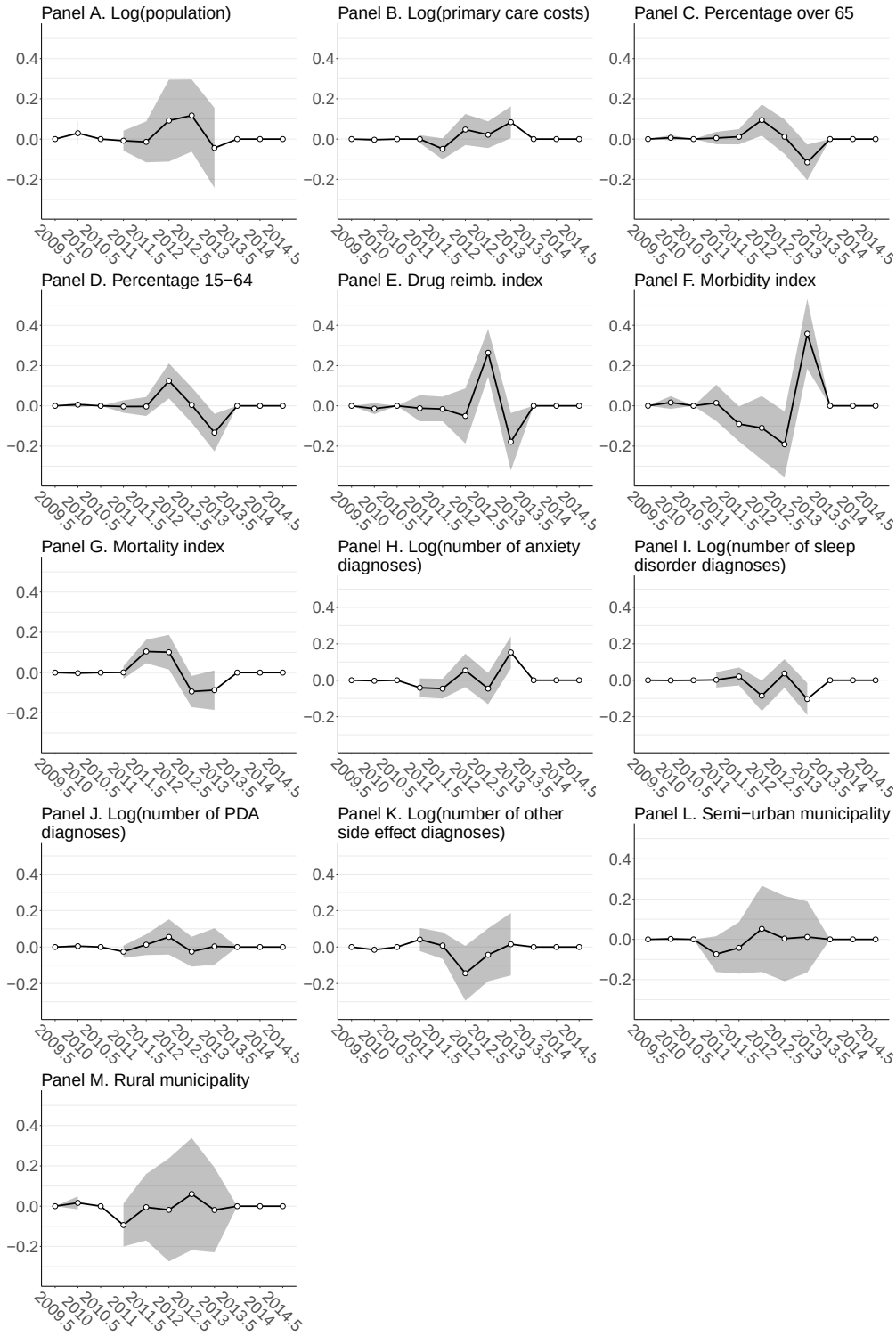

FIGURE A1: Implementation of E-Prescribing by Baseline Municipality Characteristics

Notes: Each panel plots coefficient estimates from a separate regression for interaction terms between a specific municipality covariate from year 2009 and biannual dummies for the time of e-prescribing adoption by the municipality. Regressions are estimated using municipality-level data. 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 coefficient estimates are standardized by dividing the covariates by their corresponding standard deviations. See Table A1 notes for data sources and equation A1 for details on the specifications.

A.4 Additional Figures and Tables

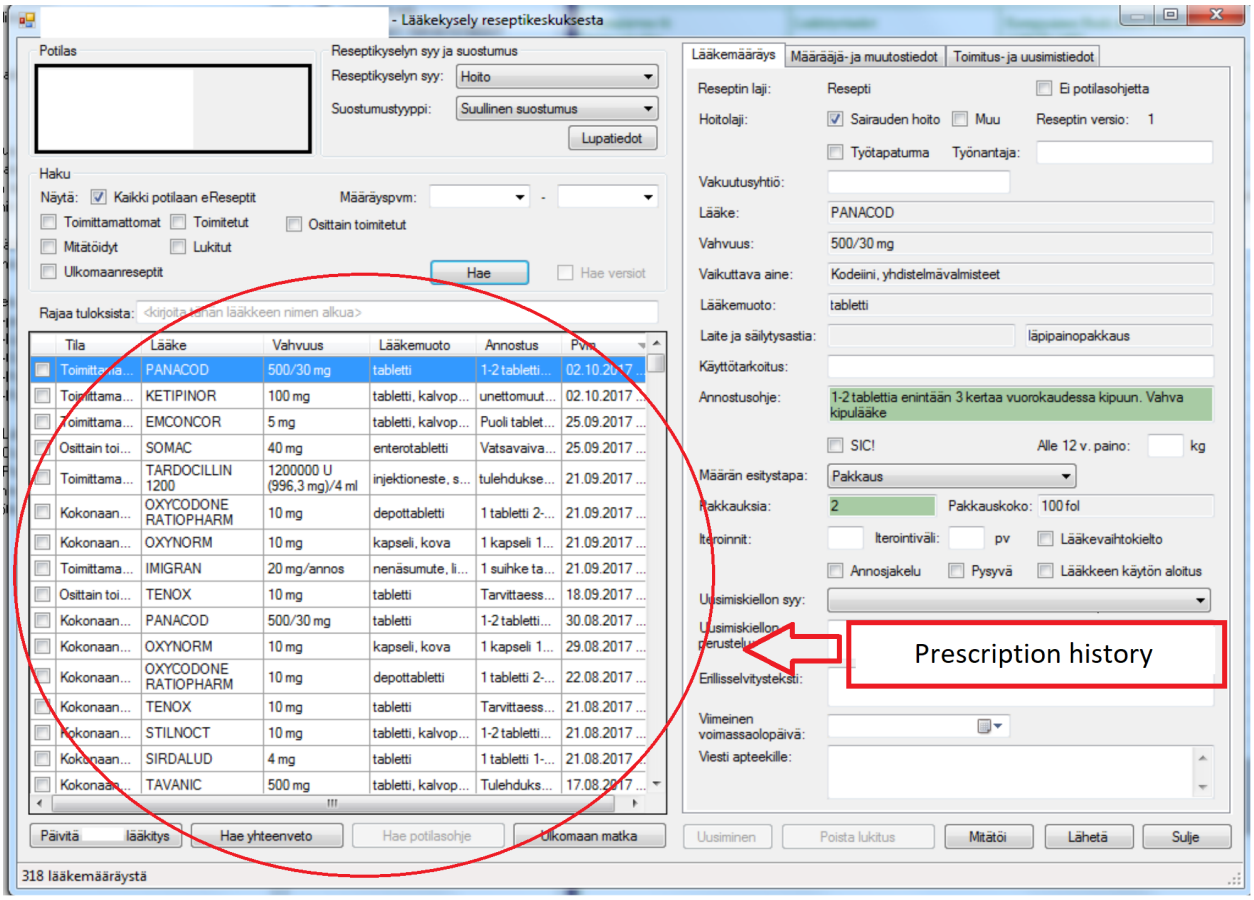

Figure A2: E-Prescribing Technology, Physician's View

TABLE A2: Summary Statistics

	All ages		Ages < 40		Ages ≥ 40	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Age	55.843	19.362	28.337	7.915	63.477	13.904
Benzodiazepine use outcomes						
Number of defined daily doses	55.084	149.593	29.083	153.136	62.300	147.786
Number of renewed defined daily doses	45.104	131.396	22.334	130.219	51.423	131.022
Number of new defined daily doses	9.980	51.438	6.749	49.686	10.877	51.878
Number of prescriptions	0.635	1.307	0.418	1.301	0.695	1.302
Number of renewed prescriptions	0.490	1.141	0.280	1.079	0.548	1.151
Number of new prescriptions	0.145	0.434	0.138	0.448	0.147	0.430
Health outcomes						
Anxiety	0.0106	0.1023	0.0252	0.1568	0.0065	0.0805
Panic disorder	0.0012	0.0348	0.0034	0.0582	0.0006	0.0247
Depression	0.0207	0.1422	0.0365	0.1875	0.0163	0.1265
Sleep disorder	0.0008	0.0289	0.0013	0.0361	0.0007	0.0266
Epilepsy	0.0072	0.0845	0.0155	0.1237	0.0049	0.0696
Number of specialized health care visits	1.7174	5.0569	1.8915	6.2917	1.6691	4.6553
Number of emergency visits	0.3753	1.4910	0.3564	1.6309	0.3806	1.4497
Prescription drug abuse	0.0015	0.0391	0.0052	0.0718	0.0005	0.0226
Other side effects	0.0108	0.1032	0.0028	0.0528	0.0130	0.1132
Prescription drug poisoning	0.0023	0.0483	0.0049	0.0698	0.0016	0.0404
Suicide attempt	0.0021	0.0458	0.0046	0.0679	0.0014	0.0373
Observations	15,436,868		3,353,662		12,083,206	

Notes: This table reports summary statistics for our patient biannual-level balanced data. For data and variable descriptions, see section 3.1 and online Appendix section A.1.

TABLE A3: Effect of E-Prescribing on the Number of Defined Daily Doses

	All ages		Ages < 40		Ages ≥ 40	
	(1)	(2)	(3)	(4)	(5)	(6)
Short run	-0.003	-0.001	0.009	0.016**	-0.006	-0.005
	(0.008)	(0.009)	(0.008)	(0.006)	(0.008)	(0.008)
Long run	-0.002	0.004	0.033**	0.048***	-0.008	-0.008
	(0.012)	(0.014)	(0.016)	(0.012)	(0.013)	(0.014)
Mean outcome	1.514	1.514	0.776	0.776	1.719	1.719
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcome is the log number of defined daily doses of benzodiazepine prescriptions. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

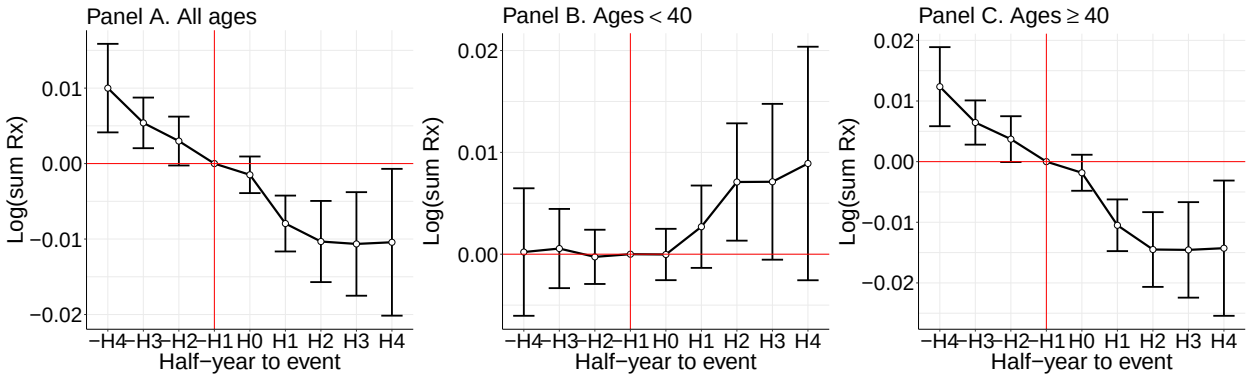

FIGURE A3: Number of Prescriptions, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcome is the the log number benzodiazepine prescriptions filled by the patient during a biannual period. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

TABLE A4: Effects of E-Prescribing on the Number of Defined Daily Doses of Renewed and New Prescriptions

	All ages		Ages < 40		Ages ≥ 40	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Log number of defined daily doses of renewed prescriptions						
Short run	-0.001	0.000	0.009	0.013**	-0.002	-0.002
	(0.008)	(0.008)	(0.007)	(0.005)	(0.007)	(0.008)
Long run	0.000	0.004	0.025*	0.035***	-0.002	-0.003
	(0.013)	(0.013)	(0.013)	(0.010)	(0.013)	(0.013)
Mean outcome	1.205	1.205	0.519	0.519	1.395	1.395
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel B. Outcome: Log number of defined daily doses of new prescriptions						
Short run	0.001	0.003	0.003	0.008*	0.000	0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Long run	0.005	0.007	0.012	0.022***	0.002	0.003
	(0.005)	(0.005)	(0.008)	(0.006)	(0.005)	(0.005)
Mean outcome	0.476	0.476	0.385	0.385	0.501	0.501
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. In Panel A, the outcome is the log number of defined daily doses of renewed benzodiazepine prescriptions. In Panel B, the outcome is the log number of defined daily doses of new benzodiazepine prescriptions. See Section 3.1 for the definitions of renewed and new prescriptions. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

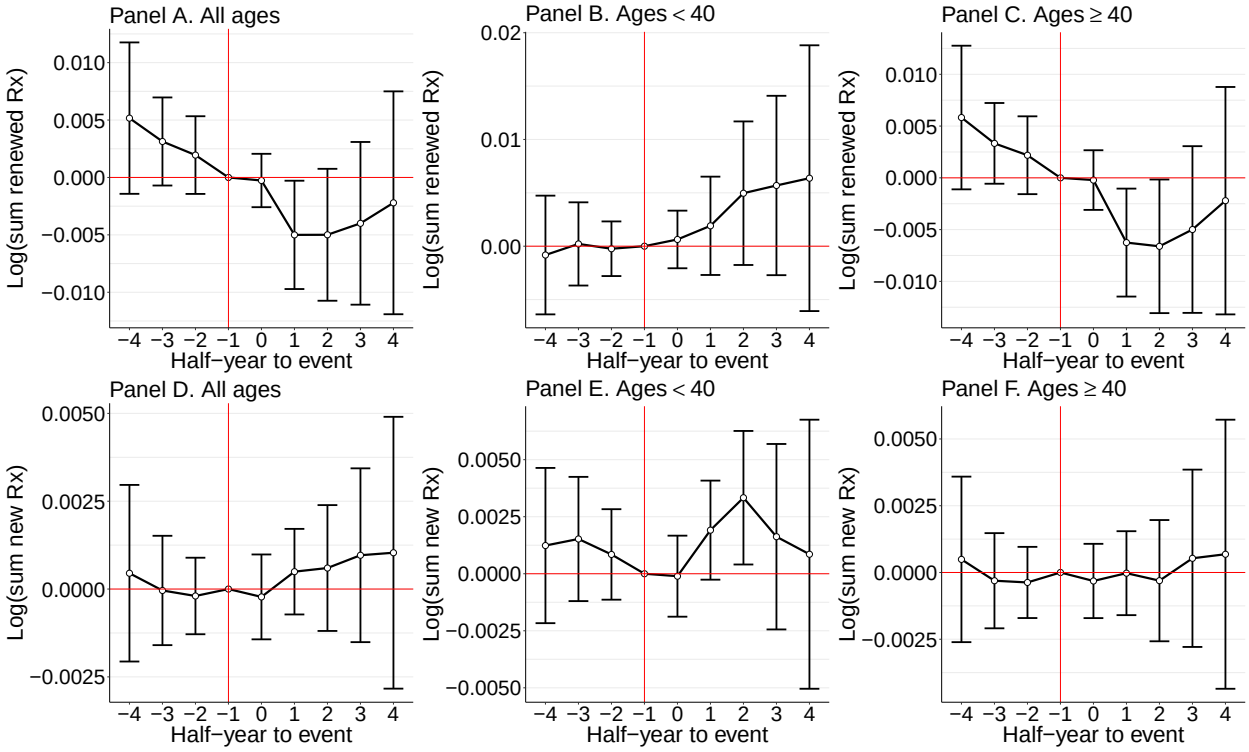

FIGURE A4: Number of Renewed and New Prescriptions, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. The outcomes are the log number of renewed benzodiazepine prescriptions (Panels A, B, and C) and the log number of new benzodiazepine prescriptions (Panels D, E, and F) filled by the patient during a biannual period. See Section 3.1 for the definitions of renewed and new prescriptions. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

TABLE A5: Effects of E-Prescribing on Number of All Prescriptions, Renewed Prescriptions, and New Prescriptions

	All ages		Ages < 40		Ages ≥ 40	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Log number of prescriptions						
Short run	-0.003	-0.002	0.001	0.003*	-0.004**	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Long run	-0.003	-0.002	0.006*	0.010***	-0.005	-0.005
	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
Mean outcome	0.324	0.324	0.196	0.196	0.360	0.360
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel B. Outcome: Log number of renewed prescriptions						
Short run	-0.003	-0.002	0.001	0.002	-0.003*	-0.003**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Long run	-0.003	-0.003	0.005	0.007***	-0.004	-0.005*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Mean outcome	0.251	0.251	0.127	0.127	0.286	0.286
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel C. Outcome: Log number of new prescriptions						
Short run	0.000	0.000	0.000	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Long run	0.001	0.001	0.002	0.004***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean outcome	0.094	0.094	0.088	0.088	0.096	0.096
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. In Panel A, the outcome is the log number of benzodiazepine prescriptions. In Panel B, the outcome is the log number of renewed benzodiazepine prescriptions. In Panel C, the outcome is the log number of new benzodiazepine prescriptions. See Section 3.1 for the definitions of renewed and new prescriptions. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. 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 Number of All, Renewed, and New Defined Daily Doses, By Finer Age Groups

	Ages 18–39		Ages 40–64		Ages ≥ 65	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Log number of defined daily doses of all prescriptions						
Short run	0.009	0.014**	-0.002	-0.002	-0.011	-0.010
	(0.009)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)
Long run	0.032**	0.042***	0.003	0.002	-0.024	-0.024
	(0.015)	(0.012)	(0.012)	(0.012)	(0.018)	(0.018)
Mean outcome	0.825	0.825	1.506	1.506	1.989	1.989
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel B. Outcome: Log number of defined daily doses of new prescriptions						
Short run	0.008	0.011**	-0.002	-0.003	-0.004	-0.004
	(0.007)	(0.005)	(0.007)	(0.006)	(0.009)	(0.009)
Long run	0.024*	0.032***	0.004	0.002	-0.012	-0.013
	(0.014)	(0.010)	(0.012)	(0.011)	(0.016)	(0.016)
Mean outcome	0.558	0.558	1.194	1.194	1.648	1.648
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel C. Outcome: Log number of defined daily doses of renewed prescriptions						
Short run	0.003	0.007*	0.003	0.004	-0.003	-0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)
Long run	0.011	0.019***	0.007	0.008	-0.004	-0.004
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Mean outcome	0.406	0.406	0.495	0.495	0.509	0.509
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. In Panel A, the outcome is the log number of defined daily doses of benzodiazepine prescriptions. In Panel B, the outcome is the log number of defined daily doses of renewed benzodiazepine prescriptions. In Panel C, the outcome is the log number of defined daily doses of new benzodiazepine prescriptions. See Section 3.1 for the definitions of renewed and new prescriptions. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

TABLE A7: Effects of E-Prescribing on Mental Health and Sleep Disorder

	All ages		Ages < 40		Ages ≥ 40	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Probability of an anxiety diagnosis						
Short run	-0.0004	-0.0005	-0.0012	-0.0015	-0.0002	-0.0002
	(0.0006)	(0.0006)	(0.0018)	(0.0017)	(0.0003)	(0.0003)
Long run	0.0000	-0.0002	0.0001	-0.0008	0.0000	-0.0000
	(0.0010)	(0.0010)	(0.0028)	(0.0027)	(0.0005)	(0.0005)
Mean outcome	0.0106	0.0106	0.0252	0.0252	0.0065	0.0065
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel B. Outcome: Probability of a panic disorder diagnosis						
Short run	-0.0001	-0.0001	-0.0004	-0.0005*	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Long run	-0.0001	-0.0001	-0.0002	-0.0004	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0001)	(0.0001)
Mean outcome	0.0012	0.0012	0.0034	0.0034	0.0006	0.0006
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel C. Outcome: Probability of a depression diagnosis						
Short run	-0.0006	-0.0009	-0.0016	-0.0025	-0.0003	-0.0004
	(0.0013)	(0.0013)	(0.0029)	(0.0029)	(0.0009)	(0.0009)
Long run	0.0009	0.0001	0.0012	-0.0011	0.0008	0.0005
	(0.0017)	(0.0017)	(0.0034)	(0.0032)	(0.0014)	(0.0014)
Mean outcome	0.0207	0.0207	0.0365	0.0365	0.0163	0.0163
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel D. Outcome: Probability of a sleep disorder diagnosis						
Short run	-0.0001	-0.0001	-0.0001	-0.0002	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Long run	-0.0001	-0.0001	0.0001	-0.0000	-0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Mean outcome	0.0008	0.0008	0.0013	0.0013	0.0007	0.0007
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnosis is anxiety in Panel A, panic disorder in Panel B, depression in Panel C, and sleep disorder in Panel D. See online Appendix A.1.2 for the definitions of the diagnoses. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

TABLE A8: Effects of E-Prescribing on Mental Health and Sleep Disorder, By Finer Age Groups

	Ages 18–39		Ages 40–64		Ages ≥ 65	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Probability of an anxiety diagnosis						
Short run	-0.0012	-0.0015	-0.0003	-0.0004	-0.0001	-0.0001
	(0.0019)	(0.0017)	(0.0005)	(0.0005)	(0.0002)	(0.0002)
Long run	-0.0001	-0.0010	-0.0000	-0.0002	0.0000	0.0000
	(0.0030)	(0.0025)	(0.0008)	(0.0007)	(0.0003)	(0.0003)
Mean outcome	0.0257	0.0257	0.0092	0.0092	0.0032	0.0032
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel B. Outcome: Probability of a panic disorder diagnosis						
Short run	-0.0005	-0.0005*	-0.0000	-0.0000	-0.0001**	-0.0001*
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Long run	-0.0004	-0.0005	0.0000	0.0000	-0.0001	-0.0000
	(0.0005)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean outcome	0.0035	0.0035	0.0009	0.0009	0.0002	0.0002
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel C. Outcome: Probability of a depression diagnosis						
Short run	-0.0018	-0.0026	-0.0006	-0.0008	0.0000	0.0001
	(0.0030)	(0.0029)	(0.0016)	(0.0016)	(0.0004)	(0.0004)
Long run	0.0011	-0.0012	0.0010	0.0007	0.0004	0.0004
	(0.0036)	(0.0031)	(0.0022)	(0.0021)	(0.0010)	(0.0009)
Mean outcome	0.0378	0.0378	0.0237	0.0237	0.0069	0.0069
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel D. Outcome: Probability of a sleep disorder diagnosis						
Short run	-0.0002	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Long run	0.0000	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean outcome	0.0013	0.0013	0.0009	0.0009	0.0005	0.0005
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Patient FE	No	No	No	No	No	No

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnosis is anxiety in Panel A, panic disorder in Panel B, depression in Panel C, and sleep disorder in Panel D. See online Appendix A.1.2 for the definitions of the diagnoses. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

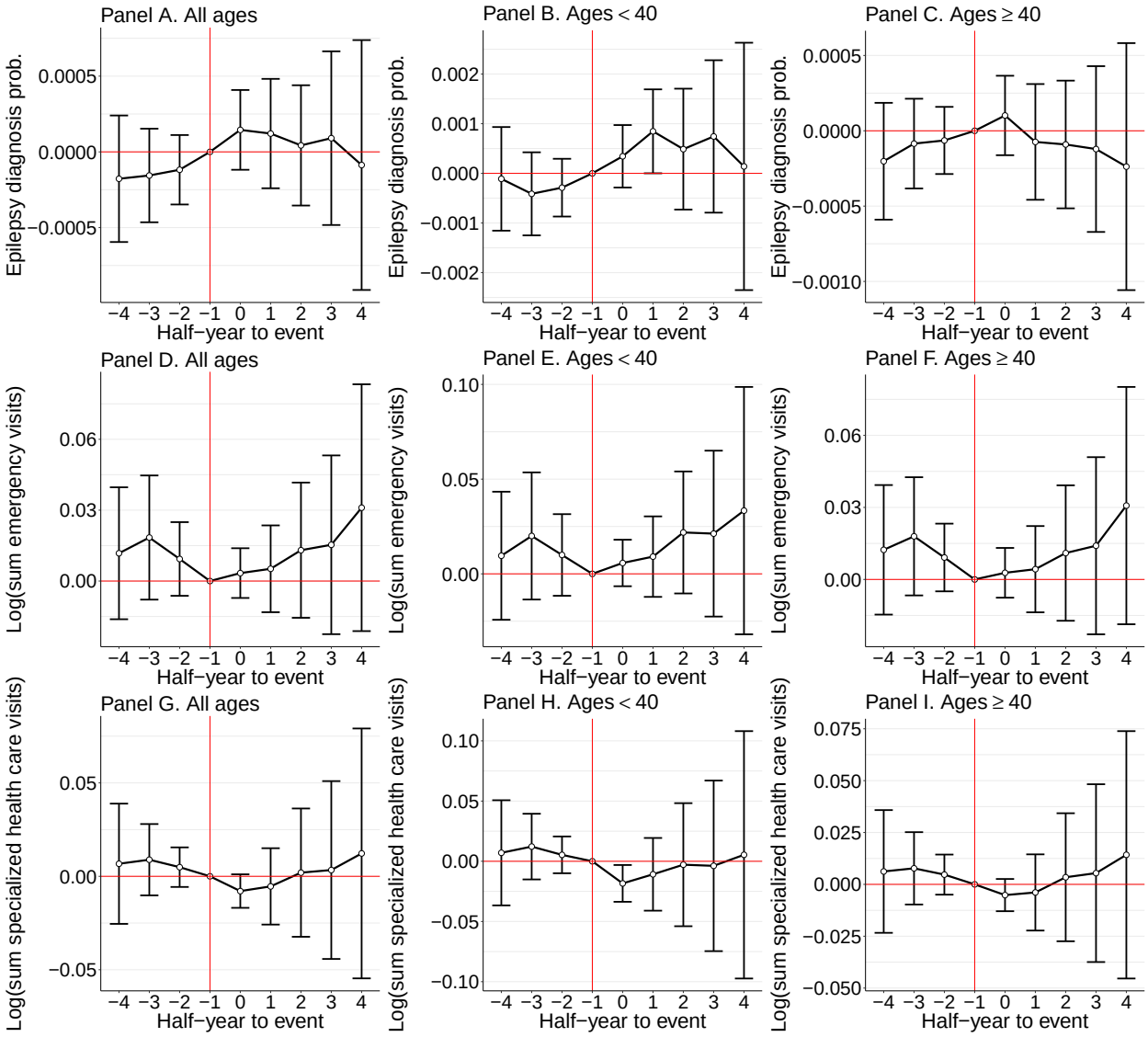

FIGURE A5: Additional Health Outcomes, by Age Group

Notes: The figures plot the coefficient estimates from event study regressions using patient biannual-level balanced data. In Panels A–C, the outcome is a binary variable indicating if the patient has obtained an epilepsy diagnosis in specialized health care during a biannual period. In Panels D–F and G–I, the outcomes are, respectively, log number of emergency visits and log number of specialized health care visits. See online Appendix A.1.2 for the definitions of the diagnosis and emergency visits. 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 control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level.

TABLE A9: Effects of E-Prescribing on Additional Health Outcomes

	All ages		Ages < 40		Ages ≥ 40	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Probability of an epilepsy diagnosis						
Short run	0.0002	0.0002	0.0006**	0.0006**	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Long run	0.0001	-0.0000	0.0005	0.0005	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0006)	(0.0005)	(0.0002)	(0.0002)
Mean outcome	0.0072	0.0072	0.0155	0.0155	0.0049	0.0049
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel B. Outcome: Log number of emergency visits						
Short run	-0.0025	-0.0034	0.0004	-0.0002	-0.0032	-0.0041
	(0.0090)	(0.0088)	(0.0105)	(0.0096)	(0.0087)	(0.0087)
Long run	0.0087	0.0055	0.0155	0.0128	0.0070	0.0037
	(0.0147)	(0.0146)	(0.0179)	(0.0160)	(0.0141)	(0.0143)
Mean outcome	0.1713	0.1713	0.1592	0.1592	0.1747	0.1747
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel C. Outcome: Log number of specialized health care visits						
Short run	-0.0105	-0.0106	-0.0199*	-0.0185**	-0.0080	-0.0082
	(0.0074)	(0.0069)	(0.0114)	(0.0088)	(0.0064)	(0.0064)
Long run	-0.0008	-0.0022	-0.0086	-0.0084	0.0013	-0.0001
	(0.0156)	(0.0152)	(0.0248)	(0.0198)	(0.0138)	(0.0136)
Mean outcome	0.5337	0.5337	0.5090	0.5090	0.5405	0.5405
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. In Panel A, the outcome is a binary variable indicating if the patient has obtained an epilepsy diagnosis in specialized health care. In Panel B, the outcome is log number of emergency visits. In Panel C, the outcome is log number of specialized health care visits. See online Appendix A.1.2 for the definitions of the diagnosis and emergency visits. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

TABLE A10: Effects of E-Prescribing on Adverse Health Outcomes

	All ages		Ages < 40		Ages ≥ 40	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Probability of a prescription drug abuse diagnosis						
Short run	0.0001	0.0001	0.0005	0.0005	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0000)	(0.0000)
Long run	0.0002	0.0002	0.0009*	0.0008	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0001)	(0.0001)
Mean outcome	0.0015	0.0015	0.0052	0.0052	0.0005	0.0005
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel B. Outcome: Probability of the other side effects diagnosis						
Short run	-0.0001	-0.0002	0.0001	0.0001	-0.0002	-0.0002
	(0.0005)	(0.0005)	(0.0002)	(0.0002)	(0.0007)	(0.0006)
Long run	0.0003	0.0001	0.0001	0.0000	0.0004	0.0001
	(0.0009)	(0.0010)	(0.0004)	(0.0004)	(0.0011)	(0.0012)
Mean outcome	0.0108	0.0108	0.0028	0.0028	0.0130	0.0130
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel C. Outcome: Probability of a suicide attempt diagnosis						
Short run	0.0001	0.0002*	0.0005*	0.0007**	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Long run	0.0001	0.0002	0.0008	0.0011*	-0.0001	0.0000
	(0.0002)	(0.0002)	(0.0006)	(0.0006)	(0.0001)	(0.0001)
Mean outcome	0.0021	0.0021	0.0046	0.0046	0.0014	0.0014
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Panel D. Outcome: Probability of a prescription drug poisoning diagnosis						
Short run	0.0001	0.0001	0.0004*	0.0004**	-0.0000	0.0000
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Long run	0.0002	0.0003**	0.0008***	0.0009***	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Mean outcome	0.0023	0.0023	0.0049	0.0049	0.0016	0.0016
Observations	15,436,868	15,436,868	3,353,662	3,353,662	12,083,206	12,083,206
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnosis is prescription drug abuse in Panel A, other common benzodiazepine-related side effects in Panel B, suicide attempts in Panel C, and prescription drug poisoning in Panel D. See online Appendix A.1.2 for the definitions of the diagnoses. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.

*p<0.1; **p<0.05; ***p<0.01.

TABLE A11: Effects of E-Prescribing on Adverse Health Outcomes, By Finer Age Groups

	Ages 18–39		Ages 40–64		Ages ≥ 65	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Probability of a prescription drug abuse diagnosis						
Short run	0.0006	0.0005	-0.0000	-0.0000	-0.0001*	-0.0001*
	(0.0005)	(0.0005)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Long run	0.0009*	0.0008	0.0000	0.0000	-0.0001	-0.0001
	(0.0005)	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean outcome	0.0056	0.0056	0.0008	0.0008	0.0002	0.0002
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel B. Outcome: Probability of the other side effects diagnosis						
Short run	0.0001	0.0001	-0.0000	-0.0001	-0.0003	-0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0011)	(0.0011)
Long run	0.0001	-0.0000	0.0005	0.0003	0.0005	-0.0002
	(0.0004)	(0.0003)	(0.0005)	(0.0005)	(0.0018)	(0.0020)
Mean outcome	0.0028	0.0028	0.0055	0.0055	0.0224	0.0224
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel C. Outcome: Probability of a suicide diagnosis						
Short run	0.0006*	0.0007**	-0.0000	0.0000	0.0000	0.0000
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Long run	0.0008	0.0011**	-0.0000	0.0000	-0.0000	-0.0000
	(0.0005)	(0.0005)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean outcome	0.0049	0.0049	0.0021	0.0021	0.0004	0.0004
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Panel D. Outcome: Probability of a prescription drug poisoning diagnosis						
Short run	0.0003	0.0004*	-0.0000	-0.0000	0.0001	0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Long run	0.0008**	0.0008***	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean outcome	0.0052	0.0052	0.0024	0.0024	0.0006	0.0006
Observations	3,083,884	3,083,884	6,742,547	6,742,547	5,340,659	5,340,659
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No	Yes	No
Patient FE	No	Yes	No	Yes	No	Yes

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes are binary variables indicating if the patient has obtained a specific diagnosis in specialized health care during a biannual period. The diagnosis is prescription drug abuse in Panel A, other common benzodiazepine-related side effects in Panel B, suicide attempts in Panel C, and prescription drug poisoning in Panel D. See online Appendix A.1.2 for the definitions of the diagnoses. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. All specifications include controls for patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

TABLE A12: Effects of E-Prescribing on Health Outcomes, Diagnosing Events With Coincidental Benzodiazepine Prescribing Dates Excluded From Outcomes

	Outcome						
	Anxiety (1)	Panic disorder (2)	Depression (3)	Sleep disorder (4)	Epilepsy (5)	Prescription drug abuse (6)	Other side effects (7)
Panel A. All ages							
Short run	-0.0004	-0.0001*	-0.0006	-0.0001	0.0001	0.0001	-0.0001
	(0.0006)	(0.0001)	(0.0013)	(0.0001)	(0.0001)	(0.0001)	(0.0005)
Long run	-0.0000	-0.0001	0.0007	-0.0001	0.0000	0.0002	0.0003
	(0.0009)	(0.0001)	(0.0017)	(0.0001)	(0.0002)	(0.0001)	(0.0009)
Mean outcome	0.0101	0.0011	0.0200	0.0008	0.0068	0.0015	0.0107
Observations	15,436,868	15,436,868	15,436,868	15,436,868	15,436,868	15,436,868	15,436,868
Panel B. Ages < 40							
Short run	-0.0012	-0.0004	-0.0018	-0.0002	0.0006*	0.0005	0.0002
	(0.0017)	(0.0003)	(0.0028)	(0.0002)	(0.0003)	(0.0005)	(0.0002)
Long run	-0.0001	-0.0002	0.0009	0.0001	0.0003	0.0009*	0.0001
	(0.0027)	(0.0005)	(0.0032)	(0.0002)	(0.0006)	(0.0005)	(0.0004)
Mean outcome	0.0243	0.0032	0.0357	0.0012	0.0147	0.0051	0.0028
Observations	3,353,662	3,353,662	3,353,662	3,353,662	3,353,662	3,353,662	3,353,662
Panel C. Ages ≥ 40							
Short run	-0.0002	-0.0001	-0.0003	-0.0001*	0.0000	-0.0000	-0.0002
	(0.0003)	(0.0000)	(0.0009)	(0.0001)	(0.0001)	(0.0000)	(0.0006)
Long run	-0.0000	-0.0000	0.0006	-0.0001	-0.0001	0.0000	0.0004
	(0.0005)	(0.0001)	(0.0013)	(0.0001)	(0.0002)	(0.0001)	(0.0011)
Mean outcome	0.0062	0.0006	0.0156	0.0007	0.0047	0.0005	0.0129
Observations	12,083,206	12,083,206	12,083,206	12,083,206	12,083,206	12,083,206	12,083,206

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. Each outcome is a binary variable indicating if the patient has obtained a specific diagnosis depicted in the column title during a biannual time period. Additionally, for these outcomes, diagnoses that have coincidental diagnosing dates with benzodiazepine prescribing dates are marked as zero instead of one. See online Appendix A.1.2 for the definitions of the diagnoses used in outcomes depicted in the column titles. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. The regressions control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.

*p<0.1; **p<0.05; ***p<0.01

TABLE A13: Effects of E-Prescribing on Health Outcomes, Referral Arrival Dates With Coincidental Benzodiazepine Prescribing Dates Excluded From Outcomes

	Outcome						
	Anxiety (1)	Panic disorder (2)	Depression (3)	Sleep disorder (4)	Epilepsy (5)	Prescription drug abuse (6)	Other side effects (7)
Panel A. All ages							
Short run	-0.0004	-0.0001	-0.0006	-0.0001	0.0002	0.0001	-0.0001
	(0.0006)	(0.0001)	(0.0013)	(0.0001)	(0.0001)	(0.0001)	(0.0005)
Long run	-0.0000	-0.0001	0.0009	-0.0001	0.0001	0.0002	0.0003
	(0.0009)	(0.0001)	(0.0017)	(0.0001)	(0.0002)	(0.0001)	(0.0009)
Mean outcome	0.0101	0.0012	0.0205	0.0008	0.0071	0.0015	0.0107
Observations	15,436,868	15,436,868	15,436,868	15,436,868	15,436,868	15,436,868	15,436,868
Panel B. Ages < 40							
Short run	-0.0012	-0.0004	-0.0017	-0.0001	0.0006**	0.0005	0.0002
	(0.0017)	(0.0003)	(0.0029)	(0.0002)	(0.0003)	(0.0005)	(0.0002)
Long run	-0.0001	-0.0002	0.0011	0.0001	0.0005	0.0008*	0.0001
	(0.0027)	(0.0005)	(0.0034)	(0.0003)	(0.0006)	(0.0005)	(0.0003)
Mean outcome	0.0243	0.0034	0.0362	0.0013	0.0154	0.0051	0.0028
Observations	3,353,662	3,353,662	3,353,662	3,353,662	3,353,662	3,353,662	3,353,662
Panel C. Ages ≥ 40							
Short run	-0.0002	-0.0001	-0.0003	-0.0001	0.0001	-0.0000	-0.0002
	(0.0003)	(0.0001)	(0.0009)	(0.0001)	(0.0001)	(0.0000)	(0.0006)
Long run	-0.0000	-0.0000	0.0007	-0.0001	-0.0000	0.0000	0.0004
	(0.0005)	(0.0001)	(0.0014)	(0.0001)	(0.0002)	(0.0001)	(0.0011)
Mean outcome	0.0062	0.0006	0.0161	0.0007	0.0048	0.0005	0.0129
Observations	12,083,206	12,083,206	12,083,206	12,083,206	12,083,206	12,083,206	12,083,206

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. Each outcome is a binary variable indicating if the patient has obtained a specific diagnosis depicted in the column title during a biannual time period. Additionally, for these outcomes, diagnoses that have coincidental referral arrival dates to specialized health care with benzodiazepine prescribing dates are marked as zero instead of one. See online Appendix A.1.2 for the definitions of the diagnoses used in outcomes depicted in the column titles. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. The regressions control for municipality fixed effects, common time trend, and patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

A.5 Additional Robustness Checks

We examine the sensitivity of our baseline results to variations in the main analysis data and covariate specifications. We report the results for benzodiazepine use in Table A14 and for our main health outcomes in Table A15. We next summarize the findings of three alternative specifications estimated for all patients, and by age group.

First, a potential concern regarding the driving mechanism of our results is the adoption of the national EMR system in municipalities at the end of the observation period. Around 100 municipalities had adopted the system in the first half of 2014 and more than double of that in the second half of 2014. The system helps physicians to identify medical records and diagnoses (such as prescription drug abuse disorders), potentially affecting prescribing decisions and patient health outcomes. If this were the case, the long run effects of e-prescribing might reflect the adoption of EMR. In order to evaluate the impacts of e-prescribing without the new EMR system, we focus on the period before July 2014, as well as exclude the (around 100) municipalities that had adopted EMR before that time from our data. The results are reported in columns 1, 2, and 3. For all the outcomes of interest the parameter estimates remain similar to our baseline estimates, showing that our findings are not driven by the adoption of EMR.

Second, we assess whether our results are sensitive to the discontinuation of the NHI coverage of some benzodiazepine products in the observation period. The list of these products, as well as the discontinuation years are documented in online Appendix A.1.1. The discontinuation of the coverage implies that we do not observe the related purchases in all periods, potentially affecting our benzodiazepine use estimates. In addition, prescription drug use and health outcomes could change as a result of the coverage change. We thereby exclude the products that lost their coverage from our data. The results are shown in columns 4, 5, and 6. For both the benzodiazepine use and health outcomes, the results remain similar to our baseline estimates.

Third, we divide municipalities to urban, semi-urban and rural-areas using the official classification of Statistics Finland. Based on this grouping, we add municipality type-by-time fixed effects to our baseline specification. This specification captures differential time trends between municipality types, for example, because of the health care and prescription drug market expansion in urban areas. Columns 7, 8 and 9 show that the estimates are very similar to our main estimates, suggesting that the differential time trends are not driving our results.

TABLE A14: Robustness Checks: Effects of E-Prescribing on Number of All, Renewed, and New Defined Daily Doses

	National EMR excl.			Discontinued NHI excl.			Municipality type trend		
	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:Log number of defined daily doses of all prescriptions									
Short run	0.001	0.010	-0.001	-0.011*	0.005	-0.014**	0.003	0.011	0.002
	(0.009)	(0.010)	(0.009)	(0.006)	(0.008)	(0.006)	(0.007)	(0.008)	(0.007)
Long run	0.003	0.033*	-0.001	-0.024**	0.028**	-0.036***	0.006	0.037**	0.002
	(0.014)	(0.019)	(0.015)	(0.012)	(0.014)	(0.012)	(0.011)	(0.015)	(0.012)
Mean outcome	1.528	0.780	1.744	1.423	0.750	1.619	1.514	0.776	1.719
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel B. Outcome: Log number of defined daily doses of new prescriptions									
Short run	0.003	0.008	0.003	-0.007	0.006	-0.010*	0.006	0.009	0.005
	(0.009)	(0.008)	(0.009)	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
Long run	0.005	0.024*	0.004	-0.019	0.022*	-0.027**	0.011	0.028**	0.009
	(0.015)	(0.015)	(0.015)	(0.012)	(0.012)	(0.012)	(0.011)	(0.013)	(0.013)
Mean outcome	1.209	0.521	1.408	1.130	0.501	1.314	1.205	0.519	1.395
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel C. Outcome: Log number of defined daily doses of renewed prescriptions									
Short run	-0.000	0.005	-0.002	-0.004	-0.002	-0.005	0.000	0.004	0.000
	(0.003)	(0.006)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Long run	0.003	0.013	0.000	-0.003	0.007	-0.007	0.002	0.014*	0.001
	(0.006)	(0.011)	(0.007)	(0.005)	(0.007)	(0.006)	(0.005)	(0.007)	(0.005)
Mean outcome	0.491	0.390	0.521	0.434	0.364	0.454	0.476	0.385	0.501
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes used in each regression are depicted in the panel titles. See Section 3.1 for the definitions of renewed and new prescriptions. Columns 1, 2, and 3 exclude municipalities that implemented the national EMR system. Columns 4, 5, and 6 exclude products that were excluded from the NHI scheme during 2007–2014. Columns 7, 8, and 9 include controls for separate time trends for urban, semi-urban, and rural municipalities. "Short run" refers to the first year of e-prescribing adoption, and "Long run" refers to periods at least one year after adoption. Each regression includes controls for the common time trend, municipality fixed effects, and patient's age and square of age. Standard errors are clustered at the municipality level and shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

TABLE A15: Robustness Checks: Effects of E-Prescribing on Mental Health and Sleep Disorder Outcomes

	National EMR excl.			Discontinued NHI excl.			Municipality type trend		
	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: Probability of an anxiety diagnosis									
Short run	-0.0010	-0.0028	-0.0005	-0.0005	-0.0012	-0.0003	-0.0005	-0.0013	-0.0003
	(0.0007)	(0.0019)	(0.0004)	(0.0007)	(0.0018)	(0.0004)	(0.0007)	(0.0019)	(0.0004)
Long run	-0.0005	-0.0021	-0.0001	0.0000	0.0000	0.0000	-0.0002	-0.0002	-0.0001
	(0.0013)	(0.0034)	(0.0007)	(0.0010)	(0.0029)	(0.0005)	(0.0011)	(0.0030)	(0.0006)
Mean outcome	0.0105	0.0240	0.0065	0.0110	0.0254	0.0068	0.0106	0.0252	0.0065
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel B. Outcome: Probability of a panic disorder diagnosis									
Short run	-0.0001	-0.0004	-0.0001	-0.0001	-0.0004	-0.0000	-0.0001	-0.0004	-0.0000
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)
Long run	-0.0000	-0.0001	0.0000	-0.0001	-0.0002	-0.0000	-0.0001	-0.0003	-0.0000
	(0.0002)	(0.0006)	(0.0001)	(0.0001)	(0.0005)	(0.0001)	(0.0001)	(0.0005)	(0.0001)
Mean outcome	0.0012	0.0031	0.0006	0.0013	0.0034	0.0006	0.0012	0.0034	0.0006
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel C. Outcome: Probability of a depression diagnosis									
Short run	-0.0018	-0.0034	-0.0013	-0.0006	-0.0016	-0.0003	-0.0007	-0.0019	-0.0004
	(0.0015)	(0.0033)	(0.0011)	(0.0014)	(0.0030)	(0.0010)	(0.0013)	(0.0029)	(0.0009)
Long run	0.0000	-0.0001	-0.0000	0.0010	0.0013	0.0009	0.0005	0.0006	0.0006
	(0.0022)	(0.0041)	(0.0018)	(0.0018)	(0.0035)	(0.0014)	(0.0018)	(0.0036)	(0.0015)
Mean outcome	0.0198	0.0336	0.0158	0.0213	0.0366	0.0169	0.0207	0.0365	0.0163
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel D. Outcome: Probability of a sleep disorder diagnosis									
Short run	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001*
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Long run	-0.0001	0.0001	-0.0001	-0.0001	0.0001	-0.0002	-0.0001	0.0001	-0.0002
	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)
Mean outcome	0.0008	0.0013	0.0006	0.0009	0.0013	0.0007	0.0008	0.0013	0.0007
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes used in each regression are depicted in the panel titles. See online Appendix A.1.2 for the definitions of the diagnoses. See Table A14 notes and the text in online Appendix A.5 for details on the specifications.
*p<0.1; **p<0.05; ***p<0.01.

TABLE A16: Robustness Checks: Effects of E-Prescribing on Adverse Health Outcomes

	National EMR excl.			Discontinued NHI excl.			Municipality type trend		
	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: Probability of a prescription drug abuse diagnosis									
Short run	0.0001	0.0007	-0.0001	0.0001	0.0006	-0.0000	0.0000	0.0005	-0.0000
	(0.0001)	(0.0006)	(0.0000)	(0.0001)	(0.0005)	(0.0000)	(0.0001)	(0.0005)	(0.0000)
Long run	0.0002	0.0012**	-0.0000	0.0002	0.0009*	-0.0000	0.0001	0.0008	-0.0000
	(0.0002)	(0.0006)	(0.0001)	(0.0001)	(0.0005)	(0.0001)	(0.0001)	(0.0005)	(0.0001)
Mean outcome	0.0016	0.0052	0.0005	0.0016	0.0052	0.0005	0.0015	0.0052	0.0005
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel B. Outcome: Probability of the other side effects diagnosis									
Short run	-0.0001	0.0002	-0.0001	-0.0001	0.0002	-0.0002	-0.0002	0.0001	-0.0002
	(0.0007)	(0.0003)	(0.0009)	(0.0005)	(0.0002)	(0.0006)	(0.0006)	(0.0002)	(0.0007)
Long run	0.0004	0.0004	0.0005	0.0002	0.0001	0.0003	0.0003	0.0001	0.0003
	(0.0013)	(0.0005)	(0.0015)	(0.0009)	(0.0004)	(0.0011)	(0.0010)	(0.0004)	(0.0011)
Mean outcome	0.0107	0.0026	0.0130	0.0104	0.0028	0.0126	0.0108	0.0028	0.0130
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel C. Outcome: Probability of a suicide diagnosis									
Short run	0.0001	0.0006*	0.0000	0.0001	0.0005	0.0000	0.0001	0.0005*	0.0000
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)
Long run	0.0001	0.0007	-0.0000	0.0001	0.0008	-0.0001	0.0001	0.0008	-0.0000
	(0.0002)	(0.0007)	(0.0002)	(0.0002)	(0.0006)	(0.0001)	(0.0002)	(0.0006)	(0.0001)
Mean outcome	0.0021	0.0046	0.0014	0.0021	0.0046	0.0014	0.0021	0.0046	0.0014
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206
Panel D. Outcome: Probability of a prescription drug poisoning diagnosis									
Short run	0.0001	0.0006**	-0.0000	0.0001	0.0004*	-0.0000	0.0001	0.0004*	-0.0000
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Long run	0.0002	0.0009***	0.0000	0.0002*	0.0008***	0.0000	0.0002	0.0008***	0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Mean outcome	0.0024	0.0050	0.0017	0.0024	0.0049	0.0017	0.0023	0.0049	0.0016
Observations	10,610,043	2,382,369	8,227,674	14,546,671	3,291,522	11,255,149	15,436,868	3,353,662	12,083,206

Notes: Each column shows parameter estimates from a separate regression using patient biannual-level balanced data. The outcomes used in each regression are depicted in the panel titles. See online Appendix A.1.2 for the definitions of the diagnoses. See Table A14 notes and the text in online Appendix A.5 for details on the specifications.
*p<0.1; **p<0.05; ***p<0.01.