Information Integration, Coordination Failures, and Quality of Prescribing*

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

Abstract

Poor information flows hamper coordination, potentially leading to suboptimal decisions in health care. We examine the effects of a large-scale policy of health information integration. We use the staggered adoption of a nationwide electronic prescribing system over four years in Finland and prescription-level administrative data. Our results show no discernible effect on the probability of co-prescribing harmful drugs on average, but the heterogeneity analysis reveals that this probability reduces in rural regions, by 35 percent. This substantial reduction is driven by interacting prescriptions from different physicians and generalists. Information integration can therefore improve the coordination of physicians' interdependent decisions.

*Petri Böckerman is a Professor at University of Jyväskylä, a Research Economist at Labour Institute for Economic Research, and a Research Fellow at IZA Institute of Labor Economics. Liisa T. Laine is an Assistant Professor at University of Missouri (lainel@missouri.edu). Mikko Nurminen is a Senior Researcher at the Social Insurance Institution of Finland. Tanja Saxell is a Senior Researcher at VATT Institute for Economic Research, and Helsinki GSE. *Liisa T. Laine worked on this paper while being a Postdoctoral Fellow at the University of Pennsylvania. We thank Tuomas Markkula for the excellent research assistance and the anonymous reviewers, Leila Agha, Norma B. Coe, Leemore Dafny, Guy David, Meltem Daysal, Craig Garthwaite, Risto Huupponen, Mika Kortelainen, Timothy Layton, Claudio Lucarelli, Ismo Linnosmaa, Martin Salm, Jonathan Skinner, and Mark Pauly, in addition to the participants at the American Economic Association Annual Meeting (poster session) 2022, the NBER Summer Institute IT and Digitization 2022 , the European Association for Research in Industrial Economics 2022, the Nordic Health Economics Study Group, the Penn Bioethics Seminar Series, the Tilburg Structural Econometrics Group, the Helsinki Graduate School of Economics Labor and Public Economics Seminar, the University of Missouri Research Seminar, the University of Pennsylvania Postdoc Work-in-progress Research Seminar, and the TSE Economics Research Seminar for their comments. The authors also gratefully acknowledge the Yrjö Jahnsson for funding this research (research grant No. 6701). The authors have no relevant financial interests to disclose. This study uses confidential administrative data from the Social Insurance Institution of Finland and the National Institute for Health and Welfare. The data can be obtained upon reasonable request to and with the permission of Findata – Finnish Social and Health Data Permit Authority (https://findata.fi/en/). The authors are willing to assist. Online Appendix is included.*
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I. Introduction

Organizations aim to improve the coordination of interdependent decisions to achieve more desirable outcomes (Gibbons and Roberts 2012). The difficulty for improving coordination is that information is often incomplete and dispersed among decision makers (Hayek 1945). Health care is a prominent example: a patient's care delivery is spread across multiple physicians, and each physician has different knowledge of the patient's health and medical history (Arrow 1963; Elhauge 2010). The relevant medical information is costly for the physicians to acquire and is imperfectly shared between them, especially with incompatible and incomplete health information systems (Cebul et al. 2008). Motivated by the difficulties in information-sharing and the substantial financial burden of coordination failures (Shrank, Rogstad, and Parekh 2019), policy makers have highlighted the need for implementation of integrated information systems (Michelsen et al. 2015; European Commission 2020). Empirical evidence on the benefits of the large-scale adoption of such technologies for coordination is, however, very limited, because of the considerable implementation costs and the practical challenges of adoption.

We analyze a public policy of health information integration and study its effects on physicians' decision making, coordination, and related outcomes in Finland. The country was one of the first to adopt a nationwide system for electronic prescribing (e-prescribing), together with other countries such as Estonia, Sweden, Portugal, and Australia. The salient feature of the Finnish e-prescribing system is its interoperability and standardization at the national level, allowing for comprehensive information exchange between different physicians through a centralized national prescription database. E-prescribing was specifically designed to improve physicians' prescribing decisions and coordination, whereas a broader policy goal for nationwide adoption and standardization was to mitigate regional gaps in healthcare provision (STM 2015; WHO 2016).

Our identification approach is based on the staggered adoption of e-prescribing across all municipalities between 2010 and 2014. Compared to individual providers' incompatible and incomplete information systems, e-prescribing systems provide more comprehensive information on prescriptions across different physicians involved in a patient's care. The adoption of an interoperable e-prescribing system by municipalities serves as a plausibly exogenous shock to the information environment of physicians, being directly relevant to the quality of their prescribing decisions and

coordination.[1]

Empirical analyses of coordination face two challenges. First, defining and measuring coordination is non-trivial. In the absence of direct measures, previous studies have focused on indirect outcomes of coordination such as measures of patient health (Peikes et al. 2009; McCullough, Parente, and Town 2016; Agha, Frandsen, and Rebitzer 2019; Agha et al. 2021). Second, administrative claims data used in prior work have been limited to a specific region, payer, or policy program (for example, Medicare fee-for-service), making it difficult for researchers to measure coordination and identify shared-patient relationships across different regions or programs (Trogdon et al. 2019; Agha et al. 2021). The main contribution of our paper is to analyze the quality of care and coordination by developing direct measures for coordination and using the large-scale quasi-experiment together with comprehensive administrative data representing treatment relationships for the entire patient and physician population.

To estimate the effects of the policy of information integration on the quality of prescribing, we use data on interacting prescriptions for one of the most common and harmful combinations of drugs: blood thinners and non-steroidal anti-inflammatory drugs (NSAIDs, such as ibuprofen) (Malone et al. 2005; Roughead et al. 2010; Rikala et al. 2015). These data cover interacting prescriptions obtained from different physicians over time and throughout the whole country, which allows us to provide more direct evidence than in prior work of the effects in terms of coordinating physicians' interdependent decisions. The scope of our data and of the quasi-experiment also allow us to examine the heterogeneous effects across different types of regions and providers to get a more complete picture of how they are affected by the technology adoption.

Besides using a quasi-experimental design and providing a novel prescribing-based measure of coordination, our empirical setting has other major advantages for analyzing the effects of information integration policies. Blood thinners, and warfarin in particular, are widely prescribed to prevent serious conditions such as strokes and heart attacks (Kirley et al. 2012; Fimea and Kela 2019). The national clinical guidelines stated by health authorities, however, clearly warn against simultaneous prescribing of warfarin with NSAIDs because of the increased risk of major bleeding complications (Lindh, Andersson, and Mannheimer 2014; Malone et al. 2005). Using a theoretical model by Becker and Murphy (1992), we illustrate the benefits of information integration in coordination and avoiding prescriptions for such drug combinations.

Our register-based administrative data contain 1.7 million prescriptions for over 250,000 warfarin patients in the period 2007–14. Despite well-established clinical guidelines, the co-prescribing of warfarin and NSAIDs was fairly common before the adoption of e-prescribing; the share of interacting prescriptions was 8 percent in the average municipality in 2007–9, with large variation across regions (between 2 and 19 percent). These findings are consistent with a lack of information integration and coordination in the pre-adoption period.

Using our prescription-level data, we find a sharp increase in the take-up rate of e-prescriptions by individual physicians (or patients) after the policy adoption by municipalities.[2] The intention-to-treat estimates of the effects of the e-prescribing policy, however, show no statistically significant effect on the overall probability of co-prescribing harmful drug combinations. Therefore, the nationwide system has little benefits for the quality of prescribing on average.

Motivated by the considerable evidence on urban-rural differences in health care provision and outcomes (Jonathan Skinner 2011; Loccoh et al. 2021), we also evaluate whether the policy of information integration has heterogeneous effects on the quality of prescribing in rural and urban regions. Besides improving information, technology adoption has the potential to compensate for the geo-graphic isolation of smaller rural communities, with aging populations, barriers to health care access, and persistent physician shortages (Keskimäki et al. 2019; OECD 2021).

Similar to the average effect, we find no statistically significant effect on the probability of co-prescribing warfarin with NSAIDs in urban regions; the confidence intervals of our baseline difference-in-differences (DiD) estimates rule out effects larger than 9 percent compared to the mean. However, in rural regions, the measure of low-quality prescribing reduces substantially, by approximately 35 percent. This result is not explained by differences in patient composition between rural and urban areas. Thus, the benefits of information integration for the quality of prescribing are much larger in rural than in urban regions, possibly because of pre-existing regional differences in physicians' expertise or knowledge.

We find that the improvement in the quality of prescribing in rural regions is driven by unspecialized physicians (generalists), who have fewer years of education and less expertise in treating complex warfarin patients than specialized physicians such as internists. In the presence of agglomeration economies and knowledge spillovers, observationally identical workers (for example, generalists) have lower levels of knowledge in rural than in urban regions (Glaeser 2008). The pol-

icy of information integration may compensate for shortages in human capital (expertise) and its externalities (knowledge spillovers or information sharing with other physicians) in geographically isolated rural regions by facilitating information acquisition and sharing, especially for generalists.

Consistent with our hypothesis of information integration improving coordination, we find that e-prescribing predominantly reduces interacting prescriptions from different physicians, rather than the same physician, in rural regions with sparse physician networks. Because all physicians should know that the interaction is harmful for patients, our results suggest that e-prescribing improved substantially sharing of information about a patient's current prescriptions from one of their physicians to the other. Finally, we show evidence that the reduction in interacting prescriptions in rural regions can potentially reduce hospitalizations for bleeding, even though, based on our DiD estimates, the overall effectiveness of e-prescribing in improving this health outcome seems to be only marginal.

Our paper contributes to the empirical literature on coordination by studying the effects of a nationwide policy of information integration. Previous literature has analyzed monetary incentives, team experience, and various organizational or management structures (for example, hospital-physician integration, accountable care organizations, hospitalists) as potential means for improving coordination (Gaynor, Rebitzer, and Taylor 2004; Cebul et al. 2008; Meltzer and Chung 2010). However, empirical work examining other fundamental drivers such as policies affecting the information environment is very limited (Bloom et al. 2014). Despite the underwhelming results on average, our results for rural regions support the conclusion that information integration has the potential to improve coordination and mitigate the harms of fragmentation in health care (Cebul et al. 2008; Elhauge 2010).

Our results complement prior work on fragmented care delivery, physician team relationships and performance (Jonathan S. Skinner, Staiger, and Fisher 2006; Agha, Frandsen, and Rebitzer 2019; Agha et al. 2021; Chen 2021). The results are also broadly consistent with earlier work on the determinants of physician practice style such as education or information (Epstein, Nicholson, and Asch 2016; Molitor 2018; Schnell and Currie 2018; Shapiro 2018) and with research on the roles of human capital, knowledge spillovers, and other supply-side factors in causing regional variations in and outside of the health care sector (Chandra and Staiger 2007; Gennaioli et al. 2012; Bartel et al. 2014; Finkelstein, Gentzkow, and Williams 2016; Cutler et al. 2019).

We also contribute to the literature analyzing how information technology affects patient health (for example, McCullough et al. 2010; Miller and Tucker 2011; Agha 2014; McCullough, Parente, and Town 2016; Böckerman et al. 2019). Our paper is most closely related to work by McCullough, Parente, and Town (2016), who examine health effects at the hospital level for patients whose diagnoses require cross-specialty coordination. In contrast, we explicitly analyze physicians' treatment decisions and coordination, in addition to analyzing heterogeneous effects across different types of regions and specialists. Much of the evidence is from the U.S., where providers' incompatible, non-standardized health information systems integrate information locally, within a hospital or a hospital network (Cebul et al. 2008). Our analysis, instead, studies a nationwide interoperable information system, which also improves information flows between different providers and organizations. Our study also complements prior research on local interventions (randomized controlled trials) to study the effects of care coordination on patient outcomes (Peikes et al. 2009).

II. Theory of Information Technology Adoption and Coordination Costs

In fragmented health care systems, a patient's care provision is frequently divided between multiple physicians and organizations (Cebul et al. 2008). We use a canonical model by Becker and Murphy (1992) to show (i) how such division of labor affects the quality of prescribing, (ii) how the adoption of health information technology affects the trade-off in the division of labor between productivity gains and coordination costs, and (iii) why this technological change can have heterogeneous effects in different types of production settings or regions, as later observed in our empirical analysis.

A group of physicians produces health care services for patient i. Production requires know-how (Garicano 2000). Physicians confront a complex decision-making and coordination problem regarding, for instance, appropriate combinations of prescription drugs because information is dispersed and imperfectly shared between them. Following Chandra et al. (2016), we investigate the production of quality (output) conditional on the inputs used in the treatment process, including the number of treating physicians n, and their human capital or knowledge H.[3] We start with the

following patient-level health production function:

$$y_i = B_i(H, X, n; \theta) - C_i(n; \lambda), \tag{1}$$

where y_i is the quality output and B_i is the gross output or benefit, which depends on the inputs and patient characteristics X through parameter θ. The coordination costs C_i depend on n and parameter λ, $\partial C_i/\partial\lambda > 0$ (Becker and Murphy 1992). Coordination costs include the costs of acquiring, processing, and sharing information (between multiple treating physicians n) (Garicano 2000; Myatt and Wallace 2012), in addition to other types of coordination costs such as those related to free riding (Holmström 1982) and incomplete contracting (Hart 2017). Such costs are a source of inefficiency in health care production: higher C_i implies that lower quality of care is produced from the given amount of inputs.

Productivity gains from the division of labor are captured by the positive marginal product of the number of physicians: $\partial B_i/\partial n > 0$. The division of labor can improve the output by reducing excess workload, filling staffing gaps with temporary workers, or specializing in a narrower set of tasks in the treatment of complex comorbidities. However, as the number of treating physicians increases, the coordination costs also increase $\partial C_i/\partial n > 0$.[4]

The adoption of information technology reduces coordination costs C_i by decreasing the parameter of coordination (information acquisition) costs λ in the production function (Garicano 2000).[5] As a result, the technology adoption also mitigates the trade-off in the division of labor between productivity gains and coordination costs. Because of the negative shock to λ, productivity improves, that is, higher quality of care is produced for the patient using the given amount of inputs.

The benefits from technology adoption can also be heterogeneous across different types of production settings (Chandra and Jonathan S. Skinner 2012). Clearly, with $\partial C_i/\partial n > 0$ (and $\partial C_i^2/\partial\lambda\partial n > 0$), technology adoption benefits patients, who require care coordination ($n \geq 2$). In addition to n, coordination costs may also depend on the characteristics of the patient, X, such as the complexity of their disease. With $C_i = C_i(X, n; \lambda)$, the benefits from technology adoption and the extent of cost reduction associated with improved coordination (decrease in λ) also depend on X.

Even though coordinating complex tasks and sharing information between decision makers is difficult (Becker and Murphy 1992), better knowledge embodied in human capital H can also reduce the cost of information acquisition required for successful coordination, $\partial C_i/\partial H < 0$ for $C_i = C_i(H, X, n; \lambda)$. Instead, physicians with lower levels of medical knowledge may pay less attention to acquiring the relevant information on each other's treatment choices (interacting prescriptions), be less efficient in finding or processing that information, and therefore have less effective patterns of coordinating prescribing practices.[6] A physician's medical knowledge and expertise depend on individual characteristics such as specialization, education, or skills and this knowledge is diffused between physicians when they are located near one another (Chandra and Staiger 2007; Agha et al. 2021). There are greater shortages of high-skilled human capital and its externalities in the form of such knowledge spillovers in rural than in dense urban regions, making rural regions less productive and causing regional differences in information or coordination costs (Becker and Murphy 1992; Glaeser 2008; Serafinelli 2019).[7] Thus, we hypothesize that the adoption of information technology mitigates the productivity disadvantage of rural regions created by the shortages in human capital or knowledge.

III. Empirical Setting

Our aim is to examine the adoption of a nationwide e-prescribing system in Finland and its effects on the quality of physicians' prescribing decisions and coordination on average, as well for different types of providers or regions. In this section, we describe the relevant institutional background for our empirical analysis.

A. Finnish Health Care System and Organizational Fragmentation

Finland has a decentralized single-payer health care system, in which regional governments are responsible for the organization and provision of health care services. By law, municipalities ($N = 304$ in 2014) are responsible for organizing primary care for their residents at the local level. The primary care system is based on municipal health centers, and every resident of the municipality is entitled to its health care services.

Municipalities, however, differ substantially in their ability to provide primary care services.

Regional differences in health care provision are almost unavoidable in Finland as a significant proportion of its surface area, nearly 70 percent, is sparsely populated rural areas, and health centers (and their physicians) are often separated by long distances (Kotavaara et al. 2021). These differences are most striking between urban and rural regions, especially as rural regions often struggle with geographic remoteness, limited financial resources, and persistent physician shortages (Keskimäki et al. 2019).

Each municipality belongs to one of the hospital districts ($N = 20$). Hospitals provide specialized medical care in urban areas or larger cities, and hospital districts are responsible for the organization of this provision in their region. The sectors providing complementary private and employer-sponsored occupational health care services are fairly small due to the universal provision of public primary and specialized health care services (Vuorenkoski, Mladovsky, and Mossialos 2008; THL 2019). Because service delivery and decisions related to organization are distributed across distinct regional care providers, the system is highly fragmented. This fragmentation makes the transmission of relevant medical information between providers challenging.

Before e-prescribing, health information systems were incompatible and operated within a region or even a single health care unit. The platforms (electronic medical records, EMRs) were produced by private companies for different health care providers (Keskimäki et al. 2019). Also, the development of health information systems was uncoordinated at the national level (Teperi et al. 2009). The local and incompatible EMR systems generally contained information on a patient's prescription history as it was recorded by the individual health care provider or unit; this information was incomplete to the extent that physicians' (paper) prescriptions were not recorded in the EMR systems (Hyppönen et al. 2006). Notably, prescription information was not available in a uniform and transferable electronic format and thus not accessible for physicians at the national level. The transfer of prescription information was not possible even between local providers that had the same EMR platform. Similarly, prescription information did not transfer between pharmacies because of their incompatible information systems.[8]

Physicians themselves had a crucial role in searching for relevant medical information and prescribing appropriate medications for their patients because there was/is no automatic nationwide notification system for harmful drug interactions.[9] When medical information was not integrated across providers before e-prescribing, it was difficult for physicians to identify all existing medica-

tions that may cause an adverse event when combined with new medications. This was particularly true for elderly patients who commonly suffer from complex diseases and use multiple medications simultaneously.[10] Consequently, a lack of information integration made it difficult to establish care coordination.

B. E-prescribing: Information Integration and Quality of Prescribing

E-prescribing is a globally widely used but understudied health information technology for digitizing prescriptions and the transfer of information on these across providers. In addition to Finland, e-prescribing systems have been adopted in many other European countries, the U.S., Australia, and Canada, among others, over the last decade. Next, we describe the key mechanisms through which nationwide e-prescribing affects the quality of prescribing, as measured by prescriptions for harmful drug combinations.

The central goal of implementing an integrated e-prescribing system is to enhance the quality of prescribing and coordination by improving information flows between physicians (Bell and Friedman 2005; Esmaeil Zadeh and Tremblay 2016), corresponding closely to the predictions of our model in Section II. In contrast to providers' pre-existing incompatible and incomplete information systems, e-prescribing systems provide physicians access to a patient's complete e-prescription history; this information is illustrated in Online Appendix Figure A2 in the Finnish health care provider setting. By improving information flows between physicians both within and across provider organizations, the systems reduce the likelihood of one physician not knowing about prescriptions from another physician.[11] Therefore, the system can also reduce prescriptions for harmful drug combinations, especially when they are written by different physicians ($n \geq 2$ in the theory model). Similarly, by integrating prescription information across pharmacies, the system can reduce the purchasing of harmful combinations of drugs from multiple pharmacies.

Böckerman et al. (2019) focus on another important objective of e-prescribing: improvements in the efficiency of the prescribing process through digital generation and transfer of a patient's prescriptions between physicians and pharmacies. Compared to traditional paper prescriptions, e-prescribing reduces the hassle and time costs of renewing and filling prescriptions, also eliminating lost prescriptions. E-prescribing can thus increase prescription drug use and therefore also the co-prescribing of harmful drug combinations. However, we hypothesize that the renewal channel has

a smaller role than the information channel in our setting: the quality of prescribing measured by harmful combinations of drugs.

C. Adoption of the Nationwide E-prescribing System

We evaluate a large-scale public policy change: the adoption of a nationwide e-prescribing system, including all e-prescriptions and their dispensing records, and covering both public and private health care providers. The common standards and interoperability of the fully integrated nationwide system enable access to prescriptions for all physicians and pharmacies involved in a patient's care. This access, however, requires a patient's permission.[12]

We use the staggered adoption of e-prescribing by municipalities in (public) primary care as our identification strategy for four reasons. First, municipalities are responsible for organizing primary care for their residents by law. Second, primary care physicians write most prescriptions, especially for warfarin and non-steroidal anti-inflammatory drugs (NSAIDs) (Lindh, Andersson, and Mannheimer 2014). Third, in Section VI, we document a sharp increase in the take-up rate of e-prescriptions by physicians and their warfarin patients after the patients' municipality adopted e-prescribing. Hence, our results for the adoption of e-prescribing are not driven by the low take-up rates.

Fourth, there is substantial and plausibly exogenous regional heterogeneity in the adoption time of the e-prescribing system across municipalities (Figure 1). Our expert interviews indicate that the adoption time was determined by technical difficulties in the integration of the e-prescribing system with pre-existing local information systems in health care units and pharmacies (Section III.A), rather than by trends in prescribing and health outcomes. In Online Appendix Table A1, we confirm that observable municipality-level characteristics are uncorrelated with the adoption time.

Figure 1 documents the staggered rollout of the e-prescribing system across municipalities over the period 2010-2014.[13] The figure shows the adoption time at the quarter level and we also use this level of precision in our estimations. By the first quarter of 2013, all municipalities had adopted the new system. The figure also indicates some geographical clustering of the reform. These clusters are explained by some municipalities being affiliated with one of the hospital districts, which coordinate some of their activities. However, this clustering is not a threat for identification of the effects because there is also relevant variation for identification within hospital districts.

D. Market Description

We focus on prescriptions for one of the most common and harmful combinations of drugs in primary care settings (Andersson et al. 2018): warfarin (international brand names Coumadin, Marevan, among others) and NSAIDs such as ibuprofen. Warfarin is an effective treatment for blood clots, which can cause serious health problems such as heart attacks and strokes (Beckman et al. 2010). It is also widely used: in Finland, warfarin expenditures totaled approximately EUR 3 million with 13 defined daily doses per 1,000 inhabitants per day in 2018 (Fimea and Kela 2019). For comparison, in the U.S., approximately 8–9 million prescriptions for warfarin are written per quarter and the total quarterly expenditures were approximately USD 144 million in 2011/Q4 (Kirley et al. 2012).

Despite the proved effectiveness of warfarin, making safe, clinically appropriate prescribing decisions for warfarin patients is challenging. Warfarin has clinically significant, potentially dangerous, but preventable interactions with other medications, especially with NSAIDs, which are widely prescribed to treat conditions such as acute or chronic pain and inflammation.[14] Combinations of warfarin and NSAIDs increase the risk of bleeding (hemorrhage) as both of these drugs have blood-thinning effects (Zapata et al. 2020). As a result, a patient may experience, for example, continuous bleeding, especially in the gastrointestinal tract (Battistella et al. 2005), which can result in hospitalization and even death.

Because warfarin and NSAIDs are both widely prescribed medications, there is scope for prescribing them together. Warfarin patients are typically older (the average age of patients in our data is 71), and they have an elevated risk of arthritis, which can be treated effectively with NSAIDs. Older patients are also particularly reliant on physicians' recommendations and information regarding the appropriate use of medication, because of their possibly limited capacity to acquire information themselves, for example, from online sources.

Although NSAIDs are also available over the counter in Finland, strong or high-dose NSAIDs, with more potential for health harms, are only available by prescription.[15] Moreover, Finland has a universal health insurance system, in which the national insurer, the Social Insurance Institute of Finland (Kela), reimburses a significant share of the costs of prescribed medications only. Arguably, the financial incentives for obtaining prescribed medications are particularly important for

older (warfarin) patients due to their limited financial resources.

Against this institutional background, we turn next to documenting significant shortcomings and variations in the quality and coordination of physicians' prescribing choices for warfarin patients using nationwide administrative datasets.

IV. Administrative Datasets

We use administrative data on warfarin patients and their NSAID prescriptions over the period 2007–14. Using additional administrative data on hospital discharges, we measure patients' bleeding complication (gastrointestinal hemorrhage), a well-documented and clinically significant health harm of the drug combination. Obviously, these complications are only one subset of health outcomes. Also, the main results for warfarin patients do not necessarily generalize to users of other prescription drugs.

Our sample construction covering warfarin patients is fairly similar to those used in related work on harmful drug combinations (Holbrook et al. 2005; Rikala et al. 2015). It also improves the statistical power, because we study the users of prescription drugs with the potential for harmful combinations and who are thus targeted by the e-prescribing policy. We examine separately the extensive margin of prescription drug use and return to this issue more closely in Section VII.B. Next we provide an overview of the datasets, sample construction and key variables.

1. Prescription data

The prescription data are from the Social Insurance Institution of Finland. The data record the universe of warfarin and NSAID prescriptions filled at Finnish pharmacies and covered by the National Health Insurance (NHI) scheme over the period 2007–14.[16] The key advantage of our comprehensive register-based data covering both the public and private sectors is that we can follow patients over time, even if they switch physicians, providers or employers.[17] Using these data, we construct our main sample of patients who filled at least one warfarin prescription during the observation period. This sample construction leads to a relatively homogeneous group of patients, who are mostly elderly (Section V). For warfarin patients, we include the complete records of all their NSAID prescriptions over the years. We also confirm that our main results are robust to

using an alternative sample, including all NSAID patients in the prescription data. The unit of observation is a prescription.

The data record the coded patient identifier, the patient's date of birth and death, and the municipality of residence. We use the 2014 municipality classification, providing a consistent definition of municipalities over time. Using the statistical municipality classification by Statistics Finland, we identify patients in urban, semi-urban, and rural municipalities (regions). For the detailed description of this official classification, see Statistics Finland (2020) and the notes in Online Appendix Figure A3, which plots the map of municipalities by group. We use two aggregated municipality groups in our main analyses: urban (or semi-urban) and rural. We group together urban and semi-urban municipalities (and call them urban municipalities for brevity) because there is no apparent heterogeneity in the main effects of e-prescribing between these two groups (Section VII.A).

The prescription data also record the physician identifier, the date of prescribing, the e-prescribing status, the anatomical therapeutic chemical (ATC) code of the prescription, and the number of defined daily doses (DDD) of the prescription.[18] See Online Appendix I for the ATC codes. The WHO's metric of defined daily dose is widely and internationally used, defined as the assumed average maintenance dose per day for a drug used for its main indication in adults. In our data, a very small fraction of prescriptions, less than one percent, lacks this information, and we drop these observations. In addition, our data record physician specialty and the date of specialization. However, an important limitation of our data is that they do not identify the local health care units of prescribing physicians. For this reason, our data are particularly well suited to studying the implications of improvements in information flows and coordination between physicians, but not within and between local units.

We use the amount of defined daily doses a patient filled from each prescription and the date of prescribing to construct our prescribing quality measure, an indicator of the co-prescribing of warfarin and NSAIDs. We assume that one (theoretically) defined daily dose corresponds to one (actual) day of drug consumption. If the previous prescription is not fully consumed before the current prescription is issued, we flag the current prescription as an interacting prescription. Also, a necessary condition for a harmful interaction is that the previous prescription is for warfarin and the current prescription is for NSAID, or *vice versa*.[19] In addition to the quality of prescribing, we

measure the intensive and extensive margins of warfarin and NSAID use, as described in Online Appendix Section VI.

2. Discharge data

The discharge data are from the the National Institute for Health and Welfare. The data contain comprehensive information on Finnish public hospital (specialized health care) discharges in 2007–14. The deidentified data record coded patient identifiers, the patient's diagnoses (ICD-10 coding), the date of discharge, and the patient's municipality of residence. Using the unique coded patient identifiers, we link the discharge data to the prescription data for the population of interest (warfarin patients).

We construct a dummy variable that equals one if the patient has a hospital admission for gastrointestinal hemorrhage (bleeding) during a 3-month period based on the diagnoses in the discharge data. To calculate this bleeding outcome, we aggregate the data into a balanced panel form in which observations are at the patient-quarter-level. See Online Appendix I for the ICD-10 codes.

3. E-prescribing adoption data

Our analysis uses data on the dates of the adoption of e-prescribing by municipalities from the National Institute for Health and Welfare. We link the data on regional adoption dates to our other two datasets (prescription data and aggregated discharge data) by the patient's municipality of residence. A patient typically chooses a public health care unit or health centre within their municipality of residence. For this reason, the municipality of residence also serves as a good proxy for the location of the prescribing physician. Because the aggregated discharge data are at the patient-quarter level, we consider the adoption of e-prescribing within this 3-month period.

V. Evidence on Pre-Adoption Prescribing Behaviors

The Finnish health care system is highly decentralized and fragmented, with an uneven distribution of health care resources, such as the physician workforce, between urban and rural regions (Section III.A). Hence, the system is prone to coordination failures and disruptions in information

transmission, prompting a long-standing need for nationwide integration of information systems (OECD 2017).

Figure 2 provides evidence for the hypothesis that coordination failures and disruptions in information transmission were prominent in prescribing in the pre-adoption period 2007–9. The co-prescribing of warfarin and NSAIDs was fairly common, despite the fact that there is a well-established, nationwide clinical guideline against such co-prescribing and these guidelines are well-known by physicians and taught in medical schools. The regional share of interacting prescriptions (warfarin and NSAIDs) was 8 percent among warfarin patients in the average municipality, with variation across regions of between 2 and 19 percent. Notable regional variation is consistent with previous research in other settings and outside Finland (Zhang, Newhouse, and Baicker 2011).

Figure 3 presents a more detailed characterization of the regional differences in the quality of prescribing for urban/semi-urban and rural regions in the pre-adoption period. In absolute terms, the regional share of interacting prescriptions was slightly higher in rural compared to urban regions on average (8 and 7 percent, respectively), but the relative difference in the municipality-level averages was quite significant (14 percent). Moreover, the cross-municipality variation was much larger in rural than in urban regions (2–19 versus 3–13 percent).[20] Considerable variation in the quality of prescribing in rural regions indicates fragmentation and delivery systems characterized by incomplete information integration.

Table 1 reports the summary statistics in the pre-adoption period, using the prescription-level data. Panel A shows that 16 percent of warfarin patients had an interacting prescription (with NSAIDs) at least once. At the prescription level, the probability of a warfarin-NSAID interaction was 7 percent on average and 14 percent higher for patients in rural than in urban regions.

Our findings on the fairly high rates of interacting prescriptions are consistent with related research using U.S. and Finnish data (Malone et al. 2005; Rikala et al. 2015). Revealing further evidence on coordination and information failures due to fragmentation, we also find that nearly 70 percent of all interacting prescriptions originated from different prescribing physicians.

Panel B shows warfarin and NSAID use per patient during the pre-adoption period (2007–9). Warfarin use was much higher than that of NSAIDs on average, as the data are constructed using warfarin users. In addition, there is only little difference in warfarin use, but there was some

difference in NSAID use between patients in urban and rural regions.

Panel C reports prescription shares by physician speciality (see Online Appendix Table A2 for the counts of all and interacting prescriptions by specialty). In Finland, physicians without a specialization are typically licensed physicians with a Licentiate's degree, which is a degree below a Doctoral degree and above a Master's degree. Basic medical education in Finland lasts at least six years. A physician with a medical licence does not always have a Doctoral degree, unlike in the U.S., for example. We call licensed physicians without a specialization unspecialized physicians or generalists, the latter terminology being similar to physicians specialized in general medicine. In contrast to unspecialized physicians, specialized physicians have a Doctoral degree with additional specialty education that takes five or six years. Thus, compared to unspecialized physicians, specialized physicians have more formal medical education, better clinical expertise, and the number of them per specialty is also more limited (FMA 2016).

Panel C shows that a much greater proportion of prescriptions were obtained from unspecialized physicians (generalists) in rural than in urban regions: 55 versus 46 percent. A stylized empirical fact is that there is a greater proportion of generalists and fewer specialists such as internists in rural than in urban regions, in part because the hospitals (providers of specialized care) are located in urban regions or larger cities (Section III.A).[21] The lack of specialists in rural regions limits the availability of human capital resources in the production of health care services, but potentially also the opportunities for unspecialized physicians to acquire up-to-date medical information from specialists (knowledge spillovers).[22]

Panel C reveals the division of a patient's care provision between multiple physicians, which is an important driver of care fragmentation (Agha, Frandsen, and Rebitzer 2019).[23] The probability of receiving a prescription from a different physician than last time was quite similar in rural and urban regions (53 and 52 percent, respectively). The ratio of unique physicians to patients was, however, much larger in rural regions ($6,357/25,623 \approx 0.25$) compared to urban regions (0.16).

Panel D shows information on additional patient variables. The share of patients hospitalized for gastrointestinal hemorrhage (bleeding) was 7 percent on average, with a 6 percent difference between rural and urban regions. Bleeding can result from warfarin use, and especially its combination with NSAIDS (Section III.D), being harmful, even lethal, for older patients; warfarin users were 71 years old on average and their mortality was also high, approximately 10 percent in the

pre-adoption period (2007–9).

Finally, there are substantially fewer physicians in rural health centres and they are geographically more isolated than their counterparts in urban regions or large cities (Kotavaara et al. 2021; FMA 2021).[24] The number of prescribing physicians per municipality was also considerably smaller in rural than in urban regions in the pre-adoption period (Figure 4). Based on this, local social networks available for physicians are much narrower in rural than in urban regions. Urban regions may have better scope for knowledge spillovers between physicians because these are the regions where physicians can interact with sufficient frequency and proximity.

VI. Econometric Approach

We use the staggered adoption of the nationwide e-prescribing system across all municipalities and over four years to estimate the effects on the quality of prescribing on average and separately for each municipality group (urban or rural). Specifically, we estimate the following parametric event study specification for patient i in municipality m in period t, using the prescription-level data:

$$y_{imt} = \sum_{\tau=-8}^{8} \delta_\tau D_{\tau,mt} + X_{imt}^{'}\beta + \alpha_m + \gamma_t + \epsilon_{imt}, \tag{2}$$

where y_{imt} is the prescribing quality outcome and $D_{\tau,mt}$ indicates the period relative to the adoption period of e-prescribing in municipality m. The parameter vector of interest, δ, measures the changes in the outcome around the adoption of e-prescribing in municipality m. We omit the first leading period before adoption ($\tau = -1$). Thus, the other δ_τ parameters are normalized relative to this period. Also, $D_{-8,mt}$ ($D_{8,mt}$) equals one when the relative period is eight or more periods before (after) adoption. We include in the model the full set of the municipality fixed effects, α_m, which absorb any differences between municipalities that do not change over time; time fixed effects, γ_t, which capture time-varying national-level shocks that may affect the outcome; and controls for patient-specific covariates, X_{imt}, which include age and the square of age. We also report the results for a specification in which we replace municipality fixed effects, α_m, with patient fixed effects, η_i. This specification uses within-patient variation in identification and controls for unobserved, time-invariant heterogeneity across patients such as their gender. To allow for within-

municipality correlation in patients' unobservables, we cluster standard errors at the municipality level. The overall number of clusters (municipalities) is 304.

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

$$y_{imt} = \rho_1 SR + \rho_2 LR + X_{imt}^{'}\beta + \alpha_m + \gamma_t + \epsilon_{imt}. \tag{3}$$

Here ρ_1 and ρ_2 denote the short-run and long-run point estimates, respectively. We define short-run as the first four quarters after (Q0–Q3) the adoption of e-prescribing and long-run as the subsequent remaining quarters.

Because of the staggered adoption of e-prescribing, the later-treated units use already-treated units as controls in the estimation. Goodman-Bacon (2021) shows that the treatment effect estimated by the two-way fixed effects DiD estimator (the so-called pooled DiD estimator) is the weighted average of all possible two-group, two-period treatment effects. He shows that if the treatment effect varies over time, negative weights could arise for later-treated units, potentially biasing the treatment effect estimate. We present robustness checks to address these concerns in Online Appendix Section V and conclude that negative weighting is not an issue in our setting.

The take-up of e-prescriptions by physicians and their patients was voluntary during the observation period. This implies that the parameters of interest (δ_τ for $\tau \geq 0$, ρ_1, ρ_2) are the intention-to-treat (ITT) effects of e-prescribing. Figure 5 shows the take-up rate of e-prescriptions for warfarin patients around the adoption of e-prescribing by their municipality of residence (in primary care). The take-up rate of e-prescriptions increases sharply in the adoption quarter and continues to increase gradually over time on average. One year after adoption, approximately 60 percent of prescriptions are issued electronically on average. The take-up rate is only slightly higher for rural than for urban patients after adoption. A marginally higher take-up rate for rural patients may result from the fact that their prescriptions are more frequently obtained from generalists (unspecialized physicians or specialists in general medicine) working in primary care, as opposed to specialists working in hospitals (Section V). This observation is further highlighted in Online Appendix Figure A4, which shows a higher take-up rate after adoption for patients who get their prescriptions from generalists rather than from internists. Overall, these findings show that our results for the

adoption of e-prescribing are not driven by low take-up rates and also provide additional support for our empirical approach, which is based on the adoption of the technology by municipalities in primary care.[25]

VII. Results

A. Quality of Prescribing: Harmful Drug Combinations

1. Average effects of the policy

We first present the main results from estimating the average effect of e-prescribing on the quality of prescribing, as measured by the probability of a warfarin-NSAID interaction. Figure 6 plots the δ_τ coefficients and their confidence intervals from estimating the event study specification based on Equation 2. The figure does not reveal notable pre-trends, supporting the key identification assumption of our empirical specification. Panel A of Figure 6 shows that e-prescribing has a statistically insignificant effect on the probability of a warfarin-NSAID interaction on average. The corresponding DiD estimates based on Equation 3 are also very close to zero and statistically insignificant both in the short and long run (Column 1 of Table 2). Given that we are analyzing the adoption of a nationwide system and focus on a well-established and well-known harmful drug combination, the estimated average effects are strikingly small although somewhat imprecisely estimated.

2. Regional heterogeneity of the effects

Motivated by the ample evidence on urban-rural gaps in health care provision and outcomes (Skinner 2011; OECD 2017; Loccoh et al. 2021) and the broader policy goal of the nationwide system (standardization) of mitigating such differences (STM 2015; WHO 2016), we also examine whether e-prescribing has differential impacts on the quality of prescribing in rural and urban regions. [26] Similar to the average effects in Panel A of Figure 6, we find no statistically significant effect for urban/semi-urban municipalities, as shown in Panel B. The corresponding DiD estimates are very close to zero and fairly precisely estimated (Column 1 of Table 2). There is no improvement in the quality of prescribing in urban regions despite the fact that the baseline probability of

drug interaction was notable (7 percent) in these regions, although 14 percent smaller than in rural regions prior to e-prescribing (Table 1).

In contrast to the underwhelming effects on average and in urban regions, Panel C of Figure 6 shows a statistically significant and large decrease in the interaction probability in rural regions after e-prescribing. The magnitude of the corresponding long-run point estimate is -36 percent compared to the mean in the observation period (Table 2).[27] The decrease is gradual, coinciding with the increasing take-up rate of e-prescribing over time (Figure 5).

The estimated benefits of the policy of information integration for the quality of prescribing are much larger in rural than in urban regions. As suggested by our results and the large variation in the quality of prescribing among rural regions (Figure 2), information flows and coordination could have been hampered in these regions before e-prescribing. In addition to limited economic resources and geographic remoteness, rural regions have a productivity disadvantage resulting from the shortages of high-skilled human capital and its labor market interactions, which lead to the accumulation of knowledge in urban regions (Glaeser 2008).

If the number and proximity of interactions between physicians facilitate knowledge spillovers and coordination in urban regions, then regional differences in human capital and its externalities in the form of knowledge spillovers might provide a plausible explanation for the null effect of information integration in urban regions, alongside the large effect in rural regions. Consistent with this hypothesis and similar to the large effect in rural regions, we find the largest improvement in the quality of prescribing in municipalities with the smallest number of prescribing physicians during the pre-adoption period (Online Appendix Figure A6). This result supports the conclusion that e-prescribing improves the information environment, which is characterized by limited knowledge spillovers and social interactions between physicians.

The heterogeneous effects of e-prescribing are possibly also driven by differences in the characteristics of patients or physicians between urban and rural regions. However, Column 2 of Table 2 shows the robustness of the results to controlling for patient fixed effects.[28] The negligible contribution of patients' time-invariant characteristics in explaining the effects emphasizes the role of physicians and their characteristics as potentially important factors in explaining heterogeneous responses to e-prescribing in urban and rural regions. The importance of physicians and their characteristics in explaining the observed patterns is plausible because e-prescribing was specifically

designed to impact physician decision-making by improving their information and making them aware of the patient's previous prescriptions. After presenting sensitivity and placebo analyses, we further study the role of physician expertise or knowledge and pin down the potential mechanisms of e-prescribing such as improvements in the information environment and coordination.

3. Sensitivity analyses

To establish the robustness of the main findings, the remaining columns in Table 2 report the results by making various changes to the baseline specification. These changes include using patient fixed effects instead of municipality fixed effects (Column 2); adding hospital district-specific linear time trends (Column 3); adding an extra linear time trend for individual ATC codes or active ingredients (Column 4); excluding all prescriptions with a visit to a private physician from the estimation sample, as we are investigating the adoption of e-prescribing in public primary care (Column 5); including prescriptions for all patients who have at least one NSAID prescription, but not necessarily a warfarin prescription (Column 6), as opposed to using the baseline sample that limits the data to prescriptions for warfarin patients; and including prescriptions only for patients who do not die during the observation period, in order to confirm that nonrandom attrition caused by mortality does not bias the baseline estimates (Column 7).[29] The point estimates and their standard errors remain remarkably similar across all these specifications. Online Appendix Figures A7 and A8 plot the results of these robustness checks in the event study framework. To ensure that changes in the patient population or its composition do not bias the main results, Online Appendix Figure A9 shows the robustness of the results to limiting the set of patients to those who received a warfarin prescription before the adoption of e-prescribing.

When a harmful drug combination occurs, it may be easier for the patient to stop using NSAIDs than warfarin as the latter is an essential, even life-saving, medication. Failing to find similar results when considering only one-way interactions where NSAID is prescribed on top of warfarin would cast doubt on the validity of our results. Online Appendix Figure A10 shows that the results for these one-way interactions are very similar to our main results for two-way interactions (warfarin on top of NSAIDs or the other way round).

We also conduct several sensitivity tests regarding the measurement of the main outcome variable. First, we artificially decrease (increase) the length of prescriptions in Panels A–C (D–F) of

Online Appendix Figure A11. Second, we exclude all interactions that interact for less than 10 days (and over 100 days) in Panels A–C (D–F) of Online Appendix Figure A12.[30] Third, we use patient-specific average prescribing intervals as an alternative proxy for prescription length in Online Appendix Figure A14 and Table A3. Our baseline results are not sensitive to these changes in the outcome variable.

4. Placebo regressions

As a supplementary analysis, we estimate placebo regressions for the interaction probability. For this purpose, we use an interaction between warfarin and benzodiazepines as an outcome. Benzodiazepines are widely used medications for treating anxiety and sleep disorders (Olfson, King, and Schoenbaum 2015), and they do not have known harmful interactions with warfarin, according to the medical literature (Orme, Breckenridge, and Brooks 1972). Therefore, e-prescribing should not reduce warfarin-benzodiazepine interactions (with a mean value of 0.224). As expected, Online Appendix Figure A15 shows no statistically significant reduction in these interactions, supporting the validity of our main findings.

B. Mechanisms and Additional Outcomes

1. Physician expertise and improvement in the information environment

Next we provide further evidence on the roles of human capital (individual expertise) and its externalities (knowledge spillovers) in driving the observed benefits of information integration in rural regions. Conceptually, coordinating prescribing choices and acquiring relevant medical information on interacting prescriptions with warfarin could have been more difficult for physicians with less specialty expertise in treating warfarin patients. In our theory model (Section II), physicians with lower levels of medical expertise or knowledge H have higher costs of information acquisition and coordination C_i, which implies that lower quality of care is produced for a given patient before e-prescribing. Consistent with this, a substantial body of studies have documented physician expertise as a key contributor to the quality of medical decision-making (Currie and MacLeod 2017; Schnell and Currie 2018; Currie and MacLeod 2020).

In terms of expertise, we consider the three most common types of classifications of medi-

cal specialties in our data: unspecialized, general medicine, and internal medicine. Compared to physicians specialized in the diagnosis and treatment of internal diseases such as blood clots, unspecialized physicians have less expertise in treating complex warfarin patients.[31] Compared to specialized physicians, unspecialized physicians have less formal medical education. In the presence of agglomeration economies and knowledge spillovers, observationally identical workers such as unspecialized physicians have lower levels of knowledge (and higher C_i) in rural than in dense urban regions (Glaeser 2008; Serafinelli 2019). Consistent with this, an extensive literature has also highlighted the role of knowledge spillovers in improving medical decision-making, especially in team production involving social interactions or coordination (Chandra and Staiger 2007; Bartel et al. 2014; Chen 2021; Agha et al. 2021).

Figure 7 presents the event study results for the three specialties in rural regions (Online Appendix Figure A16 shows the results for urban municipalities and Table A4 shows the corresponding short- and long-run point estimates for the two municipality groups). We find no statistically significant effects in urban regions despite the large of number of observations supporting statistical power. In rural regions, the interaction probability decreases substantially for unspecialized physicians (Panel A of Figure 7). For specialists in general medicine, the decrease is much smaller and statistically insignificant (Panel B). For internists, the event study estimates are also negative but more imprecisely estimated than for the other specialties (Panel C). Note that internists have the highest probability of writing an interacting prescription, most likely because of the complexity of their patient population.

To summarize, the observed benefits of e-prescribing in rural regions are overwhelmingly driven by unspecialized physicians, highlighting the importance of information integration for the decision-making and coordination of physicians with the least medical expertise or education. This finding suggests that information acquisition about prior prescriptions has been most difficult for less educated physicians in rural regions that have sparse physician networks.[32] However, there are no significant benefits for similar physicians in urban regions, where the scope for knowledge spillovers and social interactions is better than in rural regions. These two findings are consistent with the policy of information integration mitigating the productivity disadvantage of rural regions created by the shortage of human capital (expertise) and its externalities (knowledge spillovers) in the context of physicians' prescribing decisions.

2. Coordination and information integration between physicians

E-prescribing substantially improves a physician's information on the prescribing choices of the patient's previous physicians. Consequently, the quality of prescribing and coordination should improve. To investigate this, we construct a binary outcome variable that equals one if the prescription interacts (overlaps) with the previous underlying prescription *and* the two prescriptions are from different physicians. For comparison, we present the results for the outcome that the same physician writes the interacting prescriptions. We also present the results for the baseline (overall) effect that equals the sum of the two decomposed effects. Figure 8 plots the event study results for rural regions. Online Appendix Figure A17 presents the results for urban regions and reveals only little evidence for an improvement in the quality of prescribing and coordination in those regions.[33]

Figure 8 shows that the overall reduction in the interaction probability in rural regions is predominantly driven by interacting prescriptions from different physicians, rather than from the same physician.[34] The decrease for different physicians is statistically significantly larger in the short and long run than for the same physician (Online Appendix Table A5). Note that in the table the coefficient estimates for a different physician are estimated relative to the same physician. All in all, although e-prescribing does not fully eliminate cross-physician drug interactions, it seems to provide critical information for coordinating the prescribing choices of geographically isolated physicians in rural regions. In those regions, coordination and information costs are usually higher than in dense urban regions, where providers locate near each other (Becker and Murphy 1992).

3. Coordination and information integration within versus between generalists and specialists

A great need for information integration and coordination can arise when patients rely on care from different types of physicians. Patients with multiple diseases often seek care from both generalists and specialists, and a greater share of prescriptions is obtained from generalists as opposed to specialists in rural than in urban regions, for example due to longer distances to hospitals (Section V).

On the other hand, information integration and improved coordination can also be beneficial to patients whose care is divided among many physicians with similar education (for example, general medicine), but with potential differences in, for example, location, waiting time, and idiosyncratic

skills or ability. Compared to cross-specialty coordination, it may even be easier to improve coordination between physicians of the same type (generalists) with the aid of information integration because of the similarity in the physicians' training and expertise in treating patients.

We analyze improvements in information flows and coordination as a result of e-prescribing within versus across generalists and specialists. For this particular purpose and unlike in the analyses above, we include specialty in general medicine in the same category as unspecialized physicians (generalists). Generalists and specialists are likely to work in different units (primary care units and hospitals, respectively), and generalists also act as gatekeepers by making referrals to specialists.[35] Online Appendix Figure A18 shows the results from the decomposition in rural regions (see Online Appendix Figure A19 for the decomposition in urban regions). The overall decrease in the point estimate in rural regions is almost entirely driven by the decrease in interactions within unspecialized-unspecialized and specialized-specialized pairs. Taking the findings together, the improvement in the quality of prescribing in rural regions seems to result from improved information flows and coordination between physicians of the same type (generalists), as opposed to physicians of different types (generalists and specialists).

4. Coordination and information integration between pharmacies

Pharmacies also adopted the e-prescribing system and, as a result, information flows between different pharmacies may have improved. We proceed similarly as above and decompose the main outcome into interactions where the patient fills the interacting prescriptions in different pharmacies versus the same pharmacy. Figure 9 shows the results from this decomposition in rural regions (see Online Appendix Figure A20 for urban regions). The decrease in interactions in rural regions comes almost entirely from prescriptions filled in the same pharmacy. Based on this, it is clear that information integration between pharmacies does not drive our main results and physicians' response to the policy provides the key to understanding the effects of e-prescribing technology.

5. Prescription drug use and patient health

We analyze the effects on prescription drug use to gain a broader understanding of the underlying mechanisms of e-prescribing. We also analyze whether improvements in the quality of prescribing

and coordination in rural regions translated into improvements in patient health. Next we summarize only the main results and leave the details to Online Appendix Section VI.

E-prescribing can either decrease (via better monitoring) or increase prescription drug use (via easier renewal and decreased hassle costs). If more drugs are being prescribed, there is a greater chance that there will be an interaction among the drugs. The effect is the opposite if e-prescribing leads to less drugs being prescribed.

We estimate the effects on the quarterly number of prescriptions per patient (extensive margin), and find the effects to be fairly small in both warfarin and NSAID use on average and in urban and rural regions. We also confirm that there is only a small effect on the aggregate numbers of all and initial warfarin prescriptions at the municipality and quarterly level, and find no apparent change in the composition of the patient population around the adoption of e-prescribing.[36]

We estimate the effects on the sizes of warfarin and NSAID prescriptions (intensive margin). Again, we find no statistically significant effects on average and in urban regions. However, in rural regions the size of warfarin prescriptions increases whereas the size of NSAID prescriptions decreases after e-prescribing. Moreover, the decrease in the interaction probability in rural regions does not seem to be solely explained by the decrease in the length of NSAID prescriptions. In those regions, e-prescribing still seems to improve physicians' practices so that prescribing NSAIDs to warfarin users can be more frequently avoided.

As comprehensive analysis of various direct and indirect health effects is beyond the scope of our study, we focus only on the most direct and widely used health outcome of the interaction of warfarin and NSAID: hospitalization for gastrointestinal bleeding (Battistella et al. 2005; Zapata et al. 2020). We find no evidence for a decrease in this outcome after e-prescribing, not even in rural regions. In addition to estimating the overall effects of e-prescribing on the bleeding outcome, we present a complementary back-of-the-envelope calculation to provide more explicit evidence on the potential health effects of the decreased warfarin-NSAID interaction risk (Online Appendix Section VI.B). We found that e-prescribing decreased the probability of such interaction by approximately 35 percent in rural regions (Section VII.A). In addition, the probability of hospitalization for bleeding is 30 percent higher for patients with an interacting prescription compared with those having a warfarin prescription alone in a given quarter (Online Appendix Table A13). Based on these two estimates, the e-prescribing-induced decrease in the drug interaction risk could

potentially reduce the bleeding outcome by $100 \times (0.3 \times 0.35) \approx 11$ percent in rural regions. Thus, reducing drug interactions through the adoption of e-prescribing can be beneficial for patient health, even though the overall effectiveness of e-prescribing in reducing hospitalizations for bleeding seems to be only marginal, based on DiD estimates.

VIII. Conclusion

This paper studies a large-scale policy of health information integration, based on the staggered adoption of a nationwide e-prescribing system across all municipalities in Finland. The fully digitalized and interoperable system provides a unique opportunity to improve the quality of prescribing and coordination by sharing information on prescriptions among all physicians involved in a patient's care. Comprehensive administrative data on interacting prescriptions for one of the most common and harmful combinations of drugs (warfarin and NSAIDs) allow us to investigate the quality and coordination of physicians' interdependent decisions in a fragmented system.

We find only little evidence that e-prescribing improves the quality of prescribing on average, despite the fact that we examine a nationwide system and focus on a well-established harmful drug combination. The benefits of information integration for the quality of prescribing, however, vary substantially across regions. Whereas there is no statistically significant effect in urban regions, the probability of co-prescribing warfarin with NSAIDs reduces by approximately 35 percent in rural regions after e-prescribing.

Consistent with information integration improving physicians' coordination, e-prescribing predominantly reduces interacting prescriptions from different physicians in rural regions. Moreover, the policy of information integration primarily benefits unspecialized physicians in rural regions with low number of physicians and sparse physician networks, whereas for similar physicians in urban regions we observe no statistically significant effects. Our results are consistent with the existence of information and coordination frictions before e-prescribing in geographically isolated rural regions, where the scarcity of human capital and its externalities in the form of knowledge spillovers is much greater than in urban regions. Regional variation in demand-side factors such as patient demographics may also have a role, but the results remain intact after we account for patient fixed effects, suggesting that our findings are not explained by unobserved or observed differences

in patient composition across urban and rural regions.

The Finnish e-prescribing system is designed for interoperability and standardization at the national level. In terms of generalizability to other institutional contexts, our evidence is particularly relevant for other developed countries that have not yet adopted nationwide systems or are integrating their existing local e-prescribing systems or upgrading their systems with additional features.

Coordinating care is a major policy priority in health systems around the world (Doty et al. 2020). In complex systems such as health care, information is dispersed and the organizational structures and decision-making power decentralized to separate agents or providers (for example, by region or speciality). Although decentralization of governance can improve the efficiency of health care provision, it can also lead to fragmentation and a breakdown in coordination. As decentralization has been the focus of many health system policies, much less attention has been paid to optimizing and integrating a patient's care provision. Our findings show that a nationwide policy of information integration can mitigate some of the coordination failures across different physicians, thereby enabling patient medication to be tracked efficiently and improving the quality of care.

Notes

1. E-prescribing systems contain only prescription information, in contrast to electronic medical and health records that contain a varying collection of data (for example, treatments, free-text descriptions of clinical notes, and X-ray images).

2. The take-up of e-prescriptions was voluntary during the observation period. One year after adoption, approximately 60 percent of prescriptions were issued electronically on average.

3. More generally, inputs also include physical inputs such as facilities and medical equipment K.

4. The result derived from the first-order condition $\partial B_i/\partial n \geq \partial C_i/\partial n$ for the equilibrium division of labor n^* shows that both n^* and the optimal level of output y^* are limited by coordination costs.

5. In the analysis of technology adoption, we take n (and human capital inputs H) as given. Adjustments in n may occur in the long term after the shock to λ depending on the availability or education of physicians, as well as on various contractual and organizational arrangements. Analyses of adjustments in team size and labor markets are beyond the scope of our study.

6. For well-established and well-known drug interactions such as warfarin and non-steroidal anti-inflammatory drugs (NSAIDs), less knowledgeable physicians would know that they should not prescribe one drug on top of the other but may not be aware of the other prescriptions because of the higher costs of information acquisition.

7. As noted by Becker and Murphy (1992), in their model, productivity is higher and coordination (information) costs are lower in urban regions, where providers locate near each other and can communicate more easily.

8. The pharmacy market is also fragmented because regulation prohibits the establishment of pharmacy chains. All pharmacies are operated by private providers.

9. Physicians and pharmacies had access to a drug interaction database (INXBASE/SFINX) that was/is integrated with many local EMR and pharmacy platforms. These systems automatically warn about drug interactions using information on a patient's medications but only in that *local* platform and they do not allow information flows between physicians or pharmacies across platforms. Local INXBASE/SFINX systems were nationally fragmented and they are not integrated with e-prescribing.

10. The use of different prescription drugs simultaneously is very common among elderly in Finland (Klaukka et al. 1993).

11. Some (rural) municipalities may have only one primary health care unit. In these cases, e-prescribing may also improve physician coordination and information flows, for example within a single unit or between primary care units and hospitals.

12. Giving permission is in the patient's interest, because it allows the identification of drug combinations (warfarin and NSAIDs) that are harmful for the patient's health.

13. Adoption of the system became mandatory in public health care units by 2014 and in private health care units by 2015. Very small private units issuing less than 5,000 prescriptions annually were excepted, and had the system by 2017.

14. In Finland, expenditures for NSAIDs using wholesale prices totaled approximately EUR 44 million and there were 1.4 million recipients of reimbursements for prescription drugs under national health insurance in 2018 (Fimea and Kela 2019). Approximately 50 percent of expenditures resulted from over-the-counter medicines (ibuprofen and ketoprofen in lower doses) and only 2 percent from sales to hospitals.

15. For example, in the case of a popular painkiller, ibuprofen, it is not possible to obtain tablets stronger than 400 mg from a Finnish pharmacy without a valid medical prescription.

16. The original data record all purchases related to a prescription (the items or daily doses of the prescription may be filled at a pharmacy on multiple occasions). We use prescription-level data and identify prescriptions based on the patient and physician identifier, active ingredient, and the date of prescribing.

17. The main limitation of register-based claims data is that there is no information on the actual use of medication or whether the patients follow the instructions given to them by physicians. Moreover, the data do not contain purchases for lower-dose NSAIDs in the OTC market.

18. Our data may include a limited number of prescriptions issued by nurses, who have been able to administer drugs in Finland since 2012. However, the total number of prescriptions written by nurses is very small during our observation period: only 3,310 prescriptions in 2013 (Virta 2014).

19. We compare the current prescription to all the patient's previous prescriptions rather than only to the previous one. This is important because elderly patients typically have several overlapping and potentially interacting prescriptions. In constructing the interaction indicator, we also take into account rare cases where warfarin and NSAIDs are prescribed at the same time.

20. This variation is not caused by measurement error in the administrative data. Municipalities are responsible for providing primary health care for their residents. Thus, rural regions are large enough (and cover 20 percent of the patient population, as shown in Table 1 below) that the variation in quality of care would be purely random.

21. For example, the vast majority (70 percent) of internists work in hospitals and only 10 percent work in municipality health centres in Finland (FMA 2022).

22. Unspecialized physicians may consult specialists such as internists. On the other hand, it may be more common for unspecialized physicians to interact and communicate with other generalists than with specialists, who focus on

different fields of medicine.

23. Workforce turnover may partially explain the division of a patient's care provision. In urban regions, the opportunities to switch jobs are better than in rural regions due to the thickness of the labor market. In rural regions, temporary workers are typically used to fill persistent staffing gaps, and the doctor-patient relationship often ends with the termination of their fixed-term contracts.

24. For example, the health centre of Espoo, the second largest city in Finland, filled approximately 108 physician job positions in 2021. In contrast, the health centre of Kolari, a remote rural municipality in Northern Finland, filled only four physician positions in the same year (FMA 2021).

25. Incomplete take-up (and adoption of e-prescribing in other sectors than in public primary care) may cause some imprecision to the estimates.

26. Our classification of urban regions includes both urban and semi-urban municipalities because the main effects of e-prescribing are very similar in these two municipality groups, as shown in Online Appendix Figure A5.

27. The effect is also large (-23 percent) when compared to the mean for rural regions in the pre-adoption period 2007–9 (0.08 in Table 1), but note that some municipalities adopted e-prescribing much later (2012–2013) (Figure 1).

28. For example, urban patients might be more highly educated and be better aware of the potential dangers of interactions than rural patients. As we do not observe patients' education or other socioeconomic background characteristics in the data, we do not investigate this issue further.

29. Mortality among warfarin patients is approximately 10 percent in both urban and rural regions (Section V). If patients who have a higher probability of suffering from harmful drug interactions during the pre-adoption period are also more likely to die, attrition due to mortality would bias downwards the estimated impact of e-prescribing on the interaction probability. The specification in Column 2 of Table 2 (with patient fixed effects) is an alternative approach to address this potential concern.

30. See Online Appendix Figure A13 for the density of interaction days.

31. Compared to internists, unspecialized physicians are more likely to work in primary care, instead of hospitals.

32. A possible interpretation is that less educated physicians in rural regions are also subject to cognition cost, for example, due to their lower ability.

33. This occurs despite the fact that patients have better opportunities to switch health care units or physicians in urban than in rural regions because there are more of them in urban regions. In our data, a patient's care provision is, however, almost equally often divided between multiple physicians in the two municipality groups (Table 1).

34. For different physicians in rural regions, the long-run effect in Online Appendix Table A5 is also substantial (-17 percent) when compared to the mean in the pre-adoption period (0.054 in Table 1).

35. Our data do not permit direct analyses of physicians' information flows within versus between primary care units and hospitals.

36. Theoretically, e-prescribing could change the composition of the patient population through changes in the selection of patients into warfarin use. The small effect on the number of initial warfarin prescriptions is, however, expected, because warfarin is an essential, even life-saving, medication. Moreover, our main results were robust to limiting the data to the fixed set of patients who received a warfarin prescription before e-prescribing (Section VII.A).

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Table 1
Summary Statistics for Pre-Adoption Period 2007–9

	All municipalities		Urban		Rural	
	Mean	SD	Mean	SD	Mean	SD
Panel A. Quality of prescribing						
Share of patients with an interaction	0.157		0.154		0.167	
Interaction probability						
Any warfarin-NSAID interaction	0.072	0.259	0.070	0.255	0.080	0.272
NSAID on top of warfarin	0.043	0.204	0.042	0.200	0.050	0.218
Warfarin on top of NSAID	0.029	0.167	0.028	0.166	0.031	0.172
Different prescribing physician	0.048	0.215	0.047	0.212	0.054	0.227
Same prescribing physician	0.024	0.152	0.023	0.150	0.026	0.159
Different pharmacy	0.017	0.129	0.018	0.133	0.013	0.112
Same pharmacy	0.055	0.229	0.052	0.222	0.068	0.251
Overlapping days, conditional on interaction	38.882	36.469	38.821	36.467	39.086	36.478
Panel B. Utilization						
Warfarin DDDs per patient	390.575	291.025	390.705	292.427	382.999	283.287
Warfarin Rx per patient	2.867	1.588	2.858	1.579	2.853	1.623
NSAID DDDs per patient	52.921	150.112	51.092	145.929	59.056	163.520
NSAID Rx per patient	1.021	2.028	0.994	1.966	1.105	2.229
Panel C. Physician variables						
Share of prescriptions by specialty						
Unspecialized	0.477		0.458		0.548	
General medicine	0.207		0.205		0.214	
Internal medicine	0.054		0.059		0.037	
Panel D. Other patient variables						
Different prescribing physician	0.518	0.500	0.515	0.500	0.531	0.499
Age (on the date of prescribing)	71.014	13.188	70.666	13.421	72.327	12.177
Share of patients who die	0.104		0.101		0.114	
Share of patients hospitalized for gastrointestinal hemorrhage	0.068		0.067		0.071	
	N		N		N	
Observations (prescriptions)	484,247		382,823		101,424	
Patients	124,539		99,380		25,623	
Physicians	17,184		16,390		6,357	
Municipalities	304		121		183	

Notes: This table reports summary statistics for warfarin patients in the pre-adoption period 2007–9. The variables are calculated from the prescription-level data, including both warfarin and NSAID prescriptions for these patients. The only exception is "Share of patients hospitalized for gastrointestinal hemorrhage" in Panel D, which is from the discharge data. In Panel A, "Probability of any warfarin-NSAID interaction" depicts the probability of this interaction (drug combination), resulting from NSAIDs (warfarin) prescribed on top of existing warfarin (NSAID) prescriptions. "Share of patients with an interaction" shows the share of patients with a warfarin-NSAID interaction.

Table 2

Effects of E-Prescribing on Warfarin-NSAID Interaction Probability

	Baseline (1)	Patient FE (2)	Hosp. distr. trend (3)	ATC trend (4)	No private visits (5)	All NSAID patients (6)	No dying patients (7)
Panel A. All municipalities							
Short-run	−0.002	−0.002**	−0.003*	−0.002	−0.002	−0.000	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Long-run	−0.003	−0.004*	−0.001	−0.002	−0.003	−0.000	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.002)
Mean outcome	0.045	0.045	0.045	0.045	0.044	0.010	0.046
Observations	1,689,506	1,689,506	1,689,506	1,689,506	1,624,852	7,752,317	1,243,189
Panel B. Urban municipalities							
Short-run	0.000	−0.001	−0.001	0.000	0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
Long-run	0.000	−0.001	0.000	0.000	0.000	0.000	−0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.002)
Mean outcome	0.044	0.044	0.044	0.044	0.043	0.009	0.045
Observations	1,347,198	1,347,198	1,347,198	1,347,198	1,289,846	6,548,763	1,000,947
Panel C. Rural municipalities							
Short-run	−0.011***	−0.009***	−0.013**	−0.010***	−0.011***	−0.003***	−0.010***
	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)	(0.001)	(0.003)
Long-run	−0.018***	−0.014***	−0.023***	−0.016***	−0.017***	−0.004***	−0.015***
	(0.004)	(0.004)	(0.009)	(0.003)	(0.004)	(0.001)	(0.004)
Mean outcome	0.050	0.050	0.050	0.050	0.049	0.014	0.049
Observations	342,308	342,308	342,308	342,308	335,006	1,203,554	242,242

Notes: This table reports the coefficients from the difference-in-differences regressions using the prescription-level data. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. "Short-run" refers to the first year after adoption, and "Long-run" refers to all subsequent periods. Each panel-column combination is estimated from a separate regression. All specifications include municipality fixed effects, time fixed effects, and age and age squared, except that Column 2 replaces municipality fixed effects with patient fixed effects, Column 3 adds hospital district-specific time trends, and Column 4 adds ATC code-specific time trends. Column 5 eliminates all prescriptions with a private physician visit from the regressions. Column 6 uses data on prescriptions for all patients who have at least one NSAID prescription, but not necessarily a warfarin prescription, as opposed to using the baseline sample that limits the data to prescriptions for patients who have at least one warfarin prescription over the period 2007–14 (other columns). Column 7 excludes all prescriptions for patients who die during the observation period of the data. The standard errors are clustered at the municipality level.

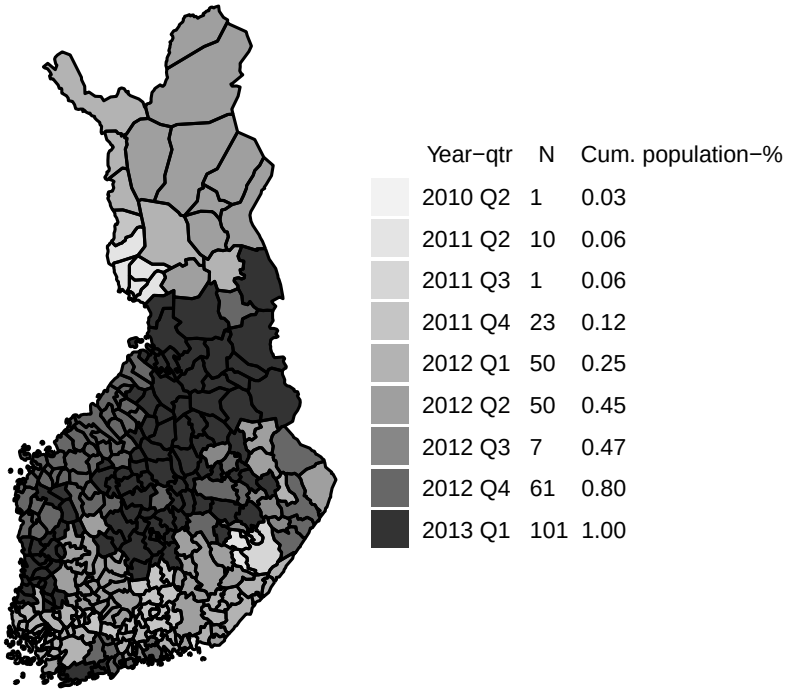

Figure 1
Staggered Adoption of E-prescribing in Municipalities

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

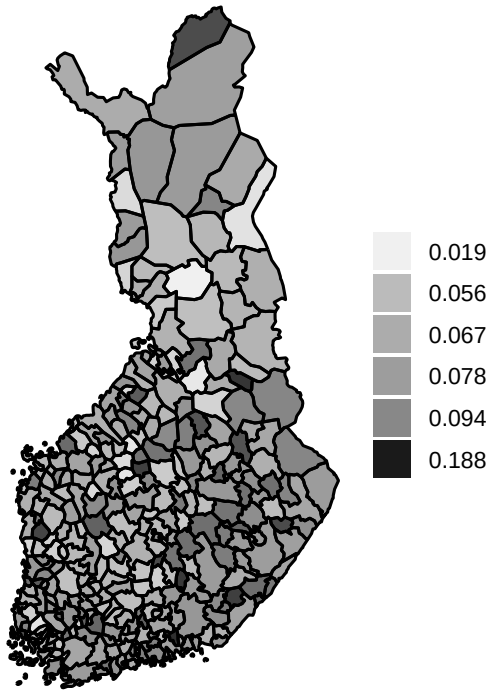

Figure 2
Average Interaction Probability in Municipalities

Notes: This figure plots the regional variation in the average probability of co-prescribing interacting drugs (NSAIDs) for warfarin patients by their municipality of residence in the pre-adoption period 2007–9 ($N = 191,614$ patients).

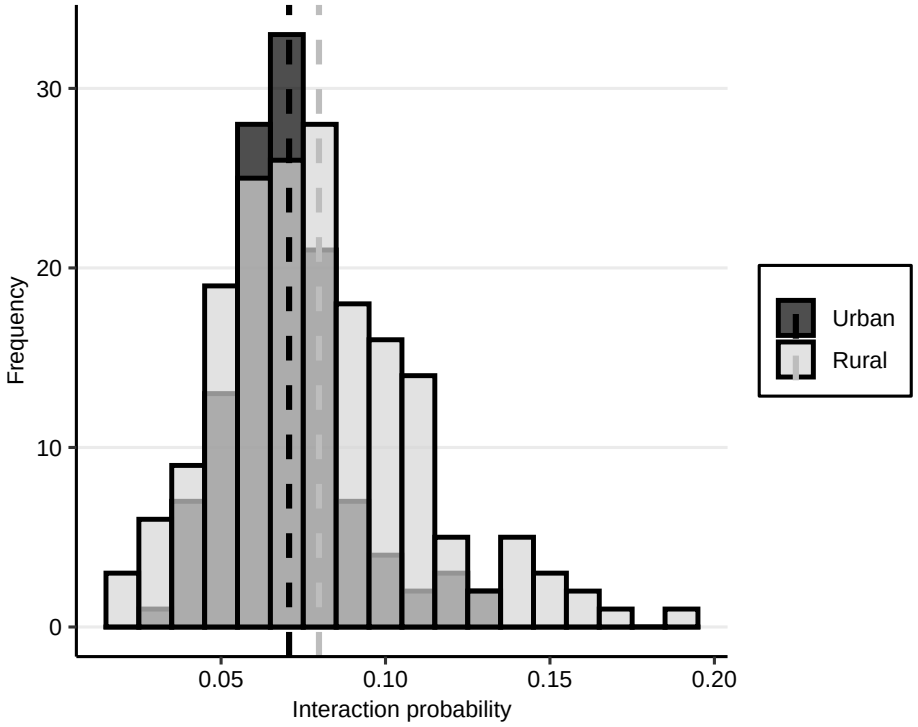

Figure 3

Average Interaction Probability in Urban and Rural Municipalities

Notes: The histogram in this figure plots the regional variation in the average probability of co-prescribing interacting drugs (NSAIDs) for warfarin patients by their municipality of residence and municipality group (rural or urban) in the pre-adoption period 2007–9. The mean values for urban and rural regions are marked with dashed vertical lines. For more information on the municipality groups according to the official classification by Statistics Finland, see the notes in Online Appendix Figure A3.

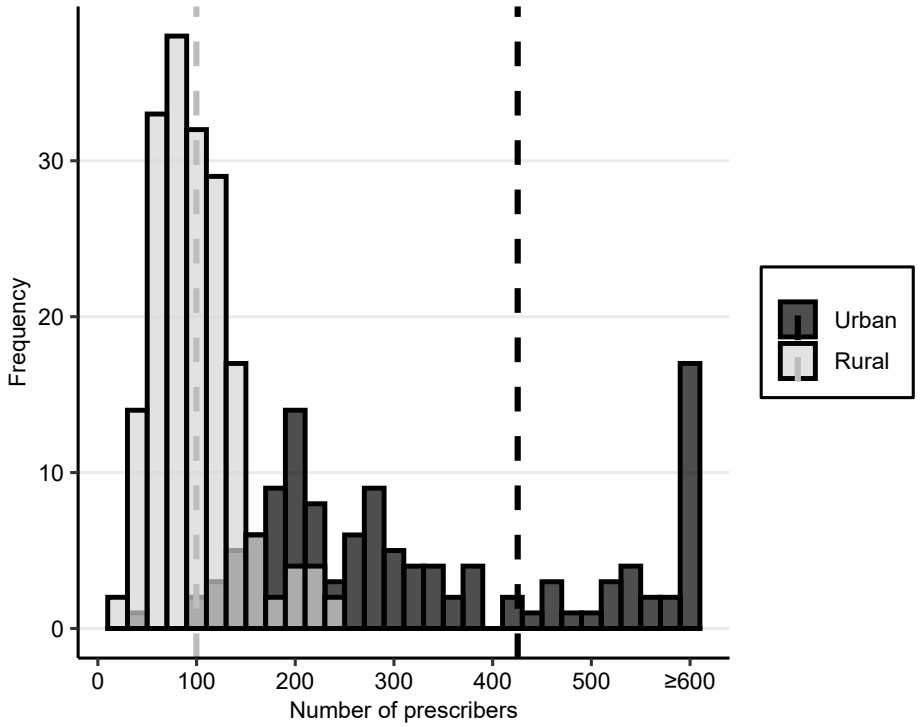

Figure 4

Number of Prescribing Physicians in Urban and Rural Municipalities

Notes: This histogram plots the number of distinct prescribers of warfarin and NSAID prescriptions by patients' municipality of residence and municipality group (rural or urban) in the pre-adoption period 2007–9. The mean values for urban and rural regions are marked with dashed vertical lines. For more information on the municipality groups based on the official classification by Statistics Finland, see the notes in Online Appendix Figure A3.

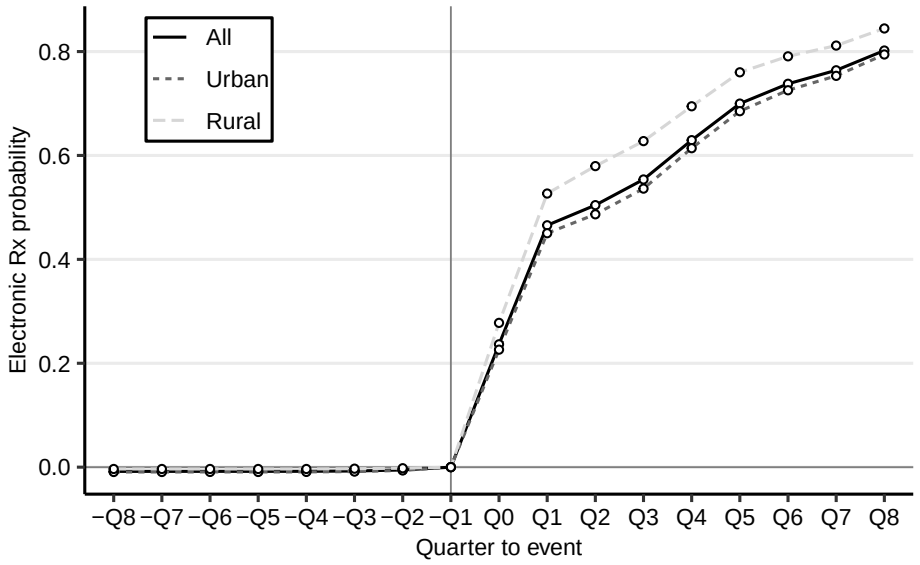

Figure 5

Take-up Rate of E-prescriptions, by Municipality Group

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data for warfarin patients. The outcome is a dummy variable that equals one if the prescription (warfarin or NSAID) is an e-prescription. Each line is plotted from a separate regression.

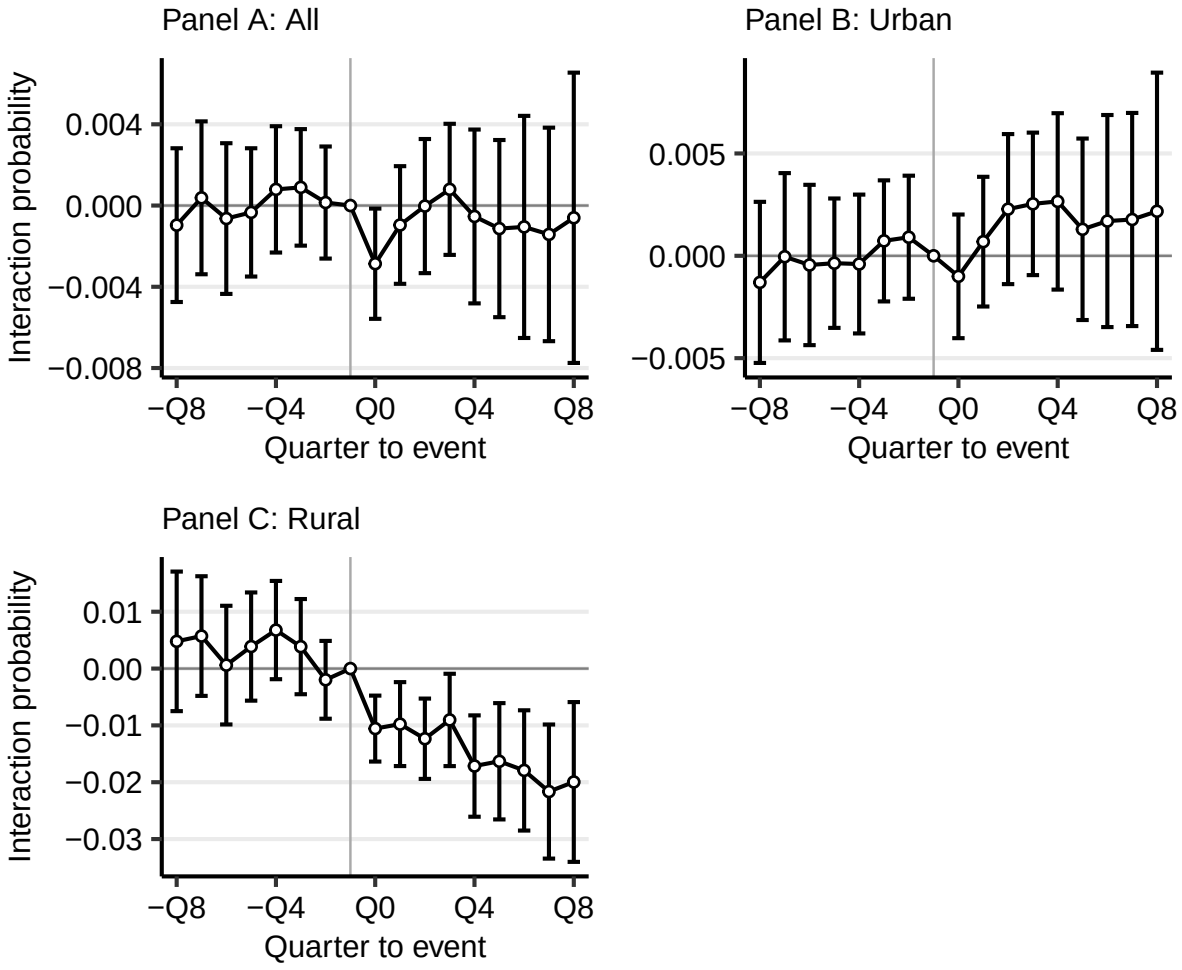

Figure 6
Probability of Warfarin-NSAID Interaction, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, patient age and age squared. Panel A plots the results for the whole sample of municipalities, Panel B plots for urban and semi-urban municipalities, and Panel C plots for rural municipalities, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

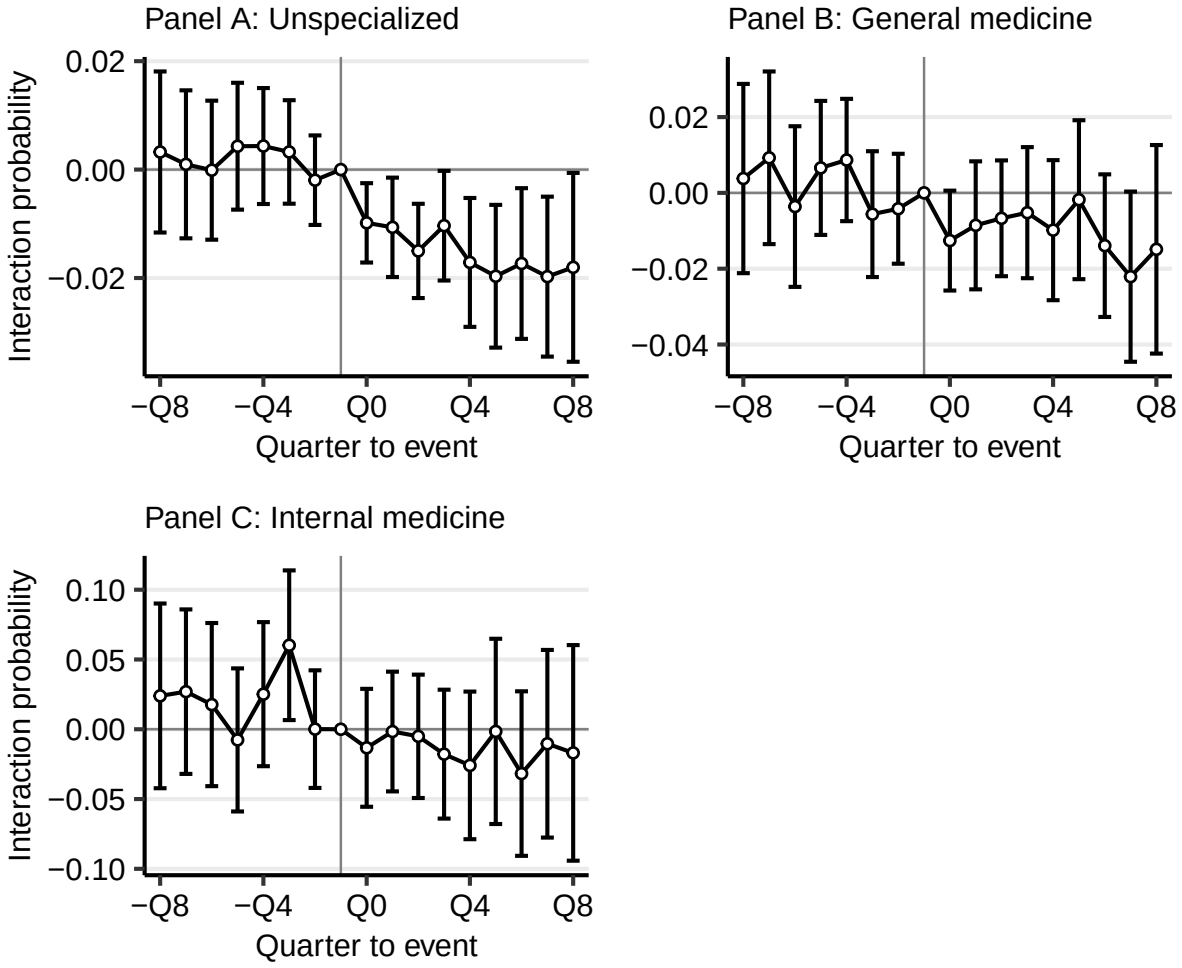

Figure 7

Probability of Warfarin-NSAID Interaction in Rural Municipalities, by Physician Speciality

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in rural municipalities. Panels A, B, and C plot the results for prescriptions written by unspecialized physicians, and physicians specialized in general medicine and internal medicine, respectively. See Figure 6 for more information on the specification of the model.

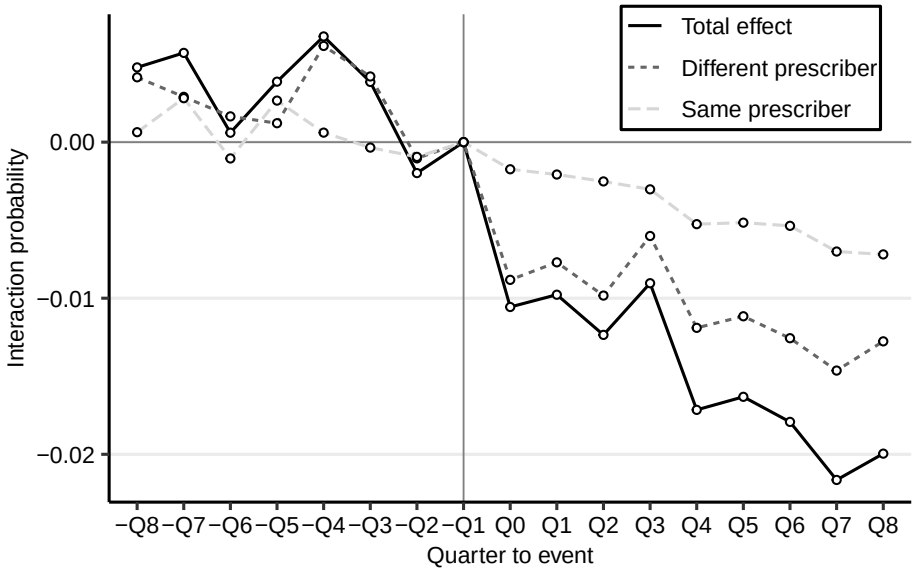

Figure 8

Probability of Warfarin-NSAID Interaction in Rural Municipalities, Different Versus Same Prescribing Physician

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in rural municipalities. The outcome labeled "Total effect" is the baseline outcome and is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The outcome labeled "Different physician" adds an additional condition to the baseline outcome that the interacting prescriptions are written by different physicians. The outcome labeled "Same physician" adds an extra condition to the baseline outcome that the interacting prescriptions are written by the same physician. See Figure 6 for more information on the specification of the model.

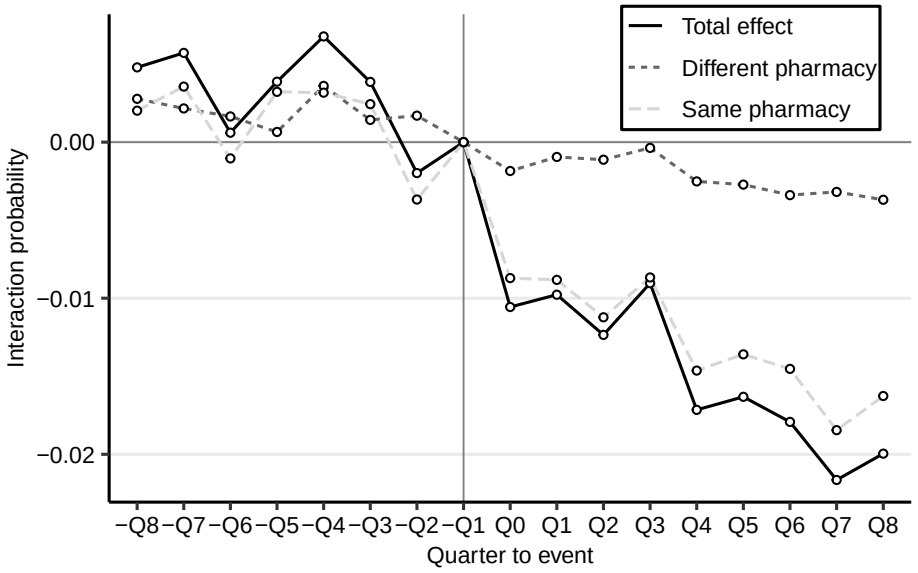

Figure 9

Probability of Warfarin-NSAID Interaction in Rural Municipalities, Different Versus Same Pharmacy

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in rural municipalities. The outcome labeled "Total effect" is the baseline outcome and is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The outcome labeled "Different pharmacy" adds an additional condition to the baseline outcome that the interacting prescriptions are fully filled at different pharmacies. The outcome labeled "Same pharmacy" adds an extra condition to the baseline outcome that the interacting prescriptions are (at least partly) filled at the same pharmacy. See Figure 6 for more information on the specification of the model.

Online Appendix for the paper "Information Integration, Coordination Failures, and Quality of Prescribing"

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

I. ATC and ICD-10 Codes

Warfarin and NSAID ATC codes used in the data.

- Warfarin: B01AA03
- NSAID: M01AB01, M01AB02, M01AB05, M01AB08, M01AB51, M01AB55, M01AC01, M01AC02, M01AC06, M01AE01, M01AE02, M01AE03, M01AE11, M01AE52, M01AG01, M01AG02, M01AH01, M01AH05, M01AX01

ICD-10 codes used for gastrointestinal hemorrhage diagnosis in the data.

- K920, K921, K922, I850, K221, K250, K252, K254, K256, K260, K262, K264, K266, K270, K272, K274, K276, K280, K282, K284, K286, K290, K625

II. Reform Exogeneity

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

To further test the exogeneity assumption, we follow Bhuller, Mogstad, and Salvanes (2017) and estimate the following model:

$$T_{mt} = (\Gamma_t \times X_{m,2009})'\Psi + \gamma_t + \nu_{mt}, \tag{4}$$

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 to one if municipality m adopted e-prescribing in 6-month period t. For simplicity, we standardize the municipality-level covariates by dividing them by the corresponding standard deviations. Figure A1 plots the coefficients and the 95 percent confidence intervals from Ψ. As expected, the coefficients do not reveal any systematic correlation between the timing of the adoption and the covariates, further supporting the conclusion that technology adoption is not systematically related to differences in municipality characteristics.

Table A1

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

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

Notes: Each column shows parameter estimates from a separate regression using municipality-level data. The 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 adoption of e-prescribing by the municipality relative to the earliest adoption time, calculated in days. The reference category for semi-urban and rural municipality indicators is urban municipalities. The variables are from the National Institute of Health and Welfare and from Statistics Finland. In each year, we exclude a few municipalities with missing observations in the covariates. Standard errors are clustered at the municipality level.

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

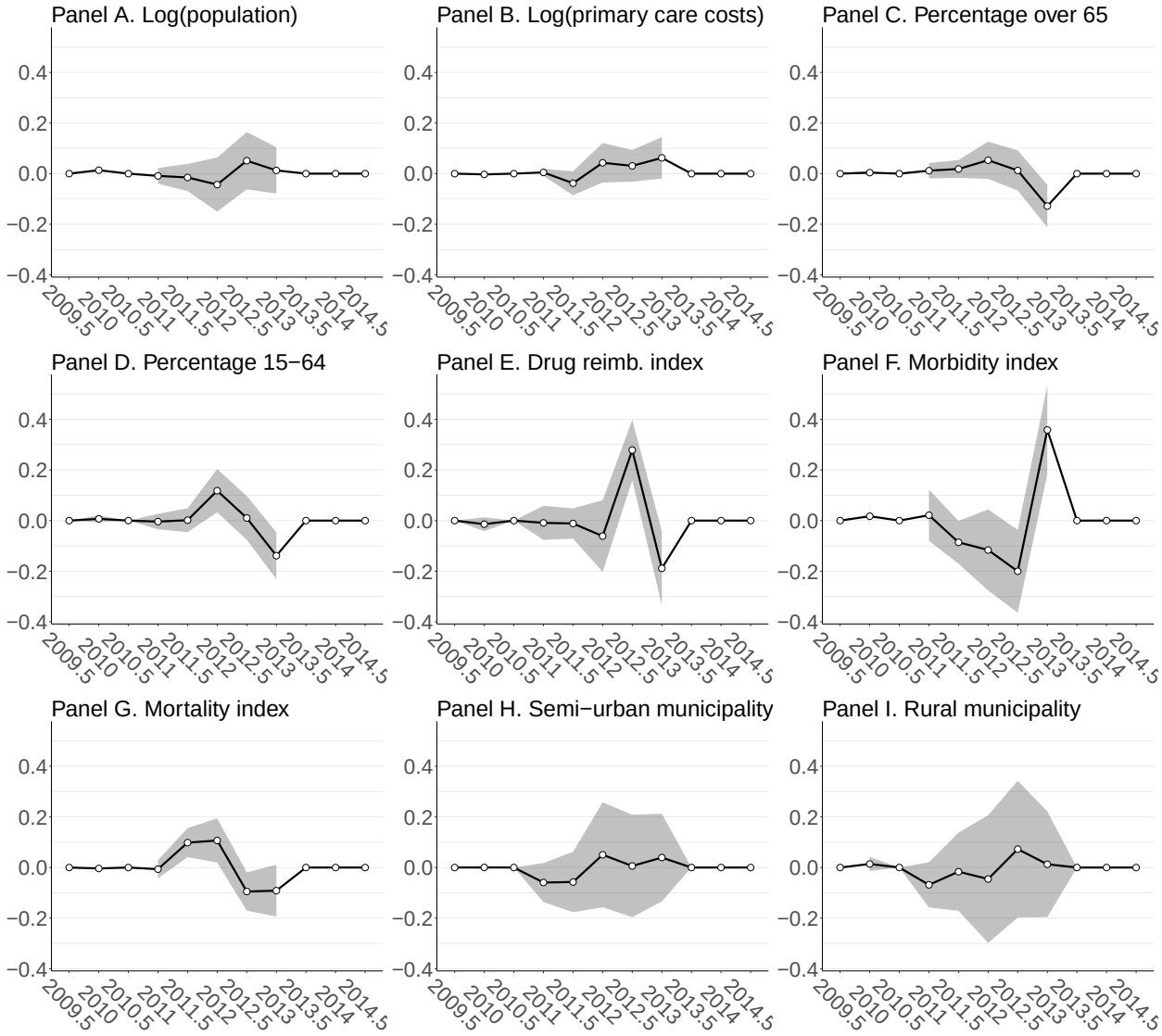

Figure A1

Adoption of E-Prescribing by Baseline Municipality Characteristics

Notes: Each panel plots coefficient estimates from a separate regression for interaction terms between a specific municipality covariate for 2009 and biannual dummies for the time of adoption of e-prescribing by the municipality. The regressions are estimated using municipality-level data. The outcome is a dummy variable that equals one when the municipality adopted e-prescribing during the particular 6-month period. The coefficient estimates are standardized by dividing the covariates by their corresponding standard deviations. See Table A1 notes for data sources and equation 4 for details of the specifications.

III. Figures

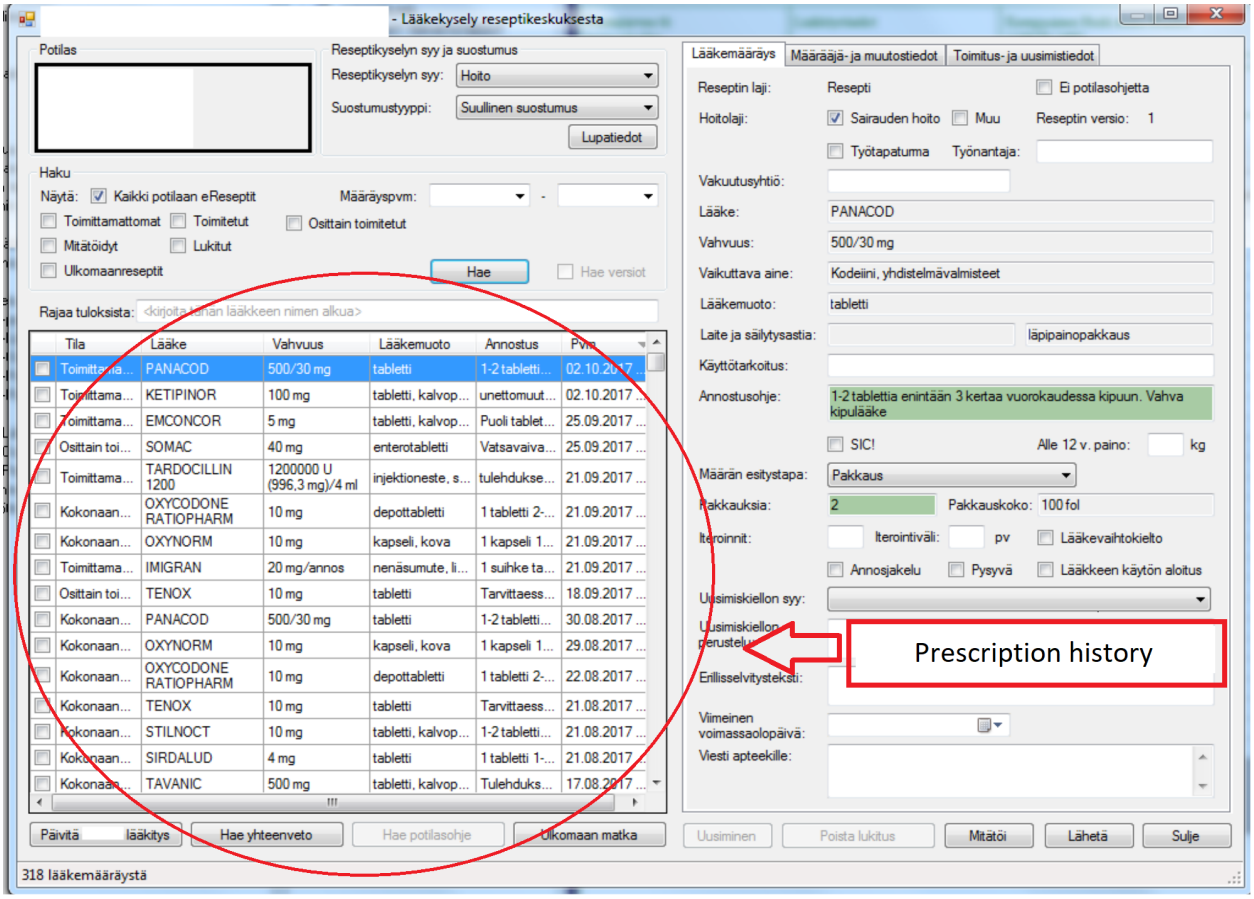

Figure A2

E-Prescribing Technology and Information Integration: Physician's View

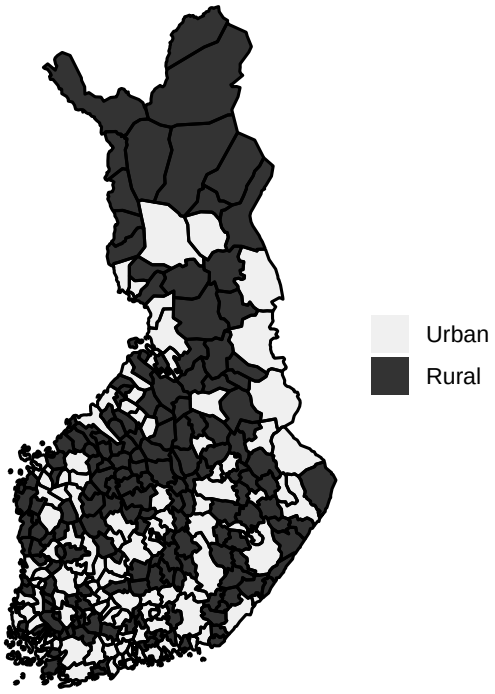

Figure A3
Regional Classification

Notes: This figure plots municipality groups (rural or semi-urban/urban), according to the official classification of Statistics Finland (2020). Statistics Finland defines rural municipalities as those in which less than 60 percent of the population live in urban settlements and in which the population of the largest urban settlement is less than 15,000 individuals; and those in which at least 60 percent but less than 90 percent of the population live in urban settlements and in which the population of the largest settlement is less than 4,000 individuals. Semi-urban municipalities are municipalities in which at least 60 percent but less than 90 percent of the population live in urban settlements and in which the population of the largest urban settlement is at least 4,000 but less than 15,000. Urban municipalities include those municipalities in which at least 90 percent of the population live in urban settlements or in which the population of the largest urban settlement is at least 15,000. In the analysis, we group together urban and semi-urban municipalities (and call them urban municipalities for brevity) because there is no apparent heterogeneity in the main effects of e-prescribing between these two groups (Section VII.A).

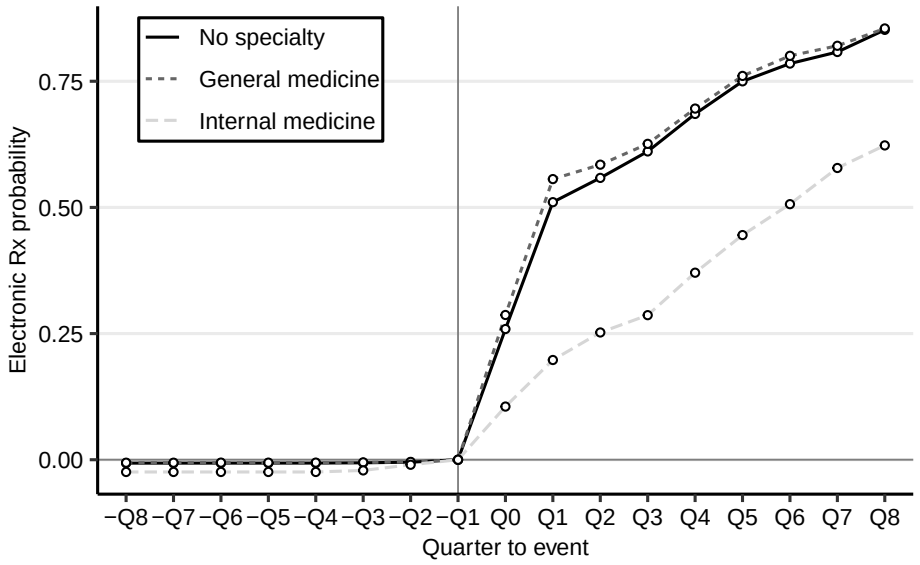

Figure A4

Take-up Rate of E-prescriptions, by Physician Speciality

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. Each line is plotted from a separate regression using data on the corresponding physician specializations. The outcome is a dummy variable that equals one if the prescription is an e-prescription.

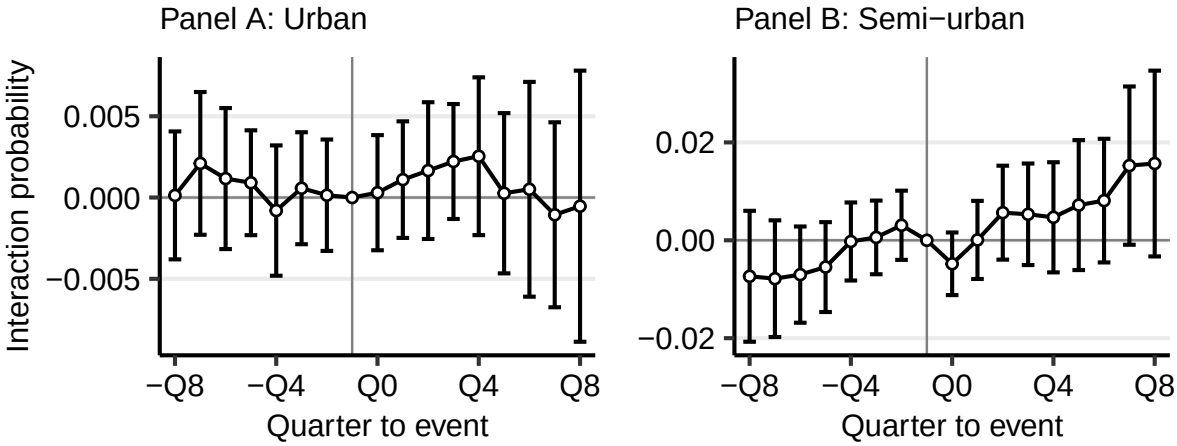

Figure A5

Probability of Warfarin-NSAID Interaction in Urban and Semi-Urban Municipalities

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. Panel A plots the results for the urban municipalities, and Panel B plots for semi-urban municipalities, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

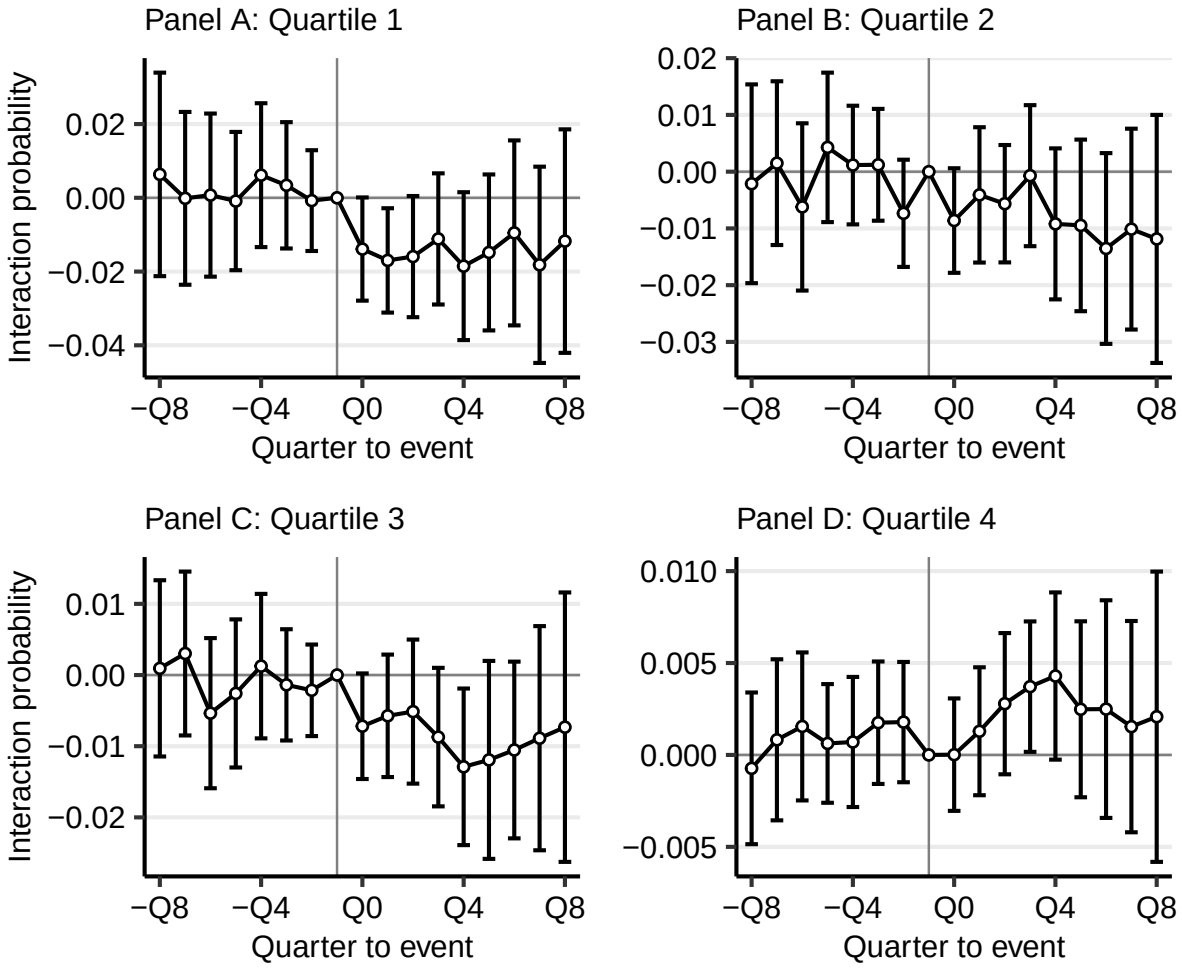

Figure A6

Probability of Warfarin-NSAID Interaction, by Number of Physicians in the Municipality

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. In the separate panels, municipalities are divided into ordered equal-sized ordered groups by the quartiles of the number of physicians in the municipalities in the pre-adoption period 2007–9. Panel A plots the results for municipalities in the first quartile and panel D for municipalities in the quartile. The standard errors are clustered at the municipality level.

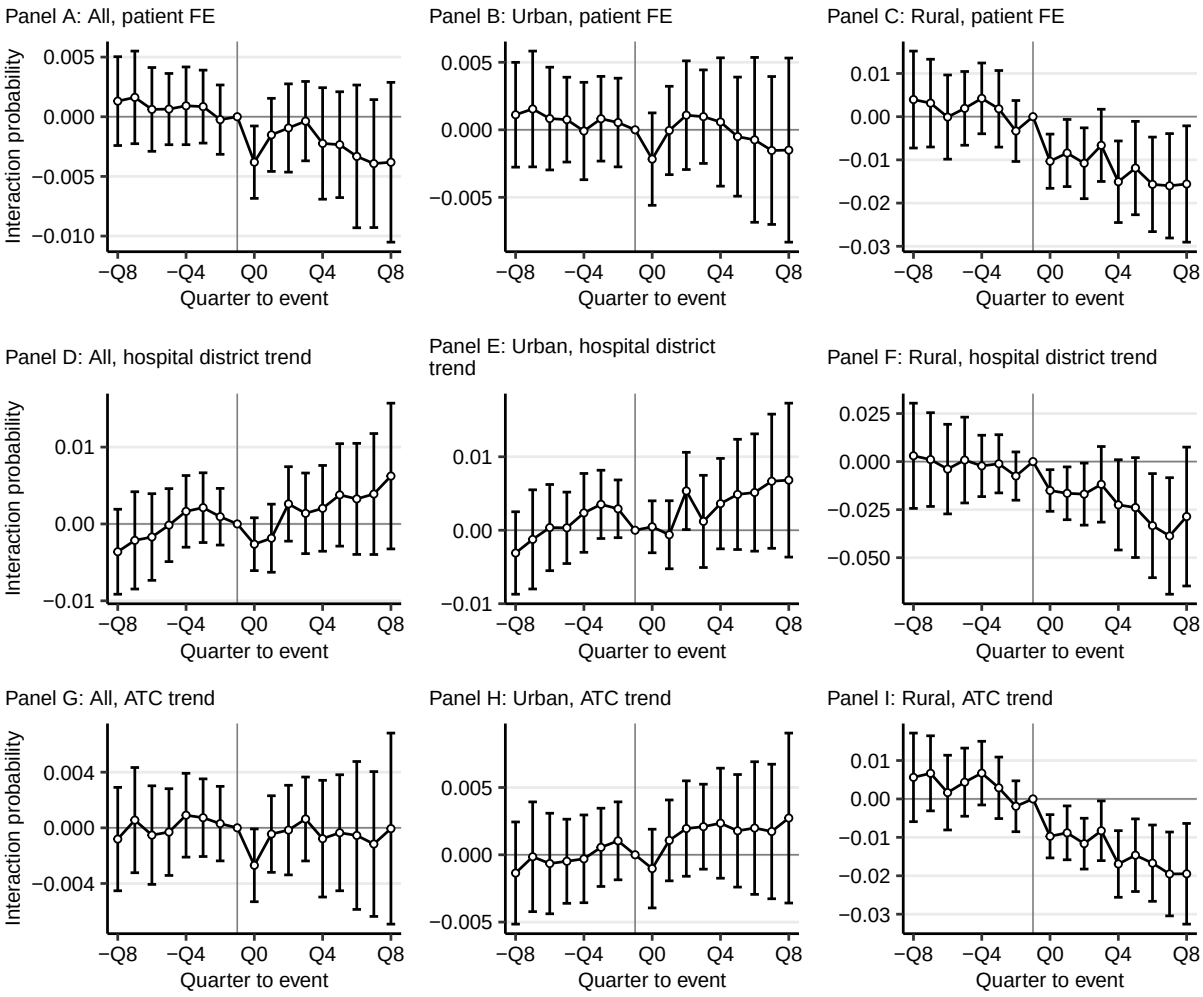

Figure A7

Probability of Interaction, Additional Robustness Checks to Baseline Results Part 1

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. Panels A, B, and C replace municipality fixed effects with patient fixed effects. Panels E, F, and G add interactions of hospital district and time fixed effects to the regressions. Panels G, H, and I plot the interaction probability with additional ATC code-specific linear time-trends added to the regressions. The first, second and third column of the panels plot the results using data on all municipalities, urban and semi-urban municipalities, and rural municipalities, respectively, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

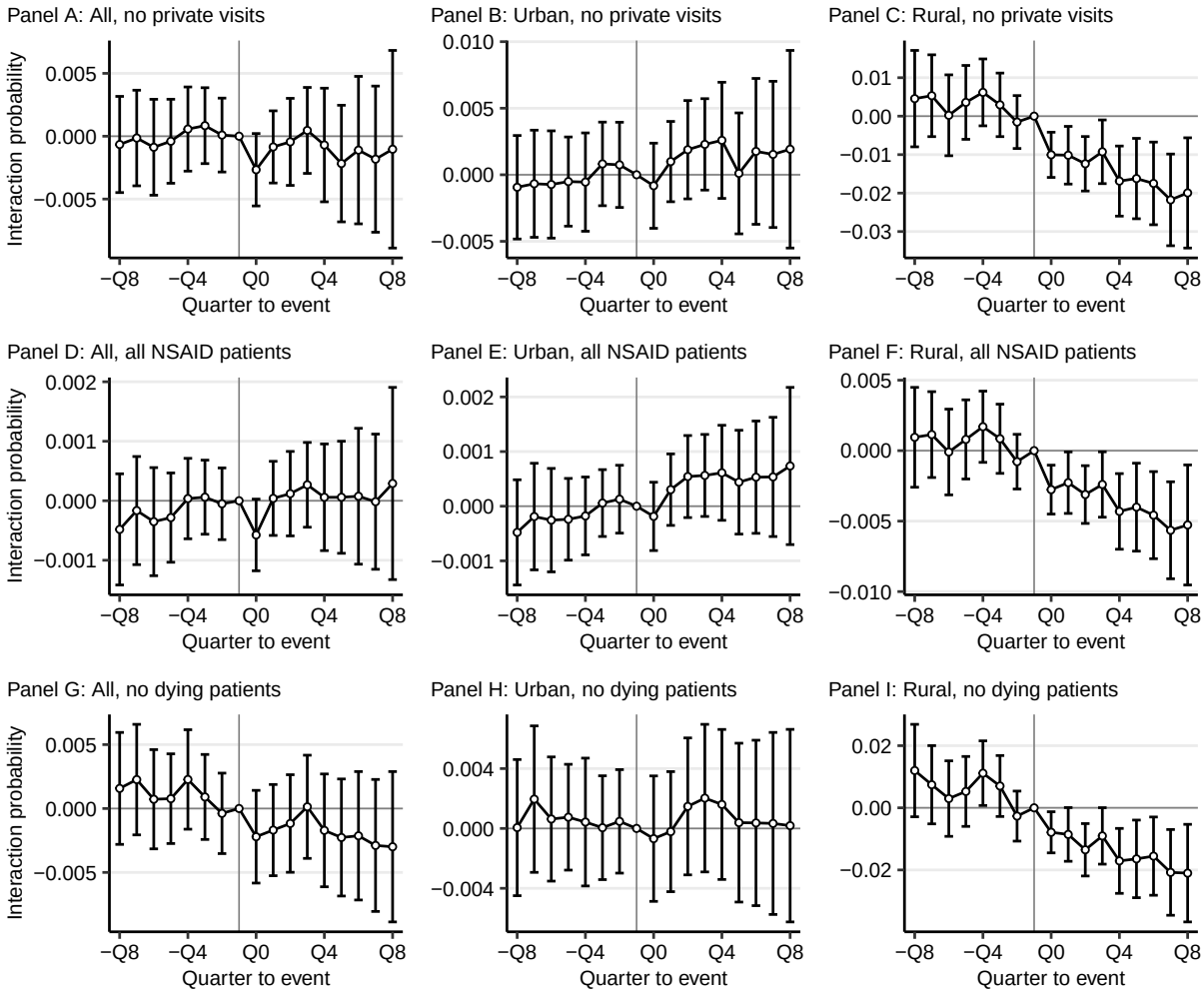

Figure A8

Probability of Interaction, Additional Robustness Checks to Baseline Results Part 2

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time trend fixed effects, age and age squared. Panels A, B, and C exclude all observations where the visit was to a private physician. Panels D, E, and F include all patients who have an NSAID prescription and who may not have a warfarin prescription during the periods in the data. Panels G, H, and I exclude all patients who died during the periods in the data. The first, second and third column of the panels plot the results using data on all municipalities, urban and semi-urban municipalities, and rural municipalities, respectively, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

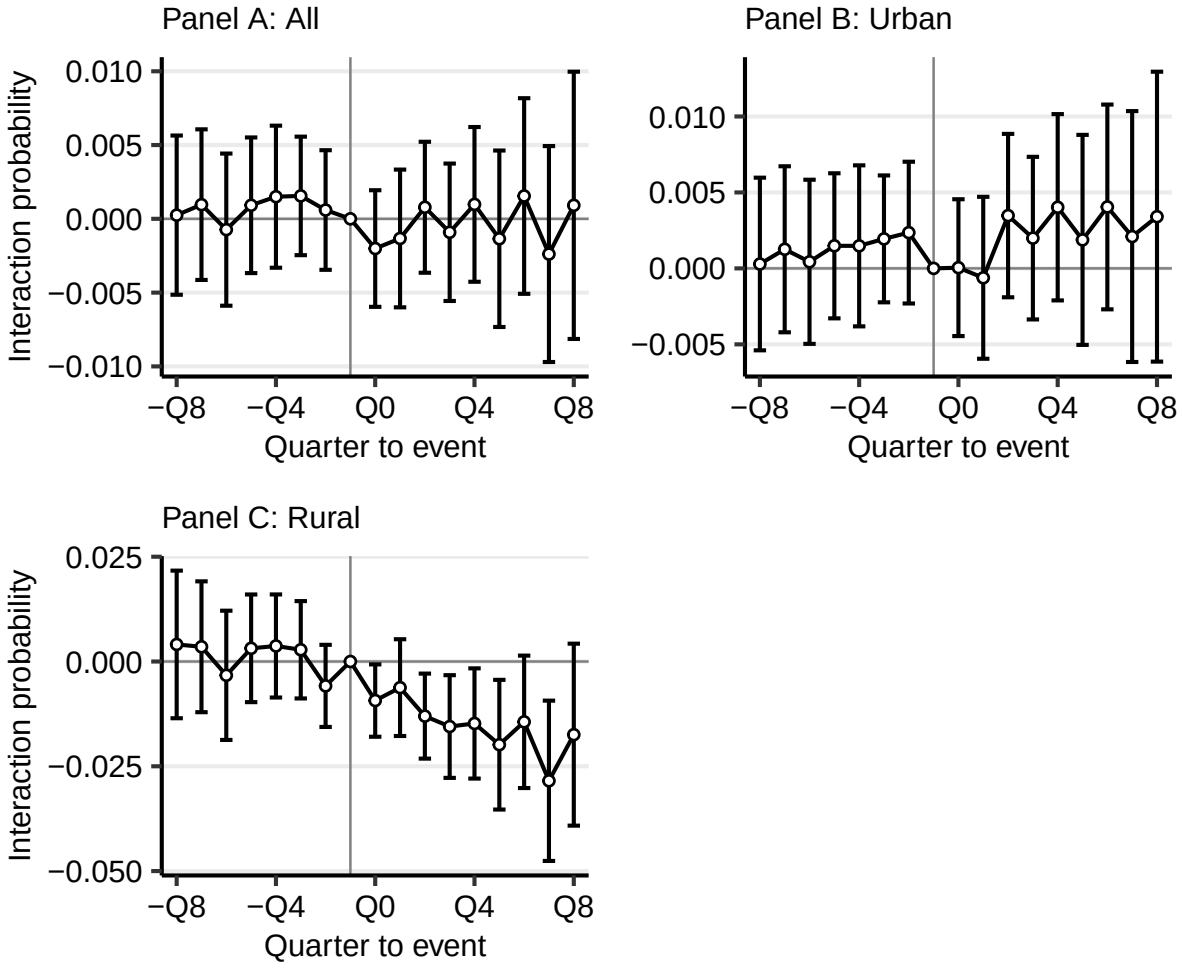

Figure A9

Probability of Interaction, Patients with Warfarin Prescription Before the Reform

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. The sample is limited to those patients who had a warfarin prescription before the first adoption of e-prescribing (April 2010). The first, second and third panel plot the results using data on all municipalities, urban and semi-urban municipalities, and rural municipalities, respectively, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

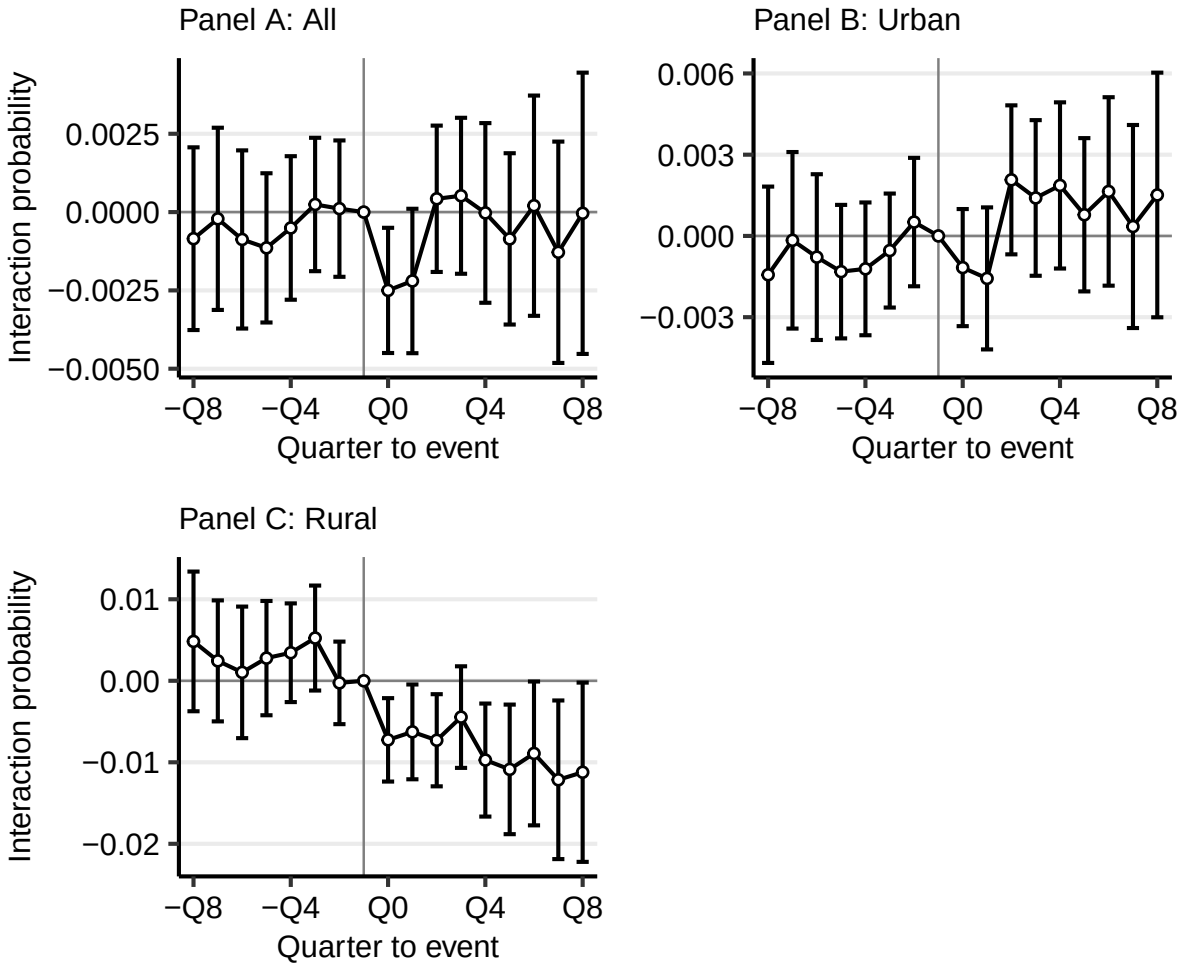

Figure A10

Probability of One-Way Warfarin-NSAID Interaction, By Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if an NSAID prescription interacts with another warfarin prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. Panel A plots the results for the whole sample of municipalities, Panel B plots for urban and semi-urban municipalities, and Panel C plots for rural municipalities, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

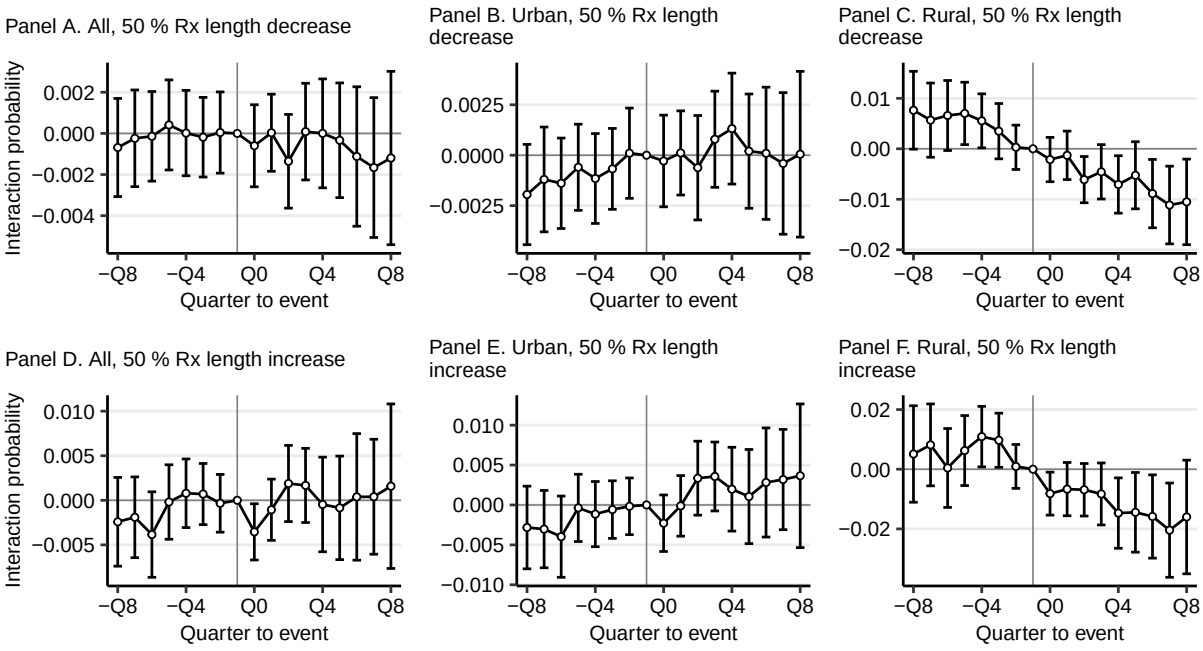

Figure A11

Sensitivity Test: Probability of Interaction, 50 Percent Reduction and Increase in Prescription Length

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients where the amount of defined daily doses in prescriptions has decreased by 50 percent. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. Panel A plots the results for the whole sample of municipalities, panel B plots for urban and semi-urban municipalities, and panel C plots for rural municipalities, according to the classification by Statistics Finland. The standard errors are clustered at the municipality level.

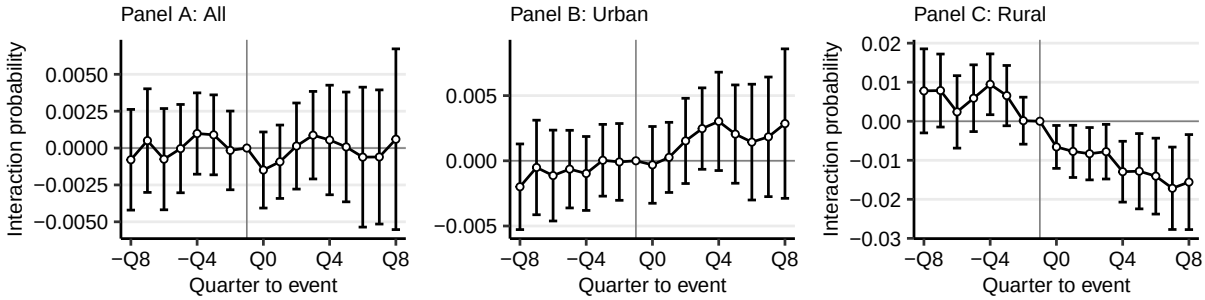

Figure A12

Sensitivity Test: Probability of Interaction, Interactions Under 10 Days and Over 100 Days Excluded

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients where prescriptions that interact for less than 10 days are dropped in Panels A, B, and C, and prescriptions that interact for over 100 days are dropped in Panels D, E, and F. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. The urban/semi-urban and rural classification is from Statistics Finland. The standard errors are clustered at the municipality level.

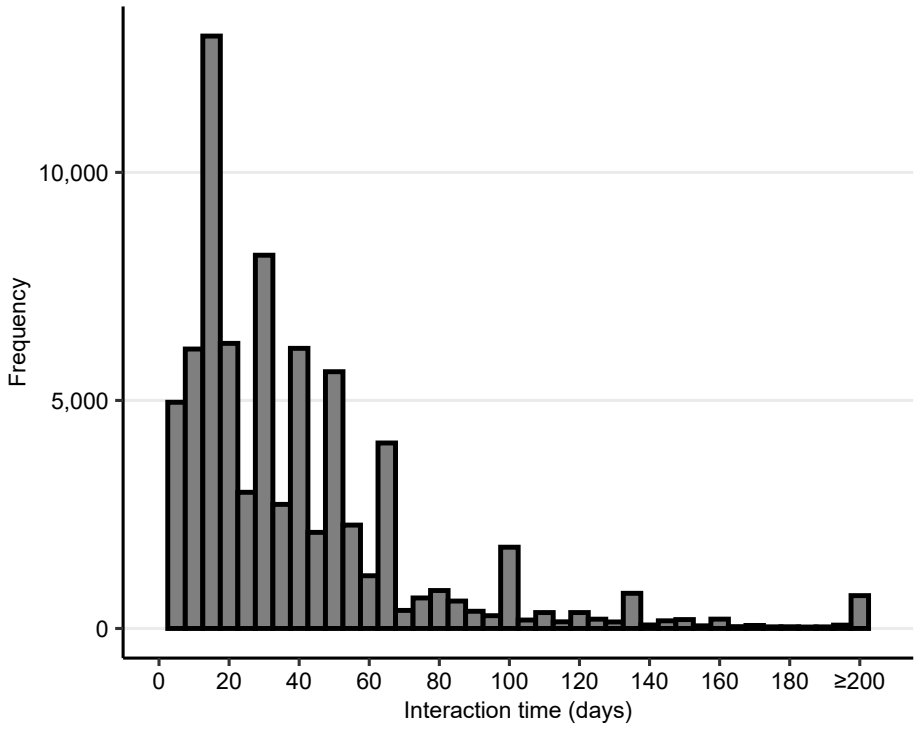

Figure A13
Duration of Warfarin-NSAID Interactions

Notes: The plot shows the conditional distribution of the duration of each overlapping warfarin and NSAID prescription, calculated in days. The length of warfarin and NSAID prescriptions is calculated using the number of defined daily doses of each prescription, where one day is assumed to equal one unit of daily dose. Bin width equals 5.

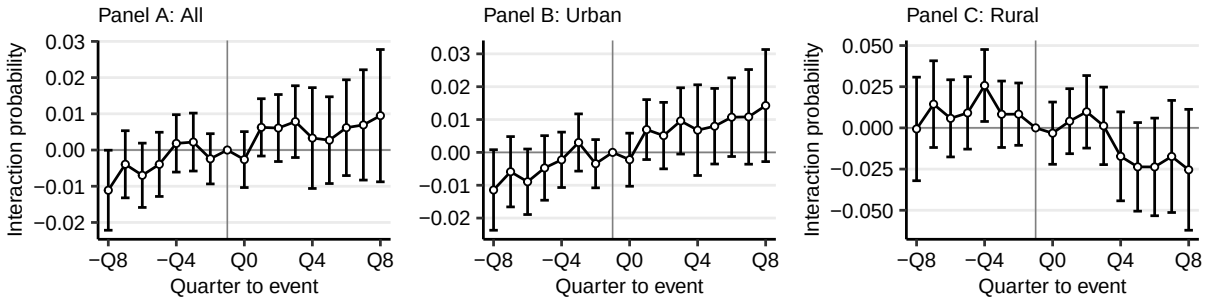

Figure A14

Probability of Warfarin-NSAID Interaction With Average Prescribing Intervals, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. Instead of defined daily doses, the prescription length is proxied by the patient and prescription type (warfarin or NSAID)-specific average prescribing intervals. Patients that do not have at least two warfarin or NSAID prescriptions are dropped. The maximum prescription length is capped at 180 days. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The omitted period is $-Q1$ and thus the coefficient estimates are relative to this period. The controls include municipality fixed effects, time fixed effects, age and age squared. The urban/semi-urban and rural classification is from Statistics Finland. The standard errors are clustered at the municipality level.

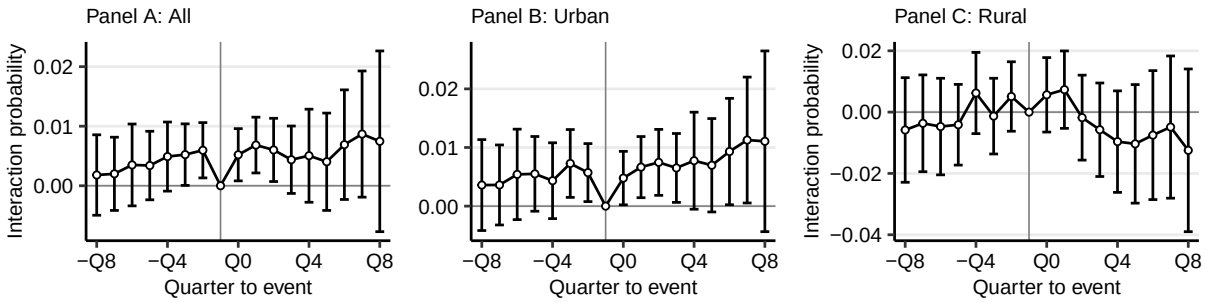

Figure A15

Placebo: Probability of Warfarin-Benzodiazepine Interaction, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (benzodiazepine) prescription interacts with a benzodiazepine (warfarin) prescription. See Figure 6 for more information on the specification of the model.

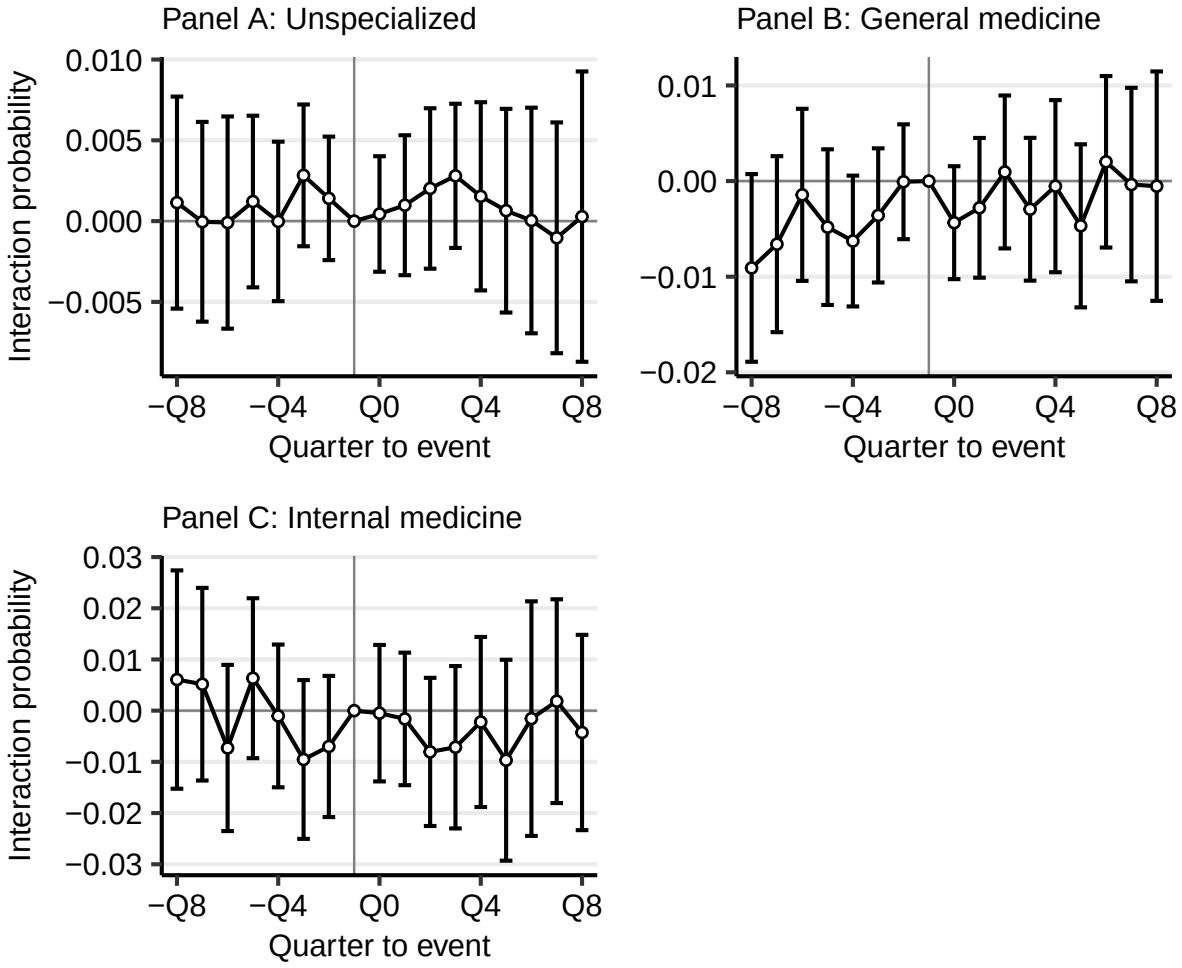

Figure A16

Probability of Warfarin-NSAID Interaction in Urban Municipalities, by Physician Speciality

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in urban municipalities. Panels A, B, and C plot the results for prescriptions written by unspecialized physicians, and physicians specialized in general medicine and internal medicine, respectively. See Figure 6 for more information on the specification of the model.

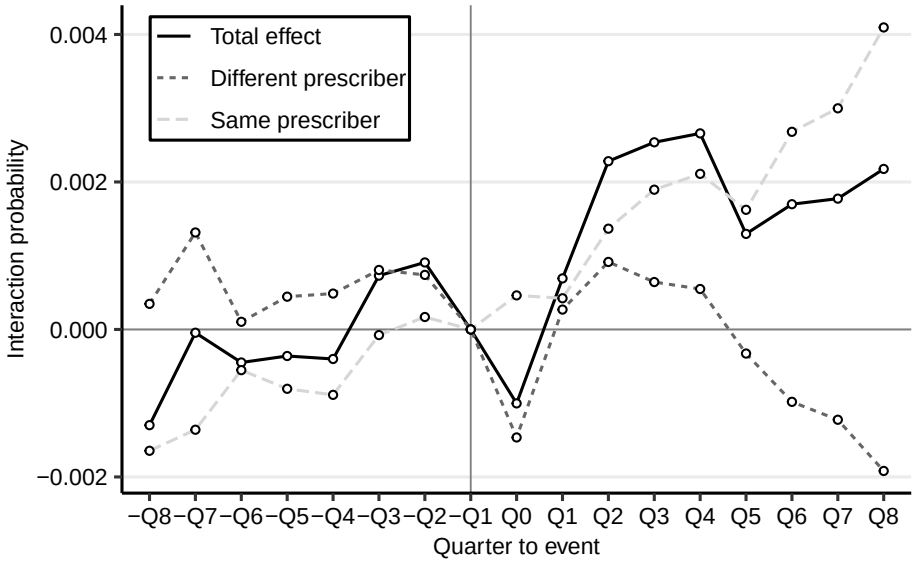

Figure A17

Probability of Warfarin-NSAID Interaction in Urban Municipalities, Different Versus Same Prescribing Physician

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in urban municipalities. The outcome labeled "Total effect" is the baseline outcome and is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The outcome labeled "Different physician" adds an additional condition to the baseline outcome that the interacting prescriptions are written by different physicians. The outcome labeled "Same physician" adds an extra condition to the baseline outcome that the interacting prescriptions are written by the same physician. See Figure 6 for more information on the specification of the model.

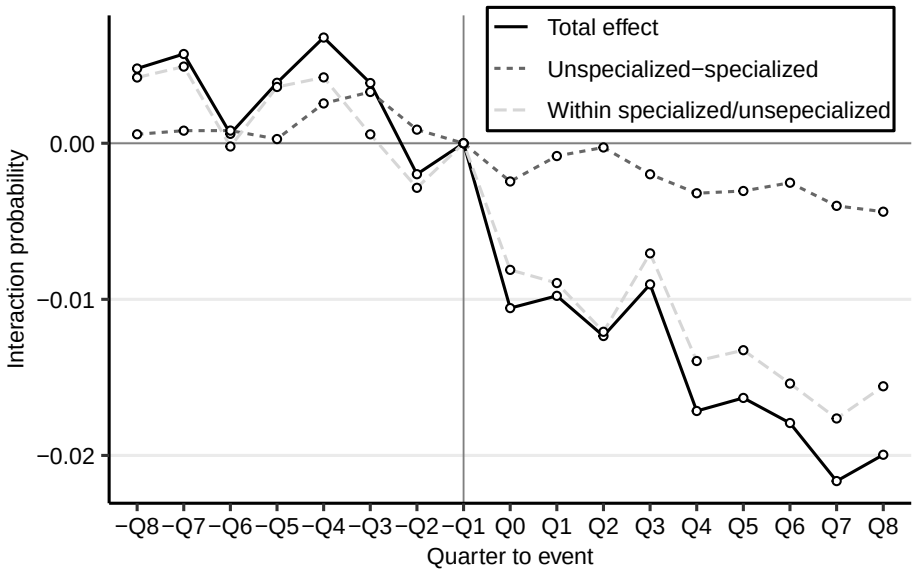

Figure A18

Probability of Warfarin-NSAID Interaction in Rural Municipalities, Within Versus Between Specializations

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in rural municipalities. The outcome labeled "Total effect" is the baseline outcome and is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The outcome labeled "Within specialized/unspecialized" adds an additional condition to the baseline outcome that the interacting prescriptions are written by physicians within specialized-specialized or unspecialized-unspecialized pairs. The outcome labeled "Unspecialized-specialized" adds an extra condition to the baseline outcome that the interacting prescriptions are written by unspecialized-specialized physician pairs. In this figure, unspecialized physicians also include general medicine physicians. See Figure 6 for more information on the specification of the model.

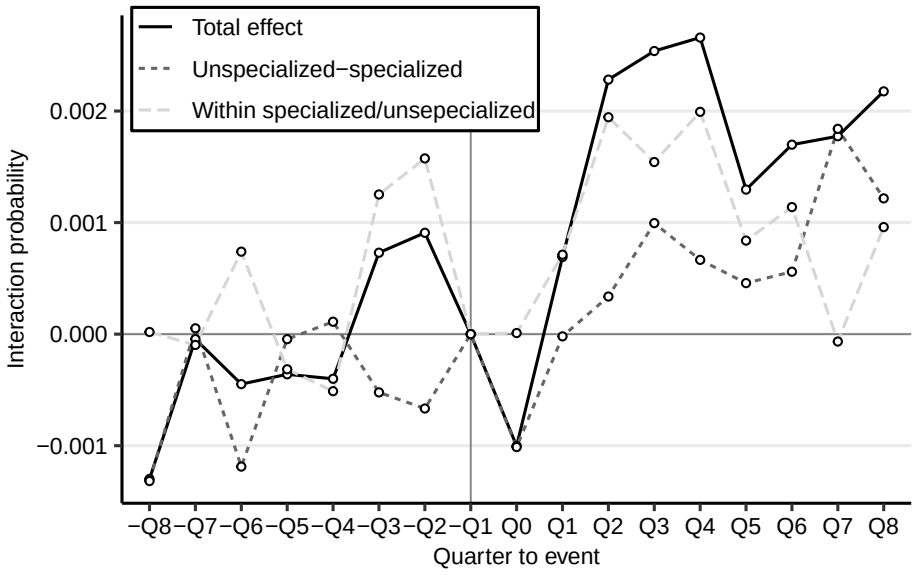

Figure A19

Probability of Warfarin-NSAID Interaction in Urban Municipalities, Within Versus Between Specializations

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in urban municipalities. The outcome labeled "Total effect" is the baseline outcome and is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The outcome labeled "Within specialized/unspecialized" adds an additional condition to the baseline outcome that the interacting prescriptions are written by physicians within specialized-specialized or unspecialized-unspecialized pairs. The outcome labeled "Unspecialized-specialized" adds an extra condition to the baseline outcome that the interacting prescriptions are written by unspecialized-specialized physician pairs. In this figure, unspecialized physicians also include general medicine physicians. See Figure 6 for more information on the specification of the model.

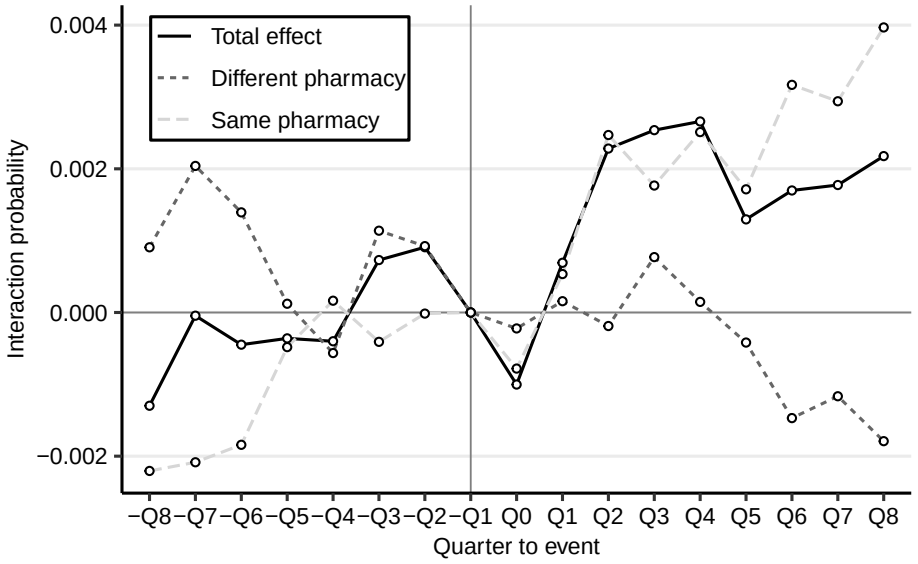

Figure A20

Probability of Warfarin-NSAID Interaction in Urban Municipalities, Different Versus Same Pharmacy

Notes: This figure plots the coefficient estimates from an event study framework using the prescription-level data on warfarin patients in urban municipalities. The outcome labeled "Total effect" is the baseline outcome and is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. The outcome labeled "Different pharmacy" adds an additional condition to the baseline outcome that the interacting prescriptions are fully filled at different pharmacies. The outcome labeled "Same pharmacy" adds an extra condition to the baseline outcome that the interacting prescriptions are (at least partly) filled at the same pharmacy. See Figure 6 for more information on the specification of the model.

IV. Tables

Table A2

Prescription Counts and Shares by Physician Speciality for Pre-Adoption Period 2007–9

	All municipalities		Urban		Rural	
	N	Share	N	Share	N	Share
Warfarin	357,114	0.74	284,006	0.74	73,108	0.72
Unspecialized	171,165	0.48	130,632	0.46	40,533	0.55
General medicine	76,014	0.21	60,237	0.21	15,777	0.22
Internal medicine	22,346	0.06	19,183	0.07	3,163	0.04
NSAID	127,133	0.26	98,817	0.26	28,316	0.28
Unspecialized	59,796	0.47	44,758	0.45	15,038	0.53
General medicine	24,272	0.19	18,361	0.19	5,911	0.21
Internal medicine	4,005	0.03	3,381	0.03	624	0.02
Interacting Rx	34,970	0.07	26,811	0.07	8,159	0.08
Unspecialized	16,178	0.46	11,987	0.45	4,191	0.51
General medicine	6,760	0.19	4,943	0.18	1,817	0.22
Internal medicine	1,999	0.06	1,691	0.06	308	0.04

Notes: The numbers are based on patients with at least one warfarin prescription in the period of 2007–9.

Table A3

Effects of E-prescribing on Warfarin-NSAID Interaction With Average Prescribing Intervals, by Municipality Group

	All municipalities (1)	Urban (2)	Rural (3)
Short-run	0.002	0.003	−0.006
	(0.004)	(0.004)	(0.008)
Long-run	−0.001	0.004	−0.031***
	(0.007)	(0.007)	(0.011)
Mean outcome	0.083	0.080	0.092
Observations	444,111	355,071	89,040

Notes: This table reports the coefficients from difference-in-differences regressions using the prescription-level data on warfarin patients. Instead of defined daily doses, the prescription length is proxied by the patient and prescription type (warfarin or NSAID)-specific average prescribing intervals. Patients who do not have at least two warfarin or NSAID prescriptions are dropped. The maximum prescription length is capped at 180 days. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. "Short-run" refers to the first year after adoption, and "Long-run" refers to all subsequent periods. Each column is estimated from a separate regression. All specifications include municipality fixed effects, time fixed effects, and age and age squared. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A4

Effects of E-prescribing on Warfarin-NSAID Interaction, by Municipality Group and Physician Specialty

	All municipalities (1)	Urban (2)	Rural (3)
Panel A. Unspecialized			
Short-run	−0.002	0.000	−0.012***
	(0.001)	(0.001)	(0.003)
Long-run	−0.004*	−0.001	−0.018***
	(0.002)	(0.002)	(0.005)
Mean outcome	0.043	0.042	0.047
Observations	917,214	709,548	207,666
Panel B. General medicine			
Short-run	−0.003	−0.002	−0.008
	(0.002)	(0.002)	(0.006)
Long-run	−0.004	−0.002	−0.010
	(0.003)	(0.003)	(0.007)
Mean outcome	0.040	0.038	0.049
Observations	337,702	266,726	70,976
Panel C. Internal medicine			
Short-run	−0.001	0.001	−0.023
	(0.004)	(0.005)	(0.015)
Long-run	0.001	0.004	−0.030
	(0.007)	(0.007)	(0.024)
Mean outcome	0.056	0.055	0.063
Observations	73,862	63,477	10,385

Notes: This table reports the coefficients from difference-in-differences regressions using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. "Short-run" refers to the first year after adoption, and "Long-run" refers to all subsequent periods. Each panel-column combination is estimated from a separate regression. All specifications include municipality fixed effects, time fixed effects, and age and age squared. Panel A uses prescriptions written by physicians without any specialization, Panel B by physicians specialized in general medicine, and Panel C by physicians specialized in internal medicine. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A5
Effects of E-prescribing on Warfarin-NSAID Interaction, Different Versus Same prescribing Physician

	All municipalities (1)	Urban (2)	Rural (3)
Short-run × same physician	0.000	0.001	−0.002
	(0.000)	(0.000)	(0.002)
Long-run × same physician	0.000	0.001	−0.004**
	(0.001)	(0.001)	(0.002)
Short-run × different physician	−0.002**	−0.001	−0.008***
	(0.001)	(0.001)	(0.003)
Long-run × different physician	−0.003**	−0.003*	−0.009**
	(0.001)	(0.002)	(0.004)

Notes: This table reports the coefficients from difference-in-differences regressions using the prescription-level data on warfarin patients. The outcome is a dummy variable that equals one if a warfarin (NSAID) prescription interacts with another NSAID (warfarin) prescription. "Short-run × same physician" and "Long-run × same physician" refer to the interaction between drug interactions where the prescribing physician is the same as the previous prescribing physician and, respectively, the first year after adoption and all subsequent periods after adoption. "Short-run × different physician" and "Long-run × different physician" refer to the same interactions but when the interacting prescription is written by a different physician than the prescriber of the underlying prescription. The coefficients for different physician are estimated relative to the coefficients of same physician, meaning that the total effect for different physician is the sum of coefficients of same physician and different physician. Each column is estimated from a separate regression. All specifications include municipality fixed effects, time fixed effects, and age and age squared. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

V. Identification in the Early Versus Later Treated Municipalities

Goodman-Bacon (2021) shows that, in the case of a staggered adoption of policy where the treatment occurs at different times across units, the two-way fixed effects DiD estimator is a weighted average of all possible individual two-period/two-group DiD estimators in the data. In the case of dynamic treatment effects, this could induce negative weights to later-treated groups as these units are compared to already-treated units.

We follow Goodman-Bacon (2021) to examine the potential bias in the overall DiD estimates in the quality of prescribing stemming from the later-treated municipalities. Specifically, we perform

an explicit decomposition of the summed weights and average DiD estimates for early- versus later-treated municipalities and later- versus early-treated municipalities. The shortcoming of this approach is that as such it does not allow us to partition the treatment effect into short- and long-run effects as in our main analysis.[1] To reduce the computational burden, as we have to compute all two-by-two DiD estimates separately for each municipality group (urban and rural) and adoption time, we use aggregated municipality-quarter-level data and the log number of warfarin-NSAID interactions as an outcome. Thus, the estimates are not fully comparable to our baseline estimates obtained from the prescription-level data, but the results should give an idea of whether using early-treated municipalities as a control group is worrisome in our setting.

The results for the municipality-level DiD estimates and the decompositions beneath them are shown in Tables A6. We find that the number of warfarin-NSAID interactions decreases by 14 percent in rural municipalities and there is no statistically significant effect in urban municipalities. Based on the decompositions, we conclude that negative weighting is not a major issue, especially in rural municipalities. Although not fully comparable, our conclusions regarding the effects of e-prescribing based on the aggregated data remain fairly similar to those drawn from our baseline estimates using the prescription-level data.

Table A6

Goodman-Bacon Analysis on the Number of Interactions in Municipality

	All municipalities (1)	Urban (2)	Rural (3)
DiD	-0.066^{**}	0.031	-0.140^{***}
	(0.029)	(0.034)	(0.042)
Observations	9,728	3,872	5,856
Adjusted R^2	0.78	0.823	0.502
Earlier vs. Later (Weight $\times$ DiD)	0.693$\times$-0.064	0.686$\times$0.054	0.698$\times$-0.149
Later vs. Earlier (Weight $\times$ DiD)	0.307$\times$-0.071	0.314$\times$-0.019	0.302$\times$-0.119

Notes: This table reports the coefficients from difference-in-differences regressions using municipality-quarter-level balanced data. The outcome is the log number of interactions in the municipality. "DiD" is the binary variable for the treatment effect and it gets the value of one after the municipality gets treated. "Earlier vs. Later" and "Later vs. Earlier" show the summed weights and the average DiD coefficients from all two-by-two decompositions of earlier and later adopting municipalities, respectively. All regressions include municipality fixed effects and time fixed effects. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

[1] Another shortcoming is that the approach does not allow for weights in the regressions when doing the full decomposition.

VI. Prescription Drug Use and Health Outcome

A. Prescription Drug Use and Change in the Composition of Patient Population

We analyze the effects on prescription drug use to get a broader picture of the effects of e-prescribing and of the underlying mechanisms such as changes in the patient population. E-prescribing can either decrease (better monitoring) or increase prescription drug use (easier renewal and decreased hassle costs), see Section III.B. If more drugs are being prescribed, there is a greater chance that there will be an interaction among the drugs. The effect is obviously the opposite if e-prescribing leads to less drugs being prescribed.

We analyze the effects on the intensive and extensive margins of prescription drug use. The intensive margin (prescription size) is measured by the number of defined daily doses per prescription. The extensive margin is measured by the total number of new and repeat prescriptions that a patient has in a given quarter. In the extensive margin analysis we aggregate the data to the patient-quarter-level balanced panel.

We find that the size of warfarin prescriptions increases by 4 percent in urban regions and by 6 percent in rural regions in the long run after e-prescribing, as shown in Figure A21 and Table A7. However, the effects are overestimated in the two municipality groups because the prescription size is smaller one quarter before the adoption of e-prescribing ($-Q1$) than in the previous periods.[2] We interpret this decrease as being consistent with anticipation effects, with physicians writing shorter warfarin prescriptions in $-Q1$ as they expected that patients would benefit from the new technology. However, because prescriptions were shorter, physicians had to renew more prescriptions in the periods immediately following the adoption of e-prescribing. Consistent with this, we find that the number of a patient's warfarin prescriptions increases by approximately 1 percent in the short run after e-prescribing, but remains close to zero in the long run in the two municipality groups.[3]

[2]If we omit the period $-Q1$ from the sample, the long-run increase is 2 percent in urban regions and 3 percent in rural regions, and the latter effect is statistically insignificant (Table A8). Moreover, we have checked that the decrease in prescription size is not mechanically caused by the event study design and its normalization. The decrease occurs in $-Q1$ even if we normalize a different period than $-Q1$ to zero.

[3]Our extensive margin results are robust to using the inverse hyperbolic sine transformation.

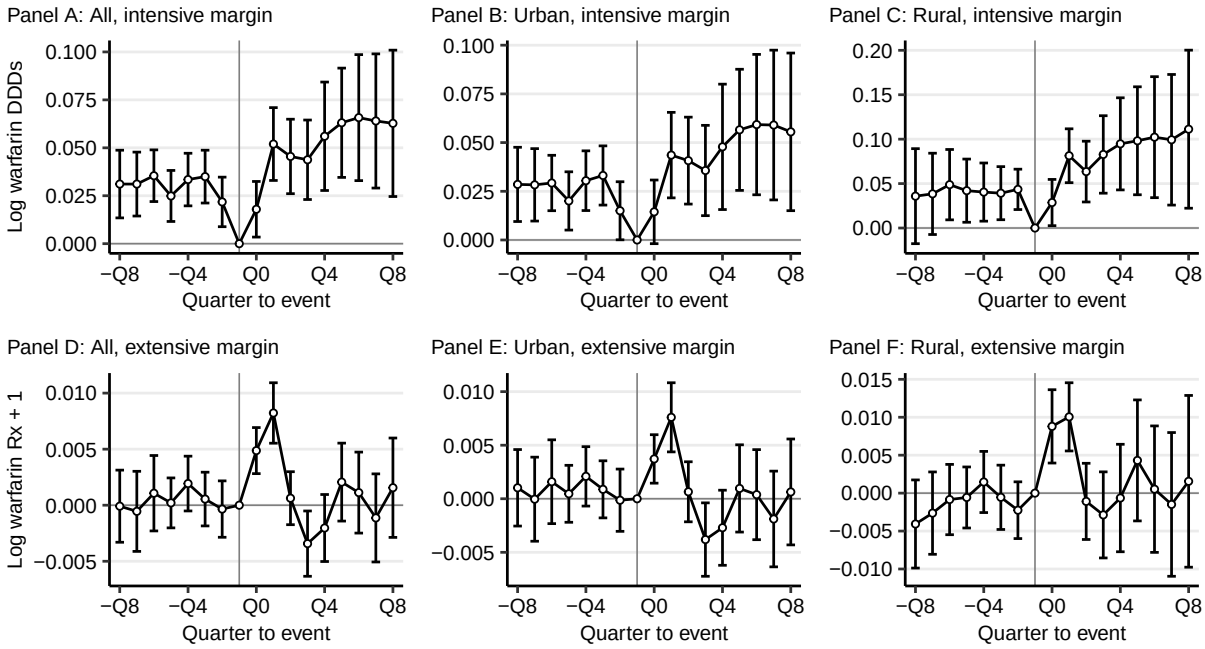

Figure A21

Intensive and Extensive Margins of Warfarin Prescriptions, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data (Panels A–C) and patient-quarter-level balanced data (Panels D–F) on warfarin patients. In Panels A–C, the intensive margin outcome is the log number of defined daily doses of warfarin prescriptions, and the data include only warfarin prescriptions. In Panels D–F, the extensive margin outcome is the log number of warfarin prescriptions$+1$ to adjust for zeros in the balanced panel. The controls include municipality fixed effects, time fixed effects, age and age squared. The urban/semi-urban and rural classification is from Statistics Finland. The standard errors are clustered at the municipality level.

Figure A22 and Table A9 show no statistically significant effect on the intensive and extensive margins of NSAID use in urban regions. In rural regions physicians write smaller NSAID prescriptions after e-prescribing, but they do not increase the quarterly number of NSAID prescriptions for warfarin patients.

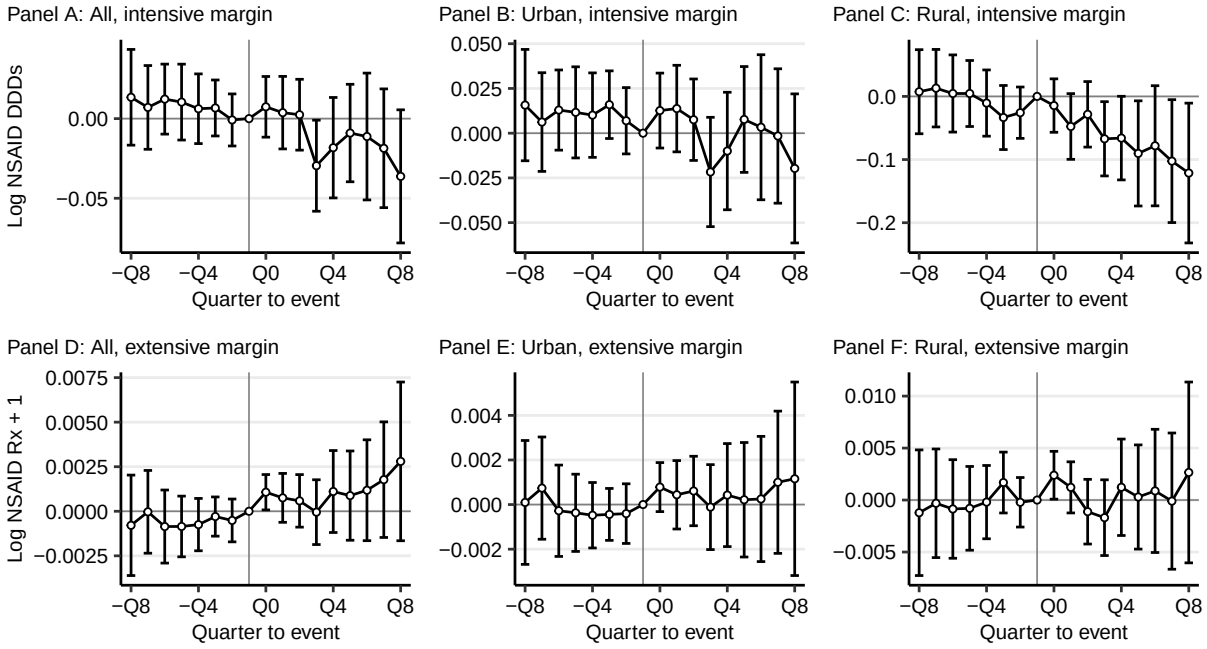

Figure A22

Intensive and Extensive Margins of NSAID Prescriptions, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data (panels A–C) and patient-quarter-level balanced data (panels D–F) on warfarin patients. In Panels A–C, the intensive margin outcome is the log number of defined daily doses of NSAID prescriptions, and the data include only NSAID prescriptions. In Panels D–F, the extensive margin outcome is the log number of NSAID prescriptions$+1$ to adjust for the zeros in the balanced panel. The controls include municipality fixed effects, time fixed effects, age and age squared. The urban/semi-urban and rural classification is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A7

Intensive and Extensive Margins of Warfarin Prescriptions, by Municipality Group

	All municipalities (1)	Urban (2)	Rural (3)
Panel A. Intensive margin: Log warfarin DDDs			
Short-run	0.018**	0.016*	0.029**
	(0.008)	(0.009)	(0.012)
Long-run	0.038***	0.035**	0.056**
	(0.013)	(0.014)	(0.023)
Mean outcome	140.086	140.548	138.234
Observations	1,050,380	840,392	209,988
Panel B. Extensive margin: Log warfarin prescriptions			
Short-run	0.003***	0.003***	0.006***
	(0.001)	(0.001)	(0.002)
Long-run	0.002*	0.001	0.005
	(0.001)	(0.001)	(0.003)
Mean outcome	3.103	3.102	3.107
Observations	7,422,752	5,952,632	1,470,120

Notes: This table reports the coefficients from difference-in-differences regressions using the prescription-level data in Panel A and patient-quarter-level balanced data in Panel B on warfarin patients. In Panel A the outcome is the log number of defined daily doses of warfarin prescriptions, and the data include only warfarin prescriptions. In Panel B, the outcome is the log number of warfarin prescriptions$+1$ to adjust for the zeros in the balanced panel. "Short-run" refers to the first year after adoption, and "Long-run" refers to all subsequent periods. Each panel-column combination is estimated from a separate regression. All specifications include municipality fixed effects, time fixed effects, and age and age squared. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A8

Intensive Margin of Warfarin Prescriptions Without $-Q1$, by Municipality Group

	All municipalities (1)	Urban (2)	Rural (3)
Short-run	0.003	0.002	0.007
	(0.006)	(0.007)	(0.015)
Long-run	0.021*	0.021*	0.030
	(0.011)	(0.012)	(0.025)
Mean outcome	139.921	140.369	138.129
Observations	1,015,591	812,526	203,065

Notes: This table shows the intensive margin results for warfarin prescriptions with the first pre-quarter of e-prescribing, $-Q1$, dropped from the data. See Table A7 for more information on the specification.

Table A9

Intensive and Extensive Margins of NSAID Prescriptions, by Municipality Group

	All municipalities (1)	Urban (2)	Rural (3)
Panel A. Intensive margin: Log NSAID DDDs			
Short-run	0.000	0.003	−0.013
	(0.008)	(0.009)	(0.018)
Long-run	−0.008	0.000	−0.046
	(0.011)	(0.011)	(0.034)
Mean outcome	53.036	52.607	54.677
Observations	639,126	506,806	132,320
Panel B. Extensive margin: Log NSAID prescriptions			
Short-run	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)
Long-run	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)
Mean outcome	2.952	2.950	2.963
Observations	7,422,752	5,952,632	1,470,120

Notes: This table reports the coefficients from difference-in-differences regressions using the prescription-level data in Panel A and patient-quarter-level balanced data in Panel B on warfarin patients. In Panel A the outcome is the log number of defined daily doses of NSAID prescriptions, and the data include only NSAID prescriptions. In Panel B, the outcome is the log number of NSAID prescriptions+1 to adjust for the zeros in the balanced panel. "Short-run" refers to the first year after adoption, and "Long-run" refers to all subsequent periods. Each panel-column combination is estimated from a separate regression. All specifications include municipality fixed effects, time fixed effects, and age and age squared. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

E-prescribing could affect initial warfarin prescriptions, and thereby change the warfarin patient population. Another benefit of this approach is that the dependent variable is scaled in a welfare-relevant way.[4] Table A10 shows separately the effects on the number of all and new warfarin prescriptions per municipality and quarter, using aggregated data and population weights in the estimation. We find the point estimates to be small and imprecisely estimated, especially for the outcome of new warfarin use. However, for the quarterly number of warfarin prescriptions, the imprecise point estimates suggest a 3–6 percent increase in rural municipalities. Overall, the extensive margin adjustments are much smaller compared to the main effects on harmful drug combinations.

Theoretically, e-prescribing could change the composition of the patient population through the extensive margin adjustments. This poses a potential threat for the identification of the main effects using prescription-level data. For example, if warfarin users were less likely to need NSAIDs after e-prescribing, the coefficients of interest would reflect the change in the patient composition rather than the true effects of information on the interaction probability.[5] Therefore, as an additional check, we also estimate regressions for the total number of warfarin-NSAID interactions per municipality and quarter, as shown in Table A10. Using municipality aggregates, we estimate the effects without any concern about the potential effects of compositional changes. Consistent with our main results, e-prescribing decreases the number of interactions by 19 percent in the long run in rural municipalities and the effect is statistically significant. Table A11 additionally confirms that the characteristics of new warfarin patients and their prescriptions look fairly similar one year before versus one year after the adoption of e-prescribing.[6]

[4] A challenge of switching the unit of observation to a municipality-quarter level is how to pursue the heterogeneity analyses around the number of prescribing doctors and pharmacies.

[5] Note that our main results are robust to limiting the data to the fixed set of patients who received a warfarin prescription before e-prescribing, as discussed in Section VII.A and shown in Online Appendix Figure A9.

[6] Migration between urban and rural regions may change the compositions of the urban and rural populations. However, the fraction of patients who have changed their status in terms of urban and rural region is only 1.3 percent, and the fraction of patients who have changed their municipality is 4.4 percent, respectively. Our results remain intact when we exclude the patients (4.4 percent) who have changed their municipality over the estimation period.

Table A10

Extensive Margin of Warfarin Use and Interactions in Municipality

	All municipalities (1)	Urban (2)	Rural (3)
Panel A. Log number of new patients			
Short-run	0.007	−0.013	0.019
	(0.023)	(0.025)	(0.034)
Long-run	0.018	−0.001	0.027
	(0.032)	(0.034)	(0.050)
Observations	7,296	2,904	4,392
Adjusted R^2	0.872	0.921	0.572
Panel B. Log number of warfarin prescriptions			
Short-run	0.032**	0.027*	0.033
	(0.016)	(0.015)	(0.025)
Long-run	0.050*	0.034	0.056
	(0.026)	(0.023)	(0.041)
Observations	7,296	2,904	4,392
Adjusted R^2	0.945	0.972	0.827
Panel C. Log number of interactions			
Short-run	−0.054**	0.040	−0.124***
	(0.027)	(0.038)	(0.035)
Long-run	−0.056	0.126*	−0.188***
	(0.044)	(0.069)	(0.055)
Observations	9,728	3,872	5,856
Adjusted R^2	0.727	0.776	0.419

Notes: This table reports the coefficients from difference-in-differences regressions using municipality-quarter-level balanced data. In Panel A, the outcome is the log number of new warfarin patients. New patients are defined as those patients who have their first warfarin prescription in a given quarter in the data. In Panel B, the outcome is the log number of overall warfarin prescriptions in the municipality. In Panel C, the outcome is the log number of warfarin-NSAID interactions. In Panels A and B, because of left-censoring, those patients who have their first warfarin prescription in 2007–2009 are dropped and only data for the years 2009–14 are used in the regressions. "Short-run" refers to the first year after adoption, and "Long-run" refers to all subsequent periods. All regressions include fixed effects for municipality and time trend. All regressions are weighted by the population size in the municipality. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A11

Summary Statistics for New Patients in Pre- and Post-Adoption Years

	Urban		Rural	
	Pre-adoption	Post-adoption	Pre-adoption	Post-adoption
Warfarin DDDs per patient	181.008	188.077	176.905	185.715
	(120.254)	(123.949)	(119.651)	(117.267)
Warfarin Rx per patient	1.510	1.482	1.502	1.450
	(0.748)	(0.702)	(0.769)	(0.702)
DDDs in first warfarin Rx	118.017	121.372	119.025	123.918
	(79.547)	(83.033)	(83.252)	(83.256)
NSAID DDDs per patient	18.913	18.244	20.896	19.701
	(51.600)	(51.985)	(56.474)	(56.687)
NSAID Rx per patient	0.390	0.363	0.413	0.363
	(0.815)	(0.799)	(0.899)	(0.809)
DDDs in first NSAID Rx	12.778	12.372	12.952	12.885
	(32.895)	(31.826)	(33.475)	(34.660)
Share of Rx by specialty				
Unspecialized	0.568	0.603	0.631	0.668
	(0.425)	(0.422)	(0.419)	(0.408)
General medicine	0.118	0.126	0.139	0.139
	(0.268)	(0.279)	(0.295)	(0.295)
Internal medicine	0.069	0.070	0.060	0.051
	(0.223)	(0.225)	(0.206)	(0.196)
Age	67.750	68.463	70.206	70.684
	(14.698)	(14.545)	(13.665)	(13.403)
Number of new patients	17,736	17,735	4,176	4,274

Notes: Mean values are taken over per patient values. The standard deviations are in parentheses. The table includes only those patients who have their first warfarin prescription either during the year immediately before or during the year immediately after the adoption of e-prescribing. The time of the patient's first warfarin prescription is defined as the first time a warfarin prescription is observed for the patient in the data. The urban/semi-urban and rural classification in the columns is from Statistics Finland.

Next, we proceed to analyze whether the decreasing probability of a harmful interaction originates solely from the decrease in the length of NSAID prescription. Any major decreases in the length should not only show up as a reduction at the extensive margin of the interacting prescription (our baseline results), but also as a reduction at the intensive margin (interaction time). Note that the length of NSAID prescriptions does not affect one-way interactions of prescribing NSAIDs on top of warfarin, which decreased after e-prescribing (Section VII.A).

Figure A23 plots the event study estimates for the number of interacting days of each interacting prescriptions. As the number of observations is quite small, the estimates are more imprecisely estimated, but show no clear evidence for a decrease in the outcome. Figure A24 shows the density of interaction time separately for the pre-reform period and the long-run post-reform period. Again, no discernible differences can be detected between the densities. In sum, the decrease in the probability of a harmful interaction is not solely explained by the decrease in the length of NSAID prescriptions.

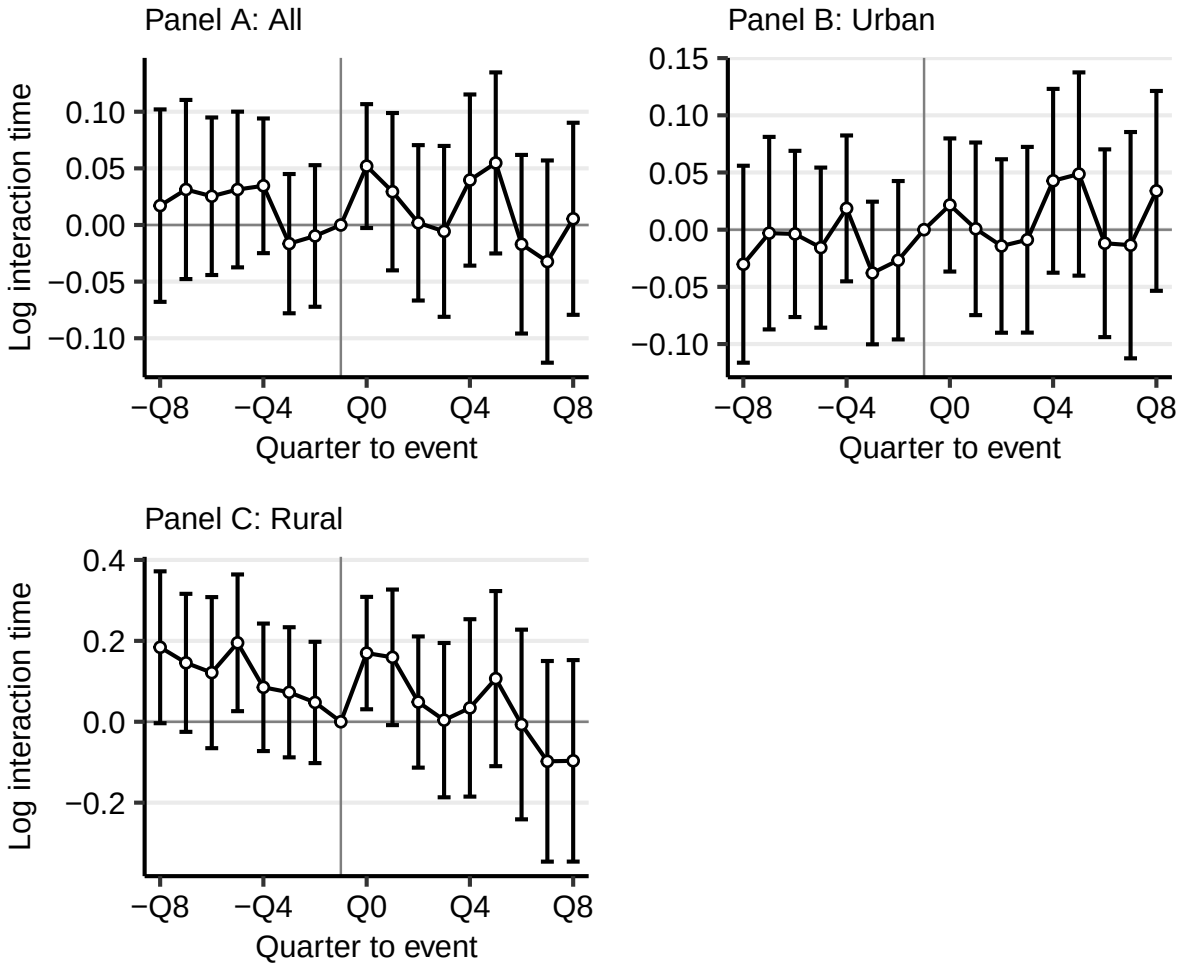

Figure A23
Duration of Warfarin-NSAID Interaction, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using the prescription-level data on interacting (wafarin and NSAID) prescriptions for warfarin patients. The outcome is the log number of days that the prescription interacts with another prescription. See Figure 6 for more information on the specification of the model.

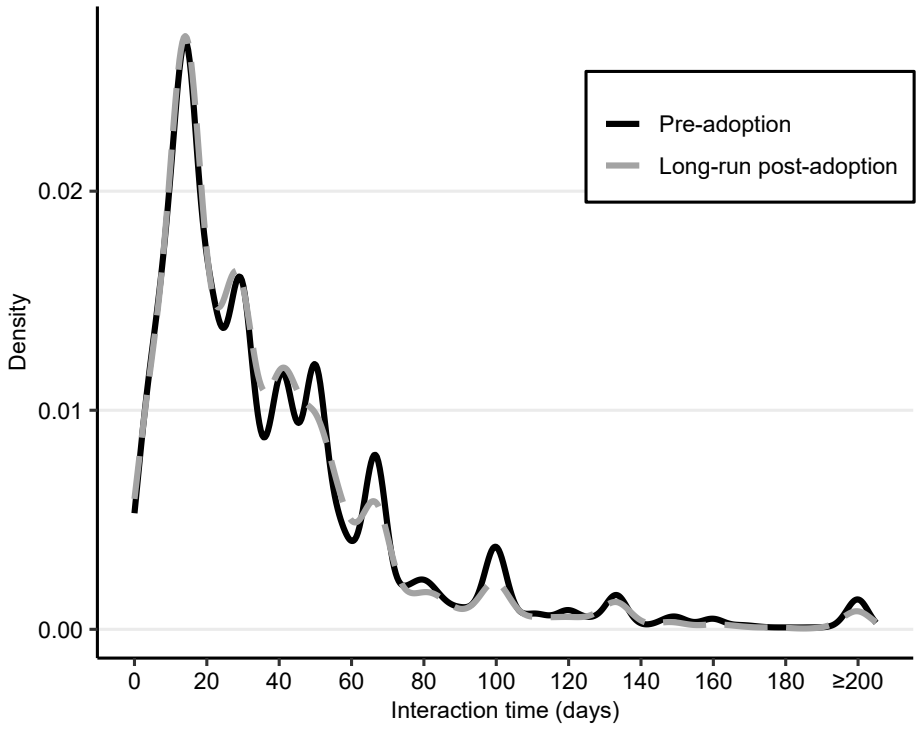

Figure A24

Density of Duration of Warfarin-NSAID Interaction

Notes: This figure plots the conditional density of the duration of each interacting (warfarin or NSAID) prescription, calculated in days, separately for the pre-adoption period (before 2010) and the long-run post-adoption period (at least one year after adoption). The length of warfarin and NSAID prescriptions is calculated using the number of defined daily doses of each prescription, where one day is assumed to be equal to one unit of daily dose.

B. Health outcome: Hospitalization for Gastrointestinal Bleeding

The focus of our paper is to study whether e-prescribing improved the coordination and quality of prescribing. However, it is also of interest to investigate whether these improvements translated into meaningful improvements in patient health. Because comprehensive analysis of various direct and indirect health effects is beyond the scope of our paper, we focus only on the most direct health outcome of the interaction of warfarin and NSAID: gastrointestinal bleeding.

The medical literature has documented that the simultaneous use of NSAIDs and warfarin significantly increases the risk of major bleeding complications, especially in the gastrointestinal tract (Battistella et al. 2005). Motivated by this evidence and the large decrease in such drug interactions in rural regions after e-prescribing (Section VII.A), we estimate the effects of e-prescribing on the probability of hospitalization for gastrointestinal bleeding (hemorrhage). We use aggregated patient-quarter-level balanced panel data for warfarin patients with at least one warfarin prescription during the observation period 2007–14. We find no evidence for a decrease in this bleeding outcome among warfarin patients after e-prescribing, even in rural regions (Figure A25 and Table A12).

There are several explanations for this finding. First, warfarin use by itself can cause excessive bleeding, especially when used in higher doses. We found that e-prescribing (digitization and easier renewal of prescriptions) increased the number of defined daily doses of warfarin prescriptions in rural regions. The increase in bleeding complications stemming from this increased size of warfarin prescriptions may counteract the complications stemming from fewer interacting prescriptions. In fact, Table A12 shows positive and statistically significant effects on the bleeding outcome.[7]

Second, the bleeding outcome may not be sensitive enough to capture the full short- and long-term positive effects of the decreased warfarin-NSAID interaction risk on latent health. Even though we study a well-established and widely used health outcome of warfarin-NSAID interactions in the medical literature (Battistella et al. 2005; Zapata et al. 2020), it is rare in the patient population (mean quarterly probability of 0.2 percent), and not all warfarin patients have an interacting prescription in a given quarter. Diagnosing bleeding complications is also complex, time-

[7]E-prescribing (improved information on a patient's prescriptions) may also improve diagnosing, thereby increasing their prevalence.

consuming, and may require several diagnostic tools (Kim et al. 2014). For example, a Finnish post-mortem study (Launiainen et al. 2010) shows that it is not uncommon that bleeding is diagnosed only after a patient's death.

The limitations of the data may also be relevant for finding no reduction in the probability of bleeding complications after e-prescribing for two reasons. First, we cannot completely rule out the potential role of the over-the-counter (OTC) market for NSAIDs. It is possible that substitution of prescription NSAIDs with OTC alternatives contributes to the health effect of e-prescribing, although physicians who stopped prescribing NSAIDs might have instructed their patients not to use or buy them OTC. Our prescription-level data do not permit us to study changes in the use of NSAIDs in the OTC market, but based on the aggregate consumption statistics for a commonly used NSAID, ibuprofen (Fimea and Kela 2015), use of this drug did not change much after municipalities started to adopt e-prescribing (years 2010-2014). Second, our data do not record information on the actual use of medications or whether patients are taking interacting medications (warfarin and NSAIDs) at the same time. This applies to nearly all administrative data from non-hospital settings.

Nonetheless, we find that the probability of hospitalization for gastrointestinal bleeding is 30 percent higher for patients with an interacting prescription for warfarin and NSAIDs compared to those with a warfarin prescription alone in a given quarter (Table A13), supporting the role of interacting prescriptions contributing to bleeding. In addition, as presented in Section VII.A, e-prescribing reduced the interaction probability by approximately 35 percent in rural regions. Based on these two estimates, we roughly approximate that the e-prescribing-induced decrease in drug interaction reduced the bleeding outcome by approximately $100 \times (0.3 \times 0.35) \approx 11$ percent.[8] Compared with the DiD estimate of the overall effect of e-prescribing on the bleeding outcome in rural regions (Table A12), this complementary back-of-the-envelope calculation yields a larger and more explicit estimate of the potential effects of e-prescribing in reducing the bleeding outcome through reduced drug interactions.

[8] In a meta-analysis (Zapata et al. 2020), the drug interaction increases gastrointestinal bleeding by 98 percent, but variation across and within study settings is large. This estimate implies even a larger reduction ($100 \times (0.98 \times 0.35) \approx 34$ percent) in the bleeding outcome as a result e-prescribing-induced decrease in the drug interaction than our raw data estimate of 30 percent.

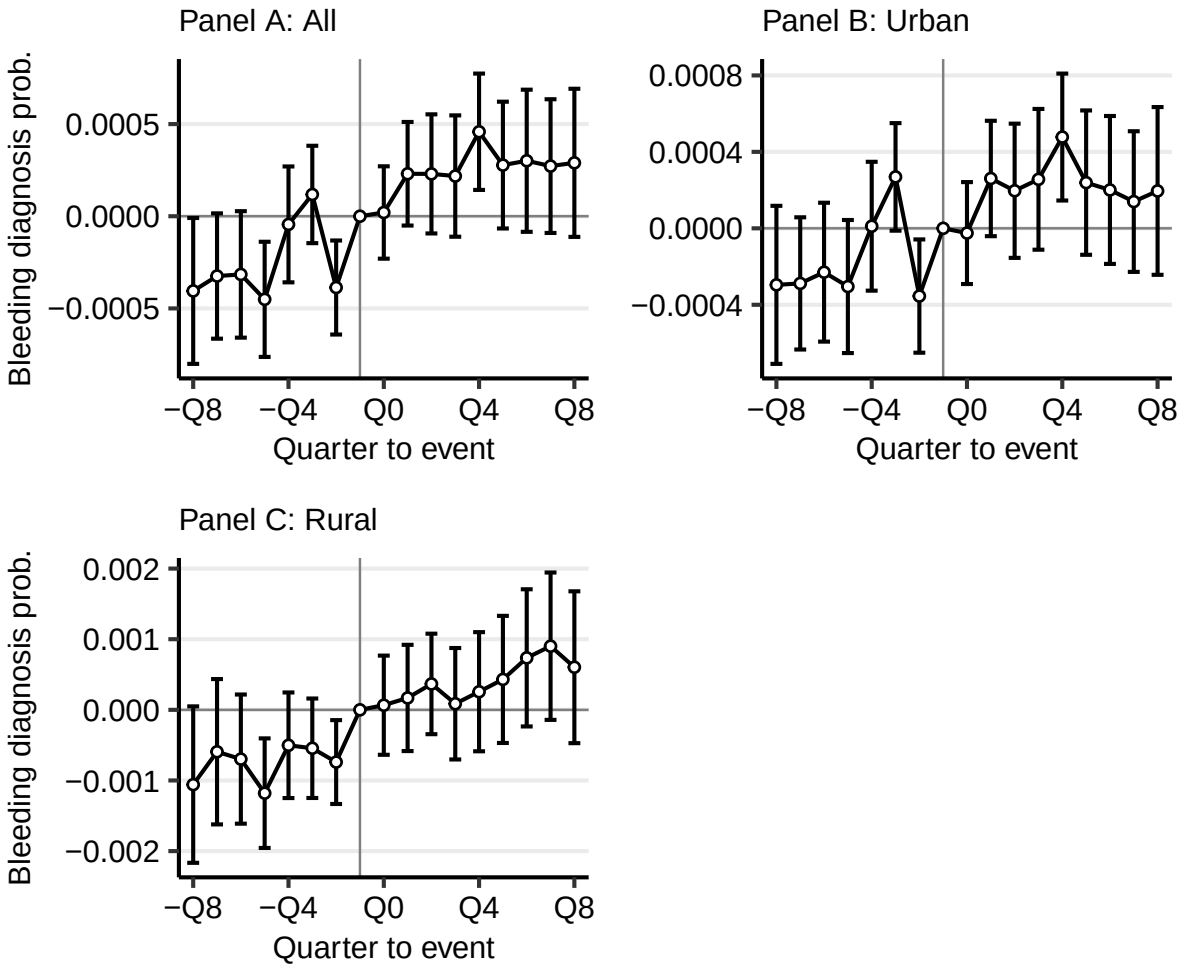

Figure A25
Probability of Hemorrhage (Bleeding) Diagnosis, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using patient-quarter-level balanced data on warfarin patients with at least one warfarin prescription during the observation period 2007–14. The outcome is a dummy variable that equals one if the patient has a hospital admission for gastrointestinal hemorrhage (bleeding) in a given period. The controls include municipality fixed effects, time fixed effects, age and age squared. The urban/semi-urban and rural classification is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A12

Effects of E-prescribing on Hospitalization for Gastrointestinal Bleeding

	All municipalities	Urban	Rural
	(1)	(2)	(3)
Short-run	0.0003***	0.0002**	0.0005*
	(0.0001)	(0.0001)	(0.0003)
Long-run	0.0004***	0.0003**	0.0007**
	(0.0001)	(0.0001)	(0.0003)
Mean outcome	0.0020	0.0020	0.0021
Observations	7,361,632	5,920,658	1,440,974

Notes: This table reports the coefficient estimates from difference-in-differences regressions using patient-quarter-level balanced data for warfarin patients with at least one warfarin prescription during the observation period 2007–14. The outcome is a dummy variable that equals one if the patient has a hospital admission for gastrointestinal hemorrhage (bleeding) a given period. All regressions include municipality fixed effects, time fixed effects, age and age squared. The urban/semi-urban and rural classification in the columns is from Statistics Finland. The standard errors are clustered at the municipality level.

Table A13

Drug Interaction and Risk of Hospitalization for Gastrointestinal Bleeding at the Quarterly Level

	Warfarin only (1)	NSAID only (2)	Warfarin and NSAID interaction (3)
Mean outcome	0.0027	0.0019	0.0035
	(0.0001)	(0.0001)	(0.0002)
Observations	990,447	534,059	66,120

Notes: This table shows the means of the health outcome for patients who have a warfarin prescription only (Column 1), a NSAID prescription only (Column 2), and interacting prescriptions of both of these (Column 3) in a given quarter using the prescription-level data on warfarin patients combined with information on the timing of the bleeding outcome. The outcome is a dummy variable that equals one if the patient has a hospital admission for gastrointestinal hemorrhage (bleeding) in that quarter. The standard errors are shown in parentheses.

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