Information Integration, Coordination Failures, and Quality of Prescribing*

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1

Abstract

Poor information hampers coordination, potentially leading to suboptimal decisions in organizations. We examine the effects of a large-scale policy of health information integration on the quality of prescribing and coordination. We identify the causal effects of this policy using the staggered adoption of a nationwide interoperable electronic prescribing system over four years in Finland and comprehensive nationwide 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. Our analysis shows that despite no effect on average, the policy of information integration may narrow regional differences in health care provision and reduce the cost of physician switches.

Keywords: Coordination, information integration, digitalization, interoperability, e-prescribing, public policy.

JEL Codes: D80, I1, L20, H51

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This version: January 10, 2022. We thank Tuomas Markkula for the excellent research assistance and Norma B. Coe, Guy David, Meltem Daysal, Risto Huupponen, Mika Kortelainen, Claudio Lucarelli, Ismo Linnosmaa, Martin Salm, and Mark Pauly, and the participants in the American Economic Association Annual Meeting (poster session) 2022, 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, University of Pennsylvania Postdoc Work-in-progress Research Seminar, and the TSE Economics Research Seminar for their feedback and comments. The authors gratefully acknowledge the Yrjo Jahnsson for funding this research (research grant No. 6701). ††:University of Jyväskylä, Labour Institute for Economic Research LABORE, and IZA Institute of Labor Economics, ‡:The Social Insurance Institution of Finland, ‡‡: VATT Institute for Economic Research and Helsinki GSE.

1 Introduction

Organizations aim to improve the coordination of individuals' 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 (Elhauge 2010). The relevant medical information is costly for the physicians to acquire and imperfectly shared, because of incompatible health information systems (for example, Arrow (1963) and Cebul et al. (2008)). Motivated by the challenges in information sharing and the substantial economic burden of coordination failures (Shrank et al. 2019), policy makers have highlighted the need for implementation of integrated information systems (Michelsen et al. 2015; European Commission 2020). Empirical evidence of large-scale adoption of such technologies on coordination is very limited, because of the considerable implementation costs and challenges in the adoption.

We analyze a public policy of health information integration and study changes in physicians' decision making, coordination, and related outcomes in Finland. The country was one of the first ones to adopt a nationwide system for electronic prescribing (e-prescribing), together with other countries such as Estonia, Sweden, Portugal, and Australia. A general policy goal for a nationwide adoption and using standardized information technologies such as e-prescribing is to mitigate regional gaps in the provision of healthcare, in addition to improving coordination (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 interoperable e-prescribing system by municipalities serves as a plausibly exogenous shock to the information set of physicians, being directly relevant to the quality of their prescribing decisions and coordination.[1]

Empirical analyses of coordination face three main challenges. First, defining and measuring

[1] E-prescribing systems contain only prescription information, in contrast to general health information systems such as electronic medical and health records that contain a varying collection of patient data (e.g., treatments, free-text descriptions of clinical notes, and X-ray images).

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 et al. 2016; Agha et al. 2018, 2019). Second, the administrative claims data used in prior work have been limited to physician services provided in a specific region or program (e.g., Medicare fee-for-service), preventing researchers from following patients and their physicians once they move away from the region or drop out of the program. Third, the economic implications of information integration, depend on the implementation of the policy. Information integration promotes coordination without harming competition if technology is implemented in an interoperable environment so that technology does not increase switching costs of changing the provider (Baicker and Levy 2013).[2] The main contributions of our paper lies in furthering the analyses of the quality of care and coordination by focusing on direct measure for coordination, using comprehensive administrative data that allows us to follow their patients and their physicians even in case they move, and exploiting the large-scale quasi-experiment of the adoption of interoperable health information technology.

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. 2005b; Roughead et al. 2010; Rikala et al. 2015).[3] Using these data, which covers interacting prescriptions obtained from different physicians over time and throughout the whole country, we provide more direct evidence than in prior work of the effects in terms of coordinating physicians' interdependent decisions. The scale 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

[2]There is often a trade-off between coordination and competition. Improving coordination through, for example, integrated networks of firms can create weaker incentives to keep prices low. On the other hand, competitive markets have lower prices, but with the cost of fragmentation and coordination failures. (Baicker and Levy 2013)

[3]No nationwide notification system of prescriptions for harmful drug interactions existed prior e-prescribing. After implementation, e-prescribing provides more comprehensive information on a patient's potentially interacting prescriptions.

prevent serious conditions such as strokes and heart attacks (Kirley et al. 2012; Fimea and Kela 2019). The national clinical guidelines, however, clearly warn against simultaneous prescribing of warfarin with NSAIDs because of the increased risk of major bleeding complications (Lindh et al. 2014; Malone et al. 2005a). Using a theoretical model by Becker and Murphy (1992), we illustrate the benefits of medical information 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 2007–2014. Despite the 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 2007–2009, with large variation across regions (between 2 and 19 percent).[4] These findings are consistent with a lack of information integration and coordination in the pre-adoption period.

Using our prescription-level data, we find that the adoption of e-prescribing by municipalities has no statistically significant effect on the overall probability of co-prescribing harmful drug combinations. Therefore, the results show that the nationwide system has little benefits for the quality of prescribing on average.

We also evaluate regional heterogeneity in the effects because there is considerable evidence of the urban-rural gap in health care provision and outcomes (Skinner 2011; Loccoh et al. 2021). Besides improving information, the technology adoption has a potential to compensate for the isolation of smaller rural communities, with aging populations, barriers to healthcare access, and fewer critical resources such as specialists (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) models 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. Thus, the adoption of e-prescribing has much larger benefits in improving the quality of prescribing in rural than in urban regions.

We find that the improvement in the quality of prescribing in rural regions is driven by unspe-

[4]For comparison, in a large U.S. prescription claims study 24 percent of warfarin patients received an NSAID during a two-year follow-up (Malone et al. 2005b).

cialized physicians (generalists). They supply a greater proportion of prescriptions in rural than in urban regions and have fewer years of education than specialized physicians. Moreover, in the presence of agglomeration economies and knowledge spillovers, observationally identical workers (e.g., generalists) have lower levels of human capital in rural than in urban regions (Glaeser 2008). E-prescribing may facilitate information sharing in rural regions, especially for unspecialized physicians. Thereby, the new technology may narrow regional differences in health care provision, which was one of the policy goals of the reform.

Consistent with our hypothesis of information integration improving coordination, we find that the improvement in the quality of prescribing in rural regions is also driven by interacting prescriptions from different physicians, rather than from the same physician. However, the resulting direct health benefits seem to be marginal. Using administrative discharge data, we find no evidence of a reduction in severe and relatively rare bleeding complications among warfarin patients as a result of e-prescribing.

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 (e.g., hospital-physician integration, accountable care organizations, hospitalists) as potential means for improving coordination (Gaynor et al. 2004; Cebul et al. 2008; Meltzer and Chung 2010). However, empirical work examining other fundamental drivers such as those affecting information environment is very limited (Bloom et al. 2014). Despite the underwhelming results on average, our results for rural regions still support the view 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 structure and related patient outcomes (Skinner et al. 2006; Agha et al. 2018, 2019). The results are also broadly consistent with earlier work on the determinants of physician practice style (e.g., education or information) (Epstein et al. 2016; Molitor 2018; Schnell and Currie 2018; Shapiro 2018) and with the research on the roles of beliefs, human capital, and other supply-side factors in causing regional variations in and outside of the health care sector (Gennaioli et al. 2012; Finkelstein et al. 2016; Cutler et al. 2019).

We also contribute to the literature analyzing how information technology affects patient health

(e.g. McCullough et al. 2010; Miller and Tucker 2011; Agha 2014; McCullough et al. 2016; Böckerman et al. 2019). Our paper is most closely related to work by McCullough et al. (2016), who examine the effects of information technology at the hospital level on the health outcomes of patients whose diagnoses require cross-specialty care coordination. In contrast to their work, we explicitly analyze physicians' treatment decisions and coordination, in addition to focusing on heterogeneity in the 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 hospital network (Cebul et al. 2008). Our analysis, instead, studies a technology, which has a great potential for improving information flows also between different providers and organizations. Our study also complements prior research on local interventions (randomized controlled trials) aiming to improve coordination (Peikes et al. 2009).

The rest of the paper proceeds as follows. Sections 2 and 3 describe our theoretical model and empirical setting. Section 4 presents our administrative data and empirical evidence on coordination failures health information integration. Section 5 describes our econometric approach. Section 6 presents our results of the effects of information integration on quality of prescribing. We first show our results over all regions. Second, we analyze heterogeneity in the effects for urban and rural regions. Third, we provide evidence of robustness of our main findings to alternative specifications and results of placebo regressions. Section 7 provides evidence of the potential underlying mechanisms such as the role of physician information and changes in treating physician in addition to coordination and information integration between physicians. The last section concludes.

2 Theory of Health Care Production and Coordination Costs

Fragmentation is a fundamental characteristic of decentralized health care systems, with a patient's care provision divided between multiple physicians and organizations (Cebul et al. 2008). We use a canonical model by Becker and Murphy (1992) to illustrate (i) how such division of labor affects the quality of care (prescribing) and (ii) how information integration affects the trade-off in the division of labor between the productivity gains and coordination costs.

In the model, a group of physicians produces health care services for patient i. Following Chandra et al. (2016), we investigate the provision of the quality of care conditional on the inputs used in

the treatment process. The inputs include the number of treating physicians n and other production assets such as physical or human capital K. In practice, the quality of care can be measured based on a variety of outcomes such as interacting prescriptions (our setting) and mortality or the readmission rate (Chandra et al. 2016).

Formally, the health care production function for patient i is the following:

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

where y_i is the quality output. B_i is the gross output or benefit, which depends on the inputs and patient characteristics X through parameter θ.

The model captures coordination costs C_i as a source of inefficiency: higher C_i implies that lower quality of care is produced from the same amount of inputs. In the spirit of the original model by Becker and Murphy (1992), the coordination costs do not only depend on n but also on the exogenous parameter λ describing the cost of acquiring medical information (from other physicians). The coordination costs increase with the cost of information acquisition $\partial C_i/\partial\lambda > 0$, for example through communication (Garicano 2000). This can occur even in the absence of other types of coordination costs such as those related to free riding (Holmström 1982) and incomplete contracting (Hart 2017).

Productivity gains from the division of labor are captured by the positive marginal product of the number of physicians and determined by θ: $\partial B_i/\partial n > 0$. 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 $\partial C_i/\partial n > 0$.[5]

Information integration systems such as e-prescribing can mitigate this trade-off in the division of labor by decreasing the coordination costs. The adoption of such systems decreases the cost of information acquisition λ to $\tilde{\lambda}$ $(0 < \tilde{\lambda} < \lambda)$, *ceteris paribus*. Consequently, $C_i(n^*; \tilde{\lambda}) < C_i(n^*; \lambda)$, where n^* is the pre-determined equilibrium division of labor.[6] Because of the negative shock

[5]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.

[6]We assume that n^* adjusts in the long term after the shock because it depends heavily on local (labor) markets and contractual and organizational arrangements. Further analyses of adjustments in team size and labor markets are beyond the scope of our paper.

to λ, productivity improves, i.e. higher quality of care is produced using the same amount of inputs, especially when $n > 1$. Crucially, $C_i = C_i(E_m, n; \lambda)$ may also depend on supply-side factors in the patient's municipality of residence m, E_m, which capture, for example, the geography and organization of service provision, as well as localized human capital externalities (knowledge spillovers) and expertise; as λ decreases, these factors should become less important for the quality of the output.

3 Empirical Setting

We examine the adoption of a nationwide e-prescribing system in Finland. This policy change improved information integration, potentially supporting physician coordination and the quality of prescribing. In this section, we describe the relevant institutional background for our empirical analysis.

3.1 Organizational Fragmentation and Coordination Failures in the Finnish Health Care System

Finland has a decentralized single-payer health care system, in which local regional governments are responsible for the organization and provision of health care services. By law, primary health care is organized by the municipalities ($N = 304$ in 2014), which differ substantially in their ability to provide services (Keskimäki et al. 2019). In particular, urban regions have generally better economic resources and workforce availability to provide services compared to rural regions (OECD 2017). Moreover, to organize specialized health care, municipalities belong to hospital districts ($N = 20$). The sectors providing complementary private and employer-sponsored occupational health care services are fairly small due to the provision of universal public health care services (Vuorenkoski et al. 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 difficult.

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). Prescription information was not available in a uniform and transferable electronic format at the national level. The transfer of prescription information was not possible even between providers that had the same EMR platform. Similarly, prescription information did not transfer between pharmacies because of their incompatible information systems.[7] A lack of information integration made it more difficult to establish care coordination and to avoid prescriptions for harmful combinations of drugs.[8]

3.2 E-prescribing: Information Integration and Quality of Prescribing

E-prescribing is a widely and globally 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 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 by improving coordination and information flows between physicians (Bell and Friedman 2005), closely following our model in Section 2. 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 within and across provider organizations, the systems reduce the likelihood of one physician not knowing about prescriptions from another physician. Therefore, the system can also reduce prescriptions for

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

[8]This occurred despite the fact that physicians and pharmacies had access to a drug interaction database (INXBASE/SFINX). The database was/is integrated with many EMR and pharmacy platforms and automatically warns about drug interactions using information on a patient's prescriptions in that *local* platform. However, INXBASE and its adoption is nationally fragmented and not integrated with the e-prescribing system itself. Moreover, it does not create flags about possible interacting prescriptions.

harmful drug combinations, especially when they are written by different physicians ($n \geq 2$ in the theory model).[9] 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 central goal 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 such interacting prescriptions.

3.3 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.[10]

We use the staggered adoption of e-prescribing by municipalities in (public) primary care as our identification strategy for three reasons. First, primary care physicians write most prescriptions, especially for warfarin and NSAIDs (Lindh et al. 2014). Second, in Section 5, 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 low take-up rates.

Third, there is substantial and plausibly exogenous regional heterogeneity in the adoption time of the e-prescribing system in primary care (Figure 1), as described in Böckerman et al. (2019). Expert interviews indicate that the adoption time was determined by technical difficulties in the

[9] Some (rural) municipalities may have only one primary health care unit. In these case, e-prescribing may also improve physician coordination and information flows, for example within that unit or between different units of primary and specialized health care.

[10] 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.

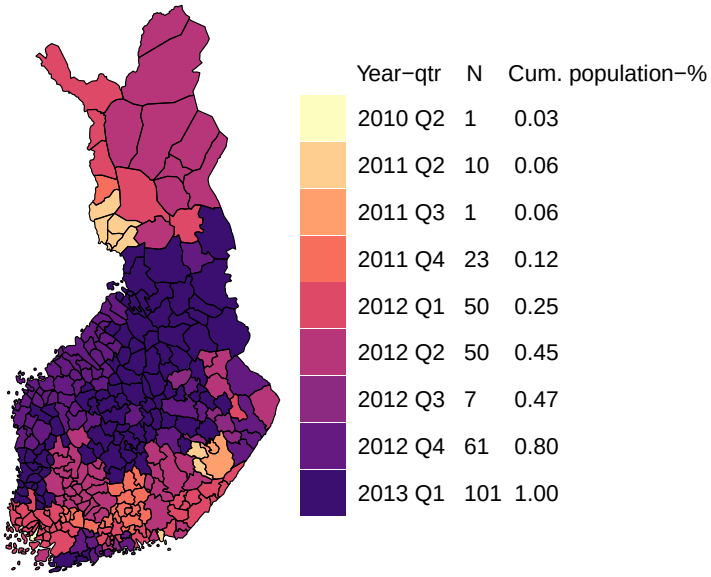

FIGURE 1: Staggered Adoption of E-prescribing in Municipalities

Note: 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

integration of the e-prescribing system with pre-existing local information systems in health care units and pharmacies (Section 3.1), 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.[11] 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.

[11] 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.

3.4 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 non-steroidal anti-inflammatory drugs (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. Although NSAIDs are available over the counter (OTC) in lower dosages in most countries, these drugs are also widely prescribed to treat conditions such as acute or chronic pain and inflammation.[12] As warfarin and NSAIDs have blood-thinning effects and can cause bleeding (hemorrhage), combinations of them increase the risk of bleeding even more. 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.

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

4 Administrative Data

We use administrative data on warfarin patients and their NSAID prescriptions over the period 2007–2014. Using additional administrative data on discharges in specialized health care, we mea-

[12] 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 the NHI in 2018 (Fimea and Kela 2019). Approximately 50 percent of expenditures resulted from OTC medicines (ibuprofen and ketoprofen) and only 2 percent from sales to hospitals.

sure patients' bleeding complications, 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 statistical power, because we focus on prescriptions for individuals who may have such combinations and are thus targeted by the e-prescribing policy. We examine separately the extensive margin of prescription drug use and return to the issues more closely in Section B.1. Next we provide an overview of the datasets, sample construction and key variables.

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 are covered by the National Health Insurance (NHI) scheme over the period 2007–2014.[13] The key advantage of our comprehensive register-based data is that we can follow patients over time, even if they switch physicians, providers or employers. 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 4.1). 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 2013 municipality classification because Finland experienced municipal mergers in the years in the data (but not in 2014). Using the statistical municipality classification by Statistics Finland, we identify patients in urban, semi-urban and rural municipalities. 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.

[13]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.

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 6).

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.[14] See online Appendix A.1 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. Additionally, 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 study the implications of improvements in information flows and coordination between physicians, but not within and between local units.

To construct our prescribing quality measure, an indicator of the co-prescribing of warfarin and NSAIDs, we use of the amount of defined daily doses a patient filled from each prescription and the date of prescribing. 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*.[15] 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 B.1.

Discharge Data—The Discharge Data are from the the National Institute for Health and Welfare. The data contain comprehensive information on Finnish public inpatient and outpatient specialized

[14]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).

[15]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.

health care discharges in 2007–2014. 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).

From the data, we construct a dummy variable that equals one if the patient has a gastrointestinal hemorrhage (bleeding) diagnosis in specialized health care during a 3-month period. To calculate this outcome, we aggregate the data into a balanced panel form in which observations are at the patient-quarter-level. See online Appendix A.1 for the ICD-10 codes.

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 within the 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.

4.1 Descriptive Evidence

As discussed in Section 3.1 the Finnish health care system is highly decentralized and fragmented, with an uneven distribution of health care resources, such as physician workforce, between urban and rural regions. 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 2007–2009. 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 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

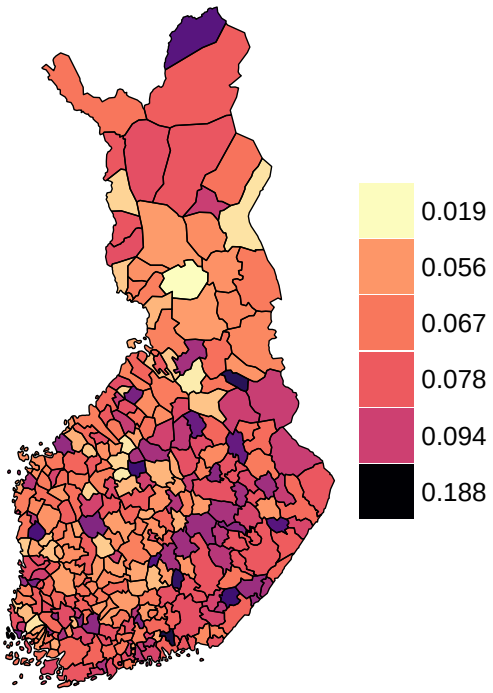

FIGURE 2: Average Interaction Probability in Municipalities

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 2007-2009 ($N = 191,614$ patients).

previous research in other settings and outside Finland (Zhang et al. 2011).

Figure 3 presents a more detailed characterization of the regional differences. We report the histograms of our quality of prescribing measure for urban/semi-urban and rural regions in the pre-adoption period. We find that, on average, the regional rate of interacting prescriptions was slightly higher in absolute terms in rural compared to urban regions. However, the cross-municipality variation was much larger in rural than in urban regions.[16] Considerable variation in the quality of prescribing in rural regions is a sign of fragmentation and of delivery systems characterized by incomplete information integration.

Table 1 reports the summary statistics on average and separately for patients in urban and rural regions in the pre-adoption period, using the prescription-level data. Panel A shows that 16 percent of warfarin patients were using interacting drugs (NSAIDs) on average. At the prescription

[16]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.

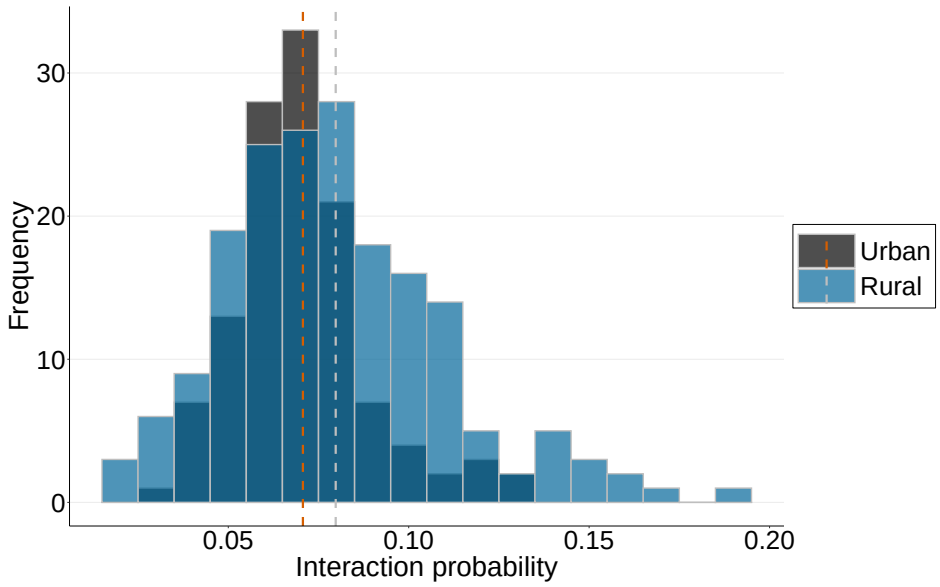

FIGURE 3: Average Interaction Probability in Urban and Rural Municipalities

Notes: The histograms in this figure plot 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 2007-2009. 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.

level, the probability of a warfarin-NSAID interaction was 7 percent on average. Moreover, the interaction probability is slightly higher in absolute terms in rural than in urban regions (8 and 7 percent, respectively), but both the relative difference (14 percent) and the corresponding standard deviations (27 and 26 percent) are notable.

Our findings on the fairly high rates of interacting prescriptions in Panel A are consistent with related research using Finnish data (Rikala et al. 2015). Revealing further evidence on coordination and information failures, we also find that interacting prescriptions predominantly originated from different prescribing physicians, instead of the same physician (nearly 70 percent of all cases).

Panel B shows warfarin and NSAID use per patient during the pre-adoption period (2007–2009). Warfarin use was much higher than that of NSAIDs on average, as the data are constructed using warfarin users. Moreover, there is only little difference in warfarin use, but there was some difference in NSAID use between patients in urban and rural regions.

The quality of prescribing and the cost of information acquisition (coordination) may depend on physician 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.

We call them generalists (non-specialists), similar to specialists of general medicine. Moreover, a licensed physician does not always have a Doctoral degree, unlike in the U.S., for example. The basic medical education in Finland lasts for a minimum of six years. Specialized physicians have a Doctoral degree with additional education that takes five or six years. Thus, specialized physicians have more formal medical education, better clinical expertise and the number of them is also more limited.

Panel C shows a striking regional heterogeneity in the supply of prescriptions by physician specialty: the share of prescriptions supplied by unspecialized physicians was 55 percent in rural regions and only 46 percent in urban regions. The lack of specialists in rural regions limits the provision of health care services, but potentially also the opportunities for unspecialized physicians to acquire up-to-date medical information and learn from specialists.

Panel C reveals the division of a patient's care provision between multiple physicians, which is an important driver of care fragmentation (Agha et al. 2019). We find that the probability of getting 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).[17]

Panel D shows information on additional patient variables. The share of patients with a hemorrhage (bleeding) diagnosis 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 3.4), being harmful, even lethal for older patients; warfarin users were typically elderly, approximately 70 years old on average and slightly older in rural than in urban regions. The mortality of warfarin users was also high, approximately 10 percent in the pre-adoption period (2007–2009).

Finally, Table 1 reveals that the number of physicians per municipality was substantially smaller in rural than in urban municipalities (35 versus 135). This implies that local physician networks are much narrower in rural than in urban regions, potentially limiting in-person interactions and knowledge spillovers between physicians.

[17] Workforce turnover may in part explain the division of care into separate tasks or patient appointments. 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 staffing gaps, and the doctor-patient relationship often ends with the termination of their fixed-term contracts.

TABLE 1: Summary Statistics for Pre-Adoption Period 2007–2009

	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
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 with a Hemorrhage diagnosis	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 2007-2009. 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 with a hemorrhage diagnosis" 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.

5 Econometric Approach

We use the staggered adoption of the nationwide e-prescribing system across municipalities and over four years to estimate the effects on our measure of the quality of prescribing for patient i in municipality m in period t, y_{imt} (Section 4). We estimate the effects on average and separately for each municipality group (urban or rural). Specifically, we estimate the following parametric event study specification, 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 $D_{\tau,mt}$ 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 the short run as the first four quarters after (Q0–Q3) the adoption of e-prescribing and the 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 (2018) 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 B 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 4 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 primary care, as opposed to specialized health care (Section 4.1). This observation is further highlighted in online Appendix Figure A5, which shows a higher take-up rate after adoption for patients who get their prescriptions from generalists (non-specialists or specialists in general medicine) than from internists. Overall, these stylized facts 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.

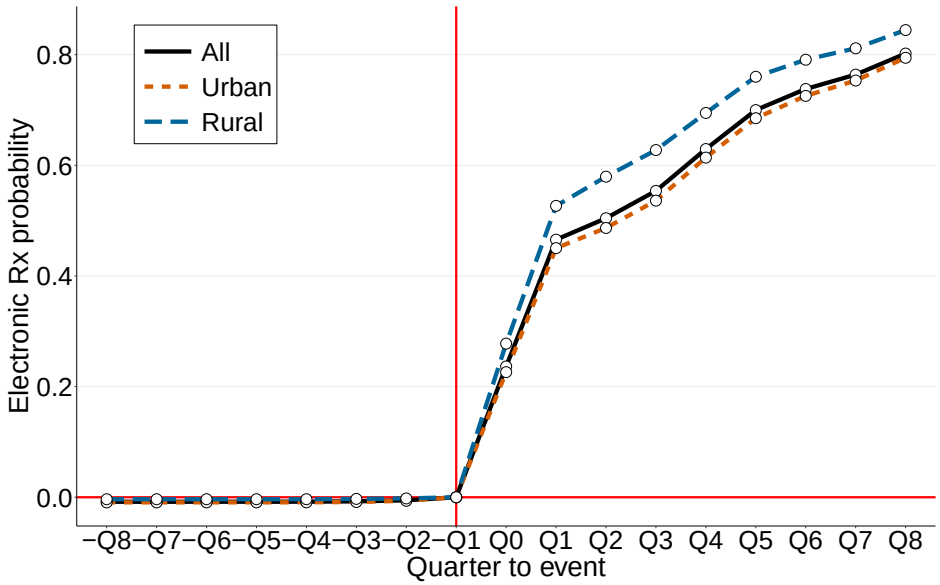

FIGURE 4: Take-up Rate of E-prescriptions, by Municipality Group

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.

6 RESULTS

6.1 QUALITY OF PRESCRIBING: HARMFUL DRUG COMBINATIONS

Average Effects.—We begin our analysis by presenting the main results from estimating the average effect of e-prescribing over all regions on the quality of prescribing, as measured by the probability of a warfarin-NSAID interaction. Figure 5 plots the δ_τ coefficients and their confidence intervals from estimating the event study specification in Equation (2), using the prescription-level data. The figure does not reveal clear pre-trends, supporting the key identification assumption of our empirical specification.

Panel A of Figure 5 shows that e-prescribing has a statistically insignificant effect on the probability of a warfarin-NSAID interaction on average. The corresponding DiD estimates from Equation (3) are also very close to zero and statistically insignificant 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 harmful drug combination, the estimated average effects are strikingly small albeit somewhat imprecisely estimated.

Regional Heterogeneity.—We analyze heterogeneity in the effects for urban/semi-urban and rural regions. Our regional heterogeneity analysis is motivated by the ample literature on urban-rural gaps in health care provision and the uneven distribution of health care resources such as the physician workforce (Skinner 2011; OECD 2017).[18] Similar to the average effects in Panel A of Figure 5, 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). In contrast, Panel C of the figure 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 (Table 2). The decrease is gradual, coinciding with the increasing take-up rate of e-prescribing technology over time.

Therefore, the benefits of e-prescribing for the quality of prescribing are much larger in rural than in urban regions. In rural regions, information acquisition and sharing could have been previously hampered not just by local information systems, but also by other regional factors related to, for example, a shortage of specialists and economies of agglomeration. In general, rural regions have a productivity disadvantage from lacking social interactions that promote the accumulation of knowledge and human capital in urban areas (Glaeser 2008). Also, the demographics of the patients treated may differ between urban and rural regions, which could affect physicians' information; column 2 of Table 2, however, shows the robustness of the results to controlling for patient fixed effects.[19]

One might have expected the benefits of information integration (e-prescribing) for the quality of prescribing and coordination to occur in urban regions also as patients there may more frequently switch providers or physicians, given the better access to health care services in urban than in rural regions. In contrast, we find no significant improvement in the quality of prescribing in urban regions, and observe that a patient's care provision is almost equally often divided between multiple physicians in the two municipality groups (Section 4.1). After presenting sensitivity and placebo analyses, we study further some of the potential mechanisms of e-prescribing such as improvements

[18]Our classification of urban 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 A6.

[19]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.

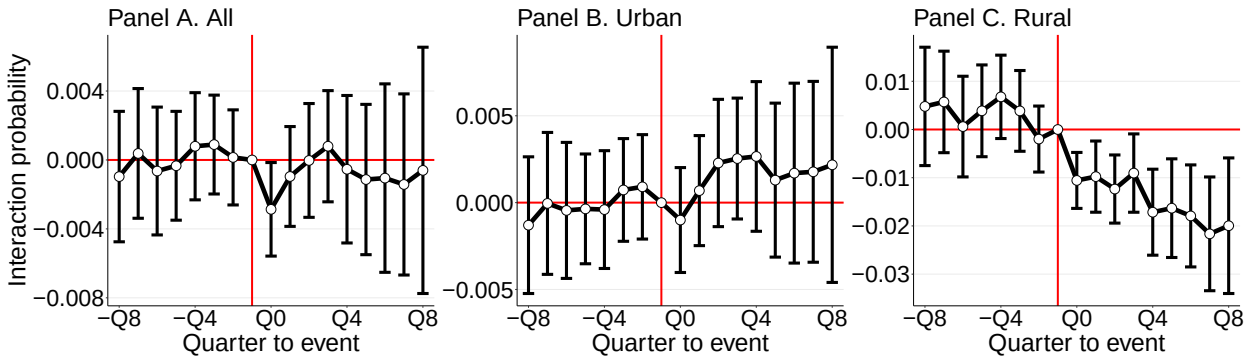

FIGURE 5: Probability of Warfarin-NSAID Interaction, by Municipality Group

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, age and age squared of a patient. 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.

in information and coordination.

Sensitivity Analyses.—To establish the robustness of our 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).[20] The point estimates and their standard errors remain remarkably similar across all these specifications. Figures A8 and A9 plot

[20]Mortality among warfarin patients is approximately 10 percent in both urban and rural regions (Section 4.1). 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 (with patient fixed effects) is an alternative approach to address this potential concern.

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 2007–2014 (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.

the results of these robustness checks in the event study framework.

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 A13 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 additionally 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 Figure A10. Second, we exclude all interactions that interact for less than 10 days (and over 100 days) in Panels A–C (D–F) of Figure A11.[21] Our baseline results are not sensitive to these changes in the model specification. In Figure A12 and Table A3 we confirm that our estimates are not sensitive to using patient-specific average prescribing intervals as an alternative proxy for prescription length.

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 et al. 2015), and they do not have known harmful interactions with warfarin, according to the medical literature (Orme et al. 1972). Therefore, e-prescribing should not reduce warfarin-benzodiazepine interactions (with a mean value of 0.224). As expected, Figure A14 shows no statistically significant reduction in these interactions, supporting the validity of our earlier findings.

7 Mechanisms and Additional Outcomes

Improvement in the Information Environment.—Next we provide suggestive evidence for some of the potential mechanisms driving the improvement in the quality of prescribing in rural regions, where we find a substantial reduction in the interaction probability. Our theoretical model high-

[21] See online Appendix Figure A4 for the density of interaction days.

lights the costs of information acquisition and coordination as determinants of poor quality of care. We therefore begin our analysis by assessing the role of physician information as well as changes in the treating physician.

We do not observe the cost of information acquisition (parameter λ of the model) directly in the data but we use proxies of physician expertise to approximate it: presumably, lack of expertise with warfarin patients increases λ. In terms of expertise, we consider the three most common types of medical specialties in our data: unspecialized, general medicine, and internal medicine for all interactions, and consider cross-physician vs. within-physician drug interactions (the coordination mechanism) separately. Compared to specialized physicians, unspecialized physicians have less medical education. Unspecialized physicians have less expertise in treating complex warfarin patients than internists, who are specialized in the diagnosis and treatment of internal diseases such as blood clots.[22] Moreover, because high-skilled workers and jobs (specialists/hospitals) are generally concentrated in urban regions, the typical generalist in a rural region may have less medical expertise or knowledge than a counterpart in an urban region.

Figure 6 presents the event study results for the three specialties in rural regions. Column 3 of online Appendix Table A4 shows the corresponding short- and long-run point estimates. Column 2 of the table shows that there are no statistically significant effects in urban regions despite the large of number of observations improving statistical power. In rural regions, the interaction probability decreases substantially for unspecialized physicians, who write a disproportionate amount of prescriptions in those regions (Panel A). 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). Interestingly, internists have the highest probability of writing an interacting prescription, most likely because of the complexity of their patient population. Based on these analyses, we conclude that the improvement in the quality of prescribing in rural regions is driven by unspecialized physicians. Lack of specialization and relevant information may have limited their ability to detect harmful drug combinations before e-prescribing.

Coordination and Information Integration Between Physicians.—E-prescribing substantially re-

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

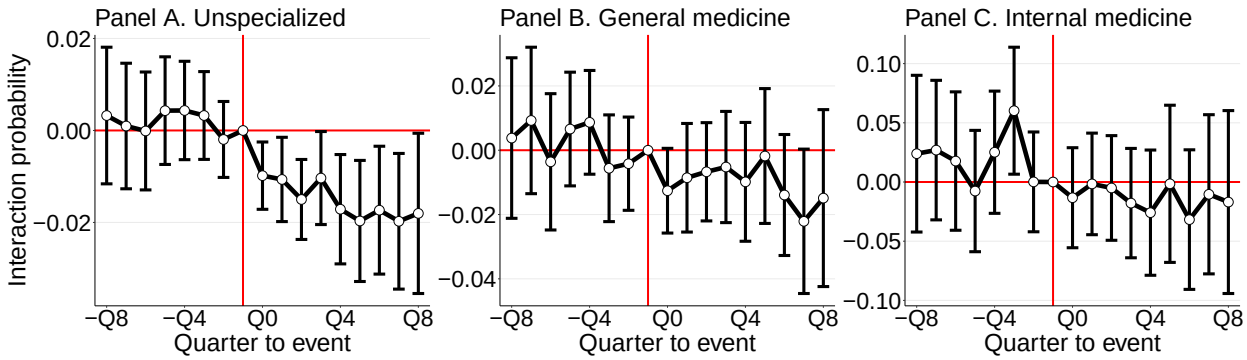

FIGURE 6: Probability of Warfarin-NSAID Interaction in Rural Municipalities, by Physician Speciality

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 5 for more information on the specification of the model.

duces information acquisition costs by improving a physician's information on the medication choices of the patient's previous physicians. Consequently, the quality of prescribing and coordination should improve. To test 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. Figure 7 plots the event study results in rural regions.[23] 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 7 shows that the overall reduction in the interaction probability is predominantly driven by interacting prescriptions from different physicians, rather than from the same physician. 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. This finding for rural regions suggests that e-prescribing provides critical information to physicians and improves the coordination of care. However, e-prescribing does not fully eliminate the cross-physician interactions.

Coordination and Information Integration Within Versus Between Physicians in Primary and Spe-

[23]Figure A7 shows the results by municipality type. Similar to our baseline estimates, we find little evidence of an improvement in the quality of prescribing and coordination in urban regions.

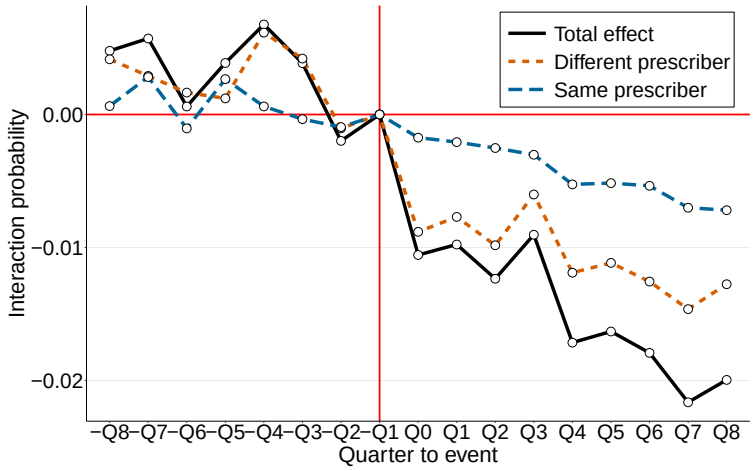

FIGURE 7: Probability of Warfarin-NSAID Interaction in Rural Municipalities, Different Versus Same Prescribing Physician

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 5 for more information on the specification of the model.

cialized Care.—A greater 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 there is a greater use of generalists as opposed to specialists in some regions (rural) than in others (urban), for example due to longer distances to hospitals (Section 4.1).

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 (e.g., general medicine), but with potential differences in, for example, location, waiting time, and idiosyncratic skills. Compared to cross-provider coordination, within-provider coordination may even be easier to improve with the help of information integration because of the similarity in physicians' training and expertise.

We analyze improvements in information flows and coordination as a result of e-prescribing within versus across physicians of primary and specialized care. As our data do not permit direct analyses of physicians' information flows within versus between primary care units and hospitals, we investigate interactions that stem from within versus between unspecialized and specialized

physicians. For this particular purpose and unlike in the analyses above, we include specialty of general medicine in our category of unspecialized physicians (generalists). Generalists and specialists are likely to work in separate units (primary care units and hospitals, respectively). Moreover, generalists are gatekeepers for specialists and hospital care. Online Appendix Figure A15 shows the results from the decomposition. The overall decrease in the point estimate is almost entirely driven by the decrease in interactions within unspecialized-unspecialized and specialized-specialized pairs. Taking all the findings together, the improvement in the quality of prescribing in rural regions seems to result from improved information flows and coordination within primary care, as opposed to between different providers of primary and specialized health care.

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 8 shows the results from this decomposition in rural municipalities. The decrease in interactions comes almost entirely from prescriptions filled in the same pharmacy. Thus, information integration between pharmacies does not drive our main results.

Prescription Drug Use, Change in the Composition of Patient Population, and Patient Health.— We analyze the effects on prescription drug use to gain a broader understanding of the underlying mechanisms of e-prescribing such as potential changes in the patient population. 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 Subsection B.1.

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) on average and in the two municipality groups: urban and rural. Overall, we find the extensive

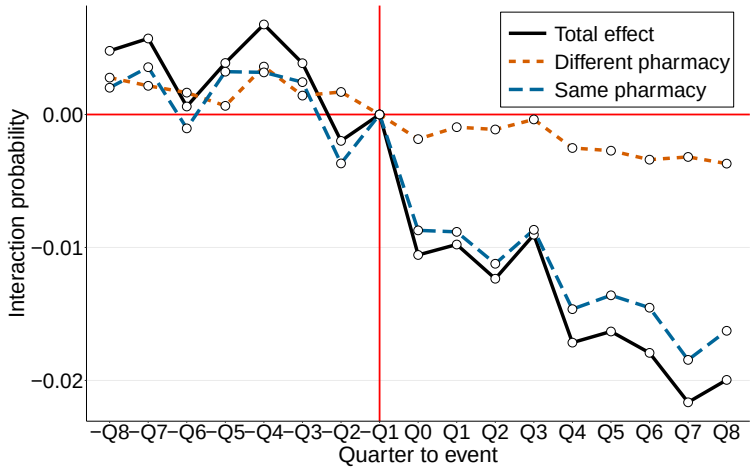

FIGURE 8: Probability of Warfarin-NSAID Interaction in Rural Municipalities, Different Versus Same Pharmacy

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 5 for more information on the specification of the model.

margin adjustments to be fairly small in both warfarin and NSAID use. We also confirm that there is only a small effect on the aggregate numbers of all and initial warfarin prescriptions at the municipality and quarter level, and find no apparent change in the composition of the patient population around the adoption of e-prescribing.[24]

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 while the size of NSAID prescriptions decreases after introduction of e-prescribing. We also show evidence that the decrease in the probability of a harmful interaction is not solely explained by the decrease in the length of NSAID prescriptions. In rural regions, e-prescribing still seems to improve physicians' practises so that prescribing NSAIDs to warfarin users can be more frequently avoided.

As a comprehensive analysis of various direct and indirect health effects is beyond the scope of our study, we focus on the most direct health outcome of the interaction of warfarin and NSAID:

[24]Theoretically, e-prescribing could change the composition of the patient population through extensive margin adjustments, posing a threat to the identification of the main effects. In this case, the coefficients of interest would partially reflect the change in the patient composition rather than the true main effects of the improved information environment on the interaction probability.

gastrointestinal bleeding. We find no evidence of a decrease in this diagnosis after e-prescribing, not even in rural regions. Hence, the direct health benefits of e-prescribing, as measured by diagnosis of bleeding, seem to be small.

8 Conclusions

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 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 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 across all regions of the country.

We find only little evidence that e-prescribing improves the quality of prescribing on average. This result is found despite the fact that we examine a nationwide system and focus on a well-established harmful drug combination. In the light of the widespread interest in urban-rural gaps in health care and the productivity disadvantage of rural regions in agglomeration economies (Glaeser 2008; Skinner 2011), we also evaluate the regional heterogeneity in the effects. We find no statistically significant effect on the quality of prescribing in urban regions. In contrast, the probability of co-prescribing warfarin with NSAIDs reduces by approximately 35 percent in rural regions. This substantial improvement in the quality of prescribing is driven by unspecialized physicians, who write a disproportionate share of prescriptions in rural regions (55 percent, in comparison to 46 percent in urban regions).

Our interpretation of these findings is that information frictions were higher in rural than in urban regions before e-prescribing. Regional variation in supply-side factors, such as the workforce, expertise and the size of local networks, may have in part caused regional differences in physicians' medical information. Variation in the demographic characteristics of patients may also play a role, but our results remain qualitatively similar to our main findings after we account for patient fixed effects.

Consistent with the idea that information integration improves care coordination (in rural re-

gions), we find that e-prescribing predominantly reduces the co-prescribing of harmful drug combinations by different physicians, rather than by the same physician. However, the resulting direct health benefits seem to be marginal.

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 are decentralized, with decision making allocated to separate agents or providers (e.g., by region or speciality). Although decentralization often improves 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 systems, much less attention has been paid to optimizing and integrating a patient's care provision. Helping physicians adhere to medical guidelines is of first-order importance. Our findings show that a nationwide policy of information integration can help by mitigating some of the coordination failures across different physicians, thereby enabling patient medication to be tracked efficiently and improving the quality of care.

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A Online Appendix

A.1 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

A.2 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 of correlation between the covariates and the timing of the adoption.

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

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

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

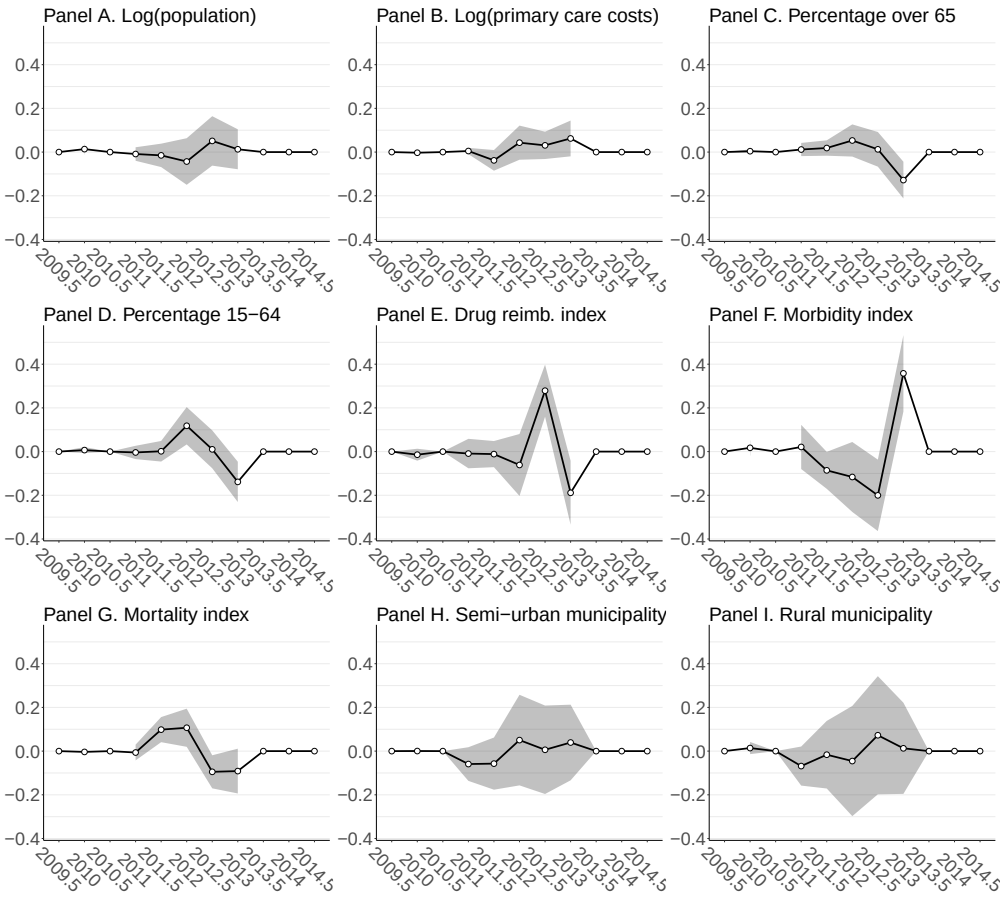

FIGURE A1: Adoption of E-Prescribing by Baseline Municipality Characteristics

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. 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.

A.3 Figures

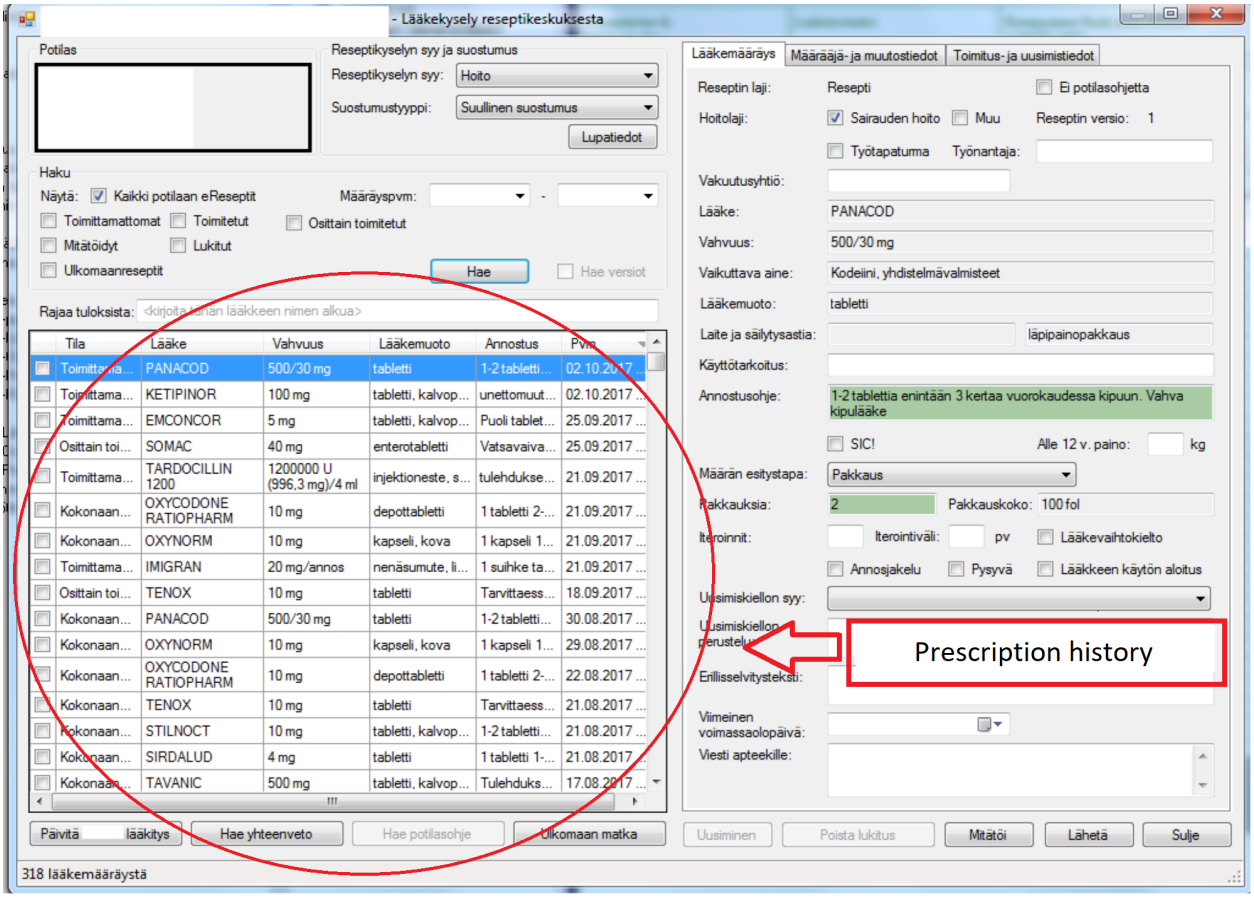

Figure A2: E-Prescribing Technology and Information Integration: Physician's View

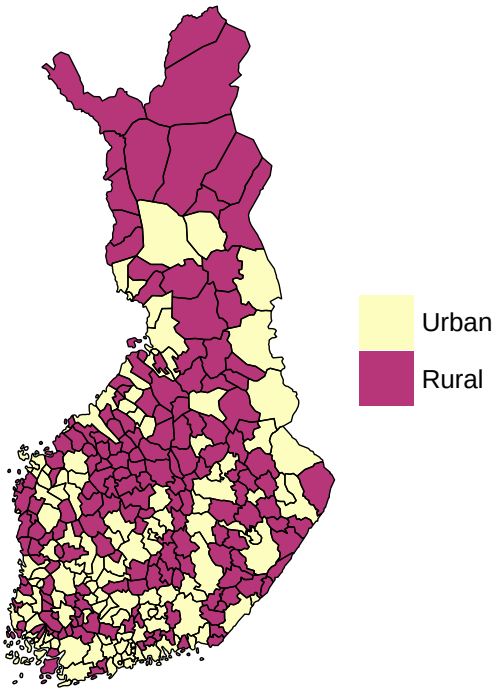

FIGURE A3: Regional Classification

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 including 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 lives 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 lives 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 6).

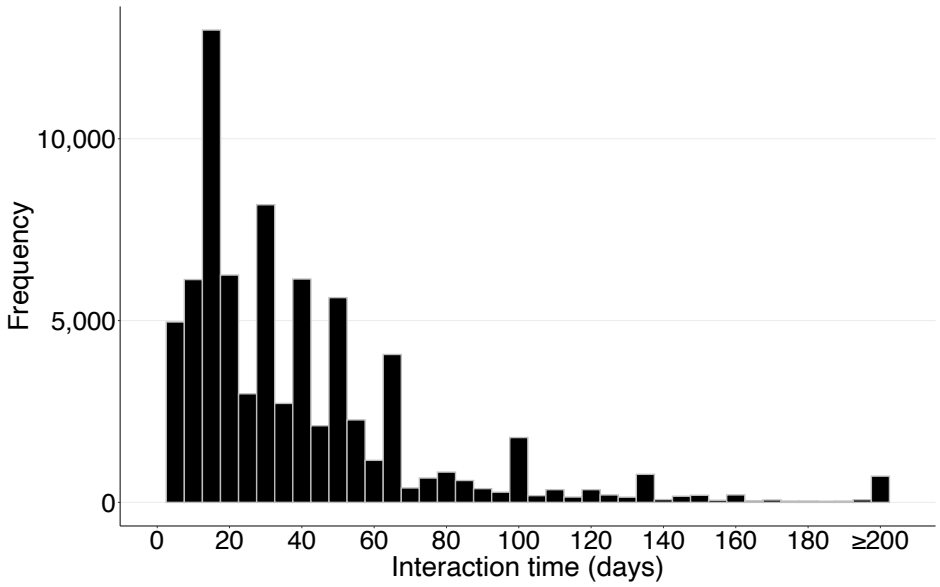

FIGURE A4: Duration of Warfarin-NSAID Interactions

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.

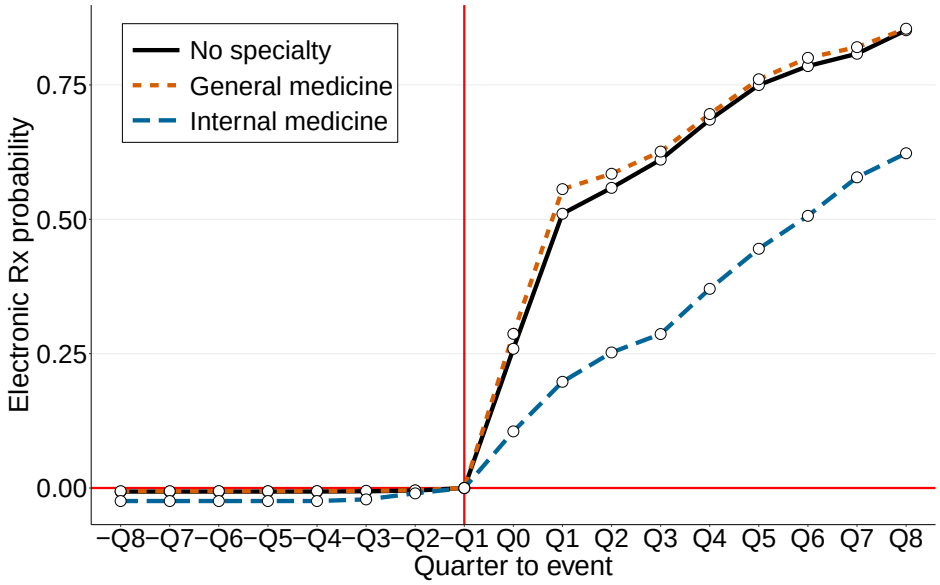

FIGURE A5: Take-up Rate of E-prescriptions, by Physician Speciality

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.

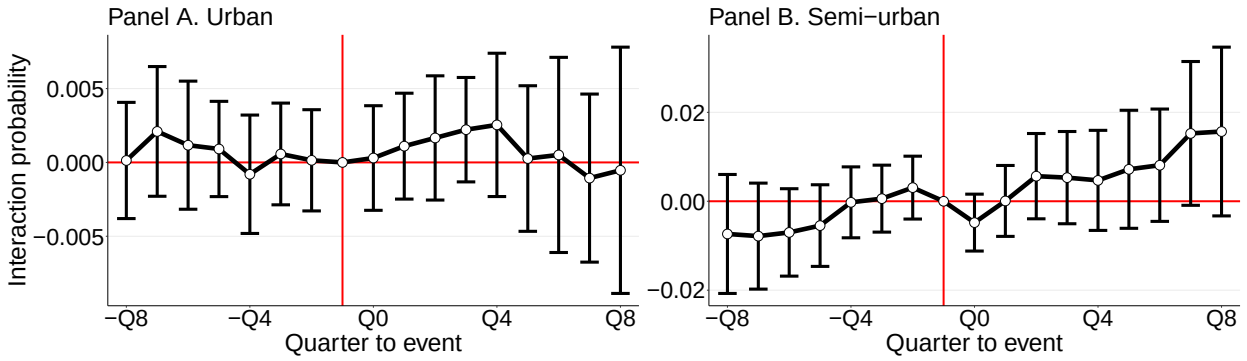

FIGURE A6: Probability of Warfarin-NSAID Interaction in Urban and Semi-Urban Municipalities

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.

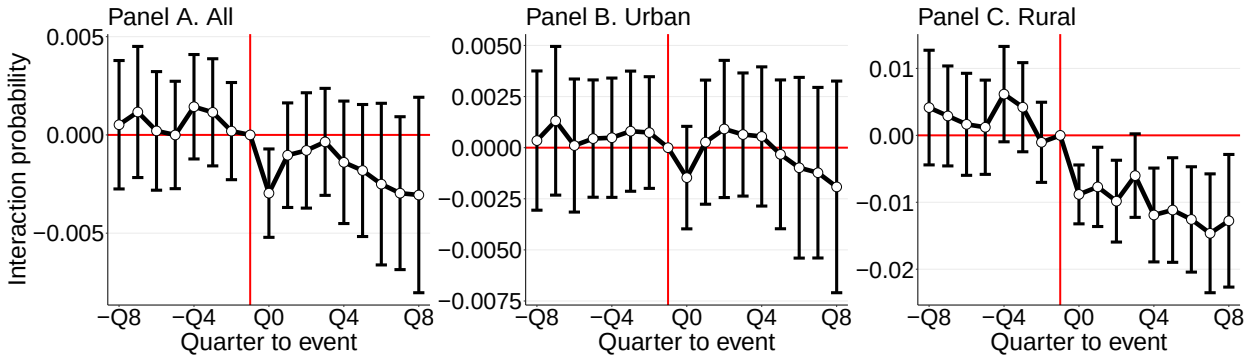

FIGURE A7: Probability of Warfarin-NSAID Interaction With Different Prescribing Physicians, by Municipality Group

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 and the interacting prescriptions are written by different physicians. 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. See Figure 5 for more information on the specification of the model.

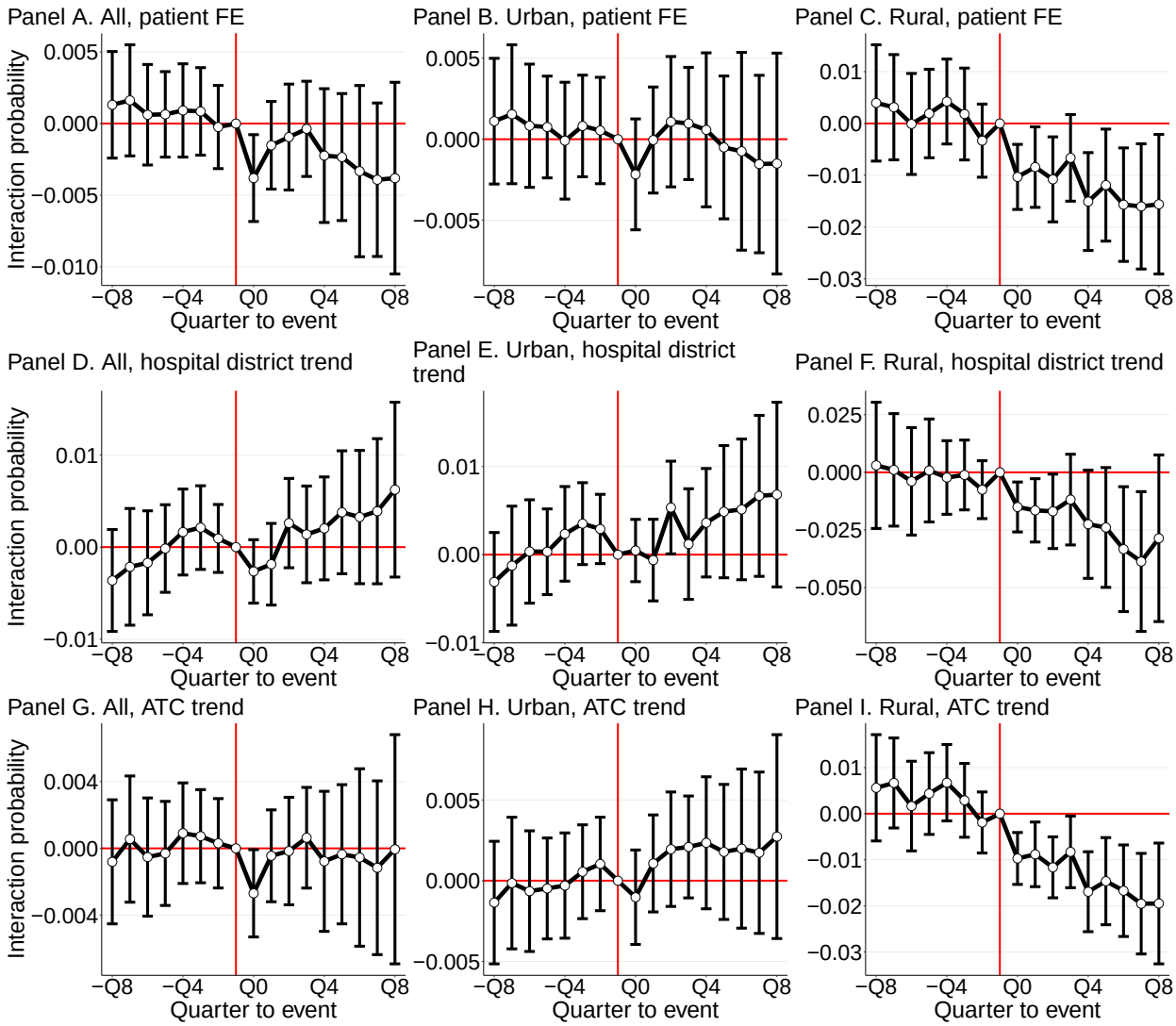

FIGURE A8: Probability of Interaction, Additional Robustness Checks to Baseline Results Part 1

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.

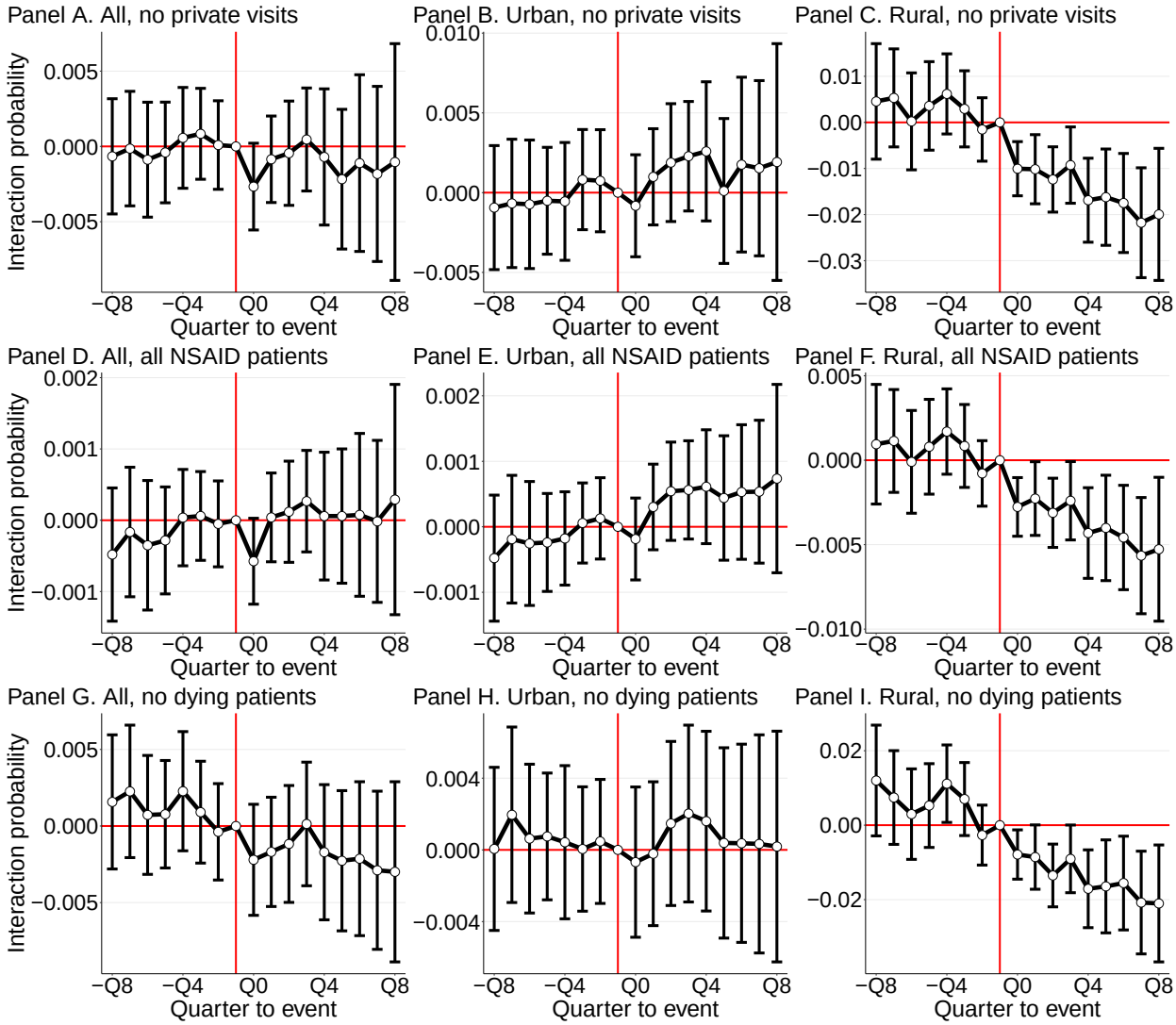

FIGURE A9: Probability of Interaction, Additional Robustness Checks to Baseline Results Part 2

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.

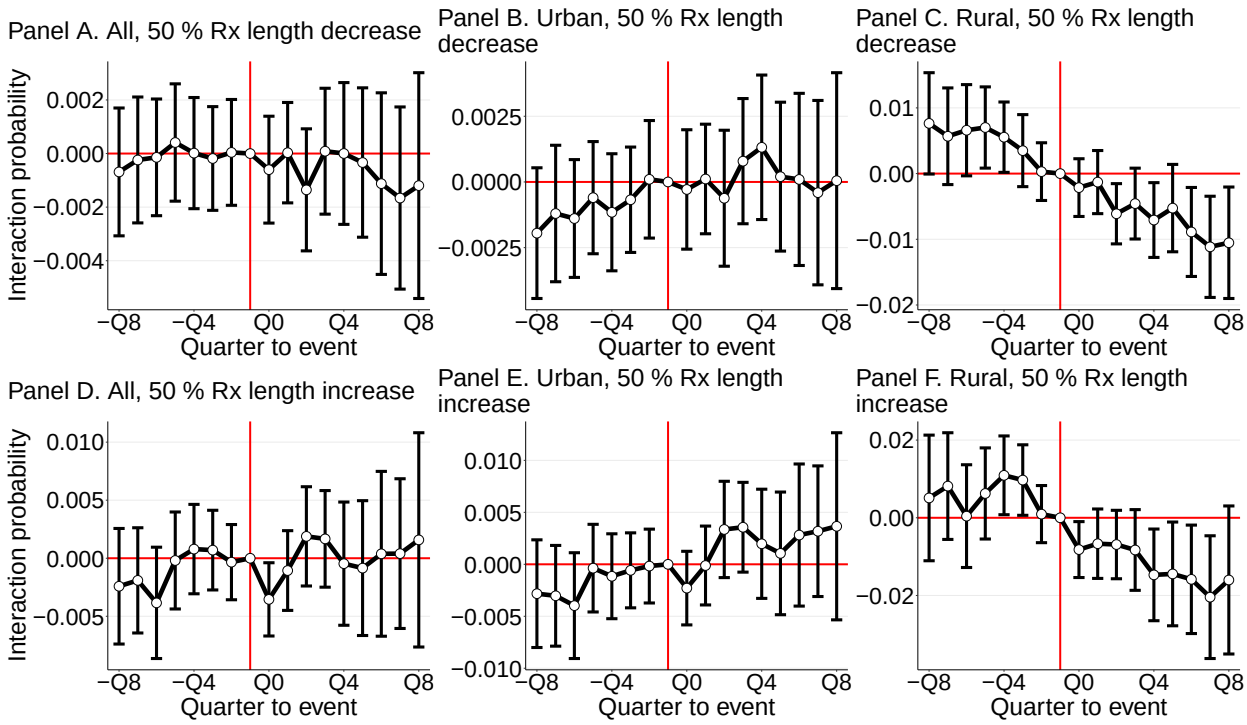

FIGURE A10: Sensitivity Test: Probability of Interaction, 50 Percent Reduction and Increase in Prescription Length

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.

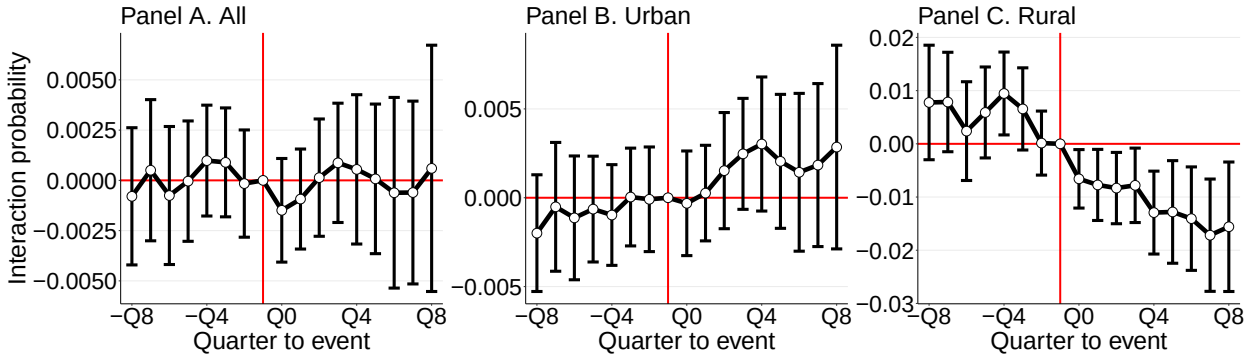

FIGURE A11: Sensitivity Test: Probability of Interaction, Interactions Under 10 Days and Over 100 Days Excluded

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.

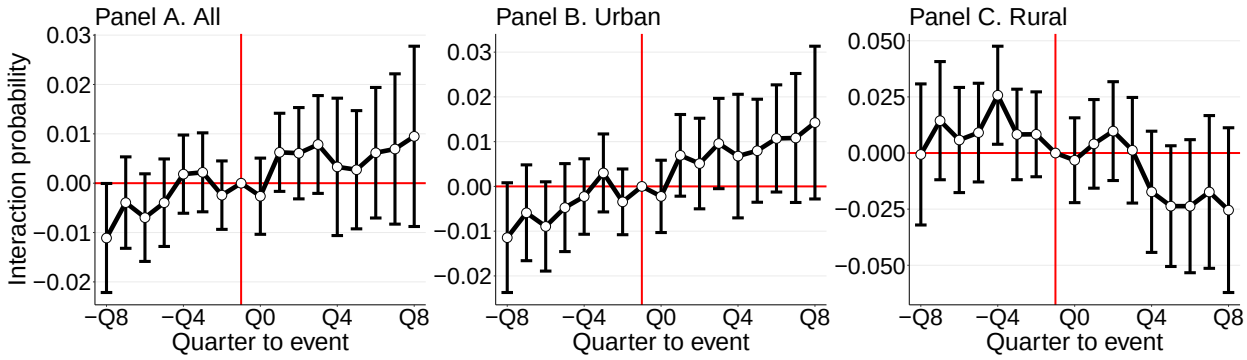

FIGURE A12: Probability of Warfarin-NSAID Interaction With Average Prescribing Intervals, by Municipality Group

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.

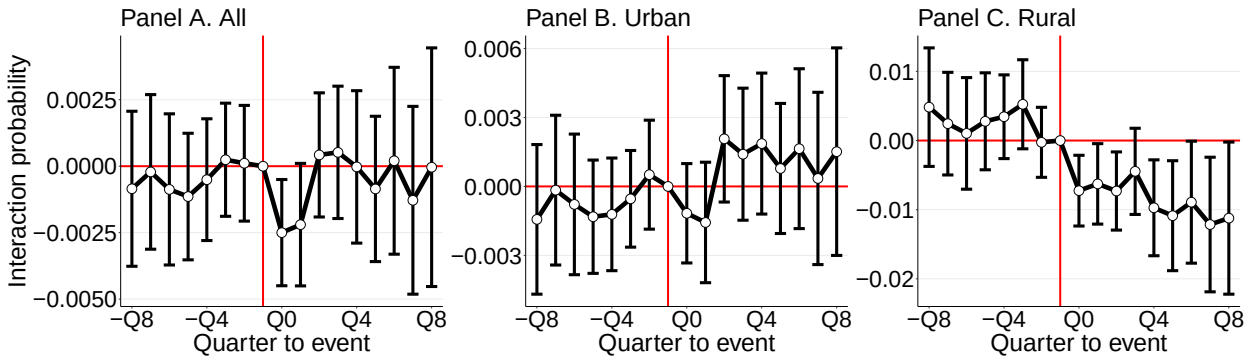

FIGURE A13: Probability of One-Way Warfarin-NSAID Interaction, By Municipality Group

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.

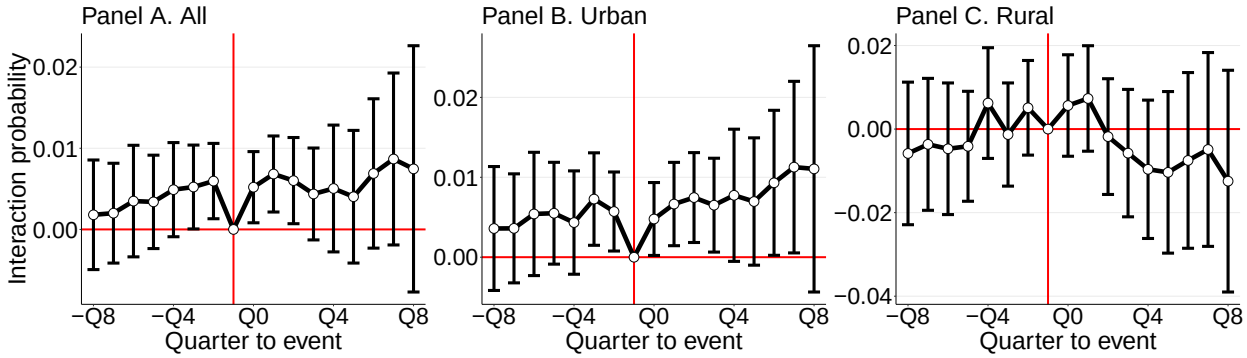

FIGURE A14: Placebo: Probability of Warfarin-Benzodiazepine Interaction, by Municipality Group

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 5 for more information on the specification of the model.

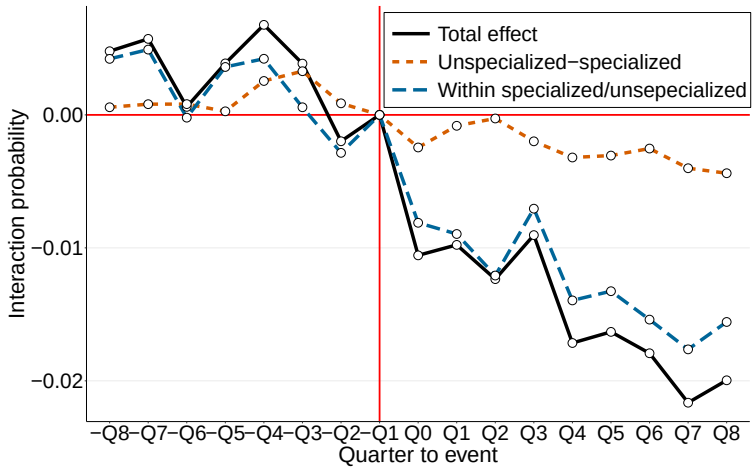

FIGURE A15: Probability of Warfarin-NSAID Interaction in Rural Municipalities, Different Versus Same Prescribing Physician

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 "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 between unspecialized-specialized physician pairs. In this figure, unspecialized physicians also include general medicine physicians. See Figure 5 for more information on the specification of the model.

A.4 Tables

Table A2: Prescription Shares by Physician Speciality for Pre-Adoption Period 2007–2009

	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 2007–2009.

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.

B Identification in the Early Versus Later Treated Municipalities

Goodman-Bacon (2018) 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 (2018) 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.[25] 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. Albeit 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 × DiD)	0.693×-0.064	0.686×0.054	0.698×-0.149
Later vs. Earlier (Weight × DiD)	0.307×-0.071	0.314×-0.019	0.302×-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.

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

B.1 Prescription Drug Use, Change in the Composition of Patient Population, and Health Outcome

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 3.2. 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 A16 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.[26] We interpret this decrease to be consistent with anticipation effects, in which physicians wrote 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 next periods right after 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.[27]

Figure A17 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 prescrip-

[26] 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.

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

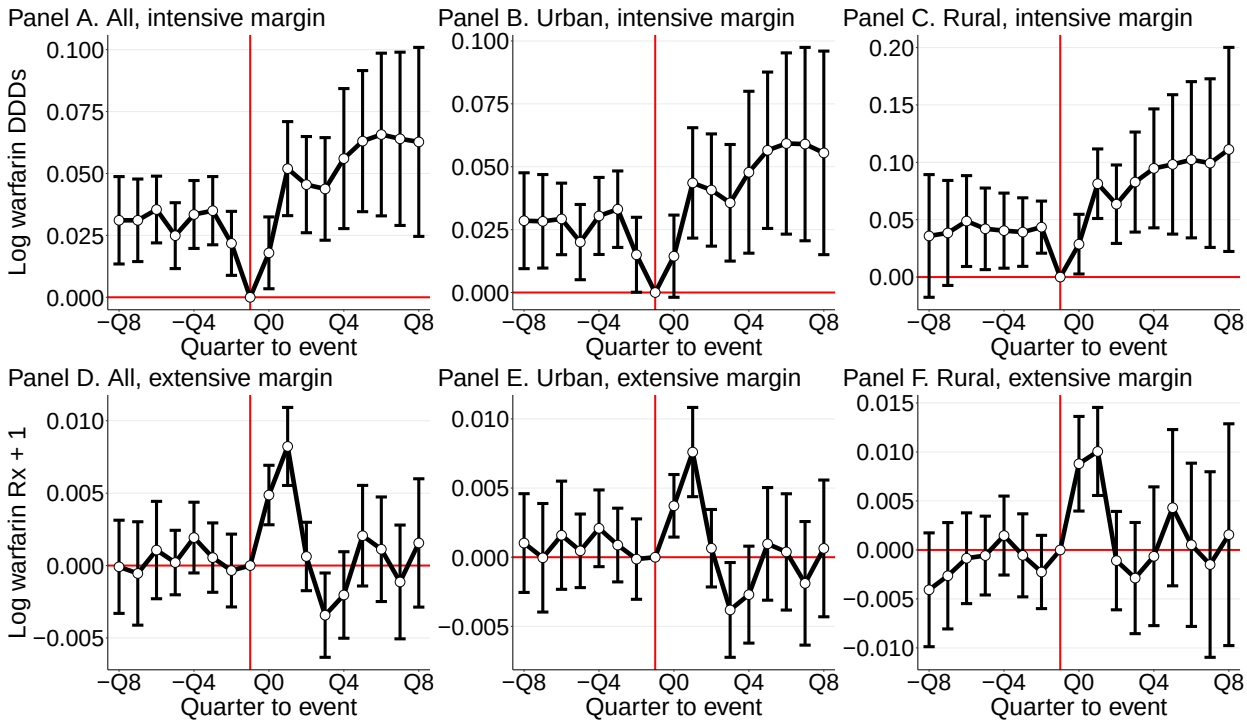

FIGURE A16: Intensive and Extensive Margins of Warfarin Prescriptions, by Municipality Group

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.

tions after e-prescribing, but they do not increase the quarterly number of NSAID prescriptions for warfarin patients.

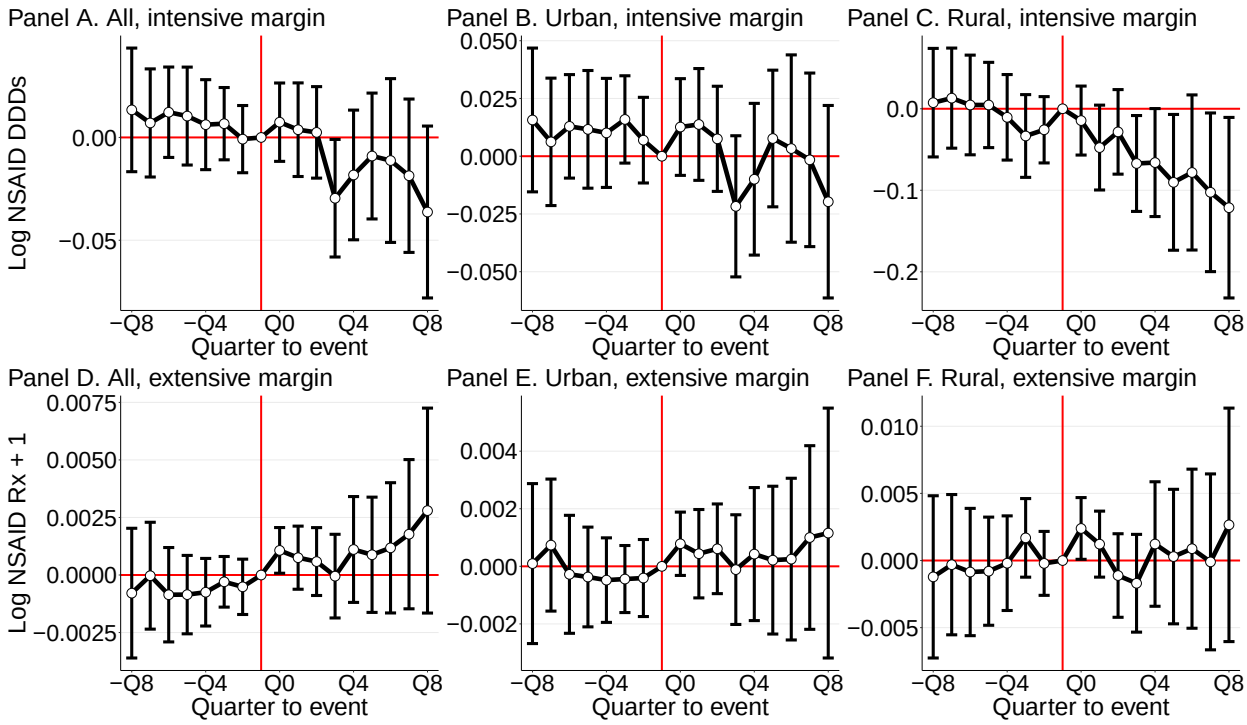

FIGURE A17: Intensive and Extensive Margins of NSAID Prescriptions, by Municipality Group

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 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	Urban	Rural
	(1)	(2)	(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 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	Urban	Rural
	(1)	(2)	(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 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.[28] Table A10 shows the effects separately 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. 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 after the adoption of e-prescribing.

[28] 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.

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 2009–2017 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 right before or during the year right 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 6).

Figure A18 plots the event study estimates for the number of interacting days of each interacting prescription. As the number of observations is quite small, the estimates are more imprecisely estimated, but show no clear evidence of a decrease in the outcome. Figure A19 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.

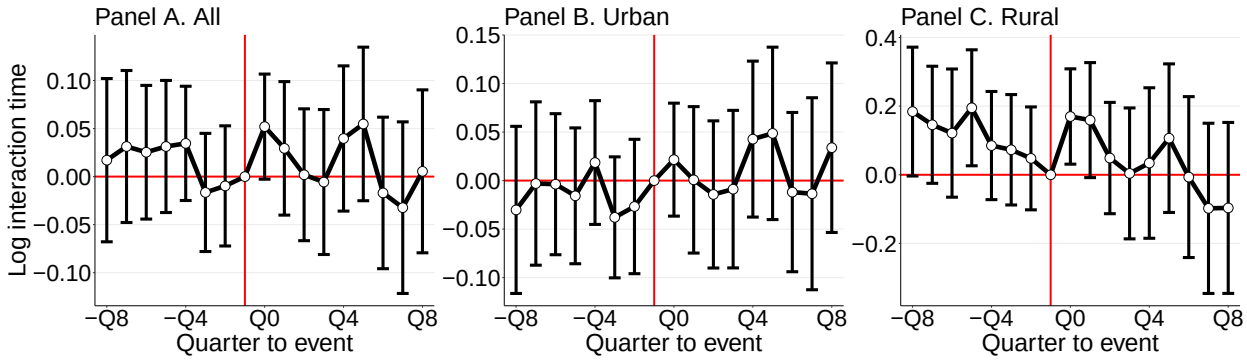

FIGURE A18: Duration of Warfarin-NSAID Interaction, by Municipality Group

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 5 for more information on the specification of the model.

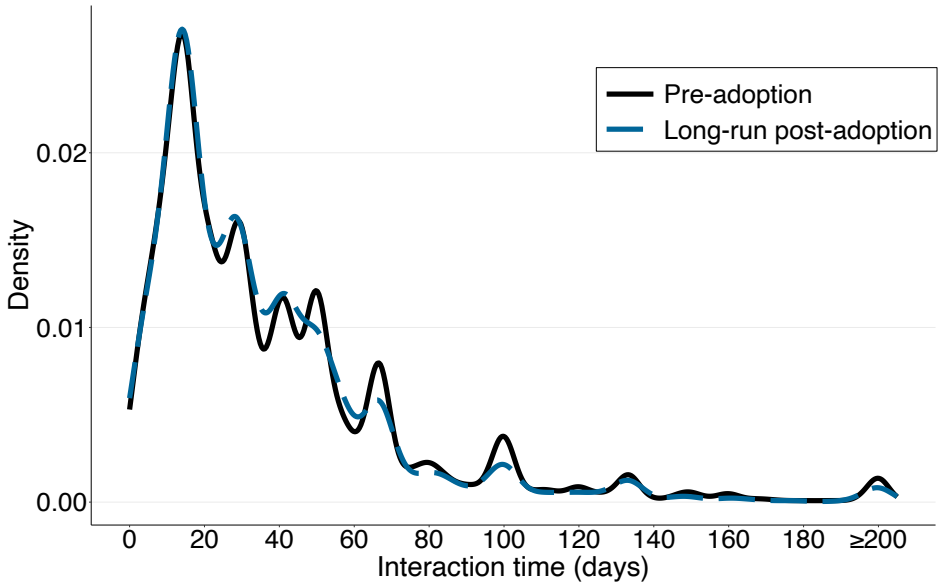

FIGURE A19: Density of Duration of Warfarin-NSAID Interaction

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 equal to one unit of daily dose.

Health Outcome: Bleeding Diagnosis.—The main focus of this paper is to study the effects of information integration on the coordination and quality of prescribing. However, it is also of interest to investigate whether improvements in coordination translated into improvements in patient health. As a comprehensive analysis of various direct and indirect health effects is out of the scope of our paper, we focus 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). We examine whether the e-prescribing-induced decrease in drug interactions affected the probability of a gastrointestinal hemorrhage diagnosis in specialized health care among warfarin patients, using aggregated patient-quarter-level data.

We find no evidence of a decrease in this diagnosis after e-prescribing, not even in rural regions (Figure A20 and Table A12). This finding can be explained by two main factors. First, warfarin use by itself can cause excessive bleeding, especially when used in higher doses. Moreover, we found that e-prescribing (digitization or 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.[29] Second, our health outcome is rare in the patient population (mean quarterly probability of 0.2 percent). Also, not all warfarin patients have an interacting prescription in a given quarter. Thus, the bleeding outcome may not be sensitive enough to capture the full (long-term) positive effects of the decreased warfarin-NSAID interaction risk on latent health.

[29]Table A12 shows positive and statistically significant effects. Diagnosing bleeding complications is complex (Kim et al. 2014), and e-prescribing (improved information on a patient's prescriptions) may also improve diagnoses, thereby increasing their prevalence.

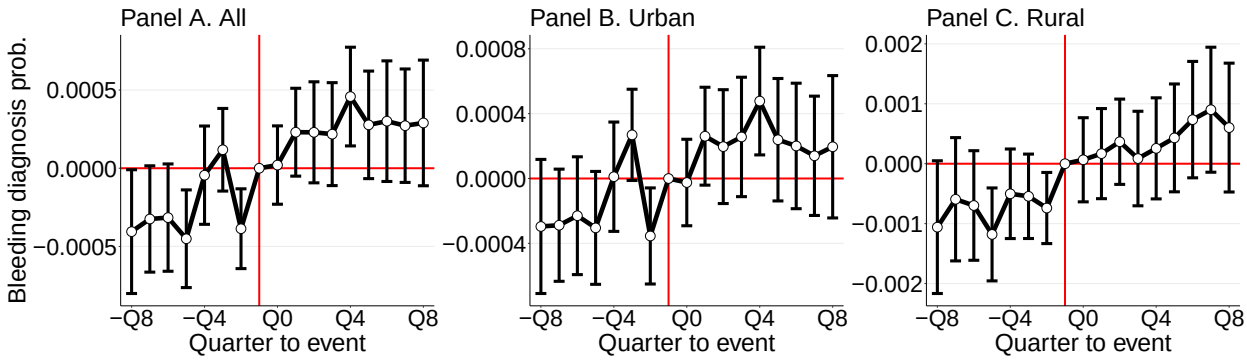

FIGURE A20: Probability of Hemorrhage (Bleeding) Diagnosis, by Municipality Group

Notes: These figures plot the coefficient estimates from an event study framework using patient-quarter-level balanced data on warfarin patients. The outcome is a dummy variable that equals one if the patient has a gastrointestinal hemorrhage diagnosis in specialized health care 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 Gastrointestinal Bleeding Diagnosis

	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. The outcome is a dummy variable that equals one if the patient has a gastrointestinal hemorrhage diagnosis in specialized health care in 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.