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Discussion Paper no. 2021-07

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Keywords: cost-control, healthcare, practice style, difference-in-differences

JEL Classification: I12, I18, O33, H75

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ABN 12 377 614 012 CRICOS Provider Number: 00008C

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A hard look at "soft" cost-control measures in healthcare organizations: Evidence from preferred drug policies in Germany*

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November 8, 2021

Abstract

Cost-control interventions that target physicians' clinical discretion are common in healthcare, but evidence on their efficacy is scarce; in particular for "soft" policies when liability is unlikely to be enforced by the regulator. We study the effectiveness of preferred drug policies (minimum prescription quotas of specific "preferred" drugs) in altering physicians' practice styles within the high volume drug class of HMG-CoA-reductase inhibitors (statins) in the German statutory health insurance system. Using a nationally representative panel of ambulatory care physicians between 2011 and 2014, we exploit the decentralized institutional setting to estimate physician responses to variation in preferred drug policies across regional physician associations over time in a generalized difference-in-differences design. Results show that although the cost-control mechanism increases average policy adherence, this effect is mainly driven by physicians with initially high use rates of preferred drugs. We argue that such misdirection may limit the policy's usefulness in reducing inappropriate practice variation among healthcare providers.

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*We like to thank Leila Agha, Diane Alexander, Lina Maria Ellegård, Thomas Mayrhofer, Mujaheed Shaikh and Gerrit Stahn for comments. We thank Coleen Carey for sharing efficacy data of statins, Friederike Arndt, Kai Miele and Paul Drecker for research assistance, and Galina Besstremyannaya and seminar, and three reviewers and conference participants at the Academy of Management Annual Conference 2021, ASHECON and IHEA conferences 2021, German Economic Association - Health Economics Division Annual Meeting, the Essen Health Economics Seminar Series, University of Duisburg-Essen, the Applied Microeconomics Seminar Series at Lund University, Sweden, and at the Centre for Health Economics Seminar Series, Monash University, Australia for providing helpful comments. Funding by the German Federal Ministry of Education and Research (BMBF grant no. 01 EH1602A) is gratefully acknowledged.

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1 Introduction

Organizations rely on a wide range of experts (physicians, teachers, software programmers) to accomplish their objectives. The efficacy of the methods these experts apply to perform their tasks are therefore vital for organizational performance, but their personal objectives may differ from those of the organization. As the work routines of experts are often unscripted, unobserved, or unsupervised, it is often difficult to verify the quality of the goods provided (Raelin, 2011). This may generate incentives among experts to "game" the system and deviate from the organization's goals (Dulleck and Kerschbamer, 2006; Iizuka, 2007). To solve such principal-agency problems, organizations rely on different types of control mechanisms to ensure that experts adhere to their standards (Cardinal *et al.*, 2017).

In this paper, we study the efficacy of cost-control policies in healthcare where the experts' (physicians) and the organization's (the healthcare regulator) objectives are often misaligned. Our analysis is motivated by that, in particular in single-payer healthcare systems, physicians rarely need to take into account the full treatment cost when consulting, treating and following up patients. In contrast, the regulator must assess the cost-efficiency of treatments to prevent unsustainable growth in expenditures in often financially strained healthcare systems. Cost-containment policies directed at healthcare providers vary in their degree of "softness", or in their relative strictness in monitoring and evaluating compliance and mandated actions taken to penalize non-compliers.[1] While "soft" cost-control measures are less costly to maintain, they are also unlikely to be effective if experts know and act on the relatively low costs of non-adherence. This raises important queries regarding the effectiveness of such policies in adjusting the behavior of healthcare providers.

Our specific context concerns ambulatory care physicians' responses to changes in a soft cost-control instrument, preferred drug policies (PDPs), with respect to

[1] We generally refer to soft cost-control measures as policies that are characterized by lax monitoring and relatively small penalties for non-adherence.

lipid-lowering drugs (statins) to treat coronary heart disease within the German statutory health insurance system. PDPs are classed as a top-down regulatory instrument where the responsible authority aims to improve the quality of healthcare amid pressures to control spending (Elshaug *et al.*, 2017). Specifically, PDPs set prescription targets for "preferred" drugs among a predefined set of equivalent drugs with respect to their safety-efficacy-cost (SEC) profiles. PDPs are similar to the US state-level Medicaid Preferred Drug Lists and prior authorization mechanisms of non-preferred drugs (Goldman *et al.*, 2007; Dillender, 2018; Buchmueller *et al.*, 2020), which restrict physicians to only prescribe certain designated drugs. However, while preferred drug lists and prior-authorization schemes are demand-focused, PDPs set limits on healthcare providers' aggregate prescription shares.

Our analysis focuses on PDPs for HMG-CoA-reductase inhibitors (statins). Statins are high-volume pharmaceuticals for preventing Coronary Heart Disease (CHD) by targeting reductions in low-density lipoprotein (LDL) cholesterol. In 2014, 3.2 million prescriptions (corresponding to 313 million daily doses at a cost of 193 Million EUR) were dispensed within the Germany statutory health insurance system (Klose and Schwabe, 2015). We focus our analysis around two major recent events in the statin drug market; the entry of generic versions of atorvastatin in 2012, a blockbuster drug that remained a non-preferred drug throughout the analysis time period; and a change in the PDP in 2013 that added a newly preferred drug, pravastatin, to the preferred list of statins. Based on predictions from a physician agency model, we conjecture that both events should lead to a relatively higher use share of preferred drugs if the PDP is effective in altering physician practice.

To test our hypotheses, we use a nationally representative panel of 928 German ambulatory care physicians between 2011 and 2014 (accounting for more than 2.6 million statin prescriptions) to compare physicians practicing in regional healthcare markets with and without an active PDP in a generalized difference-in-differences (DD) framework. As the PDPs are decentralized to a set of autonomous regional physician associations (PAs), and thereby generate policy variation across both

time and space, the German institutional setting provides us with a credible and intuitive identification strategy to study physicians' responses to the existence of a PDP. Moreover, a serious threat to identification of the causal effect of the PDP on physicians' prescribing behavior is potential endogeneity of the insurance design, as, for example, prior authorization and other regulations often differ across insurance plans. This is not a problem in our case as co-payments and other regulatory measures are independent of the PDPs we study.

Our estimation results show that physicians in PAs with active PDPs increased their relative use shares of preferred drugs with on average ten percent compared to physicians residing in PAs without active PDPs. These results are mainly driven by a more moderate diffusion of the never-preferred atorvastatin after its generic entry in 2012. Comparing drug-specific use rates, we find that a lower rate of substitution from the always-preferred drug, simvastatin, to atorvastatin among physicians who were subject to a PDP was the main mediator of this effect. In contrast, the impact of adding the newly-preferred drug, pravastatin, to the list of preferred drugs did not change its use rate to any important extent. We argue that this was likely due to the fact that pravastatin is inferior to simvastatin with respect to its SEC profile and therefore did not constitute an attractive replacement option for the market-dominating latter drug.

In order to study effect heterogeneity in more detail, we implement a synthetic control (SC) method in which we match individual physicians in PAs with active PDPs to similar synthetic physicians from areas without PDPs based on their pre-policy statin prescription rates. Matching physicians this way have the additional benefit of reducing compositional differences of physicians across areas and therefore improves chances that the crucial assumption of parallel trends for the identification of the DD estimator is valid. Reassuringly, the SC estimates are comparable with our DD results. However, when we use the distribution of pre-policy preferred drug levels to produce quantile regression estimates across physicians, we find that only physicians at the top of the distribution increase their relative adherence to

the PDP. This important result suggests that our main effect is mainly driven by physicians who were already already complying to the policy, and that the PDP is largely unable to change the behavior of non-complying physicians.

Our conceptual framework provides a potential explanation for the PDPs inability to change the behavior of non-compliers. Specifically, the agency model suggests the existence of a trade-off in the choice of prescribing a non-preferred drug based on the expected costs of non-compliance, modified by the physician's degree of risk aversion towards non-compliance, and the expected patient net benefits, modified by the physician's level of altruism. When expected costs of non-adherence are low, heterogeneity in physicians' behavioral attributes will determine the distribution of policy effects: physicians with low risk aversion (or high altruism) will be less responsive to the policy than physicians with high risk aversion (low altruism). Since the former group are more likely to be non-adhering initially, our model predicts that a soft cost-control measure, such as the PDP, will only change the behavior of already complying physicians and thereby render the policy ineffective.

Finally, given that adherence to the PDP may incur additional costs from re-matching treatments to patients, we characterize physicians' adjustment by means of three mechanisms: retention, switching and initiation of preferred and non-preferred drugs. This is important to understand how cost-control policies targeting prescribers affect health and wellbeing of patients. Our analysis suggests that physicians restricted by a PDP mainly retained relatively more patients with the always-preferred drug (simvastatin) and, to a lesser extent, initiated fewer never-preferred drugs (atorvastatin) on new patients. Switching treatments for existing patients as a means to comply with the PDP did not occur to any important extent.

Our study adds insights to the theoretical and empirical literature on the economics of expert decision-making when experts provide credence goods (Dulleck and Kerschbamer, 2006) and organizations seeking control over experts (Cardinal *et al.*, 2017). The theoretical predictions from the physician agency framework and its link to our empirical approach provide an intuitive and generalizable approach

to test the causal effects of a control mechanism on expert practice which can deliver useful policy guidance on expected adherence. Our paper also contributes to a growing body of literature examining the role of clinical guidelines, audit and feedback, and other control mechanisms to influence physician practice style (Currie and MacLeod, 2020) and technology adoption (Escarce, 1996; Baker and Phibbs, 2002). While much of the preceding literature has characterized physician practice and its implications for health and healthcare delivery for the average physician, we develop a method to investigate how and which physicians will respond under response heterogeneity. Given heterogeneity in policy adherence, the predictions from the physician agency framework and the empirical results that support these predictions provide important insights on how to effectively target non-adhering practitioners.

The paper proceeds as follows. Section 2 reviews some of the earlier literature on policies to control physician clinical practice. Section 3 provides a summary of the institutional features of the German healthcare system, specifics of PDPs, and the clinical context of lipid-lowering drugs. Section 4 introduces a conceptual model based on a physician agency model to generate predictions regarding the expected effects of a PDP with respect to the choice between prescribing preferred or non-preferred drugs. Section 5 describes our empirical framework including the data and sample and empirical modeling to estimate causal effects of the PDP. Section 6 reports results from estimation of our models on how the PDP impacts preferred prescription shares of physicians. Section 7 concludes.

2 Background and literature review

The existing evidence of the effectiveness of control mechanisms in healthcare is inconclusive. While some studies have evaluated the direct effects on cost and utilization outcomes, analysis of mediating factors, such as provider adherence to protocols, has remained scant. A meta-analysis on the effects of audit and feedback mechanisms suggested that professional practice did increase compliance with a de-

sired practice by about 1–4 percent on average, with generally smaller effects for individuals who already demonstrated high levels of compliance (Ivers *et al.*, 2012). In contrast, a randomized-controlled experiment among prescribing physicians in the US Medicare Part D program did not highlight any important changes in practice patterns when overprescribing providers were notified about their inappropriate practice behavior (Sacarny *et al.*, 2016). One study that examined the effectiveness of drug formularies and PDPs to change physician prescribing behavior found that prescription rates were on average lower in cases where a preferred drug regimen was suggested (Goldman *et al.*, 2007). An important field of application of cost-control mechanisms is prevention of high-risk prescriptions, such as opioids for pain relief, where prior authorization schemes have been shown to reduce inappropriate prescriptions to patients (Dillender, 2018).

Evidence on the effectiveness of prescription drug monitoring programs to control excessive prescribing of opioids demonstrated that low volume physicians tend to discontinue treatments when faced with a monitoring system (Buchmueller *et al.*, 2020). In the context of the US Medicare Part D, Ketcham and Epstein (2008) identified that PDPs impose additional processing cost of $1110 per year in statins and antihypertensive drugs alone. The frequently cited use of information technology to improve transparency about preferred drugs has proven to magnify the effects of such policies, but not to alter physician treatment choices overall (Gehlbach *et al.*, 1984; Epstein and Ketcham, 2014). Overall, administrative burden to manage prescription drugs is estimated to be substantial (Howell *et al.*, 2021).

In the context of implementation of control mechanisms, an important question is who responds to the policy. Heterogeneity in physician practice has been shown to be considerable, not the least in the context of adoption of new technology (Miraldo *et al.*, 2019). Physician practice styles reflect the observation that physicians in the same healthcare market and for similar patients prescribe different treatments (Grytten and Sørensen, 2003; Epstein and Nicholson, 2009; Molitor, 2018). Practice styles have been generally characterized by four major categories: how quickly and

aggressively physicians make their decisions (Finkelstein *et al.*, 2016; Avdic *et al.*, 2019; Cutler *et al.*, 2019); the types and levels of treatments physicians tend to rely on (Janakiraman *et al.*, 2008; Frank and Zeckhauser, 2007); the degree to which physicians' own practices represent other physicians' practices within groups (Berndt *et al.*, 2015); and the degree to which physicians follow current standards of care, such as evidence-based guidelines (Depalo *et al.*, 2019; Currie and MacLeod, 2020). Physicians vary extensively both across and along these categories, which often have impacts on clinical quality and patients' health outcomes (Currie *et al.*, 2016; Skinner and Staiger, 2015; Avdic *et al.*, 2019).

Physicians frequently choose options that are not considered first best, especially if there is a lack of consensus, and substantial proportions of health care spending for critical treatments, such as end-of-life care and heart attacks, relate to physician beliefs unsupported by clinical evidence (Cutler *et al.*, 2019). Nevertheless, Depalo *et al.* (2019) suggest that shocks in scientific evidence diffuse quickly across physicians and patients, leading to adaptations in practices as physicians gradually update their beliefs about treatments. Currie and MacLeod (2020) demonstrate that violating clinical guidelines is associated with worse outcomes, regardless of the physician's skill and dispersion. In Germany, compliance with cost-control measures such as budgets or PDPs is generally high (Fischer *et al.*, 2018; Blankart and Arndt, 2020).

3 Institutional setting

3.1 The German healthcare system

Germany has a universal multi-payer health care system paid for by a combination of statutory health insurance (SHI) and private health insurance (PHI) (Blümel *et al.*, 2020). Participation in the SHI is automatic through enrollment in one of the currently around 100 public non-profit sickness funds. Each fund has a common rate for all members and paid for with joint employer-employee contributions.

Membership in a sickness fund offers two mandatory health benefits, co-financed by the employer and the employee: health and long-term care insurance. The German SHI system is, generally speaking, regulated by the Federal Joint Committee (*Gemeinsamer Bundesausschuss*), an organization that reflects the self-governance structure of the SHI system consisting of members from the national associations of sickness funds and health care providers. It is authorized by the Federal Ministry of Health to make binding regulations and routine decisions regarding healthcare provision in the country, including determining the services to be covered by sickness funds, quality measures for providers and regulation of local ambulatory care capacity.

While enrolling in the SHI is compulsory for the majority of the German population, certain groups, including civil servants, self-employed, freelancers and high-income earners, may opt out of SHI to join a PHI (Blümel *et al.*, 2020). In particular, individuals with taxable earnings above the respective annual income threshold, *(Versicherungspflichtgrenze)* amounting to EUR 64,350 in 2021, are allowed to opt out of the SHI. In 2016, 87 percent of the German population were enrolled in SHI plans, 11 percent were enrolled in PHI plans and about two percent were uninsured (RKI, 2015). Insurance premiums vary between the two systems. In the SHI, premiums are set by the Federal Law and are based on a fixed set of covered services as described in the German Social Law (14.6 percent since 2011 of which half is covered by the employer). In contrast, PHI premiums are based on individual contractual agreements between the insurance company and the client which outline the set of covered services and the percentage of coverage, adjusted for the person's health risk and age of entry into the private system.

Individuals in both systems have free choice among general practitioners (GPs) and specialists. Registration with a family physician is not required and GPs have no formal gate keeping function. In the SHI system, GPs and specialists are generally reimbursed on a fee-for-service (FFS) basis according to a uniform fee schedule that is negotiated between sickness funds and regional associations of physicians

(*Kassenärztlichen Vereinigungen*, or PAs). For private patients, GPs and specialists are also paid on a FFS basis, but private tariffs are usually higher than the tariffs in the SHI fee schedule. Inpatient care is paid per admission through a system of Diagnosis Related Groups (DRGs), which are revised annually and cover all services and all physician costs. Many drugs, both patented and generic, are placed into groups with a reference price serving as a maximum level for reimbursement, unless an added medical benefit can be demonstrated. For new drugs with added benefit, the National Association of Statutory Health Insurance Funds (*GKV Spitzenverband*) negotiates a reimbursement price, based on the manufacturer's price, that is applied to all patients. In addition to the reference price system, drug rebates may be negotiated between individual sickness funds and pharmaceutical manufacturers.

Out-of-pocket spending accounted for 13.5 percent of total health spending in 2017, and most individual spending went to nursing homes, pharmaceuticals, and medical aids. Co-payments or payments for services not included in the SHI benefit package are paid directly to the provider. Bundled payments are uncommon in primary care. In the PHI system, patients pay up front and submit claims to the insurance company for reimbursement subject to the cost-sharing arrangement in place. All prescription medicines are covered by the SHI. When filling prescriptions, SHI patients face small co-payments between zero and ten euros per prescription depending on the price of the drug, the reference price and whether rebate contracts that are negotiated between the pharmaceutical manufacturer and the sickness funds of SHI are in place. Co-payments and rebates are set independently of any PDPs in place.

3.2 Preferred drug target policies

In Germany, PDPs are used as a cost-containment tool for high-volume drug classes in which several therapeutically equivalent substances are available. Within a drug class, one or several drugs are designated as preferred drugs according to the Social Code Book (§84 SGB V 1988). PAs may set target levels by defining a quota of

the preferred drugs to be prescribed by physicians. PDPs were first introduced in December 2005, based on an initiative of the governing bodies of the SHI, the pharmaceutical industry and medical associations. Drug classes were selected from an annual prescription drug report that lists pharmaceuticals with high total spending (Schwabe, 2006).

The assessments of preferred drugs are based on scientific evidence, practical experience and daily therapy costs. Preferred drug quotas that set the standard rate at which preferred drugs should be used may be defined by a minimum or a maximum reference level. Minimum reference levels aim to foster that the most cost-efficient substance is used, which is the case for PDPs in high volume drugs. Maximum reference levels aim to avoid ineffective or harmful options, for example in the case of opioids.

The set of preferred and non-preferred drugs, the levels of the quota and enforcement mechanisms in case of non-compliance vary over time and across the 17 PAs. The PAs are organized regionally and directly correspond to the regional borders in 15 of the 16 Federal states (*Bundesländer*) of Germany, while the state of North Rhine-Westphalia is divided in two regions (North Rhine and Westphalia-Lippe). Each year, based on national recommendations and negotiations between the National Association of Statutory Health Insurance Physicians (*Kassenärztliche Bundesvereinigung*) and the regional PAs, the range of drug classes that are monitored, the set of preferred drugs and the reference quotas that constitute the PDPs are negotiated regionally. Generally, PDPs are set such that physicians of the targeted PA converge towards the highest achieved share of the preferred drug among all PAs to meet nationally negotiated targets. The decision is then implemented in PA-level prescription statutes (*Arzneimittelvereinbarungen*). Using information technology, physicians can call up statistics to determine their compliance with PDPs and compare their own performance to physicians in the PA, which is reported at regular basis (Blümel *et al.*, 2020).[2]

[2]At the time of our empirical investigation, physicians only had limited options for instant reports about their compliance with PDPs and other cost-control measures.

When deviating from the preferred drug regimens, physicians indirectly face a risk of having to pay a recourse claim. Each quarter, a random draw of about ten percent of all physicians are selected for audit across a set of cost-control measures. For most PAs, prescription budgetary review is the first instance. Drug budget reviews investigate whether a physician's expenditures exceeded a pre-defined drug budget, with exemptions for very severe or special patient profiles (Fischer *et al.*, 2018). If the physician is found to have exceeded their quarterly budget, a recourse claim may be filed requiring the physician to repay some of their current earnings. However, compliance with PDPs generally exempts physicians from the recourse claim, or lowers it in cases where exemptions are not available. While evidence on the number of physicians held liable for exceeding their drug budgets is limited, some figures suggest that one to two percent of physicians annually pay recourse claims of on average EUR 25,000 (Korzilius, 2015, 2011).

In seven of the 17 PAs, there is a direct link between preferred drugs policies and the recourse claim physicians face from cost-control measures. In North Rhine, physicians are exempt from budgetary review if they fully comply to PDPs. In other PAs, compliance with the preferred drug-regimen reduces the recourse risk (Baden-Württemberg, Brandenburg, Saarland, Saxony, Saxony-Anhalt, Westphalia-Lippe). In all other PAs, compliance with preferred drug targets does not inherit a consequence in terms of a recourse risk, either because PAs have completely abolished that type of policy (Bavaria) or because PDPs are used as guidance only to consult physicians without any financial consequences (Berlin, Bremen, Hamburg, Hesse, Lower Saxony, Schleswig-Holstein).

3.3 HMG-CoA-reductase inhibitors

Our analysis focuses on PDPs for HMG-CoA-reductase inhibitors (statins). These are pharmaceuticals to treat Coronary Heart Disease (CHD) and target lowering of low-density lipoprotein (LDL) cholesterol and to prevent cardiovascular events. The primary target of statins is to lower high cholesterol as these are associated with

arterial hypertension, Type 2 Diabetes Mellitus and smoking (Naci *et al.*, 2013). In Germany in 2014, 3.2 million prescriptions that correspond to 313 million daily doses and 193 Million EUR in net cost were dispensed in statutory health insurance (Klose and Schwabe, 2015). About five million patients are served daily with statin prescriptions. Growth rates in doses dispensed amounted to 5-6 percent per annum.

Figure 1 provides information on the efficacy and safety profiles of the different statins in our sample and costs per dose. Within the statin drug class, multiple treatment options are available for which clinical data have suggested that the three agents simvastatin (brand name: Zocor), pravastatin (brand names: Mevalotin (Germany), Pravachol (US)) and atorvastatin (brand names: Sortis (Germany), Lipitor (US)) are most the effective to lower LDL cholesterol given their safety profiles. Lovastatin (brand names: Mevinacor, Mevacor) was the first statin to be approved by the US Food and Drug Administration in 1987. Simvastatin and pravastatin were both introduced in 1991 and are still considered superior in terms of safety and patient tolerability. Pravastatin is in addition considered to reduce the risk of diabetes by 30 percent. Fluvastatin (originally marketed as Locol in Germany and as Lescol, Canef or Vastin in the US) was introduced as additional option in 1993, however not showing any additional benefit over the existing options. From the launch of atorvastatin (brand name: Lipitor) in 1996, it quickly became a blockbuster drug (Jackevicius *et al.*, 2012). Atorvastatin proved to reduce LDL levels even stronger than the previous options and was capable to reduce the risk of atherosclerosis, although it has a poorer tolerability and safety profile than simvastatin and pitavastatin (see Naci *et al.* (2013) and Figure A.1).[3]

[Figure 1 about here]

In terms of clinical guidelines, physicians are recommended to use statins as a first line treatment for patients with coronary heart disease. Switching and lowering

[3]Rosuvastatin (brand names: Crestor, Ezallor) and pitavastatin (brand names Livazo, Livalo) became available in the first decade of the 2000s showing additional treatment dimensions such as reduction in the risk of venous thromboelism and desired increases in high-density lipoprotein levels, but without proving superior in terms of tolerability and safety.

of the dosage strength was recommended in case of adverse events without making mention to any specific preferred statin (BÄK/KBV/AWMF, 2013). International guidelines from 2011 suggest choosing statins that can provide the specific reduction in LDL level required for the patient, accounting for side effect profiles (Reiner *et al.*, 2011). More recent guideline editions also classify the potential in LDL reduction by the dosage strength used in addition to the type of statin.[4]

Statins were included in the 12 drug classes initially introduced as preferred drugs in Germany (Schwabe, 2006). Among the three main statins considered, simvastatin is always preferred, pravastatin was added as a newly preferred drug in 2013 in selected PAs while atorvastatin largely remained a non-preferred drug throughout the analysis period. Prescribing atorvastatin was highly discouraged prior to generic versions became available in early 2012. Given internal reference prices, patients had to pay the difference in cost between the reference price and the brand name version of atorvastatin. When generic atorvastatin became available in the German market, lowering costs to levels similar to simvastatin and pravastatin, atorvastatin was added as preferred drug by only one PA (North Rhine). The exact reasons for why other PAs decided against expanding the preferred drug regimen with atorvastatin are unknown, but potential explanations could relate to its inferior safety and tolerability profile, that clinical guidelines recommended prescribing drugs matching the needed LDL reduction to avoid overtreatment, or as implicit guidance to physicians to maintain patients on existing preferred drugs.

4 Conceptual framework

4.1 Physician agency model

To set the stage for our empirical investigation, we consider a generic physician agency model to describe a physician's choice between using preferred and non-

[4]However, this evidence and the respective recommendations to differentiate by active ingredient and strength were not part of guidelines during the time frame of our empirical investigation. See https://www.leitlinien.de/themen/khk/5-auflage/ for current German clinical guidelines on coronary heart disease.

preferred drugs (Ellis and McGuire, 1986; Chandra *et al.*, 2011). Other studies have applied the principal-agency framework to model how physicians maximize utility accounting for patient benefit and own utility derived from decision-making (see, e.g., Epstein and Ketcham, 2014; Depalo *et al.*, 2019). In the generic model, the physician acts as an imperfect agent for the patient by maximizing own welfare through the choice between two different treatments. In our specific context, we assume at the outset that each patient has been correctly diagnosed as being at high risk of cardiovascular disease and that primary prevention using cholesterol-lowering drugs is the appropriate clinical modality. Thus, we do not directly relate to research that focuses on variations in clinical practice styles when clinical guidelines are non-existent or unclear (see, e.g., Currie *et al.*, 2016; Molitor, 2018; Avdic *et al.*, 2019). Instead, we focus on the case where the choice of treatment is defined by whether the physician prescribes a preferred or a non-preferred drug as defined by the healthcare organization. In our empirical context, the distinction between preferred and non-preferred drugs in the statin drug class that we focus on is mainly based on their SEC profiles (see Figure 1 and Figure A.1).

Formally, the physician's choice between prescribing a preferred and a non-preferred drug is defined by the equations

$$\begin{aligned} \text{Preferred drugs:} \quad & W_j(1) = \beta_j B_1(\sigma_i) + V(F_1) + \varepsilon_{j1} \\ \text{Non-preferred drugs:} \quad & W_j(2) = \beta_j B_2(\sigma_i) + V(F_2) - \delta_j \lambda_j + \varepsilon_{j2}, \end{aligned} \tag{1}$$

where $W_j(k)$ is physician j's net welfare from prescribing drug $k = \{1, 2\}$. $B_k(\sigma_i)$ is the expected treatment benefit for a patient of type i, which is scaled by the physician's relative altruism $\beta_j \in [0, 1]$ where $\beta_j = 1$ indicates a perfectly altruistic physician. We define patient benefit as including the drug's (out-of-pocket) price, efficacy and safety profile as discussed above. $V(F_k)$ is the physician's net profit from treating the patient with service fee equal to F_k. λ_j is defined as the cost of prescribing a non-preferred drug, our main variable of interest in this paper, which we discuss in detail below. Consequently, $\delta_j > 0$, measuring the incremental change

in physician j's welfare from prescribing non-preferred statins, or their risk aversion to policy non-compliance, is the main parameter of interest in our empirical analysis. Finally, ε_{jk} are other, potentially unobserved, factors that influence a physician's treatment decision (e.g., idiosyncratic preferences, malpractice litigation risk and drug-specific promotions).

We model λ_j as the monetary risk of a recourse claim, R, from non-compliance to the PDP. Non-compliance occurs when a physician j's preferred drug use rate, q_j, is below the mandated quota, q'; $q_j < q'$.[5] Formally, we define λ_j by the relation

$$\lambda_j = \begin{cases} R & \text{if } \; q_j < q' \\ 0 & \text{if } \; q_j \geq q'. \end{cases} \tag{2}$$

We observe policy variation across two margins; the *intensive* margin, pertaining to a change in the *level* of the PDP quota, and the *extensive* margin, pertaining to a change in the *number* of preferred drugs. While the former is simply a change in q', the latter is more complicated to model as a physician's compliance to the policy may change without their active involvement.[6,7] This means that we need to be careful when defining compliance to avoid interpreting spurious results as causal effects of policy changes on physicians' prescribing behavior. We handle this by defining time-invariant definitions of physician compliance described below.

Given the model, represented by Equations (1)-(2), a representative physician is assumed to maximize welfare by choosing their optimal mix of preferred and

[5] In practice, R is a function of several variables: the probability of being drawn for budgetary review, the basic recourse claim penalty, and the degree of non-compliance ($\bar{q}_j = q' - q_j$) which is positively related the total recourse claim. Due to lack of reliable data on these parameters, we refrain from modeling these factors in detail. We return to the implications of this data limitation when discussing the results below.

[6] In particular, if a physician prescribe a large share of a non-preferred drug which subsequently becomes a preferred drug, this will appear as if the physician strongly reacted to the policy even without any change in drug-specific use rates.

[7] While physician responses to changes in the PDP quota are conceptually interesting to study, we do not specifically consider this in our empirical analysis because the observed variation in quotas across PAs and over time is negligible.

non-preferred drugs according to

$$\arg\max_{k\in K} W_K(k) = \beta B_k(\sigma) + V(F_k) - \delta\lambda_k + \varepsilon_k. \tag{3}$$

For a forward-looking physician, the decision rule to maximize the condition in Equation (3) is to always choose the option yielding positive net benefits, $NB(k) > 0$ where, e.g.,

$$NB(1) = W(1) - W(2) = \underbrace{(\varepsilon_1 - \varepsilon_2)}_{\text{Preferences}} + \beta \underbrace{[B_1(\sigma) - B_2(\sigma)]}_{\text{Patient benefit}} + \underbrace{[V(F_1) - V(F_2)]}_{\text{Physician fee}} + \delta\lambda_2. \tag{4}$$

Introducing patient type and physician heterogeneity and taking expectations over i, we obtain physician j's expected optimal use rate of preferred drugs,

$$\begin{aligned}\Pr(y_j = 1) &= \mathbb{E}\left[NB_j(1) > 0\right] \\ &= \mathbb{E}\left[\mathbb{1}\left\{\alpha_j + \beta_j \mathbb{E}_i\left[B_1(\sigma_i) - B_2(\sigma_i)\right] + V(F_1) - V(F_2) + \delta_j\lambda_{j2} > 0\right\}\right],\end{aligned} \tag{5}$$

where $y_j = \{0, 1\}$ is equal to one if physician j prescribes a preferred drug and zero otherwise, $\mathbb{E}_i[\cdot]$ is the expected net patient benefit averaged over physician j's distribution of patient types, and $\alpha_j = \varepsilon_1 - \varepsilon_2$. In particular, assuming that the physician's preferences and service fees are the same for both drug types, the equilibrium condition can be written

$$\frac{\beta_j}{\delta_j}\Delta\bar{B}_j = -\lambda_{j2}, \tag{6}$$

where $\Delta\bar{B}_j = \mathbb{E}_i\left[B_1(\sigma_i) - B_2(\sigma_i)\right]$ is physician j's expected net patient benefits from choosing the preferred drug conditional on their patient mix. A physician will trade off the expected net patient benefit and the cost of non-adherence of preferred and non-preferred drugs, modified by the ratio between two discount factors: the physician's level of (risk) aversion to PDP non-compliance, measured by δ_j, and

level of altruism, measured by β_j.

To see how this condition can be informative about the adherence of physicians in a context with an active PDP, first assume that all physicians discounts costs and benefits equally (i.e., $\beta_j = \delta_j,\ \forall j \in J$). Equation (6) then imply that each physician will prescribe the preferred drug as long as the expected net patient benefits of doing so exceeds the expected costs from non-adherence to the PDP. In this case, variation in PDP compliance across physicians will exclusively be derived from variation in their practice environments: patient case-mix and costs associated with non-adherence to the PDP (e.g., level of monitoring and recourse claim). If we instead allow for physician heterogeneity in response to variation in patient benefits and costs of PDP non-adherence (i.e., $\beta_j \neq \delta_j,\ \forall j \in J$), we obtain an interesting result: whenever a physician values patient benefits over policy adherence, either via a high altruism factor or low aversion for PDP non-compliance (i.e., $\beta_j/\delta_j > 1$), expected costs of non-compliance must increase more than patient benefits in order to increase policy adherence. Similarly, the reverse case, where policy compliance is valued higher than patient benefits, apply for physicians with low altruism or high risk aversion.

The physician agency model predicts that the efficacy of cost-control policies that target physicians' clinical practice style depends on the relative strength of the punitive measures taken to increase adherence to the policy. As noted in the footnote to Equation (2), the cost of PDP non-compliance in Germany is a function of the probability of being drawn for budgetary review and the size of the recourse claim penalty. If monitoring is lax and the recourse claim is negligible, the PDP policy is considered a soft cost-control measure as the expected monetary costs of non-adherence will be low. In such cases, Equation (6) suggests that physician risk aversion (or altruism) must compensate for the low costs of non-compliance and that the distribution of the behavioral parameters is crucial in determining overall physician response to the policy. In particular, heterogeneity in risk attitudes of physicians imply that the PDP will mainly change the behavior of already complying

physicians (with high aversion), while non-complying physicians (with low aversion) will remain unresponsive.

4.2 Identification of policy effects

Complete structural estimation of Equation (5) is not feasible since we do not possess information on physician preferences, altruism or patient benefits. However, under a set of identifying assumptions and an appropriate estimator, we can apply a reduced form approach by exploiting variation in PDPs to identify the partial effect of λ on a physician's practice.

Using notation from the program evaluation literature (see, e.g., Imbens and Wooldridge, 2009), we are interested in the average treatment effect of the treated (ATT) of the PDP on physician compliance behavior. Denote the ATT estimand as

$$\begin{aligned} \tau_{ATT} &= \mathbb{E}\left[Y_1^1 - Y_1^0 | D = 1\right] \\ &= \mathbb{E}\left[Y_1 | D = 1\right] - \mathbb{E}\left[Y_0 | D = 1\right] - \mathbb{E}\left[Y_1 | D = 0\right] - \mathbb{E}\left[Y_0 | D = 0\right], \end{aligned} \tag{7}$$

where Y_t^d are the potential values of our outcome of interest Y for treatment status d and time period t, where t is a binary indicator representing the period before ($t = 0$) and after ($t = 1$) a policy intervention occurred. Similarly, d is a binary indicator for the group of individuals who were affected ($d = 1$) and not affected ($d = 0$) by the policy intervention at $t = 1$, respectively (see, e.g., Rubin, 2005). In our context, Y_t^d corresponds to the (potential) share of preferred drugs prescribed by physicians given d and t.

Using this notation, we can restate Equation (5) in terms of potential outcomes and conditional expectations,

$$\begin{aligned} \mathbb{E}\left[Y_t^d | T = t, D = d\right] &= \mathbb{E}\left[\alpha_{dt} + \beta_{dt}\mathbb{E}_{dt}\left[B_{1t}(\sigma_i) - B_{2t}(\sigma_i)\right] | T = t, D = d\right] \\ &\quad + \mathbb{E}\left[V_{dt}(F_1) - V_{dt}(F_2) | T = t, D = d\right] + \delta\mathbb{E}\left[\lambda_{dt} | T = t, D = d\right], \end{aligned} \tag{8}$$

where subscripts now refer to group and time averages rather than to physicians.[8] Under the assumptions that relative preferences, altruism and patient benefits and case-mix across groups are fixed over time and physician service fees evolve uniformly over time across groups, the ATT estimand identifies

$$\tau_{ATT} = \delta \mathbb{E}[\Delta^1 \lambda], \tag{9}$$

where Δ^1 is the change in the cost of prescribing non-preferred drugs for the treatment group across time. In other words, under the stated assumptions the ATT identifies our parameter of interest, δ, the average physician response to a change in the cost of prescribing non-preferred drugs, scaled by the change in the cost of PDP non-compliance, λ, across two time periods.[9] Given the identifying assumptions, our reduced form model is thus only informative about the combined average physician response to a *given* change in the cost of PDP non-compliance among physicians in our sample.[10]

As an extension to the basic model, alluding to the equilibrium condition in Equation (6), we consider the case where drug-specific patient benefits, $B_k(\sigma_i)$, vary over time. In this case, the physician's response will depend on the combination of two factors: the expected cost of PDP non-compliance, λ, and the magnitude of the relative change in patient benefit, $\Delta B_k(\sigma_i)$, scaled by the relative value the physician associates with increased patient benefit, β_j, vis-à-vis their aversion for PDP non-compliance, δ_j. If the physician is not subject to a PDP (or if the drug that changes its patient benefits is a preferred drug), the ATT will simply identify

[8] We assume that $\delta_d = \delta$; i.e., that the average counterfactual response in the control group is the same as in the treatment group should they have been treated. This is a necessary identifying assumption for estimation of the causal policy effect without imposing further structure.

[9] Note that we do not have information on the costs of non-compliance in our empirical application, but instead consider the case of a non-preferred drug becoming preferred versus a previously preferred drug. In our conceptual framework, this can be thought of as a change in Δ^1 from one to zero.

[10] In order to study more detailed responses, we would need spatial variation in the costs of PDP non-compliance on the intensive margin such as, for example, increased monitoring intensity or higher recourse claims. Unfortunately, we do not have access to such information. As detailed in the next section, we will instead use variation in the preferred status and patient benefit of specific drugs as our empirical application to study responses to the PDP.

the physicians response from the change in relative patient benefits. In contrast, if the physician is bound by a PDP *and* the drug is a non-preferred drug, the response will be based on the combined net effect from the changed patient benefits and the expected costs from non-compliance with the PDP. In the latter case, physician heterogeneity in the behavioral parameters will play a crucial role for the overall efficacy of the policy.

4.3 Model predictions

From our analytical framework described by Equations (1)-(6), we posit a set of testable hypotheses with respect to how physicians are expected to react to changes in the PDP.

Hypothesis I: *Adding a new preferred drug weakly increases physicians' use share of that drug, with magnitude of the effect depending on the degree of patient benefit the drug has relative to other preferred drugs.*

A change in the cost λ of prescribing a previously non-preferred drug that becomes a preferred drug is reduced to zero since it no longer count towards the risk of incurring a recourse claim. The characteristics of this drug with respect to its SEC profile, or patient benefit, $B_k(\sigma_i)$, relative to other drugs in the same class, $B_{-k}(\sigma_i)$, will determine the magnitude of the substitution effect. Specifically, if the new preferred drug has similar or worse patient benefits than competing preferred drugs, $B_k(\sigma_i) \leq B_{-k}(\sigma_i)$ we expect substitution to be low. In contrast, if it has improved benefits relative to other preferred drugs, $B_k(\sigma_i) > B_{-k}(\sigma_i)$ we expect to see increased market shares for this drug.

Hypothesis II: *An increase in the patient benefit of a non-preferred drug increases the use share of this drug weakly less compared to other preferred drugs when a PDP is active.*

In the physician agency model, changes in the patient benefit of non-preferred drugs will provide a trade-off for physicians who are subject to a PDP in the decision

between prescribing preferred and non-preferred drugs if the physician's level of altruism is positive, $\beta > 0$, and risk aversion is finite, $\delta < \infty$. Assuming that physician altruism and risk aversion are constant over time, $(\beta_t, \delta_t) = (\beta, \delta)$, an increase in relative patient benefits for a non-preferred drug should increase the use rate of this drug for all physicians. This effect will be lower for physicians practicing in a PA with an active PDP since they would have to consider the cost of prescribing non-preferred drugs, while physicians residing in areas without a PDP do not need to take such costs into account.[11] All else equal, we thus expect the effect on use rate of non-preferred drugs for which patient benefits are increased to be lower for physicians who are subject to a PDP.

Hypothesis III: *The magnitude of physicians' responses in hypotheses I and II is positively related to their valuation of patient benefits (altruism) and negatively related to their valuation of the costs of PDP non-adherence (risk aversion).*

With physician-level heterogeneity with respect to altruism and risk aversion in the model framework, we can define physician-level local average treatment effects as $\tau^j_{ATT} = \delta_j \mathbb{E}[\Delta^1 \lambda]$. In this case, the policy response will depend on the relative strength of the behavioral parameters. In the first case (Hypothesis I), physicians with low risk aversion will be less responsive to the policy, because the response to a given change in cost of non-adherence will be more discounted for lower values of δ_j. In the second case (Hypothesis II), physicians will trade off the increased patient benefits and the increased costs by the ratio of their altruism and risk aversion attributes. Physicians with higher altruism or lower risk aversion will be less responsive to a PDP when the patient benefit of a non-preferred drug increases.

5 Empirical modeling

[11] To see this, first note that the equivalent equilibrium condition to Equation (6) for preferred drugs (or the absence of a PDP) is $\beta_j \Delta \bar{B}_j > 0$. Next, given that we consider an increase in patient benefits for a *non-preferred* drug, we evaluate under which conditions $\beta_j \Delta \bar{B}_j < \beta_j \Delta \bar{B}_j + \delta_j \lambda_{j2}$, which is simply when $\delta_j \lambda_{j2} > 0$. This condition holds as long as δ is non-negative and λ is positive.

5.1 Data and sample

The data used for our empirical analysis come from two sources: CEGEDIM-MEDIMED, a nationally representative panel of 3,026 ambulatory care physicians practicing in Germany 2011-2014[12], and self-collected data on PDPs by PAs.[13] The physician panel is balanced across PAs, specialties, and prescription volumes present in the German health care system. It covers the universe of medical prescriptions in a physician's practice, including all prescriptions defined by drug class and label, volumes and ex-factory prices. The panel contains selected characteristics of the prescribing physician and practice-specific characteristics as well as some patient information.

After thorough investigation, we were able to identify PDPs that listed a reference value for preferred drugs for 13 of the 17 PAs. These were taken from structured inquiry (websites and e-mail communication) and based on information extracted from drug agreements (*Arzneimittelvereinbarungen*) which are negotiated annually with respect to variation in level of drug quotas and number of preferred drugs by drug class.[14] After inspection, we opted to exclude the PAs of Hamburg and Saarland from the analysis due to a limited number of physicians included in the sample from these areas: 11 and 15, respectively. Based on the variation in PDP regimes across the remaining PAs, we define our treatment group to include the eight associations that had PDPs during the time period we study: North Rhine, Rhineland-Palatinate, Hessen, Baden-Württemberg, Berlin, Saxony, Brandenburg and Thüringen. In contrast, Westphalia-Lippe, Bavaria and Schleswig-Holstein, which did not have any active PDPs during the time period we study, are used as

[12]The physician panel is maintained by IQVIA, a private market research company, https://www.medimed.info [last accessed July 1, 2021].

[13]The National Association of Statutory Health Insurance Physicians (*Kassenärztlichen Bundesvereinigung*) consists of 17 regional PAs (*Kassenärztlichen Vereinigungen*) of which 15 coincide with a federal state (*Bundesland*). The remaining two associations span the state of North Rhine-Westphalia, which is separated into two mutually exclusive geographical areas, North Rhine and Westphalia-Lippe.

[14]To identify the variation in PDPs we collected information through a search of PA websites and direct inquiry if we could not retrieve information online. No information on drug agreements could be obtained from PAs in Bremen, Lower Saxony, Mecklenburg-Vorpommern and Saxony-Anhalt. Bavaria changed from a PDP to minimum quotas for generic drugs during the observation period, which we consider to be a separate and unrelated policy.

controls in the following analysis.

We merge the two data sets using quarter-year and PA identifiers for the 11 associations we include in the analysis. To avoid issues associated with small sample inference when computing physician-specific use rates, we restrict our analysis sample to physicians with at least 50 prescriptions in the statin drug-class each quarter in our data. This restriction implies that we work with a balanced panel in our analysis. Although sample attrition may theoretically be an issue, this restriction does not reduce the number of physicians included in the sample to any important extent. Finally, since PDP mandates are somewhat different for general practitioners and specialists, we retain only the former physician group to keep our analysis tractable. These restrictions leave us with a panel of 928 general practitioners working in German ambulatory care physicians (roughly one percent of the total physician population) between 2011 and 2014. Table 1 reports summary statistics for our analysis sample.

[Table 1 about here]

5.2 Policy variation

We exploit policy variation across PAs and over time to estimate the effects of PDPs on physician prescription behavior using the conceptual framework and model predictions outlined in the last section. To this end, we study two important events that occurred during our analysis time frame (see Figure A.2 for a timeline of the relevant events). First, we analyze the indirect effect of a PDP from estimating physician responses in the adoption of generic versions of the never preferred blockbuster drug atorvastatin entering the pharmaceutical market in the first quarter of 2012. While the price of the brand name version of atorvastatin was significantly higher than for other statins prior to 2012, the competition from generic versions of the drug led to a sharp drop in price of atorvastatin in the months following generic market entry. The left panel of Figure 2 describes the average ex-factory price per prescription for the three substances in the statin drug market we focus on. While

prices for simvastatin and pravastatin, the two preferred statins, remained largely unchanged throughout the studied time period, generic entry of atorvastatin led to a price drop of 80 percent in the first year only. Since German healthcare policy prescribes that patients must pay the difference between the ex factory and reference price out of pocket, the drop in price substantially increased patient benefit of atorvastatin. We estimate how the change in price affected the physician use rate and substitution of simvastatin and pravastatin for atorvastatin among the physicians in our sample and how the presence of a PDP alter this effect.

The second event we study is a direct change in the PDP through the addition of a newly preferred drug, pravastatin, in 2013. The right panel of Figure 2 shows the change in the number of preferred drugs in the eight PAs that had an active PDP during the period we study. The number of preferred drugs increased from one to two (three for one region, North Rhine[15]), for all associations except Westphalia-Lippe, Bavaria and Schleswig-Holstein that did not have active PDPs during this period.[16] We use this change in policy to study changes in physician use rates for pravastatin as a consequence of its changed status from non-preferred to preferred drug.

[Figure 2 about here]

We focus on prescriptions in the statin drug class for which three substances dominated the market during our analysis period; the always preferred simvastatin, the newly preferred pravastatin and the never preferred atorvastatin. The variation in preferred statin prescriptions ranges between 0.80 in Bavaria to 0.88 in Hamburg. Furthermore, while overall use of statins remained approximately constant over time, the use of simvastatin declined and the use of atorvastatin increased rapidly after the latters generic entry in 2012. The share of pravastatin (and "other" statins)

[15]We opted to keep North Rhine in the treatment group throughout our analysis since excluding it does not change our results to any important extent. Results from excluding North Rhine are available from the authors upon request.

[16]There were also minor changes to PDP quotas in some PAs in 2012. We do not consider these as important since they were not associated with changes in the number of preferred drugs.

prescriptions remained more or less unchanged during the analysis period.[17]

Our primary outcome of interest is physicians' use rate of preferred and non-preferred statins in our analysis sample over time. However, since the PDP change we study incorporated changes in the number of preferred drugs, we construct time-invariant variables of PDP compliance. Specifically, we define *pre-policy* compliance level as physicians' use rate of preferred statins according to the PDP definition *prior* to the policy change in 2013. Similarly, we define *post-policy* compliance level as physicians' use rate of preferred statins according to the PDP definition *after* the policy change. Defined this way, we circumvent the issue of estimation bias arising from mechanical correlation between physician compliance and changes in the number of preferred drugs.[18]

Furthermore, to study heterogeneity in physician response to the PDP, we classify physicians into compliance types based on their pre-policy use shares of preferred statins. In the absence of data on physicians true altruism and risk aversion, the estimated use shares serves as a proxy variable for their relative risk aversion towards the expected costs incurred from non-compliance with the policy, i.e., δ_j. To this end, we average physicians' preferred statin use rates over the four quarters of 2011 in order to avoid confounding them with endogenous reactions to the events we study. The reasoning behind this definition is simple: physicians with low use rates of preferred shares are by revealed preferences assumed to be relatively less worried of being caught not complying with the policy since the costs of non-adherence is roughly the same for everyone.

To study drug substitution, we include drug-specific physician use rates as outcome variables in stratified analyses. Figure 3–Figure 5 display drug-specific time trends in our sample for the four largest PAs we study: Baden-Württemberg, Hesse, North Rhine and Rhineland-Palatinate. The hollow markers refer to physician-

[17] Figure A.3 shows a regional map of Germany illustrating the average shares of preferred statins prescribed in 2011 by PA and Figure A.4 illustrates the total number of prescriptions by drug and quarter-year.

[18] In particular, such bias would occur when the addition of a new preferred drug changes the compliance level of physicians who were already frequent prescribers of the drug prior to the policy change.

specific use rates, whereas period-specific group averages are displayed by connected plots for treatment (triangles) and control (circles) groups, respectively. The control group, consisting of the pooled average physician use rates in three organizations that did not have an active PDP during the time period we study (Westphalia-Lippe, Bavaria and Schleswig-Holstein), is the same in all panels. Finally, the shaded background areas separate the different event regimes we analyze: the pre-policy period (2011q1-2011q4), the generic entry of atorvastatin (2012q1-2012q4), and the post-policy period (2013q1-2014q1).

First turning our attention to Figure 3, we see a gradual but steady decline in the use of simvastatin in all four PAs, beginning at the time atorvastatin made generic market entry in 2012 and continuing throughout the analysis period. The relative changes between the treatment and control groups appear similar to the naked eye in all four panels. The corresponding patterns for pravastatin and atorvastatin, displayed in Figure 4 and Figure 5 respectively, suggest that the decline in the use share of simvastatin is entirely driven by an increase in the latter drug. Even though pravastatin became a preferred drug in 2013, there is no indication of a response towards increased use of this drug in either of the four regional PAs.

[Figure 3-Figure 5 about here]

Corresponding trends in use of the three statins for the four smaller PAs constituting the treatment group, Saxony, Thuringia, Berlin and Brandenburg, the observed patterns follow a similar general trend as before but with some notable exceptions (Figure A.5–Figure A.7). In particular, the trends for Saxony and Thuringia deviate from the corresponding pooled use rates in the control areas. In Saxony, the time trend reflects a break to a relatively lower gradual decline in simvastatin use rates at the time when pravastatin was added as a preferred drug in 2013. Similarly, despite starting from a relatively lower level, the decline in simvastatin use rates in Thuringia is less pronounced throughout the entire period compared to the pooled control average. In line with the trends from the four larger PAs, we see that the reductions in simvastatin use rates are mainly driven by increased

use of atorvastatin following its generic entry, and that the relative use share of pravastatin remains essentially unchanged throughout the analysis period.

5.3 Difference-in-differences

We use a Difference-in-Differences (DD) empirical design to estimate physician responses to the two policy events we study. Specifically, from our causal identification framework described by Equations (7)-(9), we can estimate the ATTs from (i) a change in the expected cost of policy non-compliance, λ, and (ii) a change in the expected patient benefit of a drug, $B_k(\sigma)$, on a physician's prescribing behavior under a set of plausible assumptions. Consider the generalized DD regression model,

$$y_{jst} = \alpha_j + \beta Post_t + \gamma Treat_s + \tau^{DD}(Post_t \times Treat_s) + X'_{jt}\zeta + \epsilon_{jst}, \tag{10}$$

where y_{jst} is the share of preferred drugs prescribed by physician j operating in PA s in quarter-year t.[19] Furthermore, α_j indicate physician-specific effects, $Post_t$ and $Treat_s$ are binary indicators for post-policy time periods and PAs in the treatment group (i.e., PAs with active PDPs), respectively, and X_{jt} is a vector of pre-policy and possibly time-varying physician characteristics reported in Table 1. Note that the DD estimator, τ^{DD}, identifies the ATT estimand (7) under the common trend assumption that the residual, ϵ_{jst}, is uncorrelated with any changes in the outcome variable over time across groups:

$$\begin{aligned} \tau_{ATT} = (\bar{\alpha}_1 + \beta + \gamma + \tau^{DD} + \bar{x}'_1\zeta) - (\bar{\alpha}_1 + \gamma + \bar{x}'_1\zeta) \\ - (\bar{\alpha}_0 + \beta + \bar{x}'_0\zeta) - (\bar{\alpha}_0 + \bar{x}'_0\zeta) = \tau^{DD}, \end{aligned} \tag{11}$$

where bars indicate group-specific averages.

The empirical validity of the identifying assumptions for the DD estimator can be motivated by the institutional context. Since prices of prescribed pharmaceuticals are regulated on the national level and service fees for statutory health insurance

[19] As mentioned previously, the outcome is defined to be time-invariant to avoid to conflate changes in the number of preferred drugs with actual responses in physician practice.

physicians are fixed, we do not have reason to worry about endogenous trends in the costs of drugs or services across states and physicians in our sample. Moreover, other dimensions of patient benefit from a drug (i.e., efficacy and safety) should remain unchanged since the active substance in the drugs stays the same. Although changes in physicians' patient case-mix may in theory change their use rates, we do not observe large fluctuations in the number of patients treated over time. Physician altruism, risk aversion and relative drug preferences (both patient and physician) are unlikely to change endogenously with the policy we study, although we cannot entirely rule this possibility out.

Under the assumptions that relative preferences, altruism and patient benefits are fixed over time and service fees evolve uniformly over time across groups, estimation of Equation (10) by OLS yields a consistent estimate of the DD estimator that can be interpreted as the effect of a change in the PDP on physician practice. However, as can be seen from Equation (9), the ATT identified by the DD estimator is a reduced form estimator of the structural parameter, δ, augmented by the average change in λ.[20] Although our empirical approach does not allow us to quantify the *marginal* effect of increased costs of non-compliance to a PDP, we are nevertheless able to estimate the *average* causal effect of the policy we evaluate.[21]

We apply the same empirical framework to study physician responses to an increase in patient benefit from a drug in the form of a global reduction in the price of atorvastatin due to its generic entry. In contrast to other types of price variations, the price change we study affected all physicians in the same way and at the same time. This feature makes it possible to estimate the effect of the price change on physician practice in PAs with and without PDPs, respectively. Thus, the insights from Equations (10)–(11) carry over, except for the interpretation of τ^{DD}. This

[20] Note that in this basic form of the model we assume that the effect is homogeneous across regions, which may be considered a restrictive assumption. We discuss the implications of this assumption below.

[21] Access to information on and empirical variation in the specific costs of PDP non-compliance would allow us to estimate the elasticity of physician use rates of preferred statins with respect to increases in the costs of PDP non-compliance. In turn, this information would allow for simulating the cost increases needed to increase average PDP compliance to a specific level.

parameter is now interpreted as the net effect from an increase in the desirability of atorvastatin due to its lower cost and the cost of prescribing it due to its status as a non-preferred drug in PAs with active PDPs. In a sense, it is informative of the degree to which the PDP inhibits physicians' use of a non-preferred drug after it becomes more attractive to prescribe.

5.4 Synthetic control method

To study heterogeneous effects by physician pre-policy PDP compliance level, we complement our DD model with a pooled synthetic control (SC) approach. The SC method allows us to tailor micro-level comparisons of responses from physicians with similar use rates of preferred drugs prior to the events we study in PAs with and without active PDPs, respectively. Specifically, we match outcomes of each treated physician who were practicing in an PA with an active PDP to a weighted average of outcomes from untreated physicians practicing in areas without a PDP (see, e.g., Abadie *et al.*, 2010, 2015).[22] The underlying idea behind this approach is that physicians who were not subject to a PDP are assumed to represent the counterfactual trend of physicians who were subject to a PDP, should the policy not have existed.

Formally, for each treated physician $j_1 \in J_1$, we find a synthetic control using the donor pool of untreated physicians $j_0 \in J_0$ in control PAs, where $J = (J_1, J_0)$. Again, denote Y_t^d as the potential outcome of interest Y for treatment status d and time period t, and $y_{j_d,t}$ as its realization. To match treated and untreated physicians based on their pre-policy preferred drug shares, we define the $(J_1 \times k)$ and $(J_0 \times k)$ matrices $X_1 = (y_{j_1,t_{min}}, ..., y_{j_1,T_0})$ and $X_0 = (y_{j_0,t_{min}}, ..., y_{j_0,T_0})$, where t_{min} is the first quarter-year in our analysis period, T_0 is the quarter-year of the event we study, and $k = T_0 - t_{min}$. For a specific treated physician j_1, physician-specific weights $\psi_{j_1}^{j_0} \in \Psi_{j_1}$ are then obtained by minimizing the squared distance

[22] Although the synthetic control method was originally developed for a single treated unit, the framework can easily accommodate estimation with multiple treated units by fitting separate synthetic controls for each of the treated units (see, e.g., Abadie and L'Hour, 2021; Abadie, 2021).

between row j_1 of X_1, denoted x_{j_1}, and X_0 according to

$$\begin{aligned} &\min_{\Psi_{j_1}} \|x_{j_1} - X_0\| = \sqrt{(x_{j_1} - X_0\Psi_{j_1})' V (x_{j_1} - X_0\Psi_{j_1})} \\ &\text{subject to: } \psi_{j_1}^1 \geq 0, \cdots, \psi_{j_1}^{J_0} \geq 0 \text{ and } \sum_{c=1}^{J_0} \psi_{j_1}^c = 1, \end{aligned} \tag{12}$$

for a suitable weighting matrix V. This exercise is repeated for all J_1 treated physicians. Under the DD assumptions described in the previous subsection and a set of regulatory assumptions of the optimization routine applied to solve Equation (12), an unbiased and consistent estimator for the ATT is

$$\widehat{\tau}_t^{SC} = \frac{1}{J_1} \sum_{s=1}^{J_1} \left[y_{st} - \sum_{c=1}^{J_0} \psi_s^{*c} y_{ct} \right], \tag{13}$$

where ψ^* denotes optimal weights from Equation (12). Note that $\widehat{\tau}_t^{SC}$ varies across time as the difference can be estimated for each quarter-year in our data. This allows us to both study the pre-policy trend fit as well as the post-policy effect dynamics. We first apply the SC method to complement our DD analysis above and subsequently to estimate heterogeneous effects by physicians pre-policy compliance rates using quantile regression.

6 Results

6.1 Are PDPs effective in adjusting physician practice?

We first present results from estimation of our DD model on the impact of the PDP on physicians' prescription behavior based on policy variation from the two events described in the previous section: the generic entry of never preferred atorvastatin and the change in status of pravastatin from a non-preferred to a preferred drug. Table 2 reports coefficient estimates from our DD model described in Equation (10) from our analysis sample for each of the three statins we focus on; simvastatin (always preferred), pravastatin (newly preferred) and atorvastatin (never preferred)

using physicians' drug use rates as outcome. For each drug, the first column reports the combined effect from both the events we study (generic entry of atorvastatin and the addition of pravastatin as a preferred drug) using a post indicator for the period after 2011 denoted *Post*. In addition, the second column reports separate effects for each event by augmenting the DD model by adding a separate post-indicator for the timing of each event (*Post*1 and *Post*2) and their interactions with the treatment group indicator. Hence, the sum of the two separate effects from the second column should add up to the total effect displayed in the first column.

First turning our attention to the results for the always preferred simvastatin, estimates suggest that the use rate of in PAs without an active PDP dropped by 0.086 between 2012 and 2013. This corresponds to a decrease of about 10 percent from the baseline period as captured by the regression constant. Moreover, column (2) shows that this reduction was equally distributed across the two event time periods we study. The added effect for physicians residing in areas with an active PDP is displayed by the coefficients for the interaction variables. In line with expectations, the total drop in the use of simvastatin among PDP-constrained physicians is 0.011, or approximately 15 percent, lower than for physicians in the control group. Interestingly, this moderating effect of the PDP appears to be entirely driven by the addition of pravastatin as a preferred drug in 2013 as there is no statistically significant difference in the drop in use of simvastatin in the first event period in 2012. However, since the price of the never preferred atorvastatin only gradually dropped after its generic market entry in 2012 (see Figure 2), this interpretation requires further investigation. We explore effect dynamics below by estimating marginal effects by quarter-year.

Moving on to the second set of estimates for the newly preferred pravastatin reported in columns (3)–(4), we see that its average use rate dropped by 0.015 in the post-periods compared to the outset in 2011. Moreover, around two-thirds of this drop is attributed to the generic entry of atorvastatin in 2012. In contrast to simvastatin, we find no indication that physicians in PDP and non-PDP areas

responded differently for pravastatin. The interaction coefficients, although significant on the ten percent level, are all close to zero. This suggests that physicians did not react to the addition of pravastatin as a preferred drug by prescribing more of this drug, perhaps due to its similarity to simvastatin in terms of patient benefits.

Finally, the last two columns show estimates for atorvastatin. The results imply that the use share of atorvastatin in the control group increased from almost zero to 0.121 of all statins from the start of 2012 to the end of 2013. This increase is stronger in the first event period in 2012, but continues throughout 2013. This increase is somewhat lower for the treatment group with a magnitude corresponding to the relative increase in the use of simvastatin from column (1) of the table. The conclusion that the effect is driven by a substitution from always preferred simvastatin to the never preferred atorvastatin is further strengthened by that the point estimates are near mirror images. Again, caution is advised when interpreting the relative size of the point estimates as they may be artefacts of the gradual price drop of atorvastatin in the first post-event period.

[Table 2 about here]

Figure 6 complements the results from Table 2 by plotting marginal treatment effects by quarter based on the regression estimates.[23] Each panel correspond to a specific drug except for the bottom right panel, which uses the time-invariant post-policy preferred drug use rate (i.e., the physicians' use rate of preferred drugs based on the post-policy definition) as outcome to measure overall PDP compliance. The figures convey important effect dynamics that the post-event dummy variables reported in Table 2 are unable to capture. Specifically, the effect patterns are not characterized by discontinuous shifts in the relative propensity to use simvastatin and atorvastatin, but rather as gradual adjustments over time. This is not unexpected given that the change in the price of atorvastatin gradually dropped over time after its generic entry in 2012. Figure 6 shows that the shares of simvastatin

[23] In practice, a modified version of the DD model is estimated by replacing the post indicators with a set of quarter-year indicators and predicting the treatment effect at different time periods using the `margins` command in *Stata 16*.

and atorvastatin for the treatment and control groups began to gradually diverge after 2012 with physicians in the treatment group keeping a relatively larger share of the former and less of the latter drug. However, the delay in response may also be indicative of that physicians were unable to immediately adjust their preferred drug use rates in their patient populations. To investigate this, we extend our analysis in Section 6.3 by decomposing the overall effect into a set of adjustment mechanisms relating to changes in patient retention, patient switching and patient initiation.

Figure 6 also confirms that the overall use share of the newly preferred pravastatin was essentially unaffected throughout the studied time period. With respect to Hypothesis I, this result suggests that pravastatin and simvastatin, owing to their similar SEC profiles, did not differ much in terms of patient benefits and that physicians as a consequence did not see any reason to substitute between them. As a consequence of the one-to-one substitution between simvastatin and atorvastatin, the relative increase in preferred drug shares among physicians practicing in PAs with active PDPs in the bottom right panel closely resembles the effect pattern for simvastatin. This result yields support for Hypothesis II that the effect of the increase in patient benefit arising from the drop in price of atorvastatin was reduced by the presence of the PDP. However, the magnitude of this moderation effect is relatively small; only about 13 percent (0.011/0.086) from comparing the difference between the treatment and control groups for simvastatin in Table 2.

[Figure 6 about here]

Next, we report corresponding results from estimation of our SC model defined by Equations (12)-(13) in the previous section. Columns (1) and (2) of Table 3 provide group-specific (treatment and synthetic control) parameter estimates corresponding to the interaction coefficients reported in Table 2. Furthermore, column (3) reports estimates from the difference between the treatment and synthetic control groups. Each panel of the table corresponds to estimates from a specific outcome; use shares of the three statins and the preferred share, respectively.

The general conclusion from the table estimates is that it largely corresponds to the DD results presented above except for that the group differences in the use rates of the always preferred simvastatin and never preferred atorvastatin are now slightly larger. Specifically, physicians subject to a PDP reduced their use of simvastatin by 0.044 in the first post-period while the corresponding share from their synthetic controls dropped by 0.061, yielding a net difference of around two percentage points. The effect estimate from column (3) confirms this result. Similarly, the increase in the use of atorvastatin was two percentage points higher in the synthetic control group in the first post period. Other changes across groups are negligible except for the consequential increase in relative preferred drug share by physicians in PDP regions reported in the last panel.

[Table 3 about here]

Figure 7 provides corresponding graphical illustrations of estimated effects for each quarter-year in our analysis data set from the SC model to trace out effect dynamics across time from the events. As before, each panel in the figure corresponds to a specific outcome variable. Reassuringly, the treated and synthetic control physicians are well-matched on pre-policy outcome trends and levels for all outcomes. Furthermore, it is again clear from the figures that the group trends begin to diverge after the generic entry of atorvastatin in 2012. While both groups generally reduce their use rates of simvastatin in favor of atorvastatin, this change is less pronounced for physicians who are restricted by the PDP relative to their counterfactual trend based on the synthetic controls. In contrast, there is no obvious indication in the figures that the introduction of pravastatin as newly preferred drug in 2013 had any additional effect on the use rates.

[Figure 7 about here]

6.2 Who responded to the PDP?

In this section, we explore the empirical validity of Hypothesis III by estimating quantile regressions by the deciles of the distribution of preferred shares for the physicians in our sample. The results from this analysis have important implications for policy as they will be informative about potential heterogeneity across physicians in their responses to the PDP. In particular, if we find that it is mainly physicians who prescribe at the bottom of the distribution of preferred drug shares that improve their compliance to the preferred drug regimen, we would conclude that the PDP is effective in raising physician adherence in prescribing preferred statins. On the other hand, if the aggregate effect is mainly mediated by physicians in the upper part of the distribution of preferred drug shares, the PDP is less likely to be effective since this physician group may already be complying with the policy.

The upper panel of Figure 8 provides a graphical representation of the total effect heterogeneity across deciles of the pre-policy distribution of post-policy preferred use rates for physicians in the treatment group (hollow markers) and their synthetic controls (black markers). The number associated with each marker refers to the group-specific cutoff point for each decile. It is reassuring that these cutoffs are very similar for both groups as it suggests that the SC approach is able to match treated physicians with suitable controls. The lower panel of the figure illustrates the difference in the total effect across the entire post-policy period between the treated and synthetic control groups by decile of the preferred share distribution. These results are comparable to the pooled results reported in Table 3 averaged across all physicians in our sample.

The figure conveys several interesting findings. First, we observe a (weakly) monotonic relationship in the effect on using preferred drugs for both the treated physicians and their synthetic controls. This indicates that physicians with higher preferred shares in the pre-policy period reduced these shares less in the post-policy period. In terms of Hypothesis III, this could be caused by a higher degree of altruism among physicians in the upper part of the preferred share distribution.

Second, the effect pattern is stronger for the treatment group than for the synthetic controls, where, in fact, the latter's effects are generally characterized by a lack of heterogeneity (except for the first decile). Since the treatment and synthetic control groups within a preferred share category only differ to the extent of whether they are restricted by a PDP or not, this provides some evidence for that risk aversion plays a crucial role in explaining the effect heterogeneity. In terms of our physician agency model, physicians with higher pre-policy preferred shares have higher values of the risk aversion parameter, which lead the PDP to be more effective in adjusting physician prescription behavior. In contrast, since physicians in PAs without an active PDP do not have to worry about the risks of non-adherence to the policy, their risk aversion does not enter the decision to prescribe a non-preferred drug. Thus, the gradual increase in the effect of the PDP for higher deciles is in line with the predictions from Hypothesis III.

In terms of policy implications, the results described in Figure 8 suggest that the PDP is unable to target the population of physicians whose practice behavior it aims to change. The heterogeneity of the effect of the policy across the different deciles of the preferred use rate distribution is more clearly illustrated in the lower panel of Figure 8. Non-complying physicians in areas with PDPs at the bottom of the distribution become even less adhering compared to their synthetic controls, while the opposite is true at the top of the distribution. Although other explanations may exist as to what is mediating this effect pattern, one possible interpretation based on our physician agency model is that the punitive measures that the PDP uses to change medical practice are too soft to discourage non-compliant physicians to prescribe more preferred drugs.

Given the generally high use rates of preferred drugs among the physicians in our sample, even non-complying physicians have substantial experience with the preferred drug. This suggests that our results are not driven by that non-complying physicians lack knowledge in prescribing the preferred drug. While we cannot exclude the possibility that other mechanisms could explain the effect heterogeneity

displayed in Figure 8, such as physician-directed drug promotions (Janakiraman *et al.*, 2008), it is less likely that such heterogeneity plays an important role for our results given that our SC approach matches physicians based on their pre-policy preferred shares (Agha and Zeltzer, 2019).

[Figure 8 about here]

6.3 How did physicians substitute between drugs?

So far, we have provided empirical evidence for that physicians do adjust their practice when subject to a PDP, and that this effect is mainly mediated by a relatively lower uptake of never preferred atorvastatin among already complying physicians. Given this, a related question of importance for healthcare policy is *how* physicians substituted between these drugs. In particular, previous evidence suggests that switching statins can lead to higher hospitalization rates (Stargardt, 2010). While switching between different statins is not uncommon (Ofori-Asenso *et al.*, 2018), adjusting or switching treatment should, if possible, be avoided to increase patient compliance. In this section, we study the venues by which physicians in our sample substituted between statins based on their responses from our analysis of the PDP.

To decompose substitution, we consider three possible mechanisms. First, physicians can simply switch drugs for their existing patients so that a patient that previously was prescribed a particular drug is instead given another. Second, physicians can initiate the specific drug on new patients. Third, physicians can disproportionally retain patients who are prescribed specific drugs. We define the total quarterly change in use rates as the sum of switching, initiation and retention and study how these are related to the overall changes we see in use rates from the previous subsection.[24] As an example, Figure A.8 shows that switching from simvastatin became more common in the second quarter of 2012 after the drop in price of atorvastatin

[24] For example, if the share of simvastatin prescribed by a specific physician in our sample dropped by 0.10 from one quarter to the next, we decompose this change into net shares of switching (patients who previously had simvastatin but switch to another drug), initiation (new patients who are prescribed simvastatin), and net retention (change in the outflow of patients who were prescribed simvastatin).

due to its generic entry. The vast majority of drug switching relates to switching from simvastatin to atorvastatin and the number of switches for pravastatin and other statins is much smaller, although an effect of the introduction of generic versions of atorvastatin can also be discerned for these drugs.

Figure 9 shows a decomposition of the overall use of each statin by the three substitution channels over time. Since our data is only available from 2011, we are unable to identify whether patients in the beginning of our time period were new patients or retained from a previous period. Hence, the large shares of new patients in the first quarters of 2011 reflects this missing data and should be interpreted with caution.[25] The figure suggests that most of the total use of each statin, except for atorvastatin, is mainly driven by patient retention. In other words, physicians keep their patients and do not switch their medication over time. The pattern for atorvastatin is different because it was barely prescribed prior to its generic entry. Interestingly, the pattern reveals that the initial increase in atorvastatin use in 2012 arose from equal shares of drug switching and initiation, whereas over time, patient retention accounted for the dominant share of the use of the drug. Intuitively, at the outset there were no patients with atorvastatin to retain, but as new and existing patients were given the drug and retained, the latter share rose over time.

[Figure 9 about here]

To directly study the drivers of our main effects, we reestimate our DD model from Equation (10) using as outcome each of the three substitution mechanisms. Figure 10 describes the decomposition results in graphical form for the full set of statins.[26] We focus on simvastatin and atorvastatin since our previous results showed that the effects is mainly composed of substitution between these two drugs. From the figure, it is evident that the entire policy effect for simvastatin is related to an increase in the share of retained patients. This suggests that the PDP increased the likelihood that PDP-restricted physicians retained their simvastatin patients

[25] One way to overcome this problem is to start the analysis at a later quarter but we opted to keep the time series intact for comparison across estimation results.

[26] All estimation results are provided in Table A.1.

relatively more than their unrestricted counterparts. Turning to the results for atorvastatin, we see that the effect is mainly driven by patient retention and to some extent by initiation. This suggests that physicians constrained by a PDP were relatively less likely to keep patients to whom they prescribed atorvastatin, but also relatively less likely to prescribe atorvastatin to new patients. As before, pravastatin and other statins were largely unaffected by the PDP for both events.

[Figure 10 about here]

7 Conclusion

Organizations often enact policies to influence experts' work with the aim of improving compliance to predefined standards. However, controlling expert work more stringently entails additional administrative costs from monitoring and enforcement activities. It is therefore vital for organizations to know and weigh the projected benefits from reducing unwarranted variation in experts' work against the direct and indirect costs associated with ensuring their adherence to stated protocols.

We study expert (physician) responses to a cost-control mechanism, preferred drug targets (PDPs), that includes a risk of a recourse claim if the physician fails to comply with a preferred treatment standard as defined by the principal organization (healthcare regulator). We develop and test the predictions from a physician agency model that incorporates the regulator's goal to increase cost-efficiency in prescribing statins by penalizing use of non-preferred drugs. An important implication derived from our model is that behavioral attributes of the physicians (altruism and risk aversion) are potentially important when predicting the degree to which physicians will respond to changes in the control mechanism and the impact on overall adherence.

To support the theoretical evidence, we demonstrate in an empirical application using policy variation across regional physician associations in Germany over time that the PDP is able to increase use rates of preferred drugs. However, this effect

is mainly driven by physicians with high use rates of preferred drugs prior to policy change. Thus, the overall effect of the PDP on physician compliance may very well be zero, since marginal effects are derived from physicians who were already complying. Without additional knowledge that could be leveraged for identification and targeting of marginal groups, we argue that the PDP would need to be more stringent in order to effectively target the population of non-complying physicians.

The framework to evaluate the effectiveness of PDPs proposed in this paper can be further generalized. For example, a higher policy stringency could be reflected by an increase in the cost of non-compliance through higher monetary penalties or stricter documentation of non-preferred choices. Policies with high administrative burdens, such as the US prior authorization measures, may alter the stringency of the control measure by lowering costs of non-compliance while still achieving their stated targets with similar effectiveness. A prerequisite is that costs of non-compliance are high enough such that less risk averse physicians still aim to comply to the standard. The question is then how much these costs would have to be altered to reach the preferred level of adherence, for example by computing the the marginal change in physician adherence with respect to an increase in the costs of non-adherence. To estimate this elasticity, and thus to provide policy leverage, one would need to have data and empirical variation in the costs across different policy regimes; something that we were unable to gather for our analysis, but which would be a fruitful venue for further research.

References

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, **59** (2), 391–425.

—, Diamond, A. and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, **105** (490), 493–505.

—, — and — (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, **59** (2), 495–510.

— and L'Hour, J. (2021). A penalized synthetic control estimator for disaggregated data. *Journal of the American Statistical Association (Forthcoming)*.

Agha, L. and Zeltzer, D. (2019). *Drug Diffusion Through Peer Networks: The Influence of Industry Payments*. Working Paper 26338, National Bureau of Economic Research.

Avdic, D., Propper, C. and von Hinke, S. (2019). *Information shocks and provider responsiveness: evidence from interventional cardiology*. CEPR Discussion Paper No. DP13627, Centre for Economic Policy Research.

Baker, L. C. and Phibbs, C. S. (2002). Managed care, technology adoption, and health care: The adoption of neonatal intensive care. *RAND Journal of Economics*, **33** (3), 524–548.

Berndt, E. R., Gibbons, R. S., Kolotilin, A. and Taub, A. L. (2015). The heterogeneity of concentrated prescribing behavior: Theory and evidence from antipsychotics. *Journal of Health Economics*, **40**, 26–39.

Blankart, K. E. and Arndt, F. (2020). Physician-level cost control measures and regional variation of biosimilar utilization in Germany. *International Journal of Environmental Research and Public Health*, **17** (11), 4113.

Blümel, M., Spranger, A., Achstetter, K., Maresso, A. and Busse, R. (2020). Germany: Health system review. *Health Systems in Transition*, **22** (6), 1–272.

Bradford, R. H., Shear, C. L., Chremos, A. N., Dujovne, C., Downton, M., Franklin, F. A., Gould, A. L., Hesney, M., Higgins, J. and Hurley, D. P. (1991). Expanded Clinical Evaluation of Lovastatin (EXCEL) study results. I. Efficacy in modifying plasma lipoproteins and adverse event profile in 8245 patients with moderate hypercholesterolemia. *Archives of Internal Medicine*, **151** (1), 43–49.

Buchmueller, T. C., Carey, C. M. and Meille, G. (2020). How well do doctors know their patients? Evidence from a mandatory access prescription drug monitoring program. *Health Economics*, **29** (9), 957–974.

Bundesärztekammer, Kassenärztliche Bundesvereinigung, Arbeitsgemeinschaft der Wissenschaftlichen Medizinischen Fachgesellschaften (BÄK/KBV/AWMF) (2013). *Nationale VersorgungsLeitlinie Chronische KHK — Langfassung, 2. Auflage. Version 1. 2013*. Technical report. Available from: http://www.khk.versorgungsleitlinien.de.

Cardinal, L. B., Kreutzer, M. and Miller, C. C. (2017). An aspirational view of organizational control research: Re-invigorating empirical work to better meet the challenges of 21st century organizations. *Academy of Management Annals*, **11** (2), 559–592.

Chandra, A., Cutler, D. and Song, Z. (2011). Who ordered that? The economics of treatment choices in medical care. In *Handbook of Health Economics*, vol. 2, Elsevier, pp. 397–432.

Currie, J., MacLeod, W. B. and Van Parys, J. (2016). Provider practice style and patient health outcomes: The case of heart attacks. *Journal of Health Economics*, **47**, 64–80.

Currie, J. M. and MacLeod, W. B. (2020). Understanding doctor decision making: The case of depression treatment. *Econometrica*, **88** (3), 847–878.

Cutler, D., Skinner, J. S., Stern, A. D. and Wennberg, D. (2019). Physician beliefs and patient preferences: A new look at regional variation in health care spending. *American Economic Journal: Economic Policy*, **11** (1), 192–221.

Depalo, D., Bhattacharya, J., Atella, V. and Belotti, F. (2019). *When technological advance meets physician learning in drug prescribing*. Working Paper 26202, National Bureau of Economic Research.

Dillender, M. (2018). What happens when the insurer can say no? Assessing prior authorization as a tool to prevent high-risk prescriptions and to lower costs. *Journal of Public Economics*, **165**, 170–200.

Dulleck, U. and Kerschbamer, R. (2006). On doctors, mechanics, and computer specialists: The economics of credence goods. *Journal of Economic Literature*, **44** (1), 5–42.

Ellis, R. P. and McGuire, T. G. (1986). Provider behavior under prospective reimbursement: Cost sharing and supply. *Journal of Health Economics*, **5** (2), 129–151.

Elshaug, A. G., Rosenthal, M. B., Lavis, J. N., Brownlee, S., Schmidt, H., Nagpal, S., Littlejohns, P., Srivastava, D., Tunis, S. and Saini, V. (2017). Levers for addressing medical underuse and overuse: achieving high-value health care. *The Lancet*, **390** (10090), 191–202.

Epstein, A. J. and Ketcham, J. D. (2014). Information technology and agency in physicians' prescribing decisions. *The RAND Journal of Economics*, **45** (2), 422–448.

— and Nicholson, S. (2009). The formation and evolution of physician treatment styles: An application to cesarean sections. *Journal of Health Economics*, **28** (6), 1126–1140.

Escarce, J. (1996). Externalities in hospitals and physician adoption of a new surgical technology: An exploratory analysis. *Journal of Health Economics*, **15** (6), 715–734.

Finkelstein, A., Gentzkow, M. and Williams, H. (2016). Sources of geographic variation in health care: Evidence from patient migration. *The Quarterly Journal of Economics*, **131** (4), 1681–1726.

Fischer, K. E., Koch, T., Kostev, K. and Stargardt, T. (2018). The impact of physician-level drug budgets on prescribing behavior. *The European Journal of Health Economics*, **19** (2), 213–222.

Frank, R. G. and Zeckhauser, R. J. (2007). Custom-made versus ready-to-wear treatments: Behavioral propensities in physicians' choices. *Journal of Health Economics*, **26** (6), 1101–1127.

Gehlbach, S. H., Wilkinson, W. E., Hammond, W. E., Clapp, N. E., Finn, A. L., Taylor, W. J. and Rodell, M. (1984). Improving drug prescribing in a primary care practice. *Medical Care*, **22** (3), 193–201.

Goldman, D. P., Joyce, G. F. and Zheng, Y. (2007). Prescription drug cost sharing: Associations with medication and medical utilization and spending and health. *JAMA*, **298** (1), 61–69.

Grytten, J. and Sørensen, R. (2003). Practice variation and physician-specific effects. *Journal of Health Economics*, **22** (3), 403–418.

Howell, S., Yin, P. T. and Robinson, J. C. (2021). Quantifying the economic burden of drug utilization management on payers, manufacturers, physicians, and patients. *Health Affairs*, **40** (8), 1206–1214.

Iizuka, T. (2007). Experts' agency problems: evidence from the prescription drug market in Japan. *The RAND Journal of Economics*, **38** (3), 844–862.

Imbens, G. W. and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, **47** (1), 5–86.

Ivers, N., Jamtvedt, G., Flottorp, S., Young, J. M., Odgaard-Jensen, J., French, S. D., O'Brien, M. A., Johansen, M., Grimshaw, J. and Oxman, A. D. (2012). Audit and feedback: Effects on professional practice and healthcare outcomes. *The Cochrane Database of Systematic Reviews*, (6), CD000259.

Jackevicius, C. A., Chou, M. M., Ross, J. S., Shah, N. D. and Krumholz, H. M. (2012). Generic Atorvastatin and Health Care Costs. *The New England Journal of Medicine*, **366** (3), 201–204.

Janakiraman, R., Dutta, S., Sismeiro, C. and Stern, P. (2008). Physicians' persistence and its implications for their response to promotion of prescription drugs. *Management Science*, **54** (6), 1080–1093.

Jones, P., Kafonek, S., Laurora, I. and Hunninghake, D. (1998). Comparative dose efficacy study of atorvastatin versus simvastatin, pravastatin, lovastatin, and fluvastatin in patients with hypercholesterolemia (the CURVES study). *The American Journal of Cardiology*, **81** (5), 582–587.

Jones, P. H., Davidson, M. H., Stein, E. A., Bays, H. E., McKenney, J. M., Miller, E., Cain, V. A. and Blasetto, J. W. (2003). Comparison of the efficacy and safety of rosuvastatin versus atorvastatin, simvastatin, and pravastatin across doses (STELLAR trial). *The American Journal of Cardiology*, **92** (2), 152–160.

Ketcham, J. D. and Epstein, A. J. (2008). Medicaid preferred drug lists' costs to physicians. *Medical Care*, **46** (1), 9–16.

Klose, G. and Schwabe, U. (2015). Lipidsenkende Mittel. In U. Schwabe and D. Paffrath (eds.), *Arzneiverordnungs-Report 2015*, Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 745–756.

Korzilius, H. (2011). Kein Arzt wir für seine teuren Patienten bestraft. *Deutsches Ärzteblatt*, **108** (18), A984–A986.

— (2015). Arzneimittelrichtgrössen: Ärzte sollen angstfrei verordnen. *Deutsches Ärzteblatt*, **112** (33-34), A1357–A1360.

Miraldo, M., Hauck, K., Vernet, A. and Wheelock, A. (2019). Variations in the adoption of healthcare innovation: A literature review. *Oxford Research Encyclopedia of Economics and Finance*.

Molitor, D. (2018). The evolution of physician practice styles: Evidence from cardiologist migration. *American Economic Journal: Economic Policy*, **10** (1), 326–56.

Naci, H., Brugts, J. and Ades, T. (2013). Comparative tolerability and harms of individual statins. *Circulation: Cardiovascular Quality and Outcomes*, **6** (4), 390–399.

Ofori-Asenso, R., Ilomaki, J., Tacey, M., Zomer, E., Curtis, A. J., Si, S., Zullo, A. R., Korhonen, M. J., Bell, J. S., Zoungas, S. and Liew, D. (2018). Switching, discontinuation, and reinitiation of statins among older adults. *Journal of the American College of Cardiology*, **72** (21), 2675–2677.

Raelin, J. A. (2011). The end of managerial control? *Group & Organization Management*, **36** (2), 135–160.

Reiner, Ž., Catapano, A. L., De Backer, G., Graham, I., Taskinen, M.-R., Wiklund, O., Agewall, S., Alegria, E., Chapman, M. J., Durrington, P. *et al.* (2011). ESC/EAS guidelines for the management of dyslipidaemias:

The Task Force for the management of dyslipidaemias of the European Society of Cardiology (ESC) and the European Atherosclerosis Society (EAS). *European Heart Journal*, **32** (14), 1769–1818.

Robert Koch-Institut (Hrsg) (RKI) (2015). *Gesundheit in Deutschland. Gesundheitsberichterstattung des Bundes. Gemeinsam getragen von RKI und Destatis*. Technical report, RKI, Berlin.

Rubin, D. B. (2005). Causal inference using potential outcomes: Design, modeling, decisions. *Journal of the American Statistical Association*, **100** (469), 322–331.

Sacarny, A., Yokum, D., Finkelstein, A. and Agrawal, S. (2016). Medicare letters to curb overprescribing of controlled substances had no detectable effect on providers. *Health Affairs*, **35** (3), 471–479.

Saito, Y., Yamada, N., Teramoto, T., Itakura, H., Hata, Y., Nakaya, N., Mabuchi, H., Tushima, M., Sasaki, J., Ogawa, N. and Goto, Y. (2002). A randomized, double-blind trial comparing the efficacy and safety of pitavastatin versus pravastatin in patients with primary hypercholesterolemia. *Atherosclerosis*, **162** (2), 373–379.

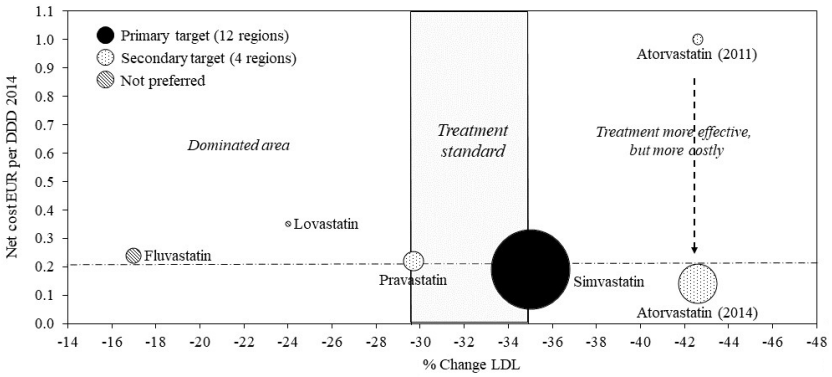
Schwabe, U. (2006). Arzneiverordnungen 2005 im überblick. In U. Schwabe and D. Paffrath (eds.), *Arzneiverordnungs-Report 2006*, Springer, pp. 3–46.

Skinner, J. and Staiger, D. (2015). Technology diffusion and productivity growth in health care. *Review of Economics and Statistics*, **97** (5), 951–964.

Stargardt, T. (2010). The impact of reference pricing on switching behaviour and healthcare utilisation: the case of statins in Germany. *The European Journal of Health Economics*, **11** (3), 267–277.

Tables and Figures

FIGURE 1.
Efficacy and net cost per defined daily dosis of statins prescribed in Germany, 2011–2014



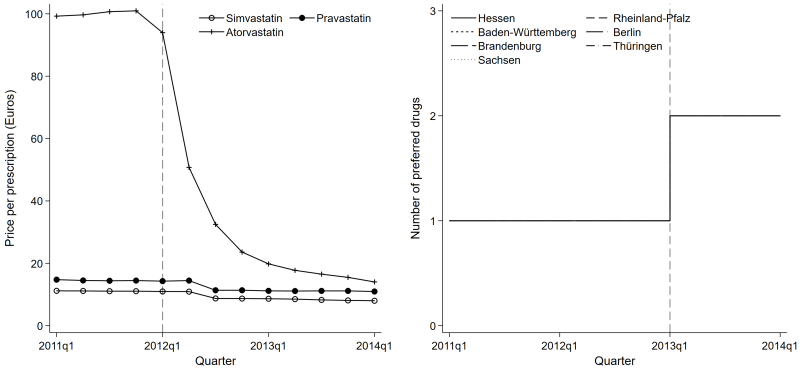
NOTE.— Illustration of all substances in the class of statins available in the German prescription drug market 2011-2014 and their preferred drug status. Size of circles highlight market share of drug in 2014 unless otherwise specified. Net cost per defined daily dosis obtained from Klose and Schwabe (2015). Generic versions of atorvastatin was introduced in the start of 2012 and indicated by the two separate circles for atorvastatin in the figure. Efficacy data were obtained from Bradford *et al.* (1991); Jones *et al.* (1998, 2003); Naci *et al.* (2013); Saito *et al.* (2002).

TABLE 1.
Sample summary statistics

	(1) Mean	(2) SD	(3) Min	(4) Max
Complier	0.609	(0.488)	0.000	1.000
Specialist	0.000	(0.000)	0.000	0.000
Female	0.298	(0.458)	0.000	1.000
Age	55.572	(6.803)	32.000	74.000
Total Prescriptions	117.411	(60.462)	41.000	412.000
Dual Practice	0.372	(0.484)	0.000	1.000
Share Private	0.116	(0.068)	0.015	0.820
N		928		

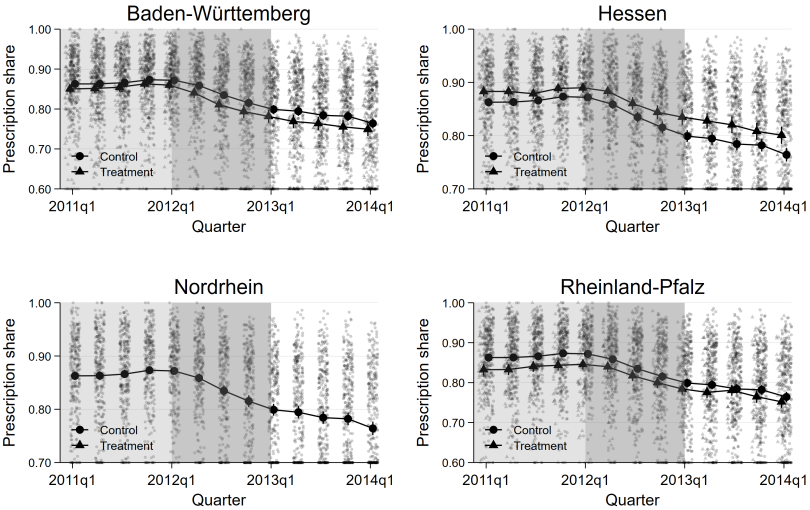
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Complier is defined as having a average preferred use rate equal to or above the post-policy PDP quota in the relevant region in 2011. Total prescriptions are defined as the total number of quarterly prescriptions. Dual practice is defined as the share of physicians who are prescribing statins to both publicly and privately insured patients. Shared practice is defined as physicians working in a group practice.

FIGURE 2.
Drug prices and preferred drug targets by health care organization administrative region in Germany, 2011–2014



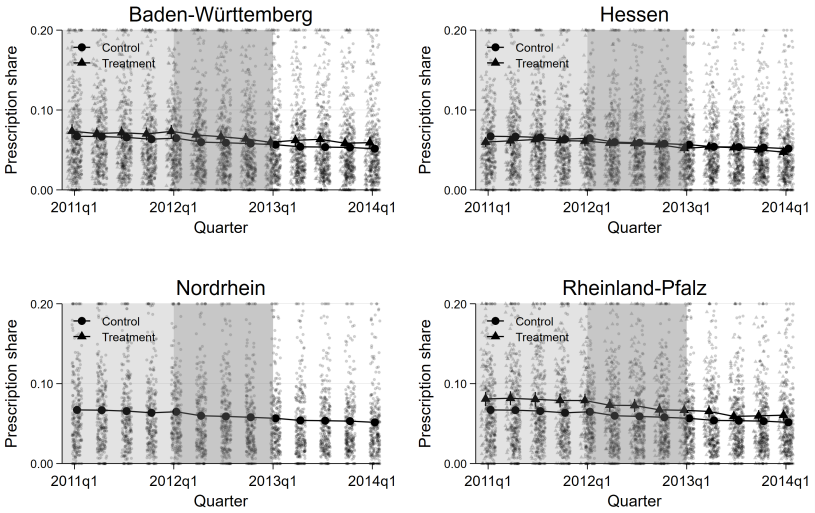
NOTE.— Left panel illustrates average quarterly price per prescription in Euros for each of the three statins considered in the analysis over time. The vertical line in the figure highlights the quarter of generic entry of atorvastatin. Right panel illustrates the number of statins included in the PDP over time by PA region. Three PAs (Bavaria, Westphalia-Lippe and Schleswig-Holstein) did not have a PDP in place during the years covered by the study. Two PAs were excluded due to low number of sampled physicians (Hamburg and Saarland) and in four PAs information on PDP could not be obtained (Bremen, Lower Saxony, Mecklenburg-Vorpommern and Saxony-Anhalt).

FIGURE 3.
State-specific trends in statin use rates: simvastatin I



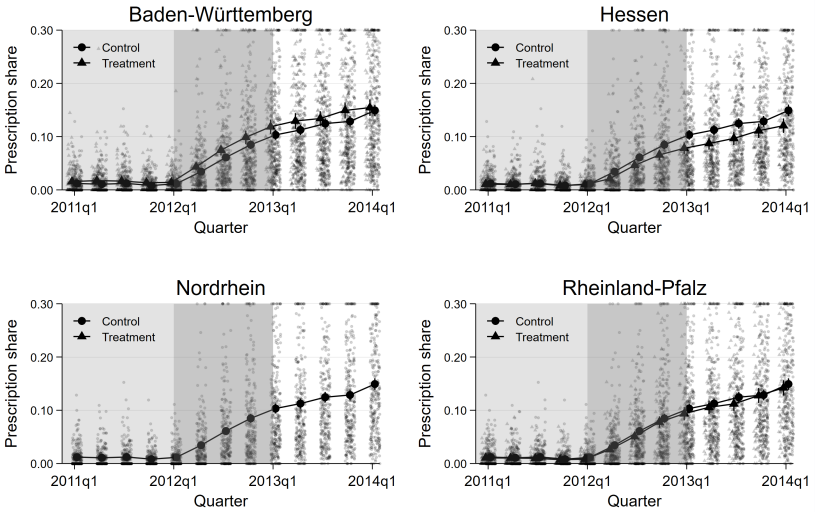
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel pertains to a specific PA region. Black triangles indicate trends in use rates for the specific PA and black circles indicate corresponding trends for the pooled control organization (Bavaria, Westphalia-Lippe and Schleswig-Holstein). Hollow observations characterize physician-specific averages in the treatment (triangles) and pooled control (circles) organizations (with associated 95 percent CIs). Light and dark shaded areas indicate periods prior to the generic entry of atorvastatin and the change in PDP, respectively. Observations winzorised to ±0.1 around group averages.

FIGURE 4.
State-specific trends in statin use rates: pravastatin I



NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel pertains to a specific PA region. Black triangles indicate trends in use rates for the specific PA and black circles indicate corresponding trends for the pooled control organization (Bavaria, Westphalia-Lippe and Schleswig-Holstein). Hollow observations characterize physician-specific averages in the treatment (triangles) and pooled control (circles) organizations (with associated 95 percent CIs). Light and dark shaded areas indicate periods prior to the generic entry of atorvastatin and the change in PDP, respectively. Observations winzorised to ±0.1 around group averages.

FIGURE 5.
State-specific trends in statin use rates: atorvastatin I



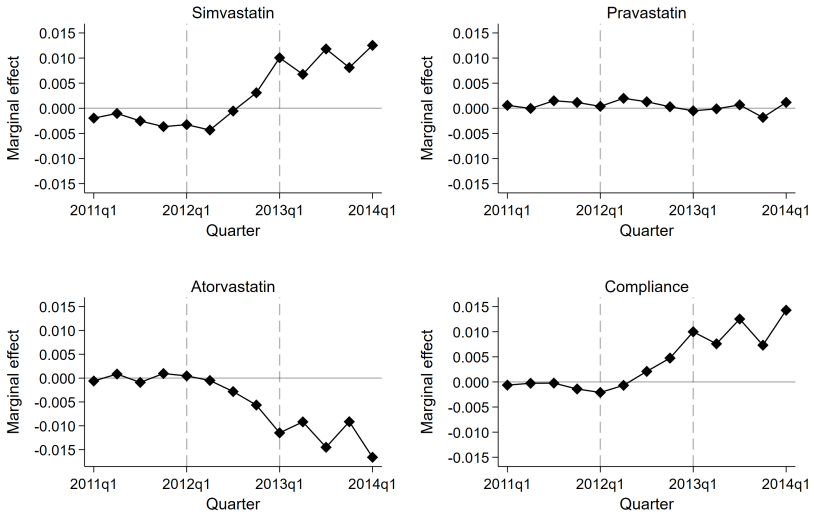
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel pertains to a specific PA region. Black triangles indicate trends in use rates for the specific PA and black circles indicate corresponding trends for the pooled control organization (Bavaria, Westphalia-Lippe and Schleswig-Holstein). Hollow observations characterize physician-specific averages in the treatment (triangles) and pooled control (circles) organizations (with associated 95 percent CIs). Light and dark shaded areas indicate periods prior to the generic entry of atorvastatin and the change in PDP, respectively. Observations winzorised to ±0.1 around group averages.

TABLE 2.
Difference-in-differences estimates: Main results

	Simvastatin		Pravastatin		Atorvastatin	
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat_s$	0.011*	0.010*	-0.012***	-0.013***	0.015***	0.016***
	(0.005)	(0.006)	(0.002)	(0.002)	(0.005)	(0.006)
$Post_t$	-0.086***		-0.015***		0.121***	
	(0.005)		(0.001)		(0.004)	
$Post1_t$		-0.045***		-0.010***		0.070***
		(0.004)		(0.001)		(0.004)
$Post2_t$		-0.041***		-0.005***		0.052***
		(0.005)		(0.001)		(0.004)
$Post_t \times Treat_s$	0.011***		-0.001*		-0.010***	
	(0.003)		(0.001)		(0.003)	
$Post1_t \times Treat_s$		0.001		0.000		-0.002
		(0.003)		(0.001)		(0.003)
$Post2_t \times Treat_s$		0.010***		-0.001*		-0.009***
		(0.003)		(0.001)		(0.003)
Constant	0.886***	0.886***	0.066***	0.066***	-0.030***	-0.030***
	(0.010)	(0.010)	(0.005)	(0.005)	(0.010)	(0.010)
Physicians	928	928	928	928	928	928
N	11,136	11,136	11,136	11,136	11,136	11,136

NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each column reports coefficient estimates from a separate regression of the use rate by prescriptions that were equal to the specific drug indicated in the column header. *Treat* is a dummy variable equal to one if a physician belonged to a PA with a PDP and zero otherwise. *Post* is a dummy variable equal to one for all time periods after the first quarter of 2013. *Post1* and *Post2* are dummy variables equal to one for all time periods after the first quarter of 2012 and 2013, respectively. All regressions control for PA fixed effects, physician age and sex, whether the physician has a clinical specialization, provides dual practice, works in a shared practice, and for the physicians total quarterly statin prescriptions. Observations weighted by number of quarterly statin prescriptions. Robust standard errors clustered by state-quarter in (parentheses). *p*-values adjusted for multiple testing using seemingly unrelated regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 6.
Predicted marginal effects, by group and drug



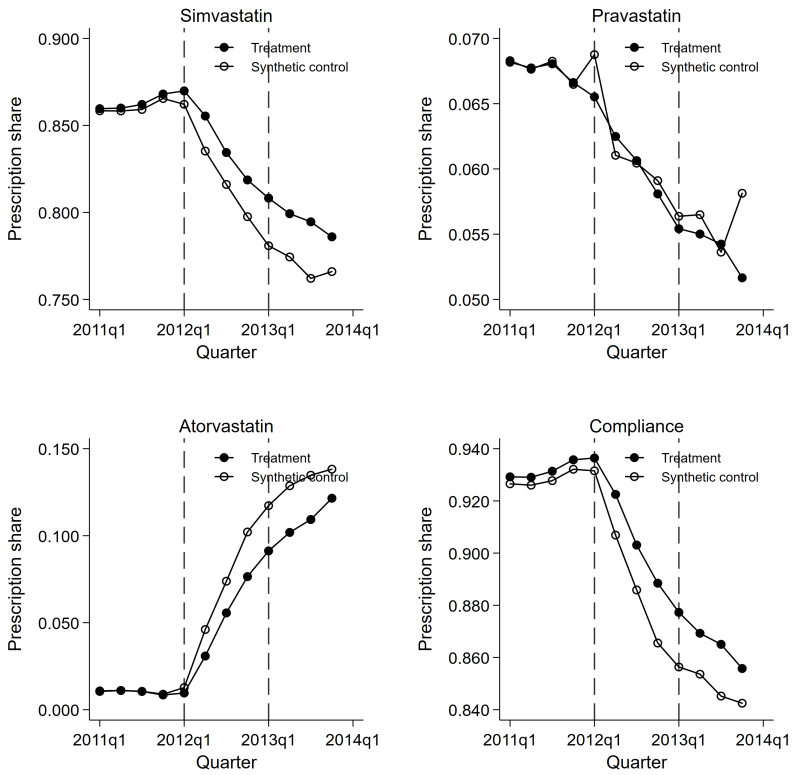
NOTE.—Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel row reports marginal effects using estimated coefficients from Table 2 of the use rate of all prescriptions that were equal to the specific drug indicated in the panel header aggregated to the group-quarter level. Treatment and control indicate group-specific trends for physicians that belonged and did not belong to a PA with a PDP, respectively. Vertical lines indicate quarter of generic entry of atorvastatin (Q1, 2012) and the change in PDP (Q1, 2013), respectively.

TABLE 3.
Synthetic control estimates: Main results

	Treatment (1)	Synthetic control (2)	Difference (3)
		Simvastatin	
$Post1_t$	-0.044***	-0.061***	0.018**
	-0.006	(0.002)	(0.005)
$Post2_t$	-0.032***	-0.031***	-0.002
	-0.004	(0.001)	(0.004)
Constant	0.897***	0.886***	0.011
	-0.032	(0.026)	(0.022)
		Pravastatin	
$Post1_t$	-0.010***	-0.008***	-0.002
	(0.002)	(0.001)	(0.002)
$Post2_t$	-0.006***	-0.001	-0.005***
	(0.001)	(0.001)	(0.000)
Constant	0.060**	0.055**	0.004
	(0.018)	(0.017)	(0.003)
		Atorvastatin	
$Post1_t$	0.067***	0.091***	-0.024***
	(0.005)	(0.004)	(0.005)
$Post2_t$	0.044***	0.036***	0.008*
	(0.004)	(0.001)	(0.004)
Constant	-0.003	0.014	-0.017
	(0.029)	(0.015)	(0.023)
		Preferred share	
$Post1_t$	-0.042***	-0.059***	0.017
	(0.011)	(0.004)	(0.009)
$Post2_t$	-0.040***	-0.044***	0.003
	(0.009)	(0.001)	(0.009)
Constant	1.013***	0.931***	0.079**
	(0.038)	(0.022)	(0.027)
Physicians	663	663	663
N	7,524	7,524	7,524

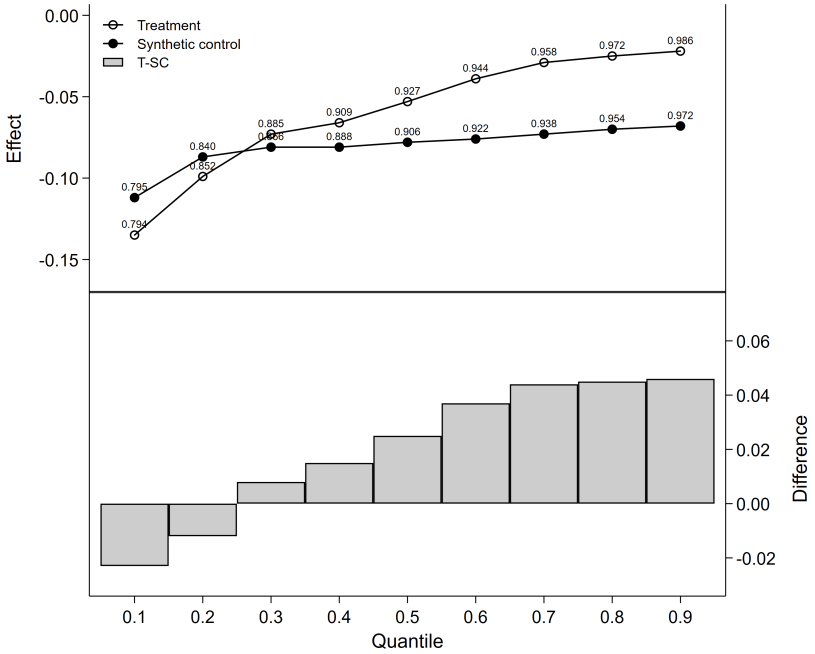
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Synthetic control estimates based on matching each physician residing in a PA with a PDP (treatment) to a synthetic control taken from the pool of physicians in PAs without a PDP (control). See Section 5.4 for details. Each column in each panel reports coefficient estimates from a separate regression of the use rate of all prescriptions that were equal to the specific drug indicated in the panel header. Columns (1) and (2) report estimates from including the treatment and synthetic control groups outcomes, respectively. Column (3) reports estimates from including the difference between the treatment and synthetic control groups outcomes. *Post1* and *Post2* are dummy variables equal to one for all time periods after the first quarter of 2012 and 2013, respectively. All regressions control for PA fixed effects, physician age and sex, whether the physician has a clinical specialization, provides dual practice, works in a shared practice, and for the physicians total quarterly statin prescriptions. Observations weighted by number of quarterly statin prescriptions. Robust standard errors clustered by state-quarter in (parentheses). p-values adjusted for multiple testing using seemingly unrelated regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 7.
Synthetic control estimates for drug-specific trends



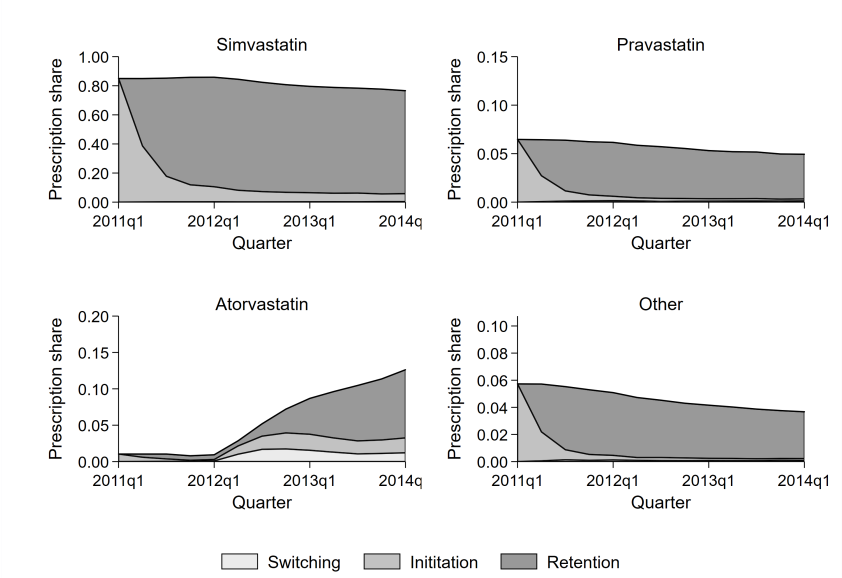
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Synthetic control estimates based on matching each physician residing in a PA with a PDP (treatment) to a synthetic control taken from the pool of physicians in PAs without a PDP (control). See Section 5.4 for details. Each panel pertains to a different outcome as indicated in the panel header. Solid and hollow markers refer to trends for the treatment and synthetic control groups. Vertical lines indicate quarter of generic entry of atorvastatin (Q1, 2012) and the change in PDP (Q1, 2013), respectively.

FIGURE 8.
Synthetic control estimates: Heterogeneity by pre-policy compliance level



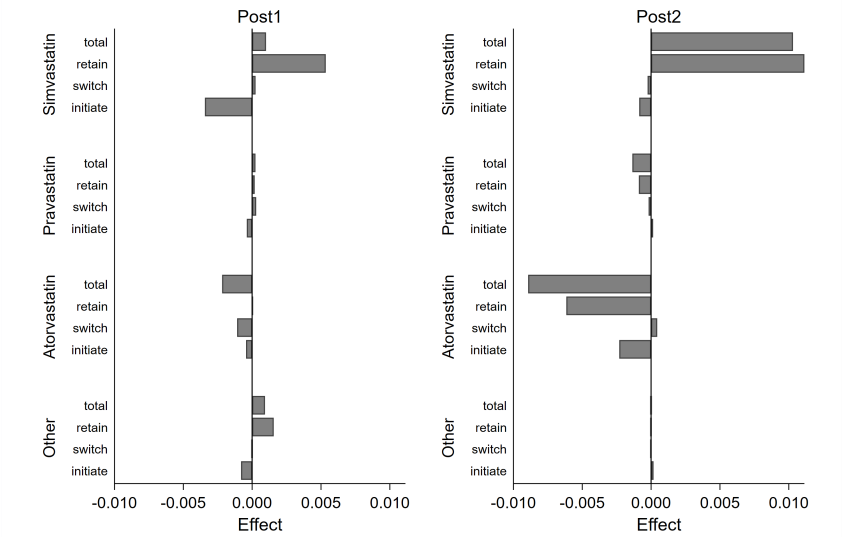
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Synthetic control estimates based on matching each physician residing in a PA with a PDP (treatment) to a synthetic control taken from the pool of physicians in PAs without a PDP (control). See Section 5.4 for details. Each observation in the upper panel indicates the point estimate of a quantile regression of a dummy variable (*Post*) equal to one for all time periods after the first quarter of 2013 on the post-policy preferred use rate for treated physicians and their corresponding synthetic control, respectively. All regressions control for PA fixed effects, physician age and sex, whether the physician has a clinical specialization, provides dual practice, works in a shared practice, and for the physicians total quarterly statin prescriptions. Observations weighted by number of quarterly statin prescriptions. Marker labels report the preferred share for each group-specific quantile. The lower panel reports the quantile-specific difference in the point estimate between the treatment and the synthetic controls groups in the upper panel.

FIGURE 9.
Decomposition of drug-specific trends: Switching, initiation and retention



NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel reports aggregate quarterly shares for a specific statin. Different shades reflect the proportion of drug switchers, initiations and retentions of the total drug share. Switching is defined as a patient-physician cell observed with different statin prescriptions across two consecutive quarters. Initiation is defined as the share of new patients whom were prescribed a specific drug across two consecutive quarters. Retention is defined as the share of existing patients that were given the same drug across two consecutive quarters.

FIGURE 10.
Difference-in-differences estimates: Decomposition of main effects



NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Graphical representation of interactions coefficients $Post1 \times Treat$ (left panel) and $Post2 \times Treat$ (right panel) based on estimates from Table A.1. Effect sizes represented by the horizontal axis. Total effect size and its three subcomponents represented by each drug on the vertical axis. Switching is defined as a patient-physician cell observed with different statin prescriptions across two consecutive quarters. Initiation is defined as the share of new patients whom were prescribed a specific drug across two consecutive quarters. Retention is defined as the share of existing patients that were given the same drug across two consecutive quarters. All regressions control for PA fixed effects, physician age and sex, whether the physician has a clinical specialization, provides dual practice, works in a shared practice, and for the physicians total quarterly statin prescriptions. Observations weighted by number of quarterly statin prescriptions.

Appendix A Additional tables and figures

FIGURE A.1.
Comparative effectiveness of tolerability and safety in the statin drug class

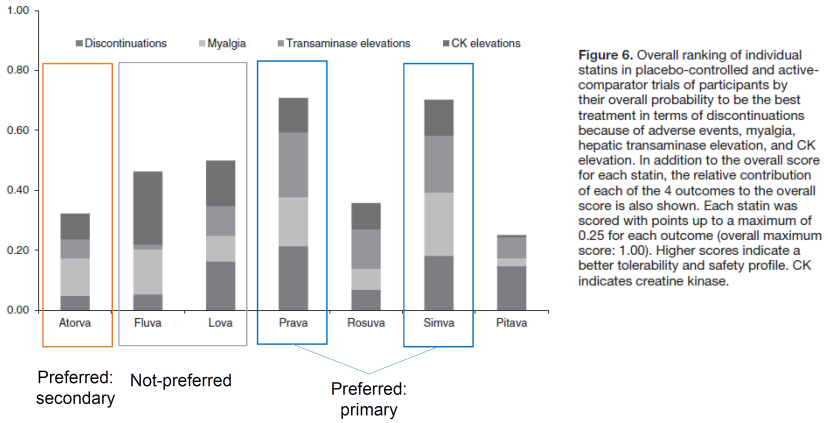
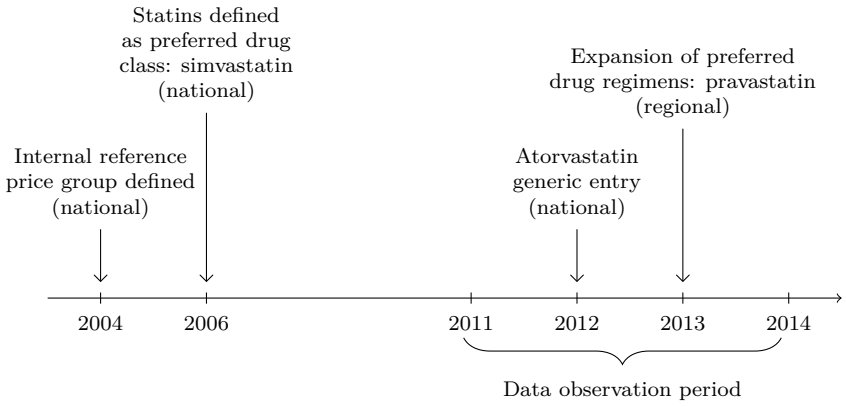


Figure 6. Overall ranking of individual statins in placebo-controlled and active-comparator trials of participants by their overall probability to be the best treatment in terms of discontinuations because of adverse events, myalgia, hepatic transaminase elevation, and CK elevation. In addition to the overall score for each statin, the relative contribution of each of the 4 outcomes to the overall score is also shown. Each statin was scored with points up to a maximum of 0.25 for each outcome (overall maximum score: 1.00). Higher scores indicate a better tolerability and safety profile. CK indicates creatine kinase.

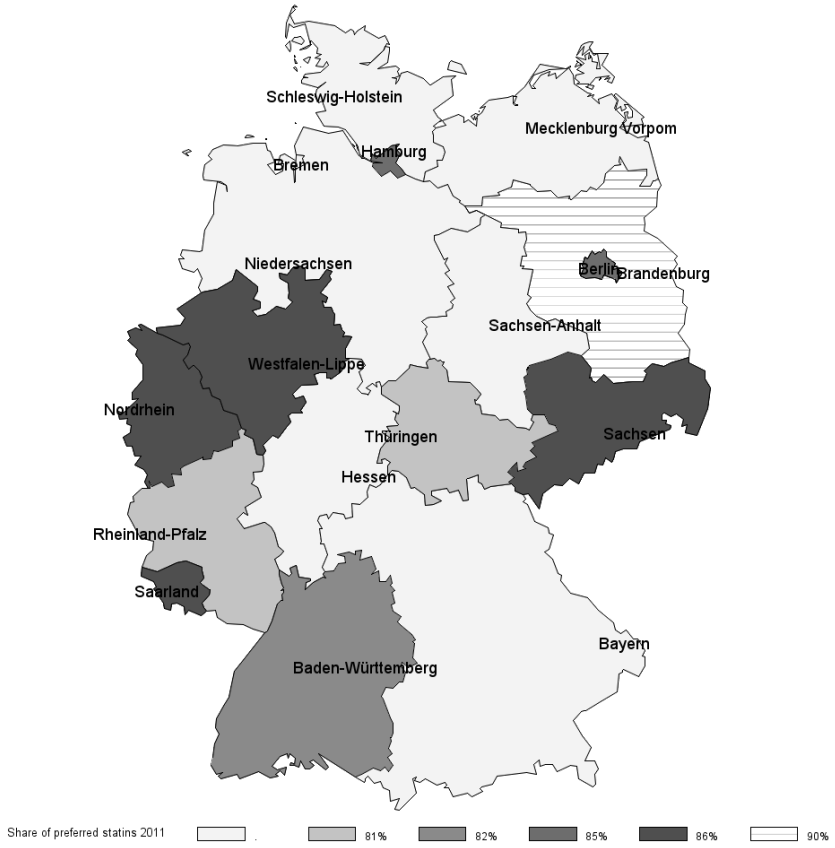
NOTE.— Sourced from Naci, H., Brugts, J. and Ades, T. 2013. Comparative Tolerability and Harms of Individual Statins. *Circulation: Cardiovascular Quality and Outcomes*, 6 (4), 390–399.

FIGURE A.2.
A timeline of events involving control measures (preferred drug policies) for the statin drug class in Germany, 2004–2014



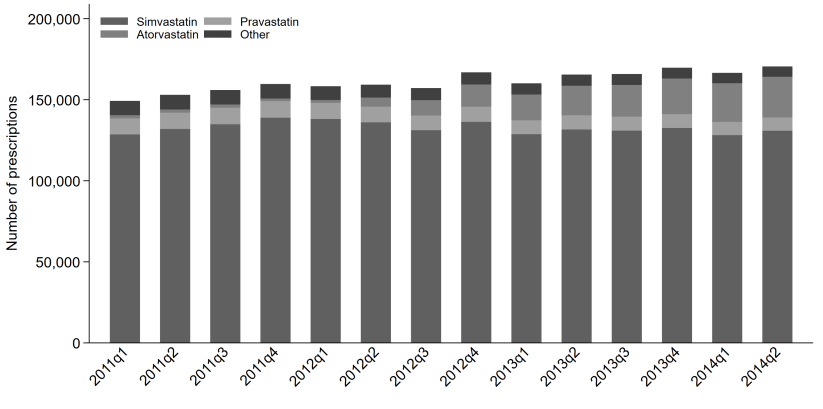
NOTE.— National and regional in parentheses pertain to whether the policy was implemented nationally or regionally. The generic entry of atorvastatin in 2012 is not a policy per se but relevant for the analysis of compliance to the PDP.

FIGURE A.3.
Preferred statin use rate by physician association, 2011



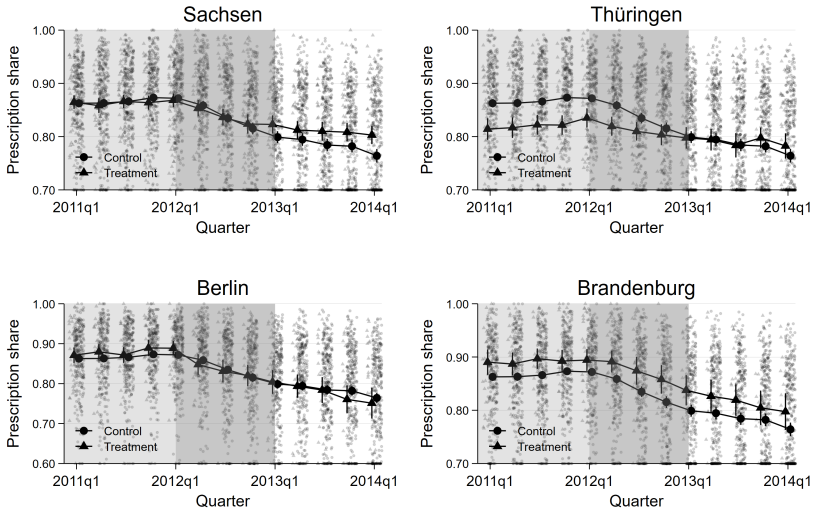
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Average rates of preferred statin use rates in PAs in 2011. Hamburg and Saarland are excluded from the analysis due to small physician samples. Information on PDP could not be obtained for four regions (Bremen, Lower Saxony, Mecklenburg-Vorpommern and Saxony-Anhalt) and are hence not included in the sample. The federal state North Rhine-Westfalia consists of two PAs, North Rhine and Westphalia-Lippe, which are not distinguished in the figure.

FIGURE A.4.
Number of statin prescriptions by drug and quarter, 2011–2014



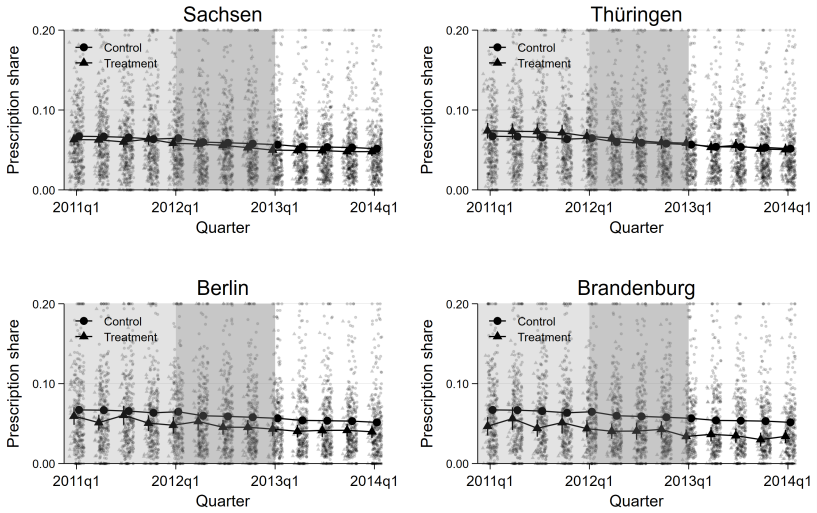
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Total number of quarterly prescriptions in Germany. Generic entry of atorvastatin in March 2013. Other statins include fluvastatin, lovastatin, pitavastatin and rosuvastatin.

FIGURE A.5.
State-specific trends in statin use rates: simvastatin II



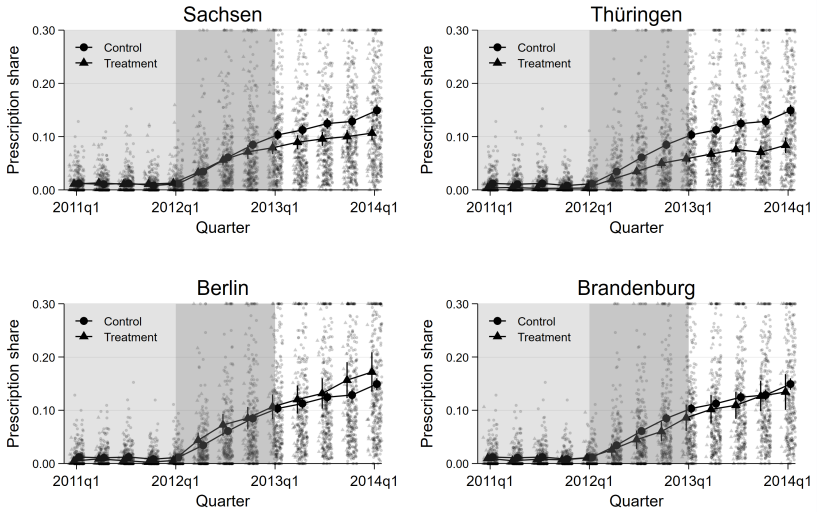
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel pertains to a specific PA region. Black triangles indicate trends in use rates for the specific PA and black circles indicate corresponding trends for the pooled control organization (Bavaria, Westphalia-Lippe and Schleswig-Holstein). Hollow observations characterize physician-specific averages in the treatment (triangles) and pooled control (circles) organizations (with associated 95 percent CIs). Light and dark shaded areas indicate periods prior to the generic entry of atorvastatin and the change in PDP, respectively. Observations winzorised to ±0.1 around group averages.

FIGURE A.6.
State-specific trends in statin use rates: pravastatin II



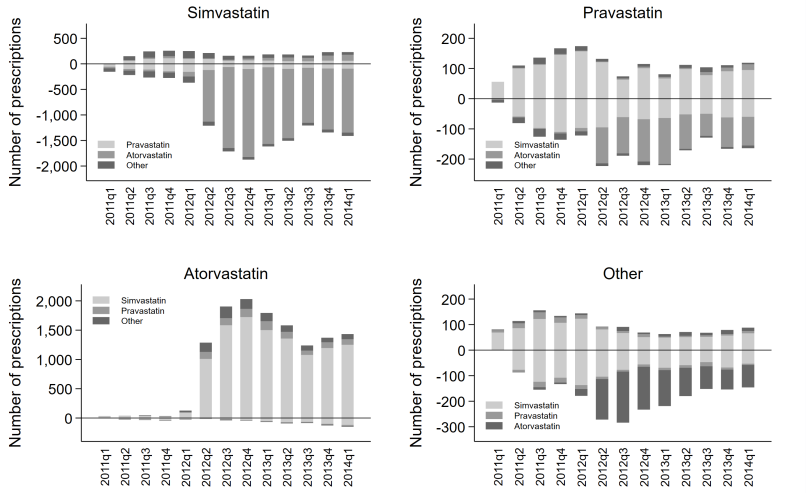
NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel pertains to a specific PA region. Black triangles indicate trends in use rates for the specific PA and black circles indicate corresponding trends for the pooled control organization (Bavaria, Westphalia-Lippe and Schleswig-Holstein). Hollow observations characterize physician-specific averages in the treatment (triangles) and pooled control (circles) organizations (with associated 95 percent CIs). Light and dark shaded areas indicate periods prior to the generic entry of atorvastatin and the change in PDP, respectively. Observations winzorised to ±0.1 around group averages.

FIGURE A.7.
State-specific trends in statin use rates: atorvastatin II



NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel pertains to a specific PA region. Black triangles indicate trends in use rates for the specific PA and black circles indicate corresponding trends for the pooled control organization (Bavaria, Westphalia-Lippe and Schleswig-Holstein). Hollow observations characterize physician-specific averages in the treatment (triangles) and pooled control (circles) organizations (with associated 95 percent CIs). Light and dark shaded areas indicate periods prior to the generic entry of atorvastatin and the change in PDP, respectively. Observations winzorised to ±0.1 around group averages.

FIGURE A.8.
Decomposition of drug-specific trends: Drug switching over time



NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each panel reports counts of drug switching for a specific statin. Positive and negative bars indicate switching to and from the specific drug, respectively. Different bar shades indicate the statin which being switched to and from the focal drug. Switching is defined as a patient-physician cell observed with different statin prescriptions across two consecutive quarters.

TABLE A.1.
Difference-in-differences estimates: Decomposition of main effects

	Simvastatin				Atorvastatin			
	(1) Total	(2) Retained	(3) Switched	(4) Initiated	(5) Total	(6) Retained	(7) Switched	(8) Initiated
$Treat_s$	0.010*	0.011	-0.001***	0.007	0.016***	0.013***	0.002	0.002
	(0.006)	(0.008)	(0.000)	(0.008)	(0.006)	(0.004)	(0.001)	(0.002)
$Post1_t$	-0.045***	0.737***	0.002***	-0.785***	0.070***	0.033***	0.018***	0.012***
	(0.004)	(0.007)	(0.000)	(0.008)	(0.004)	(0.002)	(0.001)	(0.001)
$Post2_t$	-0.041***	-0.027***	0.001***	-0.012***	0.052***	0.057***	-0.007***	-0.002**
	(0.005)	(0.004)	(0.000)	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)
$Post1_t \times Treat_s$	0.001	0.005	0.000	-0.003	-0.002	0.000	-0.001	-0.000
	(0.003)	(0.006)	(0.000)	(0.005)	(0.003)	(0.002)	(0.001)	(0.001)
$Post2_t \times Treat_s$	0.010***	0.011***	-0.000	-0.001	-0.009***	-0.006***	0.000	-0.002***
	(0.003)	(0.003)	(0.000)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Constant	0.886***	0.012	-0.000	0.863***	-0.030***	-0.022***	-0.007***	0.002
	(0.010)	(0.011)	(0.001)	(0.009)	(0.010)	(0.006)	(0.002)	(0.002)
Physicians	928	928	928	928	928	928	928	928
N	11,136	11,136	11,136	11,136	11,136	11,136	11,136	11,136

NOTE.— Data from the CEGEDIM-MEDIMED physician panel for the period 2011–2014. Each column reports coefficient estimates from a separate regression of the use rate that were equal to the specific drug indicated in the column header, subdivided into the total effect and three components that sum up to the total effect. Switching is defined as a patient-physician cell observed with different statin prescriptions across two consecutive quarters. Initiation is defined as the share of new patients whom were prescribed a specific drug across two consecutive quarters. Retention is defined as the share of existing patients that were given the same drug across two consecutive quarters. *Treat* is a dummy variable equal to one if a physician belonged to a PA with a PDP and zero otherwise. *Post* is a dummy variable equal to one for all time periods after the first quarter of 2013. *Post1* and *Post2* are dummy variables equal to one for all time periods after the first quarter of 2012 and 2013, respectively. All regressions control for PA fixed effects, physician age and sex, whether the physician has a clinical specialization, provides dual practice, works in a shared practice, and for the physicians total quarterly statin prescriptions. Observations weighted by number of quarterly statin prescriptions. Robust standard errors clustered by state-quarter in (parentheses). p-values adjusted for multiple testing using seemingly unrelated regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.