

The role of physician altruism in the physician-industry relationship*

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Abstract

Financial incentives can distort physicians' treatment decisions, fueling healthcare spending. Altruism, a core element of medical professionalism, may counteract these distortions. We link altruism elicited from a revealed preference experiment for 267 U.S. physicians to administrative data on industry transfers and prescribing. Non-altruistic physicians receive substantially higher payments (USD 1,775, or 111% more annually) and increase prescribing of promoted drugs after payment, whereas altruistic physicians do not. Divergence is largest in drug classes with high clinical substitutability. Our findings show that altruism moderates the influence of financial incentives in physician-industry ties, limiting the scope for agency problems in prescribing.

Keywords: Physician behavior; Altruism; Industry payments; Drug prescribing

JEL codes: I11; D64; L14; C91

*We are grateful to Lawrence Casalino for important groundwork and helpful discussions and to Melissa Newham for sharing data on drug approvals and ATC codes. We thank Colleen Carey, Mikael Elinder, Geir Godager, Mireille Jacobson, Iris Kesternich, Susan Mendez, Sabrina Schubert, Odd Rune Straume, Hannes Ullrich, David Whitehurst, as well as participants at the DGGÖ Health Econometrics Workshop, the University of Zurich, the SGGÖ Health Economics Conference, the Health Economics Methods Meeting, RWI Essen, the University of Oslo, the ASHEcon Conference, the NHESG meeting, Peking University, the Arne Ryde workshop on public service management and innovations, and the APPAM Fall Research Conference for valuable comments. Funding from the Physicians Foundation and the Joachim-Herz-Foundation is graciously acknowledged.

1 Introduction

Physicians have enormous influence over the allocation of healthcare resources, particularly through drug prescribing. Drug spending is rising rapidly across many developed countries, driven partly by the uptake of high-priced drugs such as diabetes and weight loss medications. In the United States, branded products account for 80% of prescription drug spending.¹ A growing literature shows that physicians’ prescribing choices are shaped by financial ties with pharmaceutical manufacturers, often established through direct-to-physician marketing. While such interactions can convey useful information about new drugs, they also generate conflicts of interest that can distort prescribing and raise costs without improving patient outcomes (Carey et al. 2025; Mitchell et al. 2023; Agha and Zeltzer 2022).²

The notion that physicians, despite their professional norms, can be influenced by financial incentives has received much attention (Arrow 1963; Town et al. 2005; Kesternich et al. 2015). Far less is known about how underlying physician traits mediate such influence. A key trait is altruism – prioritizing patient and societal welfare over self-interest – a core component of medical professionalism that underpins physicians’ role as representative agents (Arrow 1963). Altruism features prominently in models of optimal insurance and provider payment (Ma and McGuire 1997), cost-sharing (Jack 2005), and treatment-plan design (Choné and Ma 2011; Liu and Ma 2013).

Although theoretical literature typically treats altruism as private information, separate work reveals substantial heterogeneity in physicians’ and medical students’ experimentally measured altruism (Godager and Wiesen 2013; Li et al. 2017, 2022). Such heterogeneity suggests that more altruistic physicians – whose treatment decisions presumably reflect their assessment of what best serves patients – should be less susceptible to financial distortions, whereas less altruistic physicians – who prioritize self-interests – may respond more strongly

¹See the federal policy report by Parasrampur and Murphy (2022).

²Direct-to-physician marketing also attracts widespread media scrutiny, including the Dollars for Doctors project (Ornstein 2016) and reports that extensive payments for the popular weight-loss drug Ozempic may undermine doctor–patient trust (Prater 2023).

to financial incentives, potentially increasing the use of costly treatments without clear clinical benefit. Pharmaceutical prescribing provides a particularly salient setting for studying such heterogeneity in physician altruism, yet empirical evidence remains scant.

In this study, we combine novel experimental and administrative data to examine how altruism shapes physicians’ industry ties and drug prescribing. Using a revealed-preference experiment with a modified dictator game, we elicit altruistic preferences for 267 U.S. physicians in primary care and cardiology, linked to records of financial transfers from pharmaceutical firms and prescriptions in Medicare Part D. We investigate both how altruism relates to industry payments and how it moderates physicians’ prescribing responses to such payments.

We define altruism as the weight physicians place on others’ benefits relative to self-interest, capturing prosocial motives that may arise intrinsically or through professional norms. Following (Casalino et al. 2024), we use a dichotomous measure: physicians are classified as altruistic if they place significantly (5% level) less weight on self-interest than on others’ benefits. By this measure, 18% of physicians in our sample are altruistic.

We first show that non-altruistic physicians maintain stronger financial ties to the pharmaceutical industry. On average, they receive USD 1,775 (111%) more in annual transfers and are 22% more likely to receive any payment than altruistic physicians. Notably, altruism is uncorrelated with observable physician traits, suggesting that it captures a distinct determinant of industry engagement.

We then estimate within-physician effects of drug-specific payments on prescribing of the promoted drug, separately for altruistic and non-altruistic physicians, using staggered difference-in-differences event-studies (Callaway and Sant’Anna 2021). In the full sample, non-altruistic physicians increase prescribing post-payment, while altruistic physicians show non-parallel pre-trends consistent with selective targeting by drug firms. Restricting to ever-paid physician-drug pairs removes these pre-trends: non-altruistic physicians increase claims and spending after payment, while altruistic physicians reduce prescribing. These

heterogeneous responses by physician altruism are also evident in the full sample when allowing for smooth parallel trends violations ([Rambachan and Roth 2023](#)). The divergent trajectories persist for at least two years (the duration of the post-period in our event study), suggesting lasting impacts of financial interactions.

Two mechanisms may explain prescribing changes in either direction after physicians receive payments. First, physicians may differ in their responses to financial incentives and payment disclosure. Prior research shows that *on average*, physicians increase prescribing after payments, consistent with non-altruistic physicians (the majority in our sample) seeking private gains and ongoing financial ties with drug companies. Altruistic physicians may instead reduce (or stop expanding) prescribing of paid drugs to avoid the appearance of undue influence or deter additional marketing attention. Because payment data are publicly available, they may be particularly sensitive to reputational concerns among patients, colleagues, or organizations ([Chao and Larkin 2022](#)). Although non-altruistic physicians face similar pressures, they may place greater weight on financial rewards. This mechanism would generate divergent responses between altruistic and non-altruistic physicians, and aligns with our descriptive finding that non-altruistic physicians are more likely to receive – and receive higher – payments.

Second, paid encounters may convey information that updates physicians’ beliefs about a drug’s clinical value or appropriate use. These interactions can communicate new clinical trials data, peer experiences, or comparative evidence that alters (or reinforces) physicians’ prior perceptions of a drug’s efficacy, safety, or indicated population. Such information can affect all physicians, regardless of altruism: prescribing may increase, decrease, or remain unchanged depending on physicians’ belief updating ([Ching and Ishihara 2012](#); [Grennan et al. 2025](#)). Through this channel, payments may induce convergence in prescribing, as both altruistic and non-altruistic physicians respond to perceived updates in a drug’s expected clinical benefit, especially relative to its cost.

The net prescribing response depends on the relative strength of these two mechanisms,

which may vary across drug classes. For more substitutable drugs or those with ambiguous clinical value, the marginal benefit of additional prescribing is limited. Divergence by altruism should then be greater: altruistic physicians may curb prescribing or switch to alternatives to avoid perceived conflicts of interest, while less altruistic physicians respond more to financial incentives. For less substitutable drugs or those with clearer clinical benefits, payments may primarily reinforce existing positive beliefs about therapeutic value, prompting both groups to increase prescribing. This framework aligns with models of physician decision-making under mixed motives, where altruism and financial incentives interact with perceived treatment benefits (Ellis and McGuire 1986; Duggan 2000).

Consistent with this, we find heterogeneity in response patterns by drug class. Among the three classes most relevant to primary care and cardiology (diabetes, blood thinners, and cardiovascular drugs), divergence by altruism is more pronounced for diabetes drugs and blood thinners. Diabetes drugs include high-cost Glucagon-like peptide-1 receptor agonists (GLP-1RA), often used off-label for obesity, as well as sodium-glucose cotransporter-2 (SGLT2) inhibitors and long-acting insulins, which are largely interchangeable (Palmer et al. 2016). Blood thinners in our sample are mainly heavily marketed direct oral anticoagulants (DOACs), which are broadly substitutable for one another and for older oral anticoagulants such as warfarin, offering some clinical benefit but carrying potentially serious side effects and substantially higher cost (Abaluck et al. 2020; Agha and Zeltzer 2022; Vinogradova et al. 2018).

By contrast, differences by altruism are smallest for cardiovascular drugs. This class includes specialty agents for cardiac rhythm management, antihypertensive therapy (e.g., Riociguat), and heart failure (e.g., Sacubitril-Valsartan), prescribed predominantly by cardiologists. These drugs have unique clinical benefits, few close substitutes, and treat complex patient populations (McMurray et al. 2014). Marketing encounters could therefore provide valuable information encouraging their prescribing (Greene et al. 2018). Consistent with this, payments for cardiovascular drugs, especially among cardiologists, increase prescribing

regardless of altruism.

Two additional findings support these mechanisms. First, even among cardiologists, prescribing responses differ by altruism for non-cardiovascular drugs. Second, the heterogeneity in responses by drug class persists when we restrict to physicians who prescribe across multiple classes, regardless of specialty.

Our study contributes to growing empirical evidence on altruism and prosocial motivation in public service provision, including education ([Ajzenman et al. 2024](#)), scientific evaluation ([Chetty et al. 2014](#)), or volunteer work ([Carpenter and Myers 2010](#)). In healthcare, experimentally measured physician altruism has been linked to specialty choice ([Li 2018](#)), preventable utilization and overall spending ([Casalino et al. 2024](#)), and overprescription in low-resource settings ([Gertler and Kwan 2024](#)). We extend this literature by uncovering a central mechanism underlying the role of altruism in the healthcare market: physicians' responses to third-party financial incentives. Our findings provide novel evidence on how physician altruism shapes healthcare spending and, in turn, the efficiency of the healthcare market.

Our work also contributes to the literature on industry payments and their impact on physician prescribing. Physicians are central in choosing costly branded drugs over cheaper alternatives ([Hellerstein 1998](#)) and in adopting new treatments. Prior studies consistently show that industry payments increase prescribing of promoted drugs ([Iizuka and Jin 2007](#); [Dejong et al. 2016](#); [Carey et al. 2021](#); [Newham and Valente 2024](#); [Carey et al. 2025](#)) and medical devices ([Bergman et al. 2021, 2024](#); [Amaral-Garcia 2022](#)). Our study is the first to document payment effects in the opposite direction for a distinct physician subgroup – those with high altruism. By comparing across drug classes and specialties, we also demonstrate that physician-industry interactions can promote the uptake of potentially underused but effective treatments in some settings, yet pose conflicts of interest in others, generating distinct responses by physicians' altruistic preferences. Although both mechanisms have been extensively discussed, they have not been empirically separated.

Finally, we add to the broader empirical literature on heterogeneous responses to financial and non-financial incentives. In healthcare, most work has focused on demand-side behavior, with limited supply-side evidence. [Ashraf et al. \(2014\)](#) find that prosocially motivated agents (who are not formal healthcare providers) promoting HIV prevention in Zambia respond more strongly to both financial and non-financial incentives. [Schnell \(2025\)](#) shows that heterogeneity in prescribing leniency, interpreted as altruism, moderates opioid prescribing when a secondary market is present. Together, these studies highlight the importance of considering fundamental heterogeneity in provider preferences when designing and regulating incentives ([Bénabou and Tirole 2006](#); [Hennig-Schmidt et al. 2011](#)).

2 Data

To examine how altruism orientation is related to physicians’ payment receipt and prescribing responses, we construct a dataset linking experimentally measured altruism with administrative records on industry transfers and prescribing. This section describes our data.

2.1 The experiment and altruism parameter

Physicians’ altruistic preferences are drawn from an online experiment by [Li et al. \(2022\)](#). The experiment elicits physicians’ social preferences – altruistic and efficiency-equality preferences – using a modified dictator game design ([Andreoni and Miller 2002](#); [Fisman et al. 2007](#)).³ The experiment includes 283 clinically active U.S. physicians in primary care or cardiology, recruited via convenience sampling to represent a wide range in practice size and region.⁴

In the experiment, physicians allocate money between themselves and an anonymous

³An analysis plan on studying physician altruism and quality of care among Medicare patients was pre-registered after the experiment (<https://doi.org/10.17605/OSF.IO/75J8K>). While outcomes related to drug payments were not prespecified, the plan outlines a general relationship between healthcare spending and physician altruism. Altruism is defined, same as in this paper, as selfless preferences.

⁴While our sample may differ from the broader physician population, our analysis relies only on within-sample comparisons. Prior work finds experimental participants to behave slightly less altruistically than nonparticipants, but the difference is modest ([Snowberg and Yariv 2021](#)).

stranger via a series of web-based decision tasks in identical form. Appendix Figure A1 shows the experimental interface. In each task, subjects choose a point on a two-dimensional budget line. The two ‘goods’, represented by the y -axis and x -axis which the budget line intersects, are payoffs for ‘self’ and ‘other’, respectively, where ‘self’ refers to the physician subject themselves and ‘other’ is an anonymous stranger randomly drawn from an online panel representative of the U.S. population.⁵ Thus, in each decision, the physician allocates an endowment across $\tilde{\pi}_s$ (‘self’) and $\tilde{\pi}_o$ (‘other’), facing prices p_s and p_o . For a normalized endowment of 1, the set of possible budget lines are given by:

$$p_s \tilde{\pi}_s + p_o \tilde{\pi}_o = 1.$$

Each physician completes 25 decision rounds, where the budget line is drawn randomly such that the intercepts and slopes vary across rounds. At the end of the experiment, one round is randomly selected for payment: the physician receives $\tilde{\pi}_s$, and the anonymous stranger receives $\tilde{\pi}_o$ from that allocation. After the experiment, each physician completes a survey questionnaire about their socioeconomic characteristics and institutional information about their practice to receive payment.

To measure altruistic preferences, physicians’ utility function $u_s(\tilde{\pi}_s, \tilde{\pi}_o)$ is assumed to exhibit Constant Elasticity of Substitution (CES).⁶ Physicians’ utility from trading off the payoffs to ‘self’ compared to ‘other’ is then given by:

$$u_s = [\alpha \tilde{\pi}_s^\rho + (1 - \alpha) \tilde{\pi}_o^\rho]^{1/\rho}. \quad (1)$$

Parameter $\alpha \in [0, 1]$ in Equation (1) captures altruistic preferences: $\alpha = 0$ reflects fully altruistic preferences with full weight on the payoff to ‘other’, $\alpha = 1$ purely selfish, and $\alpha = 0.5$ impartial. While our analysis focuses on altruistic preferences captured by α ,

⁵The representative panel is the Understanding America Study (UAS), for which physicians are provided a public link describing the demographic, socioeconomic, and geographic distribution of panel respondents. Physicians do not receive information about the specific individual who receives the allocated payoff.

⁶To ensure that observed behavior satisfies the Generalized Axiom of Revealed Preferences (GARP), we compute Afriat (1972)’s Critical Cost Efficiency Index (CCEI). The mean CCEI across physicians is 0.96 (median: 0.998), indicating that nearly all physicians’ choices are consistent with rational choice and satisfy GARP.

variation in relative prices helps distinguish altruistic motives from equity-driven allocation choices. Parameter $\rho \leq 1$ measures the equality–efficiency trade-off, capturing how allocation choices respond to relative price changes independent of altruistic preferences.⁷ Parameters α and ρ are estimated by maximizing the utility function (1) within each physician subject. [Li et al. \(2022\)](#) describe further details on the experimental design and estimation.

2.2 Administrative data sources

We link our experimental data to administrative records from two sources: the Open Payments database, which records industry transfers to physicians, and the Medicare Part D Public Use Files, which report annual physician-level drug claims for 2014–2019.

The Open Payments program is a federal disclosure initiative established in 2013 under Section 6002 of the Affordable Care Act (Physician Payments Sunshine Act). Drug and medical device companies must report all financial or in-kind transfers to physicians, including meals, consulting fees, speaker honoraria, and other interactions, with penalties for noncompliance. The database includes physician names, practice locations, and, since 2021, National Provider Identifiers (NPIs).

We match physicians from the experiment to Open Payments records from 2014–2019 ([Centers for Medicare & Medicaid Services 2014–2019b](#)) based on names and addresses. A match is inferred when a physician’s name is unique within a state in the National Plan and Provider Enumeration System (NPPES) registry ([Centers for Medicare & Medicaid Services 2021](#)). Remaining cases are manually reviewed and validated using NPIs from the 2021 Open Payments release. Physicians not found in Open Payments are assumed to have received no industry payments. We then link physicians’ NPIs to Medicare Part D Public Use Files on drug prescriptions ([Centers for Medicare & Medicaid Services 2014–2019a](#)).

We further link payments associated with specific drugs to prescribing data by drug

⁷ $\rho \in (0, 1]$ reflects distributional preferences weighted toward efficiency: favoring higher total payoff as prices between payoff to ‘self’ relative to ‘other’ change. $\rho \in (-\infty, 0)$ reflects preferences for equality: reducing payoff differences as relative prices change. $\rho \rightarrow 0$ implies insensitivity to relative price changes.

names.⁸ To classify drugs by therapeutic class, we use data from [Newham et al. \(2025\)](#), who link ATC codes to FDA-approved drugs via exact text matching on substance names.⁹

2.3 Variables

Altruism. Our altruism measure is derived from the α parameter estimated from the experiment. α is a continuous variable ranging from 0 to 1 that captures the utility weight a physician places on private gains relative to benefits for others. When $\alpha = 0.5$, the physician values their own and others' gains equally, trading off a marginal loss in private utility for an equal gain to others.

Following our prior work, we adopt a binary categorization of altruism for the main analysis: we define physicians with selfless preferences, $\alpha < 0.5$, as *Altruistic* (where $\alpha \geq 0.5$ is rejected by a one-sided t-test at the 5% level), and all others as *Non-altruistic*.

This binary definition of altruism has three advantages. First, it provides the natural interpretation that altruistic physicians prioritize others' welfare over their own. Second, it avoids assumptions about the representativeness of our sample relative to the broader physician population. Third, using a t-test for classification accounts for statistical precision in the estimated α , yielding a more robust classification than if we directly used point estimates.

Payments and prescribing. We measure annual industry payments as the total monetary value of all general transfers in the Open Payments database, including meals, speaker fees, and other transfers, but excluding ownership and research-related payments. Aggregate payments include all general payments received by a physician, while we identify drug-specific payment events from the product information for transfers.¹⁰ Prescribing is measured at the physician-drug-year level by the number of claims and total spending, both

⁸To identify drug-specific payments, we use the product information field in Open Payments, which lists up to five drugs per payment. We include all named drugs approved by the U.S. Food and Drug Administration (FDA) via New Drug Applications or as New Molecular Entities in the Orange Book ([U.S. Food and Drug Administration 2022](#)).

⁹The ATC system classifies drugs hierarchically by therapeutic and chemical properties, unlike regulatory or billing systems such as the FDA's National Drug Code.

¹⁰About 15% of payments use generic labels (e.g., 'general therapies' or 'circulatory support').

winsorized at the 99th percentile to limit the influence of outliers.

Physician characteristics. In examining the relationship between altruism and payments, we control for a number of physician characteristics available from survey responses that may influence industry payments. Note that our staggered difference-in-differences design for examining prescribing trajectories already accounts for time-invariant physician-by-drug characteristics.

We include indicators for age groups and female, as age and gender are established correlates of physician–industry interactions (Han et al. 2022). We also include an indicator for cardiology, as our sample comprises both primary care physicians and cardiologists. To account for institutional context, we control for clinic ownership and medical group size. Finally, we include an indicator for practicing in a state with payment bans.¹¹

2.4 Analysis sample

The initial dataset comprises 283 physicians from the experiment, and 685 distinct drugs prescribed between 2014 and 2019 by those with available prescribing data. We exclude physicians without a matchable NPI (removing 1 physician) and 210 physician–years in which the physician does not appear in the Medicare Part D Public Use Files or prescribes fewer than 50 drug-level claims (removing 10 physicians).¹² To examine the effect of drug-specific payments on prescribing, we restrict to the 116 drugs with at least one associated payment. We further limit the sample to 58 drugs with a single ATC level 1 code in classes A (Alimentary tract and metabolism), B (Blood and blood-forming organs), or C (Cardiovascular system), which make up the main therapeutic areas among primary care physicians and cardiologists with over 97% of payment values and 75% of spending.¹³ Note that we do not exclude physicians or physician-years with zero prescribing of the included drugs, as zero prescribing

¹¹These states include Vermont, which has a full gift ban, and Minnesota, which bans most payments (King and Bearman 2017). Massachusetts restricts some payments, but is not represented in our data.

¹²We impose the 50-claim threshold to ensure we only include physicians in years when they actively practice. Our results are robust to alternative thresholds.

¹³As shown in Section 4, our results are similar when including all 116 drugs with any payment.

constitutes useful information. Finally, we exclude 729 physician–drug pairs with any payment in their first observed year, as we do not observe any period before payment (removing 5 physicians).

The final dataset contains 83,227 physician–drug–year observations for 267 physicians and 58 drugs.

2.5 Summary statistics

Table 1 reports summary statistics for the main outcome and control variables by physician altruism. Panel A presents physician-level characteristics. Of the 267 physicians, 48 (18%) are classified as altruistic. Both altruistic and non-altruistic physicians are observed, on average, for 5.5 years, and are broadly comparable across observable characteristics, including gender, age, specialty, and practice ownership – with only minor differences in group size and an imbalance in the likelihood of practicing in payment-restricted states. This imbalance is likely mechanical rather than reflecting selection by altruism: all physicians in payment-restricted states are non-altruistic, and their number in our sample is small. In contrast, altruistic and non-altruistic physicians differ significantly in their receipt of industry payments. Between 2014 and 2019, 69% of altruistic physicians received at least one payment compared with 82% of non-altruistic physicians. Non-altruistic physicians also receive larger payment volumes, both in terms of log-transformed average annual payment values and the number of industry interactions.

Panel B reports aggregate characteristics of physicians’ Medicare Part D patient pools. Altruistic and non-altruistic physicians treat patients who are highly similar on average in terms of risk profiles, demographic compositions, and socioeconomic characteristics, including the shares of low-income and non-white patients. This similarity indicates that differences in industry interactions by physician altruism are unlikely to be driven by differences in their patient pools.

Panel C summarizes prescribing in Medicare Part D at the physician–drug–year level.

Overall claims and spending volumes are similar across altruistic and non-altruistic physicians. These comparisons, however, do not consider the role of industry payments. Our main analysis therefore examines whether prescribing *responses to payments* vary with physician altruism.

3 Industry payments

We first examine how physicians' altruistic preferences relate to their receipt of industry payments. This analysis can also be motivated by a stylized model presented in Appendix [A.2](#).

3.1 Correlation between payments and altruism

Figure [1](#) compares average annual payment values by physician altruism. Subfigure [1b](#) presents a binscatter of the proportion receiving any payment and average payment values (including zeros) across ventiles of α , the relative weight a physician assigns to private gains, with linear fits.¹⁴ The figure shows a positive association: moving from the lowest to the highest ventile of α increases the share of physicians with any payment receipt over the observation period from 70% to 85%, and increases annual payments from about USD 1,000 to nearly USD 4,000. Subfigure [1b](#) complements this evidence using the binary altruism classification, comparing cumulative payment distributions. The distribution for non-altruistic physicians is clearly shifted to the right, indicating systematically higher payment levels.

Appendix Figure [A2](#) further shows that non-altruistic physicians receive higher payments across all categories, such as speaking engagements (non-consulting services), consulting, travel, and meals. Appendix Figure [A3](#) demonstrates that these differences persist (almost) throughout the career of physicians.

¹⁴Results are similar when conditioning on any payment receipt.

3.2 Accounting for physician characteristics

The descriptive evidence suggests that industry payments differ between altruistic and non-altruistic physicians. We next examine whether these differences persist after accounting for observable physician characteristics.

Estimation equation. We estimate the following simple regression equation:

$$Pay_i = \beta Non\text{-}altruistic_i + \delta x_i + \varepsilon_i, \quad (2)$$

where Pay_i denotes industry payments to physician i ; $Non\text{-}altruistic_i$ is an indicator for non-altruistic preferences; x_i is a vector of physician characteristics including age, gender, practice ownership and size, and an indicator for practicing in a state with payment ban; and ε_i is the error term. The coefficient β measures the payment difference between non-altruistic and altruistic physicians.

We consider two measures of Pay_i . First, at the extensive margin, we use the indicator $Pay_i = I\{p_i > 0\}$, where p_i is physician i 's average annual payment value. Second, to also capture the intensive margin, we model the log of expected payments, $\log \mathbb{E}[p_i | x_i]$. Specifically, we estimate Equation 2 using a generalized linear model with a gamma distribution and log link, which is appropriate for nonnegative, right-skewed outcomes such as payments and avoids biases from log-transforming variables with many zeros (Chen and Roth 2023; Mullahy and Norton 2024).

A positive β implies that non-altruistic physicians receive higher payments on average. Interpreting this association as causal requires altruism to be exogenous to other determinants of payments. While we do not claim causality, Appendix Table A2 shows that altruistic preferences are not correlated with most observable physician characteristics, suggesting limited bias from observables. Although altruism may proxy for other aspects of professional norms, it captures a dimension distinct from standard determinants of industry payments such as age, gender, or specialty.

Estimation results. Table 2 reports the estimates from Equation 2 and the implied

marginal effects of altruism on industry payments, with robust standard errors. Column (1) shows that non-altruistic physicians are 15 percentage points (22%) more likely to receive any payment (significant at the 5% level). Column (2) shows that they also receive higher payment amounts – on average USD 1,775 (111%) more annually (also significant at the 5% level).

Taken together, these results indicate that altruism is systematically related to the receipt of industry payments, suggesting that altruism preferences shape industry ties beyond what observable physician characteristics can explain.

4 Prescribing of paid drugs

The previous section documents differences in physicians’ payment receipt by altruism. We now ask whether prescribing responds more strongly to payments among less altruistic physicians, by comparing prescribing trajectories of paid drugs around the first observed payment. This test can also be motivated theoretically, as shown in Appendix [A.2](#).

4.1 Prescribing trajectories

We examine prescribing before and after a payment using an event-study difference-in-differences framework, where treatment is the first observed payment for a physician–drug pair. This approach exploits variation in the timing of initial payments across drugs and physicians while accounting for physician-drug-specific heterogeneity, such as time-invariant prescribing propensities, state regulations, or patient mix. We estimate trajectories separately for altruistic and non-altruistic physicians.

Empirical framework. To capture dynamic effects, we use the estimator by [Callaway and Sant’Anna \(2021\)](#), which addresses biases from treatment effect heterogeneity in staggered difference-in-differences designs ([Goodman-Bacon 2021](#); [Roth et al. 2023](#)). Let $b_{id,t}$ denote physician i ’s prescribing of drug d in year t . Treatment is defined as the first payment for a

given physician–drug pair. Each pair either receives a payment at some point, with varying timing of treatment onset, or remains never-treated.

We consider two control group specifications: (i) both never-paid and not-yet-paid observations, and (ii) only not-yet-paid observations among ever-paid physician-drug pairs. The second approach addresses the possibility that never-paid physician-drug pairs follow systematically different prescribing trajectories – for example, if some payments are targeted towards physicians with pre-existing upward trends – by excluding them from the analysis.

Let $G_{id} = g$ denote the year physician i first receives a payment for drug d , and $G_{id} = 0$ denote never-paid pairs. The potential outcome $b_{id,t}(g)$ represents prescribing in year t if the first payment occurred in year g , while $b_{id,t}(0)$ represents prescribing in the absence of any payment up to year t . Following [Callaway and Sant’Anna \(2021\)](#), we estimate group–time average treatment effects:

$$ATT(g, t) = \mathbb{E} [b_{id,t}(g) - b_{id,t}(0) \mid G_{id,g} = 1], \quad (3)$$

where time-invariant physician-by-drug heterogeneity is differenced out. We estimate the treatment effects specified by Equation 3 separately for non-altruistic and altruistic physicians, clustering standard errors at the physician-drug level.

To interpret these estimates as causal responses to payments requires parallel trends: absent the payment, average prescribing by physicians who receive an initial payment for a drug in period g would have evolved like that of unpaid or later-paid physicians. The event-study design allows us to assess whether unobserved factors differentially shift prescribing trajectories before the payment by examining pre-trends. Under such a causal interpretation, prescribing differences by physician altruism reflect differences in *responses* to payments. Even without strict causality, however, differences between altruistic and non-altruistic physicians remain informative about heterogeneity in prescribing trajectories and provide meaningful evidence on differences in physician-industry ties.

Estimation results. Figure 2 shows event-study estimates of the effect of an initial

payment on prescribing, measured by total spending and number of claims for the paid drug, relative to the first payment, aggregated from Equation 3. We report results separately for non-altruistic and altruistic physicians. Subfigures 2a and 2b use the full sample, while Subfigures 2c and 2d restrict to ever-paid physician–drug pairs.

Subfigures 2a and 2b show, for non-altruistic physicians, mild pre-trends in prescribing and a steep, statistically significant post-payment increase in spending and claims (5% level). For altruistic physicians, the figures show clear upward pre-trends, suggesting that payments may target physician–drug pairs with increasing prescribing even before payment, and/or that physicians with pre-existing upward trajectories in prescribing are more likely to accept payments. If such trends would have persisted absent payment, post-payment estimates may be upward-biased.

To mitigate concerns about potential selection into payments, Subfigures 2c and 2d restrict to ever-paid physician–drug pairs, using not-yet-paid pairs as controls. No significant pre-trends remain for either group. This supports the identifying assumption that, among physicians who eventually receive a payment, prescribing would have evolved similarly regardless of the timing of that payment. After payment, prescribing of the paid drug increases for non-altruistic physicians but declines for altruistic physicians; one year after payment, we estimate a difference of about USD 5,000 in spending (non-altruistic: +1,651; altruistic: −3,426) and about five claims (non-altruistic: +2.51; altruistic: −2.82). These effects persist for at least two years. Appendix Figure A4 shows very similar patterns when including all drugs rather than only the main therapeutic classes (ATC classes A, B, C).

Note that results for claims and spending are highly consistent across specifications, supporting that spending responses reflect changes in prescribing volume rather than changes in other factors such as price.

To further address selective targeting, Appendix Figure A5 relaxes the parallel-trends assumption following Rambachan and Roth (2023). This approach explicitly accounts for selective targeting, as long as differential trends between treated and control units evolve

smoothly over time, allowing bounded changes in slope across adjacent periods. We report robust 95% confidence intervals for average treatment effects on spending (Subfigure 2a) and claims (Subfigure 2b), aggregated over post-payment periods and separately by altruism. Relative to standard difference-in-differences estimates under strict parallel trends, effects diverge once smooth violations are allowed: for non-altruistic physicians, payment effects remain positive under linear extrapolation of pre-trends and across a range of violations, whereas for altruistic physicians they become insignificant. Thus, even with differential pre-trends, payments continue to shift prescribing (upward) for non-altruistic physicians.

These results suggest that while both physician types may be targeted by drug firms, non-altruistic physicians respond to payments by *increasing* prescribing, potentially to sustain ongoing relationships with manufacturers. This pattern is consistent with findings from Figure 1 and Table 2, which show higher payments to non-altruistic physicians during our sample period. In contrast, altruistic physicians appear to *reduce* prescribing of paid drugs relative to pre-payment levels, possibly reflecting either stronger concerns about conflicts of interest, changes in perceptions of the clinical utility and substitutability of a paid drug, or both.

4.2 Heterogeneity in differential responses

Next, we provide additional evidence consistent with the idea that clinical substitutability and the therapeutic value of a paid drug shape whether differential responses to payments by altruism arise. The remaining analysis focuses on drug spending, given the similarity between spending and claims results.

Figure 3 stratifies prescribing trajectories by drug class: Alimentary tract and metabolism (ATC A), Blood and blood-forming organs (ATC B), and Cardiovascular system (ATC C). Differences by altruism are particularly pronounced for ATC A drugs, which include predominantly antidiabetics (Appendix Table A3). Many drugs in this class, including GLP-1 receptor agonists, SGLT2 inhibitors and long-acting insulins, are considered clinically

interchangeable and offer incremental rather than transformative benefit (Palmer et al. 2016). Given high price dispersion, intense marketing, and modest clinical gains, altruistic physicians may be less responsive to payments promoting costly branded drugs and instead prioritize affordability and clinical appropriateness, whereas less altruistic physicians may respond more strongly to promotional incentives.

For ATC B drugs (blood thinners), we observe similar divergence in responses: prescribing rises among non-altruistic but falls among altruistic physicians after payments. This class consists largely of direct oral anticoagulants (DOACs)—including apixaban, rivaroxaban, dabigatran, and edoxaban—which have been heavily marketed since their approval in the early 2010s. These agents are broadly substitutable for each other and for older anticoagulants, offering modest gains in convenience and safety, such as reduced monitoring requirements and slightly lower bleeding risk, but at substantially higher cost and with potentially serious side-effects (Abaluck et al. 2020; Agha and Zeltzer 2022; Vinogradova et al. 2018). These features likely amplify the role of altruistic preferences in prescribing responses.

By contrast, responses for ATC C drugs (cardiovascular agents) show little difference by altruism. As Appendix Table A4 shows, this class is substantially more heterogeneous. On one end are lipid-lowering agents such as statins and PCSK9 inhibitors—classes with numerous generic options (e.g., rosuvastatin) and close substitutes (e.g., evolocumab, alirocumab)—commonly prescribed by primary care physicians. On the other end are cardiac therapy, antihypertensive, and heart-failure agents prescribed predominantly by cardiologists for complex patients, offering clearer clinical benefit with limited substitutability (McMurray et al. 2014; Greene et al. 2018). For these specialized drugs, industry interactions may convey useful clinical or formulary information that reinforces pre-existing prescribing trajectories.

To further examine these patterns, we stratify the event studies by physician specialty. Appendix Figure A6 shows, in the full sample, that differential responses by altruism are more pronounced among primary care physicians than cardiologists. Further analyses by both specialty and drug class (Appendix Figure A7) suggest that differences across specialties

largely reflect the composition of drug types each typically prescribes. For ATC A drugs, which cardiologists rarely prescribe, differential responses appear only among primary care physicians. For ATC B drugs, used in both specialties but more common in cardiology, both specialties display divergence by altruism consistent with the overall pattern, with more precise estimates for cardiologists. For ATC C drugs, non-altruistic primary care physicians modestly increase spending post-payment while altruistic ones weakly reduce prescribing, in line with our main results. Cardiologists, in contrast, increase prescribing regardless of altruism, consistent with heterogeneity in the types of cardiovascular drugs prescribed by them (Appendix Table A4).

To assess whether the observed heterogeneity reflects drug-class differences rather than systematic differences in who prescribe them, we re-estimate our event studies among physicians active in multiple classes: (1) physicians prescribing both ATC B and C drugs, a group that includes more cardiologists who rarely prescribe ATC A drugs (Appendix Figure A8), and (2) those prescribing across all three classes (Appendix Figure A9). This approach mitigates concerns about physician selection into prescribing specific drug classes. Results remain consistent with our main findings in Figure 3, supporting the interpretation that variation in substitutability and clinical value drive the observed heterogeneity across drug classes.

Finally, we test whether this heterogeneity reflects differences in payment size (Appendix Figure A10). Stratifying by drug class and initial payment amount yields no evidence that altruistic physicians would mirror non-altruistic physicians' responses if paid more.¹⁵ This further supports that differences in substitutability and therapeutic value, not payment intensity, drive the observed differential response patterns across drug classes.

¹⁵Moreover, results are virtually unchanged when excluding the top 1% of physician-drug pairs by total payment – over half from ATC C drugs, totaling about \$450,000, compared to roughly \$37,000 for ATC A and \$62,000 for ATC B drugs – which account for almost all total payment differences across drug classes.

5 Conclusion

By linking experimentally elicited altruism to administrative payments and prescribing data, this study shows that physician altruism fundamentally shapes industry ties. We find that industry payments increase prescribing among non-altruistic physicians but reduce it among altruistic ones. This heterogeneity is strongest for drug classes with high therapeutic substitutability and weaker clinical justification, where marketing likely amplifies financial rather than informational effects. In contrast, for drugs with clear clinical value and limited substitutes, prescribing responses are similar across physicians.

These results highlight that financial incentives in healthcare markets operate through behavioral channels shaped by intrinsic motivation, notably altruism. Disclosure and payment regulations may thus have uneven effects, affecting physicians differently depending on their altruistic preferences. More broadly, our study illustrates how heterogeneity in prosocial motives can mediate the impact of market incentives in professional settings, offering novel evidence that intrinsic and extrinsic motivations interact to determine real-world treatment and spending patterns.

Tables

Table 1. Summary statistics by altruism

	All physicians <i>Mean</i>	Altruistic <i>Mean</i>	Non-altruistic <i>Mean</i>	Difference <i>p-value</i>
Panel A: Physician characteristics and payments (physician-level)				
Altruism parameter α	0.61	0.25	0.69	[0.00]
Years active	5.53	5.52	5.53	[0.93]
Male	0.60	0.60	0.60	[0.99]
Female	0.40	0.40	0.40	[0.99]
Age below 39	0.27	0.25	0.28	[0.69]
Age: 40–49	0.33	0.33	0.33	[1.00]
Age: 50–59	0.23	0.27	0.22	[0.47]
Age above 60	0.16	0.15	0.17	[0.69]
Specialty: Primary care	0.66	0.69	0.65	[0.65]
Specialty: Cardiology	0.34	0.31	0.35	[0.65]
Ownership: Nonprofit hospital	0.16	0.15	0.16	[0.75]
Ownership: Academic medical center	0.58	0.52	0.60	[0.34]
Ownership: Physician-owned practice	0.25	0.33	0.24	[0.20]
Practice size: 1–35	0.15	0.25	0.13	[0.09]
Practice size: 36–350	0.49	0.44	0.50	[0.42]
Practice size: 351–1600	0.36	0.31	0.37	[0.48]
Payment-restricted state	0.022	0	0.027	[0.01]
Not payment-restricted state	0.98	1	0.97	[0.01]
Any payment, all years	0.79	0.69	0.82	[0.08]
Average annual payments in USD	2610.3	1600.3	2831.7	[0.40]
Log average annual payments in USD, 0 if none	4.22	3.48	4.38	[0.06]
Average annual number of payments	16.6	8.41	18.3	[0.00]
# Physicians	267	48	219	267
Panel B: Patient pool characteristics				
Average patient risk score	1.46	1.48	1.46	[0.71]
Average patient age	71.2	70.5	71.3	[0.26]
Share of female patients	0.58	0.58	0.58	[0.94]
Share of non-white patients	0.31	0.31	0.32	[0.90]
Share of Low-Income Subsidy claims	0.35	0.39	0.35	[0.29]
# Physicians	267	48	219	267
Panel C: Drug prescribing (physician-drug-year level)				
Drug spending in USD, winsorized	690.1	696.7	688.7	[0.79]
Number of claims, winsorized	1.29	1.32	1.28	[0.43]
# Physician-drug-years	83,227	15,017	68,210	83,227

Notes: This table reports summary statistics of the analysis sample for physicians (Panel A), their patient pools (Panel B), and yearly drug prescribing (Panel C). Columns show means for all, altruistic, and non-altruistic physicians; the final column reports p-values from t-tests comparing the means between altruistic and non-altruistic physicians. *Payment-restricted state* indicates that a physician practices in Vermont, Massachusetts, or Minnesota, which impose payment bans. Patient characteristics are averaged for Medicare Part D beneficiaries over physicians’ active years; *Risk score* refers to the Hierarchical Condition Category (CMS-HCC) measure, where 1 denotes average risk and higher values indicate higher risk; *Low-Income Subsidy* (LIS) indicates claims under Medicare’s Extra Help program which assists in paying prescription drug costs. *Share of female patients* and *Share of non-white patients* are available for 266 physicians. Drug prescribing is winsorized at the 99th percentile in-sample.

Table 2. Industry payments and physician altruism

	Industry payments	
	<i>Any pay</i> ^a (1)	<i>Average annual USD</i> ^b (2)
Marginal effects		
<i>Altruism</i>		
Non-altruistic	0.15** (0.066)	1775.1** (708.3)
Coefficient estimates		
<i>Altruism</i>		
Non-altruistic	0.15** (0.066)	0.75* (0.41)
Physician characteristics	✓	✓
Altruistic: Mean outcome	0.69	1600.29
Observations	267	267

This table presents estimation results for the relationship between industry payments over the period 2014–2019 and physician altruism. Column (1) shows results for payments measured on the extensive margin, with an indicator for any payment as the outcome variable. Column (2) reports results with average annual payment as the outcome variable. Physician characteristics include control variables for physicians’ age category, gender, specialty, practice ownership, practice size category, and indicator an for practicing in a state with payment bans (Vermont, Massachusetts, or Minnesota).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

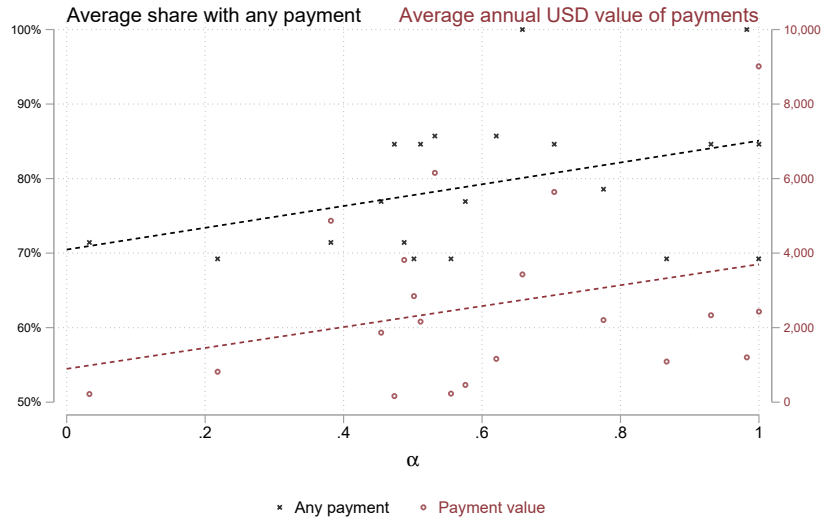
^a Linear model estimated by Ordinary Least Squares. Robust standard error of the coefficient estimate in parentheses. The average marginal effect is given by the coefficient estimate.

^b Generalized linear model with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares. The standard error for the average marginal effect is calculated using the delta method.

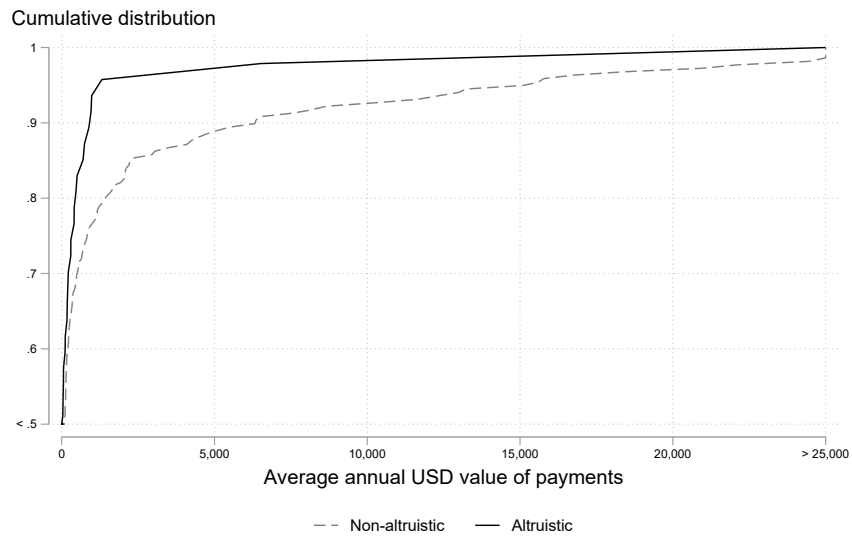
Figures

Figure 1. Descriptive figures of industry payments and altruism

(a) Payments and altruism measure α

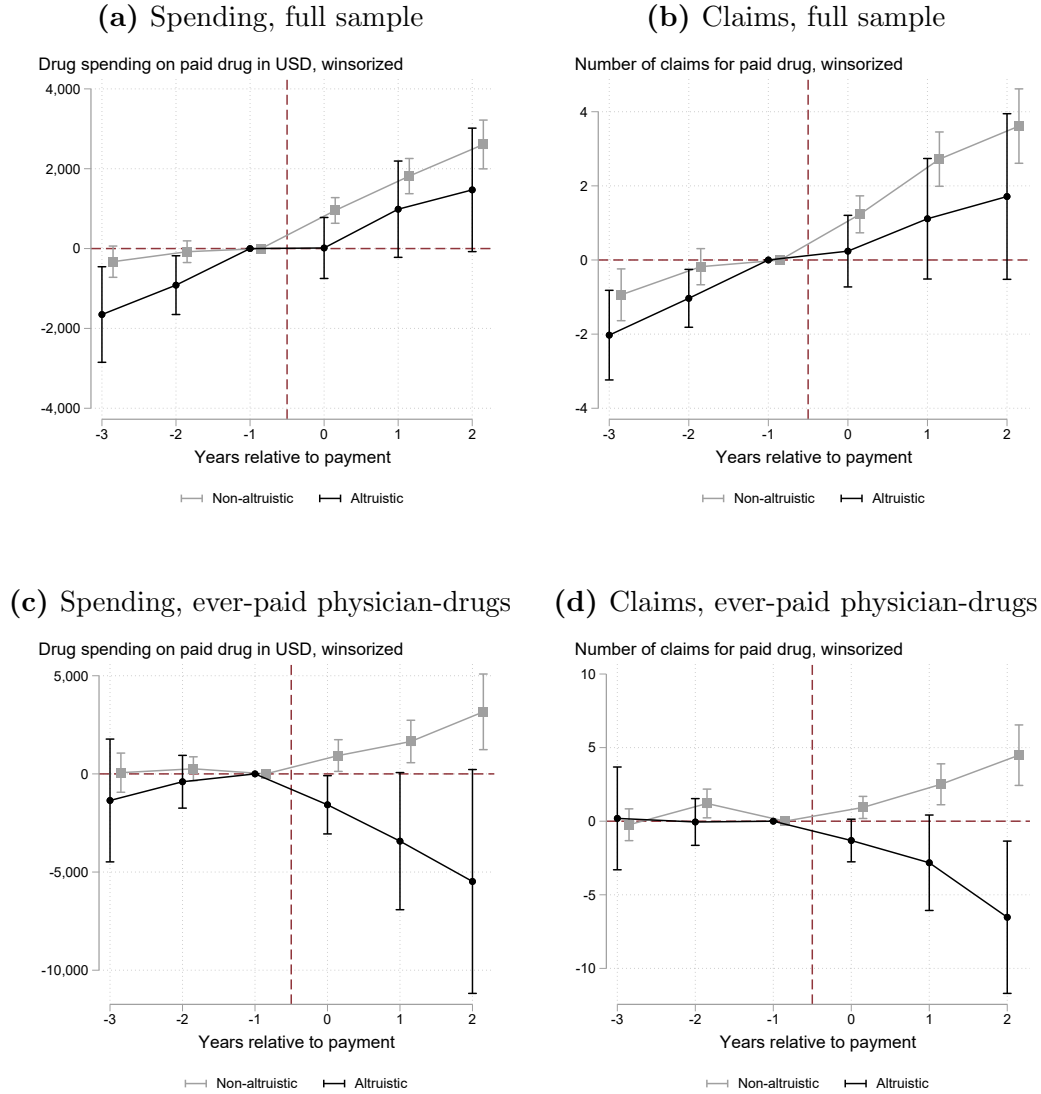


(b) Cumulative distribution of payments over altruism



Notes: This figure shows industry payments by physician altruism. Subfigure (a) shows binscatters of the mean share of physicians with any payment receipt (left axis, black) and the mean annual USD value of payments (right axis, red) over ventiles of α , with the dashed lines indicating linear fits. Subfigure (b) shows the cumulative distribution function of annual payments separately for altruistic and non-altruistic physicians.

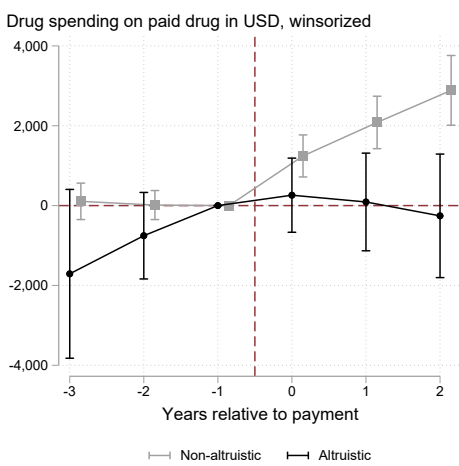
Figure 2. Event-study estimates of drug prescribing following an initial payment



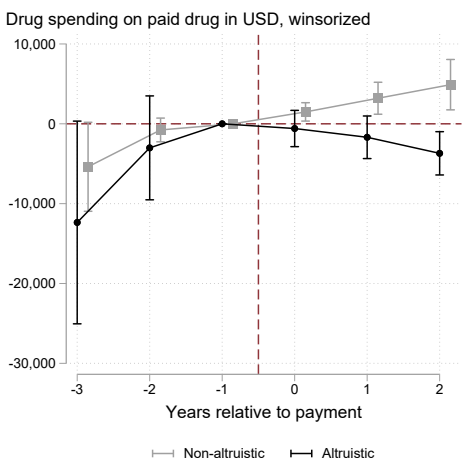
Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians. Prescribing is measured by spending (left panels) and the number of claims (right panels) for the paid drug. Subfigures 2a and 2b use the full sample of 15,017 physician–drug–year observations for altruistic and 68,210 observations for non-altruistic physicians. Subfigures 2c and 2d include only ever-paid physician–drug pairs, with a sample of 624 observations for altruistic and 3,459 for non-altruistic physicians. Outcomes are winsorized at the 99th percentile within each sample. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered on the physician-drug level.

Figure 3. Event-study estimates of drug spending following an initial payment, by drug type

(a) Alimentary tract and metabolism (ATC A)



(b) Blood and blood forming organs (ATC B)



(c) Cardiovascular system (ATC C)



Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians. Each subfigure shows spending on the paid drug, winsorized at the 99th percentile within drug class, for one of three therapeutic categories: Alimentary tract and metabolism (ATC A), Blood and blood forming organs (ATC B), and Cardiovascular system (ATC C). The full sample is included, consisting of 15,017 physician–drug–year observations for altruistic and 68,210 for non-altruistic physicians. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered at the physician–drug level.

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Online Appendix

The role of physician altruism in the physician-industry relationship

A A stylized model of altruism in prescribing with payments

A.1 Overview of model predictions

We begin with a simple conceptual framework, which considers a physician's decision-making process when presented with the opportunity to interact with pharmaceutical representatives in exchange for monetary and in-kind benefits. The physician's adherence to professional altruistic norms is captured by $\alpha \in [0, 1]$, where higher values represent greater weight on private benefits and thus weaker altruism, and lower values reflect stronger other-regarding preferences.

The model consists of two periods that capture the main dynamic considerations of physicians and pharmaceutical representatives. In the first period, the physician, given her altruism level, decides whether to accept a fixed value industry transfer. In the second period, she then chooses how much to prescribe a drug with marketing efforts, anticipating potential future payments and given her payment acceptance decision. We derive comparative statics of the equilibrium in this setup to highlight how acceptance of industry transfers and prescribing decisions vary with altruistic preferences.

The model yields two testable predictions about how industry payments interact with physician altruism to shape prescribing behavior:

- 1) *Non-altruistic physicians accept higher payments.* If payments compromise professional integrity, and the associated professional costs rise more steeply for altruistic physicians,

then the maximum acceptable transfer is lower for more altruistic physicians. In the aggregate, we expect that non-altruistic physicians receive higher payments than altruistic physicians. (See Subsection A.2.)

- 2) *Non-altruistic physicians are more responsive to payments.* If the marginal patient benefit of a paid drug increases more slowly than its marginal societal cost, and industry payments are linked to physicians' private benefits through ongoing relationships, then less altruistic physicians are more responsive to transfers in their prescribing decisions. That is, we expect the prescribing response to payments to be stronger among non-altruistic than among altruistic physicians. (See Subsection A.3.)

A.2 Industry payments acceptance decision

We consider a physician who is approached by pharmaceutical representatives in the first period and given the opportunity to interact. Interactions are in the form of free meals, travel, or paid speaking opportunities, and correspond to in-kind or cash transfers with a fixed positive monetary payment value within a period. However, accepting industry transfers negatively impacts the physician's professional integrity. The physician thus balances the monetary value of the transfer against its professional costs.

The decision to participate in these interactions for payment is contingent upon both the monetary value of the payment, represented by $\bar{p} > 0$, and the physician's level of altruism $\alpha \in [0, 1]$ where higher α represents lower altruism. We denote the realized payment to the physician by $p \in \{0, \bar{p}\}$: The physician either receives the fixed value \bar{p} as offered by the drug firms, or she receives 0 if no interaction with the pharmaceutical industry takes place.

Let the physician's utility from the payment acceptance decision be given by:

$$U_p(p; \alpha) = p - R(p; \alpha),$$

where $R(p; \alpha) \geq 0$ represents the professional costs associated with accepting the payment,

such as reputational damage (among patients and colleagues), moral guilt, and fear of conflicts of interest.¹⁶ Without payments, the physician does not face these professional costs, such that $R(p = 0; \alpha) = 0$ and $U_p(0; \alpha) = 0$. With payments, professional costs enter the physician's utility as a negative term.

We assume that professional costs increase with a higher accepted payment value at an accelerating rate, but that the slope at any given payment level is lower for less altruistic physicians. Each additional dollar that a physician accepts thus progressively harms her professional integrity, such that $R(p; \alpha)$ is a convex function of p , or $\frac{\partial R}{\partial p} > 0$ and $\frac{\partial^2 R}{\partial p^2} > 0$. Such a relationship corresponds, for example, to findings that higher accepted industry transfers increasingly undermine patient trust (Hwong et al. 2017). However, the marginal increase in a physician's professional costs for accepting an additional dollar becomes smaller with weaker altruistic preferences, such that $\frac{\partial^2 R}{\partial p \partial \alpha} < 0$. For example, a physician committed to professional norms has stronger concerns about the undue influence of payments, which may deviate her treatment choices from those that she would make if she only considered patient and societal interests without accepting transfers from the pharmaceutical industry.

The physician accepts a given payment value \bar{p} , as offered by the pharmaceutical industry, if and only if her net utility from accepting the transfer is higher than if she does not engage in it; that is, $\bar{p} - R(\bar{p}; \alpha) \geq 0$. We denote the payment at which the physician's participation constraint is binding by:

$$p^{\max}(\alpha) = R(p^{\max}; \alpha). \quad (4)$$

A physician with given altruistic preferences α accepts any payment $0 < \bar{p} < p^{\max}(\alpha)$, where $p^{\max}(\alpha)$ is the maximum payment she is willing to accept. For professional costs that are convex in payments and increasing with altruism, the maximum transfer to the physician

¹⁶Professional costs can also imply financial losses, for example due to patients choosing providers according to physicians' reputation reflected in public ratings (Bensnes and Huitfeldt 2021). In addition, these costs represent physicians' non-pecuniary and reputational motives under information disclosure (Kolstad 2013; Godager et al. 2016).

decreases with the level of altruism (increases in α). Equation (4) thus implies that the maximum value of transfers is lower for more altruistic physicians than for less altruistic physicians.

A.3 Optimal propensity to prescribe a paid drug

In the second period, the physician chooses her propensity to prescribe a given drug with any marketing efforts over its less expensive alternatives, such as older compounds. We represent the physician's prescribing of that drug by b , corresponding to the volume of prescribing. When deciding how to prescribe, the physician considers any utility gains to herself, indexed by s , as well as any altruistic motivations that may arise from benefits to others, indexed by o . In particular, she considers the benefits and costs to patients and society given a level of prescribing b , denoted by $\pi_o(b)$, as well as the private value of prescribing the drug, denoted by $\pi_s(b, p)$.

Let the physician's utility for the prescribing the drug at a given level b be given as:

$$\begin{aligned} U_b(b; p, \alpha) &= (1 - \alpha)\pi_o(b) + \alpha\pi_s(b, p) \\ &= (1 - \alpha)[H_o(b) - C_o(b)] + \alpha\pi_s(b, p), \end{aligned}$$

where $\pi_o(b)$ is comprised of $H_o(b)$, which represents the health of the patients the physician sees; $C_o(b)$, which represents the total costs to society for the treatment of these patients; and $\pi_s(b, p)$, which represents the physician's anticipation of future payments that is influenced by her prior decision of payments and her prescribing of the drug. Note that a fully altruistic physician's ($\alpha = 0$) optimal prescribing is determined by maximizing the net benefit to patients and society, π_o , and a fully selfish physician's ($\alpha = 1$) optimal prescribing is determined by maximizing the private value of prescribing π_s . In fact, $\alpha \in (0, 1)$ captures the marginal rate of substitution between the net benefits to others for benefits to the physician herself:

$MRS_{o,s} = -\frac{\partial U_b / \partial \pi_o}{\partial U_b / \partial \pi_s} = -\frac{(1-\alpha)}{\alpha}$. In the special case of $\alpha = 0.5$, a physician would be willing to

trade off a marginal reduction in her private benefit by the exact same amount of gains to patients and society.

The net benefit to patients and society, $\pi_o(b)$, is a function of prescribing for the drug. As a simplification, we assume that higher prescribing has a non-negative effect on patient health, as novel drugs are typically innovative and may have more recent information available about their safety and efficacy. However, drugs with marketing efforts are often associated with substantial price premiums over their alternatives. These higher prices are imposed upon patients and insurers, and may reflect rising inefficiencies due to the monopoly power of drug companies (Lakdawalla and Sood 2009). We assume that the marginal health benefits and costs of a higher prescribing propensity are nonnegative, with $\frac{\partial H_o}{\partial b} \geq 0$ and $\frac{\partial C_o}{\partial b} \geq 0$, but that the marginal health benefit increases at a slower rate than the marginal societal costs of additional use of the drug as costs eventually surpass the health benefits of additional use:

$$\frac{\partial^2 H_o}{\partial b^2} < \frac{\partial^2 C_o}{\partial b^2}. \quad (5)$$

We denote the private continuation value of engaging with the pharmaceutical industry by $\pi_s(b, p)$. Without loss of generality, we assume that without an industry payment, the physician does not incur any private benefits from prescribing a paid drug, $\pi_s(b, p) = 0$ for $p = 0$. In other words, choosing higher prescribing only benefits the physician privately once pharmaceutical firms can interact with her. If no industry transfers could take place, a fully selfish physician ($\alpha = 1$) is indifferent at every level of prescribing, whereas physicians who are not fully selfish $0 < \alpha \leq 1$ weigh societal costs/benefits to determine the optimal prescribing level b_o^* , such that $\frac{\partial H_o}{\partial b} = \frac{\partial C_o}{\partial b}$.

The physician only derives any private benefits from prescribing the drug, $\pi_s(b, p) \geq 0$, if she accepts a positive payment $p > 0$. If in Period 1, she refuses to interact with the drug firm, her prescribing propensity would not affect future payments. The physician's decision to accept payments is thus linked to her prescribing decision by increasing the private value of

drug prescribing, for example in the case of a novel drug producer targeting those physicians who have engaged with the pharmaceutical industry in prior interactions and who were responsive in their treatment choices. We assume that the private value from prescribing is weakly increasing in payments due to the anticipation of future payments from a maintained relationship with the drug company:

$$\frac{\partial \pi_s}{\partial p} \geq 0. \quad (6)$$

Lastly, we assume that the private returns to a higher prescribing level are positive but decreasing, for example as future industry payments are expected to increase with prescribing the marketed drug but at a decreasing rate:

$$\frac{\partial \pi_s}{\partial b} > 0, \quad \frac{\partial^2 \pi_s}{\partial b^2} < 0. \quad (7)$$

We denote the optimal prescribing level by $b^*(\alpha)$. By applying the implicit function theorem to our setup, we can characterize the optimal drug prescribing level in relation to payments. We denote the optimal prescribing level by $b^*(\alpha)$ and the utility level at the optimum by U^* . The first order condition with respect to prescribing is given by:

$$\frac{\partial U}{\partial b} = (1 - \alpha) \left(\frac{\partial H_o}{\partial b} - \frac{\partial C_o}{\partial b} \right) + \alpha \frac{\partial \pi_s(p)}{\partial b} = 0 \equiv U^*$$

By the implicit function theorem, $\frac{\partial b^*}{\partial p} = -\frac{\partial U^*}{\partial p} / \frac{\partial U^*}{\partial b}$:

$$\frac{\partial b^*}{\partial p} = - \frac{\alpha \overbrace{\frac{\partial \pi_s}{\partial p}}^{\geq 0 \text{ by (6)}}}{(1-\alpha) \underbrace{\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}_{< 0 \text{ by (5)}} + \alpha \underbrace{\frac{\partial^2 \pi_s}{\partial b^2}}_{< 0 \text{ by (7)}}$$

$\Rightarrow \frac{\partial b^*}{\partial p} \geq 0$. Thus, the optimal prescribing level moves up with higher payments.

We can then examine the relationship between prescribing, payments, and altruism, by taking the partial derivative with respect to physicians' weight on private benefits, α :

$$\frac{\partial^2 b^*}{\partial p \partial \alpha} = - \frac{\overbrace{\frac{\partial \pi_s}{\partial p}}^{\geq 0 \text{ by (6)}} \overbrace{\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}^{< 0 \text{ by (5)}}}{\left((1-\alpha) \underbrace{\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}_{< 0 \text{ by (5)}} + \alpha \underbrace{\frac{\partial^2 \pi_s}{\partial b^2}}_{< 0 \text{ by (7)}} \right)^2}. \quad (8)$$

$\Rightarrow \frac{\partial^2 b^*}{\partial p \partial \alpha} \geq 0$ for $\alpha > 0$. Thus, optimal prescribing increases with payments at a higher rate for physicians with a higher level of α , i.e. less altruistic physicians who place a higher weight on their private benefits. Equation (8) indicates that less altruistic physicians are more responsive to industry transfers in their use of paid drugs compared to more altruistic physicians.

B Additional tables

Table A1. Industry payments and physician altruism, alternative econometric models

	Payment amount		
	USD (1) Two-part	USD (2) Linear	Log USD (3) Linear
Marginal effects (levels)			
<i>Altruism</i>			
Non-altruistic	1030.8 (895.4)	1425.1 (1549.6)	0.93** (0.37)
Coefficient estimates			
<i>Altruism</i>			
Linear			
Non-altruistic	0.36 (0.44)	1425.1 (1549.6)	0.93** (0.37)
Probit			
Non-altruistic	0.54** (0.23)		
Physician characteristics	✓	✓	✓
Wald-test: Non-altruistic ^b	$\chi^2(2) = 6.243^*$		
Altruistic: Mean outcome	1600.290	1600.290	3.502
Observations	267	267	267

This table presents results on the relationship between average annual industry payments and physician altruism based on alternative econometric model specifications. Column (1) reports results from a two-part model which combines a probit model for the binary outcome of receiving any payment with a generalized linear model with the log link and gamma distribution for positive payment values, and is estimated by Iterated Reweighted Least Squares. The average marginal effect is based on the full model. The two-part model combines a probit model to estimate the binary outcome of receiving any payment, and a generalized linear model with the log link and gamma distribution for the continuous outcome of positive payment values. The overall coefficient of *Non-altruistic* is jointly significant in both parts of the model at a 10%-significance level. Column (2) reports results from a linear model of the USD value of payments estimated using Ordinary Least Squares. Column (3) reports results from a linear model estimated using Ordinary Least Squares with the natural logarithm of $1 + \text{USD payments}$ as outcome variable. Robust standard errors of coefficient estimates in parentheses. Standard errors for the average marginal effect in the two-part model are calculated using the delta method. Physician characteristics include control variables for physicians' age category, gender, specialty, practice ownership, practice size category, and an indicator for practicing in a state with payment bans (Vermont, Massachusetts, or Minnesota).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

^a The point estimate implies that payments to non-altruistic physicians are $(100 * (\exp(0.93) - 1)) \approx 153\%$ higher compared to payments to altruistic physicians, corresponding to a difference in payment levels by 2,455 USD.

^b Wald-test to test whether the coefficients associated with Non-altruistic from both parts of the two-part model are jointly zero.

Table A2. Correlation of physician altruism and payments with observable characteristics

	Altruism		Industry payments	
	<i>Non-altruistic</i> ^a	<i>Raw α</i> ^a	<i>Any pay</i> ^a	<i>USD</i> ^b
	(1)	(2)	(3)	(4)
<i>Physician characteristics</i>				
Male (omitted)	-	-		
Female	0.017 (0.056)	-0.024 (0.035)	-0.059 (0.057)	-1056.5*** (262.8)
Age below 39 (omitted)	-	-		
Age: 40–49	-0.040 (0.064)	-0.059 (0.042)	0.059 (0.069)	579.9* (351.7)
Age: 50–59	-0.061 (0.070)	-0.025 (0.045)	0.079 (0.073)	-86.1 (167.2)
Age above 60	0.0068 (0.073)	-0.060 (0.045)	0.15** (0.069)	1024.5 (642.1)
Specialty: Primary care (omitted)	-	-		
Specialty: Cardiology	0.017 (0.061)	0.0030 (0.045)	0.17*** (0.049)	2209.5*** (493.2)
Ownership: Nonprofit hospital (omitted)	-	-		
Ownership: Academic medical center	-0.033 (0.073)	-0.037 (0.053)	-0.13** (0.059)	29.9 (227.2)
Ownership: Physician-owned	-0.078 (0.093)	-0.051 (0.064)	0.028 (0.079)	679.5 (448.6)
Practice size: 1–36 (omitted)	-	-		
Practice size: 36–350	0.14* (0.082)	0.026 (0.051)	-0.045 (0.068)	-415.7 (314.4)
Practice size: 351–1600	0.11 (0.088)	0.024 (0.058)	-0.0068 (0.081)	330.7 (488.3)
Not payment-restricted state (omitted)	-	-		
Payment-restricted state	0.16*** (0.056)	0.074 (0.080)	-0.062 (0.18)	502.2 (964.2)
Mean outcome	0.82	0.61	0.79	2610.30
Observations	267	267	267	267

This table reports correlations between physician altruism and observable characteristics, and between industry payments and physician characteristics. Column (1) shows linear regressions of altruism on physician characteristics for our main measure of altruism, an indicator for non-altruistic preferences, as the outcome variable. Column (2) shows results for raw, continuous α defined in Equation (1) as the outcome variable. Column (3) shows correlations between receiving any payment and physician characteristics. Column (4) reports average marginal effects from a generalized linear model (gamma family, log link) of average annual payment amounts in USD on physician characteristics. *Payment-restricted state* indicates that a physician practices in Vermont, Massachusetts, and Minnesota, which are states that implement payment bans.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

^a Linear model estimated by Ordinary Least Squares. Robust standard errors in parentheses.

^b Generalized linear model with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares. Average marginal effects are computed at sample means. Standard errors are calculated using the delta method.

Table A3. Summary statistics by drugs

Brand	Generic	Approval	ATC	Class	Total payments	Total spending
Alimentary tract and metabolism (ATC A)						
Farxiga	Dapagliflozin Propanediol	2014	A10	Diabetes	\$15,308	\$241,371
Invokana	Canagliflozin	2013	A10	Diabetes	\$12,338	\$1,032,263
Toujeo	Insulin Glargine,Hum.Rec.Anlog	2015	A10	Diabetes	\$5,222	\$313,733
Ozempic	Semaglutide	2017	A10	Diabetes	\$2,628	\$393,845
Tresiba	Insulin Degludec	2015	A10	Diabetes	\$2,614	\$461,181
Jardiance	Empagliflozin	2014	A10	Diabetes	\$2,181	\$807,283
Movantik	Naloxegol Oxalate	2014	A06	Laxatives	\$1,762	\$41,548
Victoza	Liraglutide	2010	A10	Diabetes	\$1,240	\$2,439,082
Trulicity	Dulaglutide	2014	A10	Diabetes	\$1,145	\$1,095,361
Tanzeum	Albiglutide	2014	A10	Diabetes	\$632	\$58,736
Basaglar	Insulin Glargine,Hum.Rec.Anlog	2015	A10	Diabetes	\$590	\$405,480
Xifaxan	Rifaximin	2004	A07	Anti-diarrhoea	\$512	\$351,314
Viberzi	Eluxadoline	2015	A07	Anti-diarrhoea	\$497	\$55,665
Linzess	Linaclotide	2012	A06	Laxatives	\$468	\$181,552
Bydureon	Exenatide Microspheres	2012	A10	Diabetes	\$464	\$199,528
Amitiza	Lubiprostone	2006	A06	Laxatives	\$376	\$121,525
Januvia	Sitagliptin Phosphate	2006	A10	Diabetes	\$270	\$6,672,148
Levemir	Insulin Detemir	2005	A10	Diabetes	\$230	\$1,702,848
Janumet	Sitagliptin Phos Metformin	2007	A10	Diabetes	\$208	\$1,002,663
Tradjenta	Linagliptin	2011	A10	Diabetes	\$178	\$739,810
Onglyza	Saxagliptin	2009	A10	Diabetes	\$154	\$235,050
Humalog	Insulin Lispro	1996	A10	Diabetes	\$146	\$2,051,723
Creon	Lipase Protease Amylase	2009	A09	Digestive enzymes	\$136	\$134,854
Dexilant	Dexlansoprazole	2009	A02	Acid reducers	\$105	\$690,253
Lantus	Insulin Glargine,Hum.Rec.Anlog	2000	A10	Diabetes	\$96	\$8,711,770
Myalept	Metreleptin	2014	A16	Other gastrointestinal/metabolic	\$81	\$3,294,812
Apidra	Insulin Glulisine	2004	A10	Diabetes	\$49	\$17,563
Synjardy	Empagliflozin Metformin	2015	A10	Diabetes	\$19	\$5,194
Blood and blood forming organs (ATC B)						
Savaysa	Edoxaban Tosylate	2015	B01	Blood thinners	\$48,275	\$18,792
Uptravi	Selexipag	2015	B01	Blood thinners	\$9,905	\$1,244,760
Xarelto	Rivaroxaban	2011	B01	Blood thinners	\$4,062	\$9,915,883
Eliquis	Apixaban	2012	B01	Blood thinners	\$1,624	\$13,728,411
Pradaxa	Dabigatran Etxilate Mesylate	2010	B01	Blood thinners	\$1,211	\$2,332,615
Brilinta	Ticagrelor	2011	B01	Blood thinners	\$1,165	\$300,840
Effient	Prasugrel	2009	B01	Blood thinners	\$136	\$244,945
Orenitram	Treprostinil Diolamine	2013	B01	Blood thinners	\$92	\$0
Cardiovascular system (ATC C)						
Repatha	Evolocumab	2015	C10	Cholesterol-lowering	\$131,746	\$934,354
Adempas	Riociguat	2013	C02	Blood pressure-lowering	\$112,824	\$1,666,305
Entresto	Sacubitril Valsartan	2015	C09	Renin-angiotensin system agents	\$99,587	\$3,025,268
Corlanor	Ivabradine	2015	C01	Cardiac therapy	\$52,090	\$8,288
Northera	Droxidopa	2014	C01	Cardiac therapy	\$32,908	\$66,953
Praluent	Alirocumab	2015	C10	Cholesterol-lowering	\$22,296	\$851,836
Multaq	Dronedarone	2009	C01	Cardiac therapy	\$6,088	\$2,244,735
Bystolic	Nebivolol	2007	C07	Beta-blockers	\$830	\$1,059,293
Livalo	Pitavastatin Calcium	2009	C10	Cholesterol-lowering	\$493	\$148,386
Edarbi	Azilsartan Medoxomil	2011	C09	Renin-angiotensin system agents	\$387	\$1,877
Opsumit	Macitentan	2013	C02	Blood pressure-lowering	\$216	\$2,004,629
Edarbyclor	Azilsartan Med Chlorthalidone	2011	C09	Renin-angiotensin system agents	\$189	\$0
Letairis	Ambrisentan	2007	C02	Blood pressure-lowering	\$139	\$2,206,296
Ranexa	Ranolazine	2006	C01	Cardiac therapy	\$116	\$1,560,686
Vytorin	Ezetimibe Simvastatin	2004	C10	Cholesterol-lowering	\$104	\$398,250
Zetia	Ezetimibe	2002	C10	Cholesterol-lowering	\$63	\$2,772,968
Bidil	Isosorb Dinit Hydralazine	2005	C02	Blood pressure-lowering	\$39	\$37,571
Crestor	Rosuvastatin Calcium	2003	C10	Cholesterol-lowering	\$26	\$6,181,706
Benicar	Olmesartan Hctz	2002	C09	Renin-angiotensin system agents	\$20	\$1,021,505
Tekturma	Aliskiren Hctz	2007	C09	Renin-angiotensin system agents	\$16	\$37,941
Exforge	Amlodipine Besylate Valsartan	2007	C08; C09	Calcium channel blockers; Renin-angiotensin system agents	\$15	\$72,634
Tribenzor	Olmesartan Amlodipin Hcthiaazid	2010	C08; C09	Calcium channel blockers; Renin-angiotensin system agents	\$7	\$58,685

Table A4. Summary statistics by drug class

ATC	Class	# Drugs included	Total payments	Total spending	% Cardiologist claims of total
Alimentary tract and metabolism (ATC A)					
A02	Acid reducers	1	\$105	\$690,253	3.59%
A06	Laxatives	3	\$2,607	\$344,626	1.27%
A07	Anti-diarrhoea	2	\$1,009	\$406,978	0.00%
A09	Digestive enzymes	1	\$136	\$134,854	0.00%
A10	Diabetes	20	\$45,710	\$28,586,632	0.48%
A16	Other gastrointestinal/metabolic	1	\$81	\$3,294,812	0.00%
Blood and blood forming organs (ATC B)					
B01	Blood thinners	8	\$66,470	\$27,786,246	66.22%
Cardiovascular system (ATC C)					
C01	Cardiac therapy	4	\$91,201	\$3,880,662	95.14%
C02	Blood pressure-lowering	4	\$113,218	\$5,914,801	100.00%
C07	Beta-blockers	1	\$830	\$1,059,293	50.53%
C08; C09	Calcium channel blockers; Renin-angiotensin system agents	2	\$22	\$131,319	14.39%
C09	Renin-angiotensin system agents	5	\$100,199	\$4,086,591	67.32%
C10	Cholesterol-lowering	6	\$154,728	\$11,287,500	45.93%

C Additional figures

Figure A1. Screenshot from the experiment

In this experiment, you will make 25 decisions that share a common form. In each decision, you will be asked to allocate real money between yourself and another person. The other person will be chosen at random from the Understanding America Study panel respondents. The Understanding America Study, or UAS is a panel at the University of Southern California of approximately 6,000 households representing the entire United States. More information about the UAS can be found at this link <https://uasdata.usc.edu>. Clicking on the link opens a new window.

To further clarify, the UAS panel respondent is a real individual whose payoff from the experiment will depend on the amount of money you allocate to him or her, just as your payoff will depend on the amount of money you allocate to yourself.

In each problem you will be asked to choose a point that is on a blue line like the one shown below.

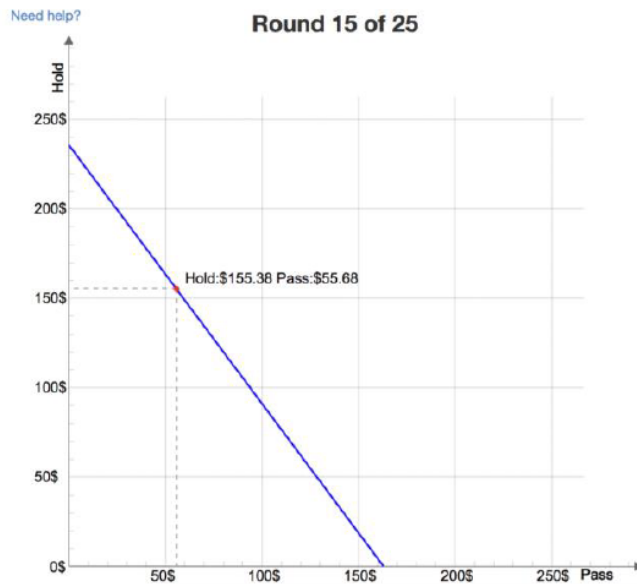


Figure A2. Nature of payments, by altruism

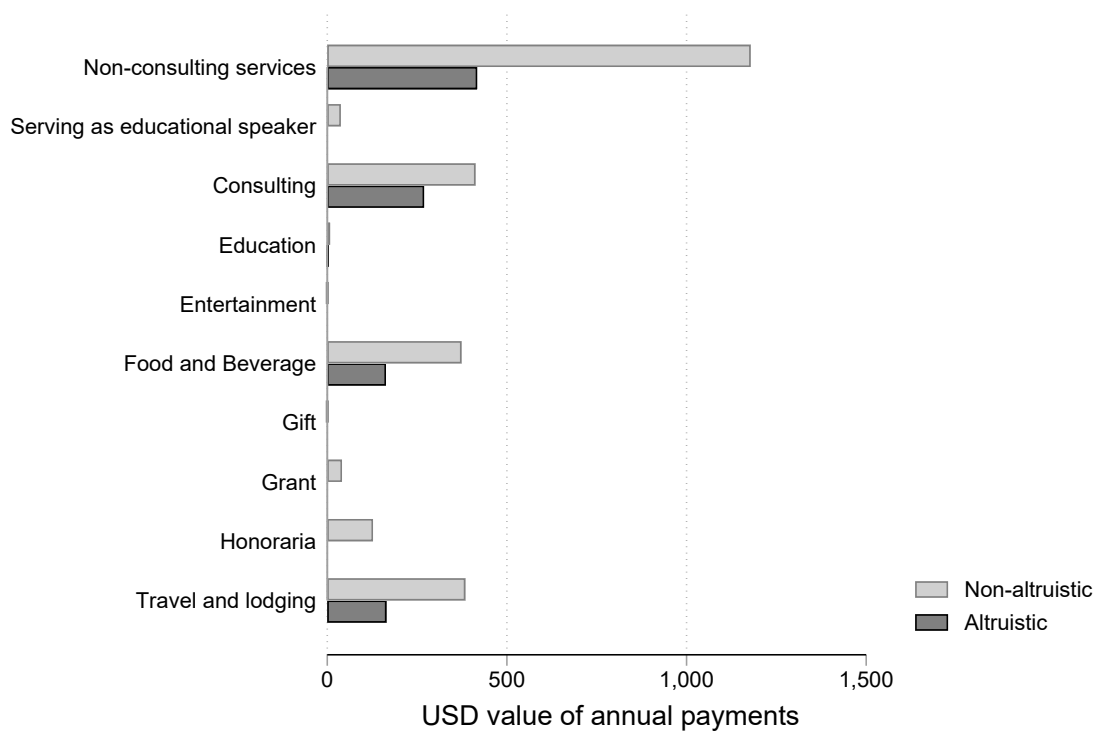


Figure A3. Annual payments over physicians' careers, by altruism

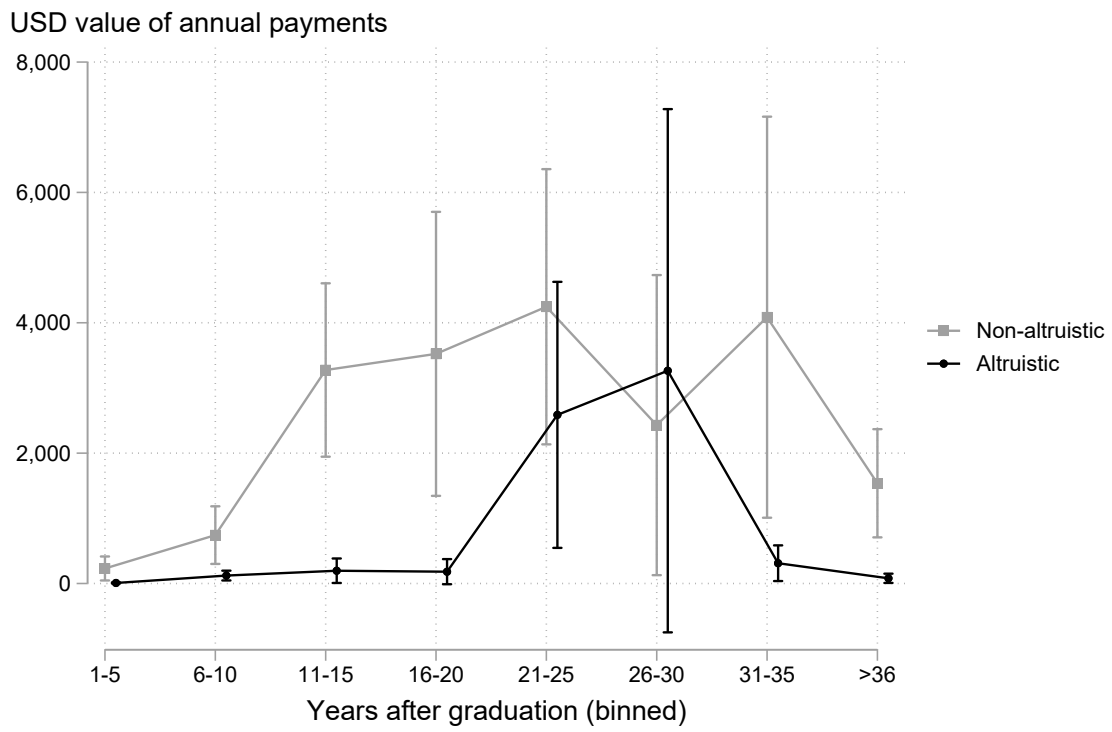
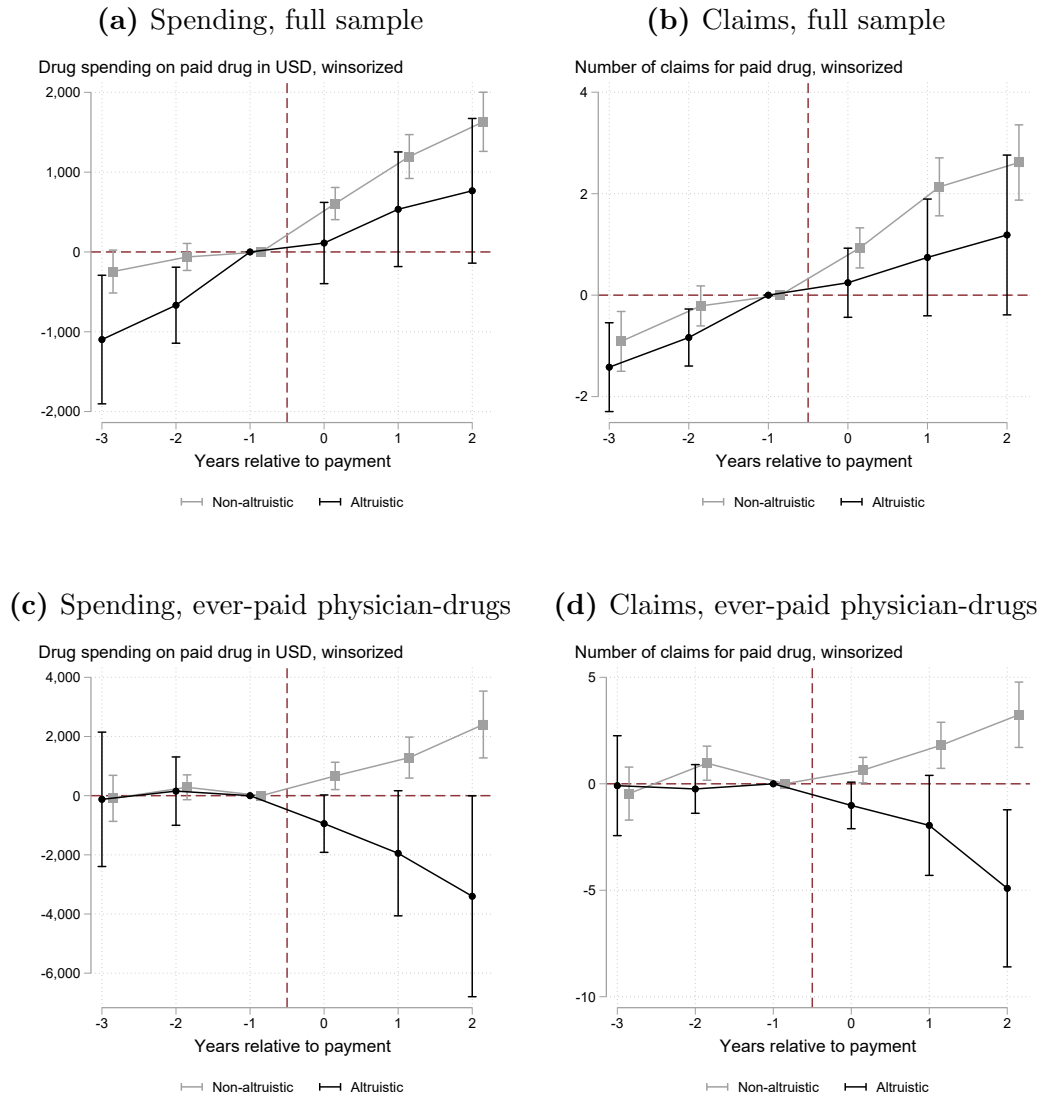
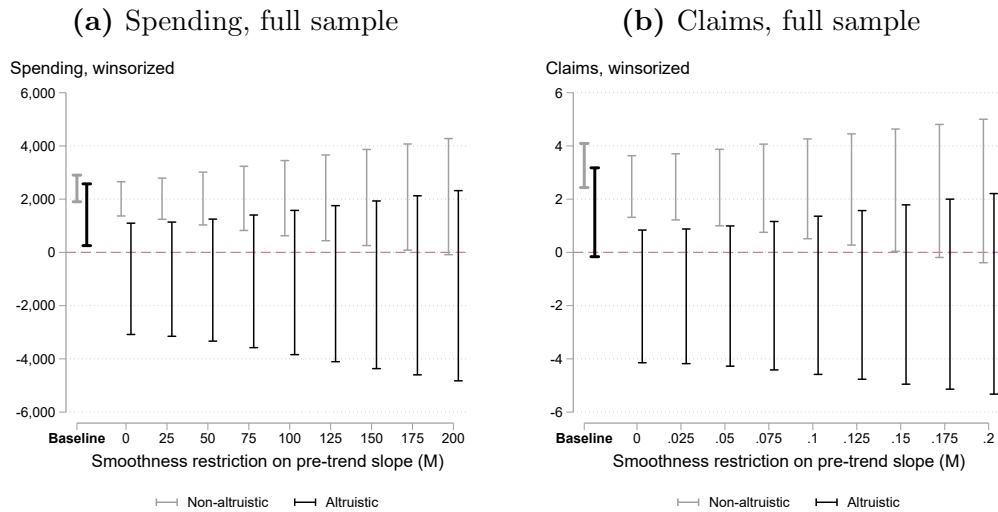


Figure A4. Event-study estimates of drug prescribing following an initial payment, all drugs included



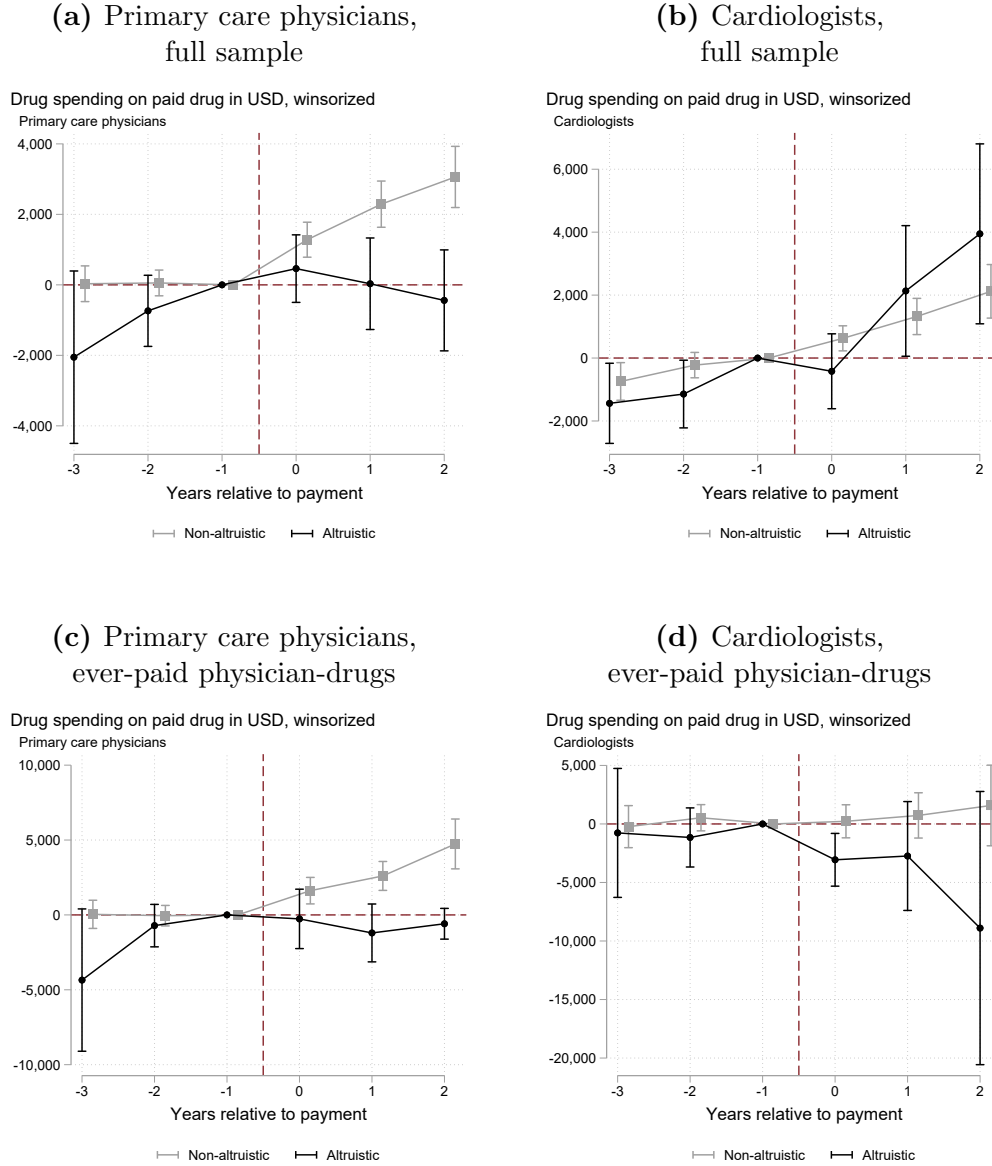
Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians. The analysis includes all 116 drugs with at least one associated payment. Prescribing is measured by spending (left panels) and the number of claims (right panels) for the paid drug. Subfigures A4a and A4b use the full sample of 30,240 physician–drug–year observations for altruistic and 137,671 observations for non-altruistic physicians. Subfigures A4c and A4d include only ever-paid physician–drug pairs, with a sample of 884 observations for altruistic and 4,942 for non-altruistic physicians. Outcomes are winsorized at the 99th percentile within each sample. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered on the physician–drug level.

Figure A5. Allowing for violations of parallel trends under a smoothness restriction



Notes: This figure reports the robustness of the baseline staggered difference-in-differences estimates in the full sample to violations of the parallel trends assumption, using the smoothness-based approach of [Rambachan and Roth \(2023\)](#). We show robust 95% confidence intervals for the average treatment effect of an initial payment across all post-treatment periods under increasingly flexible assumptions about deviations from pre-treatment trends. Deviations are parameterized by M , which bounds how much the slope of the differential trend may change between adjacent periods: $M = 0$ imposes a linear extrapolation of pre-trends, while larger values allow greater curvature. Results are presented separately for altruistic and non-altruistic physicians, with prescribing measured by the number of claims (left) and total spending (right), both winsorized at the 99th percentile. The ‘Baseline’ corresponds to conventional average post-treatment 95% confidence intervals from outcome regression difference-in-differences estimates based on ordinary least squares ([Callaway and Sant’Anna 2021](#); [Sant’Anna and Zhao 2020](#)), under no relaxation of the parallel trends assumption.

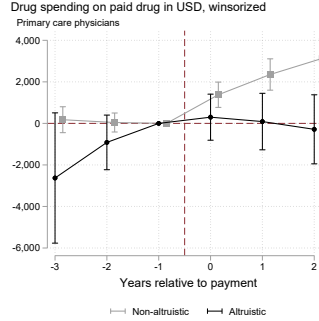
Figure A6. Event-study estimates of drug spending following an initial payment, by specialty



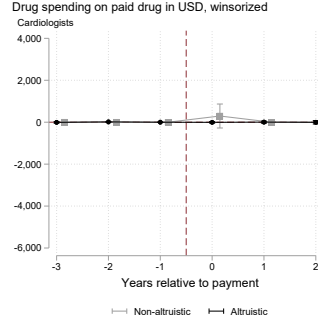
Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on spending for that drug, separately for altruistic and non-altruistic physicians. Results are shown separately by physician specialty, for primary care physicians (left panels) and cardiologists (right panels). Subfigures A6a and A6b use the full sample. Subfigures A6c and A6d include only ever-treated physician-drug pairs. Outcomes are winsorized at the 99th percentile within each sample (full and ever-paid sample). Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered on the physician level.

Figure A7. Event-study estimates of drug spending following an initial payment, by specialty and drug type

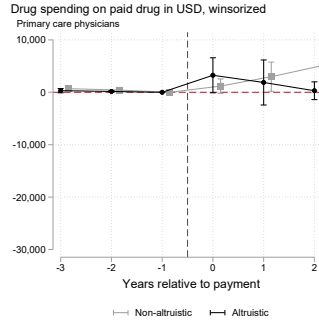
(a) Primary care physicians,
ATC A



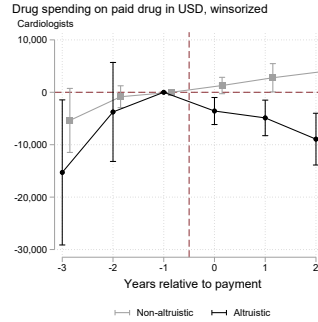
(b) Cardiologists,
ATC A



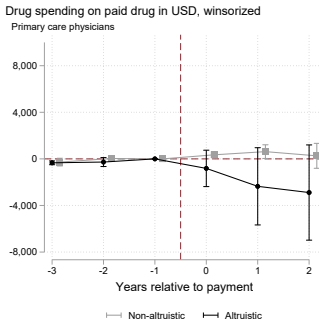
(c) Primary care physicians,
ATC B



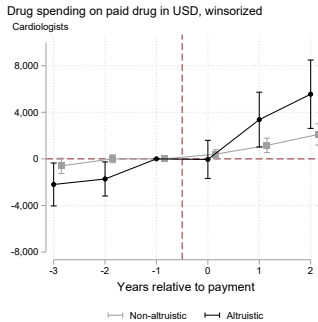
(d) Cardiologists,
ATC B



(e) Primary care physicians,
ATC C



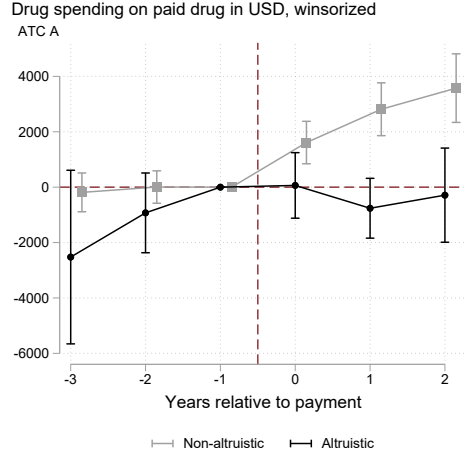
(f) Cardiologists,
ATC C



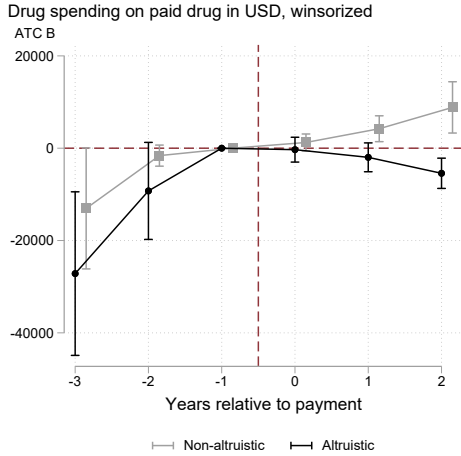
Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians. Results are shown separately by physician specialty, for primary care physicians (left panels) and cardiologists (right panels). Each subfigure shows spending on the paid drug, winsorized at the 99th percentile within drug class, for one of three therapeutic categories: Alimentary tract and metabolism (ATC A), Blood and blood forming organs (ATC B), and Cardiovascular system (ATC C). The full sample is included, consisting of 15,017 physician–drug–year observations for altruistic and 68,210 for non-altruistic physicians. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered at the physician level.

Figure A8. Event-study estimates of drug spending following an initial payment, physicians who prescribe drug categories ATC B and C

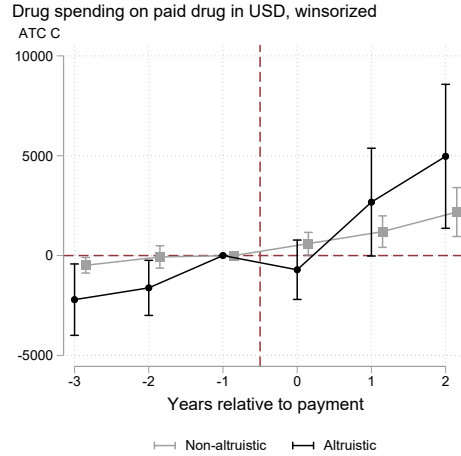
(a) Alimentary tract and metabolism
(ATC A)



(b) Blood and blood forming organs
(ATC B)



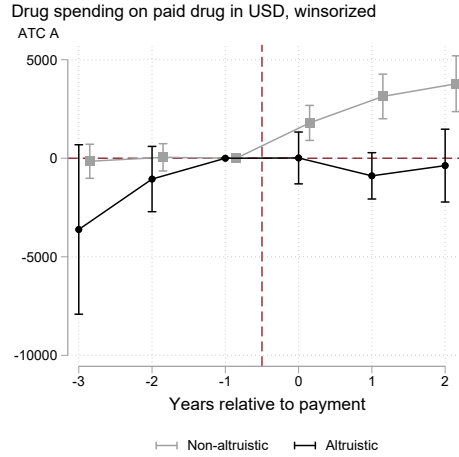
(c) Cardiovascular system
(ATC C)



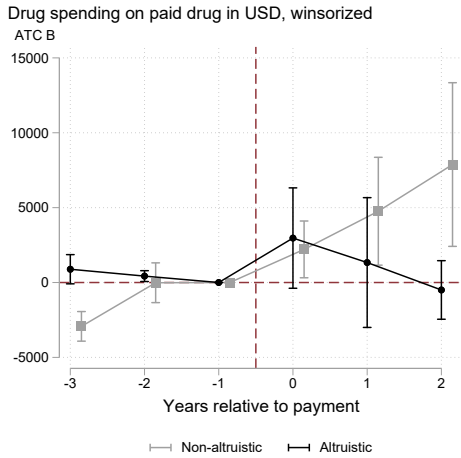
Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians, restricted to physicians who prescribe in both therapeutic categories: Blood and blood forming organs (ATC B) as well as Cardiovascular system (ATC C). Each subfigure shows spending on the paid drug, winsorized at the 99th percentile within drug classes Alimentary tract and metabolism (ATC A), Blood and blood forming organs (ATC B), and Cardiovascular system (ATC C). The sample consists of 6,174 physician–drug–year observations for 18 altruistic physicians and 26,283 for 79 non-altruistic physicians. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered at the physician–drug level.

Figure A9. Event-study estimates of drug spending following an initial payment, physicians who prescribe all drug types (ATC A, B, and C)

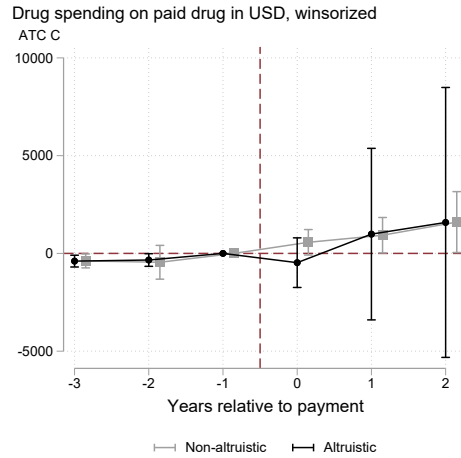
(a) Alimentary tract and metabolism (ATC A)



(b) Blood and blood forming organs (ATC B)



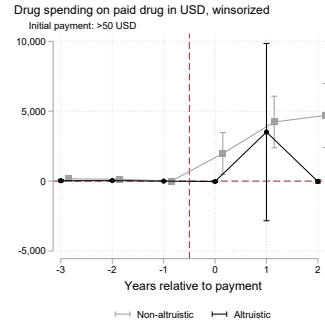
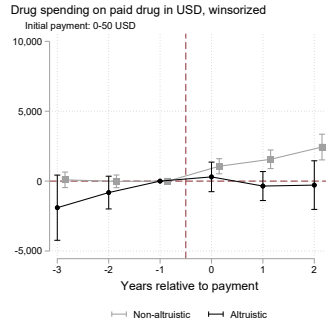
(c) Cardiovascular system (ATC C)



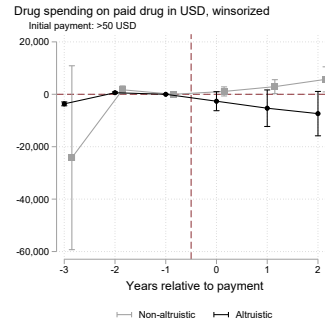
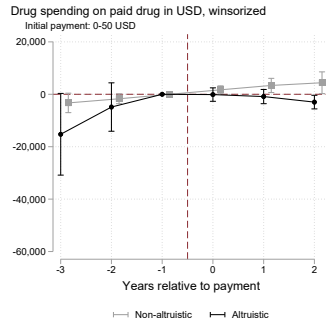
Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians, restricted to physicians who prescribe in all of the three therapeutic categories: Alimentary tract and metabolism (ATC A), Blood and blood forming organs (ATC B), and Cardiovascular system (ATC C). Each subfigure shows spending on the paid drug, winsorized at the 99th percentile within drug class. The sample consists of 9,216 physician–drug–year observations for 27 altruistic physicians and 38,186 for 118 non-altruistic physicians. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered at the physician–drug level.

Figure A10. Event-study estimates of drug spending following an initial payment, by initial payment amount

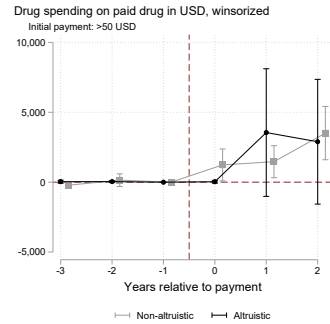
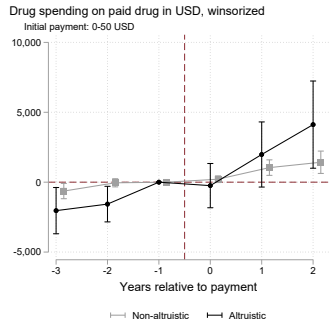
(a) Initial payments ≤ 50 USD, ATC A (b) Initial payments > 50 USD, ATC A



(c) Initial payments ≤ 50 USD, ATC B (d) Initial payments > 50 USD, ATC B



(e) Initial payments ≤ 50 USD, ATC C (f) Initial payments > 50 USD, ATC C



Notes: These figures present staggered difference-in-differences event study estimates of the effect of an initial payment for a drug on prescribing of that drug, separately for altruistic and non-altruistic physicians. Results are shown separately by initial payment amount: *Initial payments* ≤ 50 USD (below the 80th percentile of all initial payments; left panels) and *Initial payments* > 50 USD (top 20%; right panels). Each subfigure shows spending on the paid drug, winsorized at the 99th percentile within drug class, for one of three therapeutic categories: Alimentary tract and metabolism (ATC A), Blood and blood forming organs (ATC B), and Cardiovascular system (ATC C). The full sample is included, consisting of 15,017 physician–drug–year observations for altruistic and 68,210 for non-altruistic physicians. Estimates are obtained using the doubly robust difference-in-differences estimator based on ordinary least squares, aggregated by event time (Callaway and Sant’Anna 2021; Sant’Anna and Zhao 2020). Lines indicate 95% confidence intervals based on standard errors clustered at the physician level.