The role of physician altruism in the physician-industry relationship: Evidence from combining experimental and observational data*

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November 30, 2023

PRELIMINARY DRAFT - DO NOT CIRCULATE WITHOUT PERMISSION

Abstract

Altruism is a key professional norm that underlies the physician's role as a representative agent for patients. However, physician behavior can be influenced when private gains enter the objective function. We study the relationship between altruism and physicians' receipt of financial benefits from pharmaceutical manufacturers, as well as the extent to which altruism mitigates physicians' responsiveness to these industry payments. We combine data on altruistic preferences for 280 physicians, identified using a revealed preference economic experiment, with information on their receipt of monetary and in-kind transfers from pharmaceutical firms along with drug prescription claims data. Our findings reveal that physicians with less altruistic preferences obtain industry transfers that are, on average, 2,184 USD (95% CI: 979.3–3,388.5) higher in monetary value compared to physicians with stronger altruistic preferences. Furthermore, we observe that positive correlations between industry transfers and higher overall drug costs or brand prescribing rates are predominantly driven by physicians with less altruistic preferences. Our estimates suggest that, when comparing less altruistic physicians with more altruistic physicians, a 1% increase in payments is associated with an *additional* average increase of 0.005 percentage points (0.027%) in the share of brand drugs prescribed. We find limited evidence that patient vulnerability moderates industry influences among less altruistic physicians. Our results indicate that altruism is an important determinant of physicians' relationships with and responses to industry benefits.

Keywords: Physician behavior; Professional norms; Industry payments; Drug prescribing

JEL codes: I11; D64; L14; C91

*We thank Melissa Newham, Susan Mendez, Sabrina Schubert, Hannes Ullrich, as well as participants at the DGGÖ Health Econometrics Workshop 2022 in Hanover, the Business Research Seminar at the University of Zurich, the SGGÖ Health Economics Conference 2023 in Bern, and the Health Economics Methods Meeting 2023 in Vancouver for valuable comments.

1 Introduction

Physicians are, in the public eye, expected to practice medicine selflessly. Altruism is fundamental to the physician's role as a representative agent for their patients and serves to insulate them from third-party motives that may conflict with patients' interests. In the medical profession, altruism is a core norm that mandates prioritizing social benefits over personal gains. For example, the American Board of Internal Medicine underscores that 'professionalism in medicine requires the physician to serve the interests of the patient *above his or her self-interest*' (American Board of Internal Medicine 1995).

However, physician behavior can be influenced when personal gains enter their objective function. If physicians are not fully altruistic, clinical decision-making may be affected by the potential to obtain personal gains. Concerns regarding personal gains are particularly pronounced in the context of industry ties that are often expressed through financial channels. Close relationships between physicians and pharmaceutical manufacturers have attracted substantial media and policy attention, as they frequently involve financial and in-kind benefits for physicians who engage with drug company marketing efforts.[1] However, the relationship between physician altruism and financial benefits from industry transfers remains unexplored.

In this study, we combine experimental data with administrative data to examine the role of altruism in the physician-industry relationship and clinical practice. We match altruistic preferences elicited for 280 physicians in the United States to data on their receipt of monetary or in-kind transfers from pharmaceutical firms and claims data on their drug prescriptions. Our analysis focuses on the association between altruism and industry payments, and how this relationship moderates physicians' prescribing behaviors. Altruism characterizes physicians' utility weight on societal (patient or insurance) benefits compared to the weight on their own benefits. Less altruistic physicians prioritize their private gains, such as those from receiving industry payments. Interactions between physicians and the pharmaceutical industry often involve financial benefits, such as purchasing meals and beverages, lucrative consulting fees, or invitations as speakers at promotional events. We first develop a stylized model of altruism in brand prescription choices and physicians' decisions to engage with drug firms. We then empirically investigate how physician altruism relates to transfers from the pharmaceutical industry to physicians, and whether altruistic preferences are associated with the relation between industry transfers and drug prescribing.

We establish that non-altruistic physicians have stronger ties to pharmaceutical firms. On average, the

[1] For example, ProPublica focused on industry payments to physicians in 'Dollars for Doctors', a series of highly publicized media reports (see the 'Dollars for Doctors' project, last access: 23 Nov 2023), which was mirrored by a European initiative (see the 'Euros for Docs' project, last access: 23 Nov 2023). Recently, direct-to-physician marketing practices related to the drug Ozempic have been heavily critized (see reporting by Fortune: Ozempic manufacturer Novo Nordisk spent $11 million last year 'wining and dining' doctors. Experts slam the move as a breach of doctor-patient trust, last access: 23 Nov 2023). Legislative efforts such as the United States Physician Payments Sunshine Act or the French Sunshine Law attempt to increase the transparency of physician-industry relations nationwide.

monetary value of yearly industry transfers to non-altruistic physicians is 2,184 USD (95% CI: 979.3–3,388.5) higher than than payments to altruistic physicians, who receive 860 USD on average. These findings indicate a strong selection of who is targeted by the pharmaceutical industry to influence prescription behavior.

Next, we study the relationship between altruistic preferences and drug prescribing. To capture the potential effects of marketing efforts, we measure prescribing by the share of brand claims over all prescriptions and per claim drug costs. Our prescribing variables hold the number of prescriptions fixed to examine whether physicians substitute brand for generic prescriptions, as well as expensive for low-cost treatments. We find no evidence that altruistic preferences are related to prescription decisions and health care costs directly. Instead, our results point toward altruism serving as a moderating variable for the relationship between industry payments and prescriptions, such that the relationship between industry payments and prescriptions differs by altruistic preferences. We replicate previous findings, which have shown that industry transfers are associated with higher drug costs and brand prescribing rates across a range of drug classes and physician specialties (Mitchell et al. 2021). However, we find that this positive association is consistently driven by non-altruistic physicians.

We find that for an increase in payment amounts, primarily physicians with non-altruistic preferences are more likely to prescribe brand treatments and impose higher drug costs. In fact, once we control for the interaction between altruism and payments, we do not find any statistically significant (10%) association between aggregate industry transfers and drug costs or brand prescribing rates. Our estimates suggest that a 1% increase in payments to a less altruistic physician over an altruistic physician is associated with an *additional* increase of 0.005 percentage points (0.027%) in the share of brand claims, and an additional increase in the per claim costs by 2.3%, although this estimate is not statistically significant on the 10% level. Altruistic preferences might thus determine the strength of the relation between the amount of industry payments physicians receive and physicians' drug prescribing.

A back-of-the-envelope calculation based on average drug prices suggests that a physician with non-altruistic preferences incurs drug costs approximately 4,361 USD higher per year compared to physicians with altruistic preferences. Our main results are consistent with specifications in which we focus on drug-specific payments and prescribing patterns. We find little evidence that patient pool characteristics, such as patient vulnerability, change the relation between payments and prescribing among non-altruistic physicians. While physicians who treat more vulnerable patient groups, such as patients with a higher diagnostic risk score or a higher low-income patient share, are less responsive to industry payments overall, non-altruistic preferences offset physicians' lower responsiveness to payments among more vulnerable patient pools. Altruism thus moderates the correlation between industry payments and drug prescribing similarly on most dimensions of patient heterogeneity.

Our study contributes to the knowledge of direct-to-physician marketing and the impact of such interactions on physicians' treatment decisions. Physicians are central in deciding whether brand drugs are chosen over less expensive alternatives (Hellerstein 1998). Previous studies have demonstrated a strong association between industry payments and physicians' prescribing decisions, and consistently find that industry transfers are linked to physicians' prescribing of branded medical drugs (Iizuka and Jin 2007; Dejong et al. 2016; Ansari 2021). In addition, industry payments have been found to heavily influence physicians' selection of medical devices (Bergman et al. 2021, 2022; Amaral-Garcia 2022).

Several mechanisms could drive a positive correlation between marketing efforts and physicians' treatment choices. For example, industry transfers might have a promotional value that directly induces physicians to prescribe these drugs (Carey et al. 2021b,a; Mitchell et al. 2022). Apart from the persuasive elements of drug detailing, interactions between physicians and the pharmaceutical industry can also have informational value and benefit patients when new treatments are introduced (Ching and Ishihara 2012; Grennan et al. 2021). Alternatively, pharmaceutical firms may target certain physicians for promotional activities, such as those who are already high prescribers of branded drugs or hold influential positions (Agha and Zeltzer 2022). We do not take a stance on the causal direction between payments and prescribing, and we do not rule out the possibility that marketing aimed at physicians can unintentionally improve efficiency by increasing prescribing for novel, underused drugs. Instead, we focus on understanding which types of physicians are more likely to accept payments and participate in industry relations (Newham and Valente 2022). Our study highlights the role of professional norms of altruism, which prompt physicians to prioritize societal benefits over personal gains, and suggests that variation in compliance to such norms contributes substantially to heterogeneity in physicians' ties to pharmaceutical firms and the extent to which private financial benefits enter physicians' prescribing decisions.

Our study further complements existing evidence on the impact of altruism on physicians' treatment decisions. Altruism, as opposed to self-interest, is considered the 'accepted norm' of the physician profession (Arrow 1963). Professional norms of altruistic behavior underlie the role of physicians as agents for their patients, determining the degree to which self-serving motives enter into physicians' treatment decisions (Arrow 1963; Farley 1986; Ellis and McGuire 1990; Kesternich et al. 2015). However, previous research has highlighted sizeable variation in altruistic preferences among medical students and physicians, and social preferences play a central role in the choice of medical specialty (Godager and Wiesen 2013; Brosig-Koch et al. 2017; Li et al. 2017, 2022). Variation in social preferences accounts greatly for the choice of medical specialty (Li 2018). In experiments, medical students consider patient cost-sharing, alongside patient health, when making prescribing decisions (Ge et al. 2022). In addition, heterogeneity among physicians, such as habit persistence, account for brand prescribing decisions in practice (Crea et al. 2019).[2] However, the extent to which physicians' inherent altruistic preferences determine the degree of third-party influence through personal gains has not been studied. Our research examines physician altruism to investigate the interaction with industry payments as a mechanism for how differences in prescribing patterns may develop. Overall, our findings emphasize the importance of social preferences and professional norms in explaining whether tight industry-physician relationships arise.

The remainder of the paper is organized as follows. Section 2 sets up a conceptual framework that links physician altruism, payments, and prescribing decisions, and states the resulting hypotheses to test. Section 3 describes the construction of our analysis sample based on experimental and observational data. Section 4 establishes empirical tests of our hypotheses and shows the regression results. Section 5 discusses threats and extensions to our main analysis. Section 6 concludes.

2 A stylized model of altruism in prescribing with payments

We examine a physician's decision-making process when she is presented with the opportunity to interact with pharmaceutical representatives in exchange for monetary and in-kind transfers. Our conceptual framework explores a two-period model where the physician initially decides whether to accept a predetermined level of industry transfers offered to her, and subsequently determines her brand prescribing propensity in anticipation of potential future payments. The two-period setup captures the main dynamic considerations of physicians and pharmaceutical representatives in a simplified model. Based on this setup, we study the comparative statics of the equilibrium as to explore the relationship between the physician's acceptance of industry transfers, her prescribing decisions, and her underlying altruistic preferences.

We begin by describing the physician's decision on the level of industry transfers to accept. Then, we discuss the optimal propensity to prescribe branded drugs.

2.1 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, travels, 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

[2]Note that altruism refers specifically to the internalization of patient costs in Crea et al. (2019). In their study of statin prescribing in Finland, physicians do not appear to consider patient out-of-pocket expenses or insurance coverage when making prescribing decisions. In our study based on US physicians, altruism is explicitly defined over the degree to which physicians place weight on their own utility compared to other-regarding motivations, and we measure physician altruism experimentally. In addition, we take into account that the presence of industry transfers may impact physicians' prescription patterns.

thus trades off the monetary value of the transfer with its professional costs.

The decision of whether to engage in these interactions for the payment depends on the monetary value of the payment, denoted by $\bar{p} > 0$, and the physician's level of altruism α, where $\alpha \in [0, 1]$. 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 interactions with the pharmaceutical industry take 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. 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 $\frac{\partial^2 R}{\partial p \partial \alpha} < 0$. This could be justified by the fact that, all else being equal, an altruistic physician may have stronger concerns about the undue influence of payments deviating her treatment choices from those that she would make if she only considered patient and societal interests without accepting the 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:

$$p^{\max}(\alpha) = R(p^{\max}; \alpha). \tag{1}$$

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 decreases with the level of altruism (increases in α).

2.2 Optimal propensity to prescribe branded drugs

In the second period, the physician chooses her propensity to prescribe a brand-named drug over its less expensive alternatives, such as generic versions or older compounds. We represent the physician's brand prescribing propensity by b, corresponding to the proportion of claims that she fills for branded drugs. 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 for a given brand drug propensity b, denoted by $\pi_o(b)$, as well as the private value of prescribing brand drugs, denoted by $\pi_s(b, p)$.

Let the physician's utility for the propensity to prescribe branded drugs 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 brand prescribing propensity. 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.

The net benefit to patients and society, $\pi_o(b)$, is a function of the proportion of patients who are prescribed branded drugs. We assume that a higher brand prescribing rate affects patient health positively, as branded drugs typically correspond to newer drug classes or may have more information available about their safety and efficacy. However, brand drugs are associated with often substantial price premia over their alternatives. The higher prices are carried by patients and insurance, and also reflect rising inefficiencies due to the monopoly power of brand drug companies (Lakdawalla and Sood 2009). We assume that the marginal health benefits and costs of a higher brand prescribing propensity are positive, 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 brand drug use as costs eventually surpass the health benefits of additional brand drug use:

$$\frac{\partial^2 H_o}{\partial b^2} < \frac{\partial^2 C_o}{\partial b^2}.$$

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 industry payments, the physician does not incur any private benefits from prescribing branded drugs, $\pi_s(b,p) = 0$ for $p = 0$. In other words, choosing a higher brand prescribing propensity 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 brand prescribing propensity, whereas physicians who are not fully selfish $0 < \alpha \leq 1$ weigh societal costs/benefits to determine the optimal brand prescribing propensity 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 brand-name drug, $\pi_s(b,p) \geq 0$, if she accepts a positive payment $p > 0$. The physician's decision to accept payments is thus linked to her prescribing decision by increasing the private value of brand 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 brand prescribing is weakly increasing in payments due to the anticipation of future payments from a maintained relationship with the drug company:

$$\frac{\partial \pi_s}{\partial p} \geq 0.$$

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

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

We denote the optimal brand prescribing propensity by $b^*(\alpha)$. By applying the implicit function theorem to our setup, we can show that the optimal brand drug prescribing propensity moves up with higher payments.[3] Importantly, within this setup, the optimal brand prescribing propensity increases with payments at a higher rate for less altruistic physicians:

$$\frac{\partial^2 b^*}{\partial p \partial \alpha} = -\frac{\frac{\partial \pi_s}{\partial p}\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}{\left((1-\alpha)\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right) + \alpha \frac{\partial^2 \pi_s}{\partial b^2}\right)^2}, \tag{2}$$

such that $\frac{\partial^2 b^*}{\partial p \partial \alpha} \geq 0$ for any $\alpha > 0$. Thus, brand drug use is more responsive with regard to payments with increasing weight on physicians' private benefits.

[3] We show the full derivations for the comparative statics of the optimal brand prescribing propensity in Appendix A.

2.3 Model predictions

Our main observation from the two-period model is that industry payments interact with the level of altruism in determining prescribing decisions. We summarize our observations in the following predictions:

- *Non-altruistic physicians accept higher payments.* If payments progressively harm physicians' professional integrity, and these professional costs increase at a higher rate for more altruistic physicians, then Equation (1 defines the maximum value of transfers to be lower for more altruistic physicians than for less altruistic physicians. In the aggregate, we thus expect that payments made to non-altruistic physicians are higher than payments made to altruistic physicians.

- *Non-altruistic physicians are more responsive to payments.* If the marginal patient benefit from using brand drugs increases at a slower rate than the marginal societal costs, and physicians' accepted payments are linked to their private benefits from using brand drugs through an ongoing industry relationship, then Equation (2) indicates that less altruistic physicians are more responsive to industry transfers in their use of brand drugs compared to more altruistic physicians. We thus expect that the relationship between prescribing and payments is stronger for non-altruistic physicians than for altruistic physicians.

In the empirical implementation, we test our main predictions on the payment receipt and the responsiveness to payments in prescribing among physicians who prioritize others over themselves (altruistic, $\alpha < 0.5$), compared to physicians who place more weight on themselves (non-altruistic, $\alpha \geq 0.5$).

3 Data

3.1 Eliciting altruism in the experiment

Our empirical analysis studies whether altruistic preferences predict physicians' receipt of industry transfers and drug prescriptions. To do so, we link observed physician behavior from administrative information to experimental data from Li et al. (2022). The experiment elicited physicians' social preferences and identified altruism separately from distributive concerns. For this study, we focus on the altruistic preferences of physicians that were elicited in the experiment.

In the experiment, each physician is presented with a sequence of modified dictator games. Additionally, a survey questionnaire collects information about physicians' practice experience and educational background.

Our sample includes 283 individual physicians who participated in the experiment. All participating physicians are clinically active, either as primary care providers or as cardiologists. Physicians were recruited for the experiment by contacting leaders of medical groups, which include organized groups of individual practices, medical centers, and hospital departments. The medical groups were invited via email to participate in a study of physician decision-making, and selected to represent variation in size and geographic region within specialties.[4]

Physicians in the experiment are faced with a web-based graphical representation of a consumption decision problem, that is, choosing a bundle under budget constraints. The experimental task asks physicians to choose a payoff allocation between 'self' and 'other'. This choice affects both the physician's payoff ('self') as well as the payoff of a randomly drawn anonymous respondent from a representative sample of the US adult population ('other'). The randomly drawn US adult represents the general population, as both primary care providers and cardiologists are supposed to serve patients non-selectively.[5] The main experiment is a modified dictator game, where the physician allocates an endowment across 'self' $\tilde{\pi}_s$ and 'other' $\tilde{\pi}_o$ at prices p_s and p_o. For a normalized endowment of 1, the set of possible budget lines is thus provided by:

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

Each physician plays 50 rounds of independent modified dictator games, where the budget line is drawn randomly. Physicians choose an allocation on a given budget line through a point-and-click interface. At the end of the experiment, one of the 50 rounds of decisions is chosen randomly. The physician receives $\tilde{\pi}_s$, and the anonymous respondent from the general population receives $\tilde{\pi}_o$ as determined by the physician in the randomly chosen allocation.

After the experiment is conducted, each physician is asked to complete a survey questionnaire in order to receive payment from the experiment. The survey provides details on sociodemographic characteristics of the physician as well as institutional information on the physician's practice.

To measure altruistic preferences, we assume that physicians' utility function $u_s(\tilde{\pi}_s, \tilde{\pi}_o)$ exhibits Constant Elasticity of Substitution (CES).[6] Physicians' utility from trading off the payoffs to 'self' compared to 'other' is then given by:

[4]Li et al. (2022) discusses the recruitment methods used, and shows that there were no statistically significant differences in social preferences by recruitment method. While our sample might differ from a general population of physicians, we only perform within-sample comparisons of physician behavior. Generally, participants in lab experiments have been shown to behave slightly less altruistic compared to non-participants, but the differences are minor (Snowberg and Yariv 2021).

[5]The representative sample of US adults is part of the Understanding America Study. All physicians are provided with information on the distribution of demographic, socio-economic, and geographical characteristics within respondents.

[6]To ensure that the observed behavior complies with 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, with a median of 0.998, indicating that almost all physicians act perfectly rational and GARP is satisfied.

$$u_s = [\alpha \tilde{\pi}_s^{\rho} + (1-\alpha)\tilde{\pi}_o^{\rho}]^{1/\rho}. \tag{3}$$

Parameter $\alpha \in [0,1]$ in Equation 3 measures altruistic preferences: $\alpha = 0$ indicates fully altruistic preferences, where utility weight is exclusively placed on payoffs to 'other'. In contrast, $\alpha = 1$ indicates selfish preferences and $\alpha = 0.5$ indicates impartial social preferences. Parameter $\rho \leq 1$ in Equation 3 measures the equality-efficiency trade-off in response to relative price changes separately from social preferences.[7]

We estimate parameters α and ρ on the CES expenditure function of the payoff to 'self', which we obtain by maximizing the utility function (3):

$$p_s \tilde{\pi}_s = \frac{g}{(p_s/p_o)^r + g},$$

where $r = \rho/(1-\rho)$ and $g = [\alpha/(1-\alpha)]^{1/(1-\rho)} \in [0,1]$. We employ nonlinear tobit maximum likelihood to estimate g and r and then infer the underlying parameters α and ρ separately for each physician, using 50 observations from the repeated games. Our analysis focuses on estimates of α, the altruism parameter.

Physicians could achieve a maximum possible payoff of 250 USD in the experiment, and they could receive a payoff of about 156 USD on average if they never chose to give money away. On average, physicians obtained 87 USD. [8] Details on the experiment, survey, and methodological background are described in Li et al. (2022).

3.2 Sample construction

To prepare the analysis sample, we complement data from the experiment with administrative data from the Open Payments database on industry payments, along with Medicare Part D public use files on physician claims filed for the years 2014 to 2019. We discuss the administrative data sources and the sample construction below.

The Open Payments program is a national disclosure initiative published by the Centers for Medicare & Medicaid Services (CMS) and made publicly accessible in order to promote transparency of physician-industry relations. Since February 2013, Open Payments collects data on all physician-industry encounters that involve

[7] $\rho \in (0,1]$ indicates that distributional preferences are weighted towards efficiency, that is, increasing total payoff as relative prices between payoff to 'self' in relation to 'other' change. $\rho \in (-\infty, 0)$ indicates preferences toward equality, that is, reducing differences in payoffs as relative prices change. $\rho \to 0$ indicates that the relative allocation of payoffs does not change in response to relative price changes.

[8] The average session duration was 15 minutes, excluding sessions that lasted longer than two hours in which physicians had likely not logged out.

either monetary or in-kind transfers, such as meals, consulting fees, speaker fees, or any detailing efforts. The disclosure of transfers is federally mandated, and penalties are imposed against reporting violations under Section 6002 of the Affordable Care Act from 2010 (Physician Payments Sunshine Act). In addition to information on transfers, the Open Payments database contains physicians' names and practice locations, as well as their alternative names and addresses. However, the National Provider Identifier (NPI) for physicians is not included until the 2021 release. We use a fuzzy matching procedure to match physicians' experimental data to the older Open Payments data covering 2014 to 2019, where we rely on physicians' names and addresses. We infer a match if a physician's name is unique in a licensed state according to the National Plan and Provider Enumeration System (NPPES) registry. We manually check all remaining physicians for potential matches. Lastly, we use the NPIs reported in the 2021 Open Payments release to check against our matching procedure. We assume that no monetary or in-kind gifts were made to physicians not appearing in the Open Payments database.

We then link drug claims data from the Medicare Part D Public Use Files by physicians' NPI. Out of 1,981 physician-year observations from 283 physicians, we drop 364 observations in which drug prescribing was insufficient so that drug costs or the number of generic prescription claims cannot be determined.[9] The final sample contains 1,616 physician-year observations from 280 physicians.

3.3 Main variables

Altruism. Our main variable of interest is altruism, measured by α. We use one-sided t-tests to categorize physicians as having selfish social preferences ($\alpha < 0.5$ can be rejected), selfless preferences ($\alpha > 0.5$ can be rejected), or impartial preferences. In the main analysis we dichotomize altruistic preferences and distinguish between physicians with selfless preferences (Altruistic), and physicians with impartial or selfish preferences (Non-altruistic). The cutoff of 0.5 relates directly to the utility weights that a physician places on their own benefits compared to the benefits of others, thus allowing for a natural interpretation. Moreover, this threshold does not require us to rely on any assumptions about the representativeness of our sample compared to the broader physician population, in contrast to using, for example, a median. In Section 5 we discuss an alternative specification, where we use a continuous measure of altruistic preferences, where results are generally consistent with our main estimates.

Payments. We aggregate the monetary value of all transfers recorded in the Open Payments database in a given year to construct the USD value of industry payments on the physician-year level. For payments as outcome variable, we rely on estimates based on level payments to calculate marginal effects on the mean. In

[9] We drop one additional physician-year observation for which average patient age and risk score are missing, as we would not be able to control for these basic patient pool characteristics in our main estimations.

some specifications and sensitivity checks, and for illustrative purposes, we show results from log-transformed payments based on the natural logarithm of 1 + payments. In addition, we construct the natural logarithm of payments for any positive transfers, measuring the intensive margin, as well as an indicator variable for any payment, measuring the extensive margin of payments.

To measure industry payments, we only consider transfers included as general payments in the database, which excludes research and ownership payments or investment interests.[10] We aggregate payment records, as about 15% of entries from the Open Payments database for our sample of physicians are not associated with any product, and some entries refer to generic categories, such as 'general therapies', 'circulatory support', or 'general'. In additional analyses, we consider drug-specific payments and prescriptions.

In additional analyses, presented in Section 5, we also consider the sum of payments on the physician-level over the period between 2014–2019.

Drug prescribing. We construct two measures in order to capture the association between industry payments and drug prescribing: Log per claim drug costs, and Share of brand claims. To measure drug costs imposed on patients and the Medicare system, we take the natural logarithm of the sum of all costs divided by the total number of claims in a year. We measure prescribed drug types by the share of claims associated with brand drugs, that is, the share of prescriptions of non-generic drugs among all claims in a year.[11]

3.4 Additional variables

We include control variables that are not associated with altruism but might be determinants of industry payments to physicians or prescribing decisions. In addition, we investigate whether the relationship between altruism, industry payments, and drug prescribing differs between physicians with varying patient pools in heterogeneity analyses.

Individual controls. Career seniority and gender have been identified as important determinants of the industry-physician relationship (Han et al. 2022). In addition, our sample comprises both primary care providers (including family medicine and internal medicine) and cardiologists, representing groups that are likely to be targeted differently by pharmaceutical companies. As basic individual control variables, we thus include indicators for physicians' age category, gender, and specialty.

Institutional controls. Physicians in our sample also differ in institutional characteristics. In particular, the organizational structure of a clinic, such as ownership and the size of the medical group, may influence the extent to which physicians can engage with the pharmaceutical industry. To account for such differences,

[10] In Appendix B we provide additional information on the individual drugs that are associated with high prescriptions or payments. Table 8 lists the names of the most commonly prescribed drugs, and Table 7 lists the names of the drugs for which physicians in our sample received the highest-valued transfers.

[11] Non-generic drugs include brand or other drugs. For simplicity, we refer to non-generic drugs as brand drugs.

we include physicians' self-reported practice ownership type, and practice size category as indicator variables.

State-controls. Some states restrict the level of payments physicians may receive. We identify Vermont, Massachusetts, Minnesota, Washington D.C., West Virginia, California, Connecticut, Louisiana, and Nevada as states with payment regulations that are more restrictive than the federal level.[12] From these, only Vermont, Minnesota, Washington D.C., and California appear in our analysis.

Patient pool heterogeneity. For the analysis of drug prescribing, we additionally include control variables to characterize the pool of physicians' Medicare beneficiaries. We construct indicator variables based on the following patient characteristics, averaged for each physician in a given year: Risk score as evaluated by the Centers for Medicare and Medicaid Services (CMS-HCC Risk Adjustment Model), Age, Share of female patients, Share of non-white patients, and Share of dual (Medicare and Medicaid) eligibility patients. The indicator variables characterize the quartiles of a given patient pool characteristics. Because information about physicians' patient pools is incomplete, we also construct indicator variables that are one if a characteristic is missing for each patient pool characteristic.

3.5 Descriptive evidence

Table 1 presents summary statistics for our main variables of interest and control variables. Panel A of the table reports summary statistics for key physician characteristics. In our sample, 17% of the 280 physicians are identified as having altruistic preferences. Moreover, 79% of physicians in our sample receive any payments from the pharmaceutical industry during the years 2014–2019, and the sample consists primarily of primary care providers, although 34% are cardiologists.

Panel B of the table summarizes industry payments and total drug prescribing in Medicare Part D at the physician-year level. Industry transfers to physicians are observed in 52% of all 1,616 physician-years. This share is similar in comparable physician populations: For example, in 2015, 41.0% of primary care providers and 81% of cardiologists in our sample receive general payments, compared to national shares of between 39.6% and 51.1% in primary care and 74.9% in cardiology, respectively (Tringale et al. 2017). Yearly payments in our sample amount to 2,262.56 USD on average but are skewed to the right, with the median payment at 14 USD.

Panel C of Table 1 shows summary statistics for the patient pool covered by Medicare Part D for the physicians in our sample, where we observe considerable variation in the patient pools of physicians. We include control variables to adjust for the variation in patient characteristics in physicians' drug prescribing decisions.

[12] See Physician Payments Sunshine Act: Review of Individual State Reporting Requirements (Thomas Sullivan, 6 May 2018), last access: 30 Nov 2022.

Table 1: Summary statistics

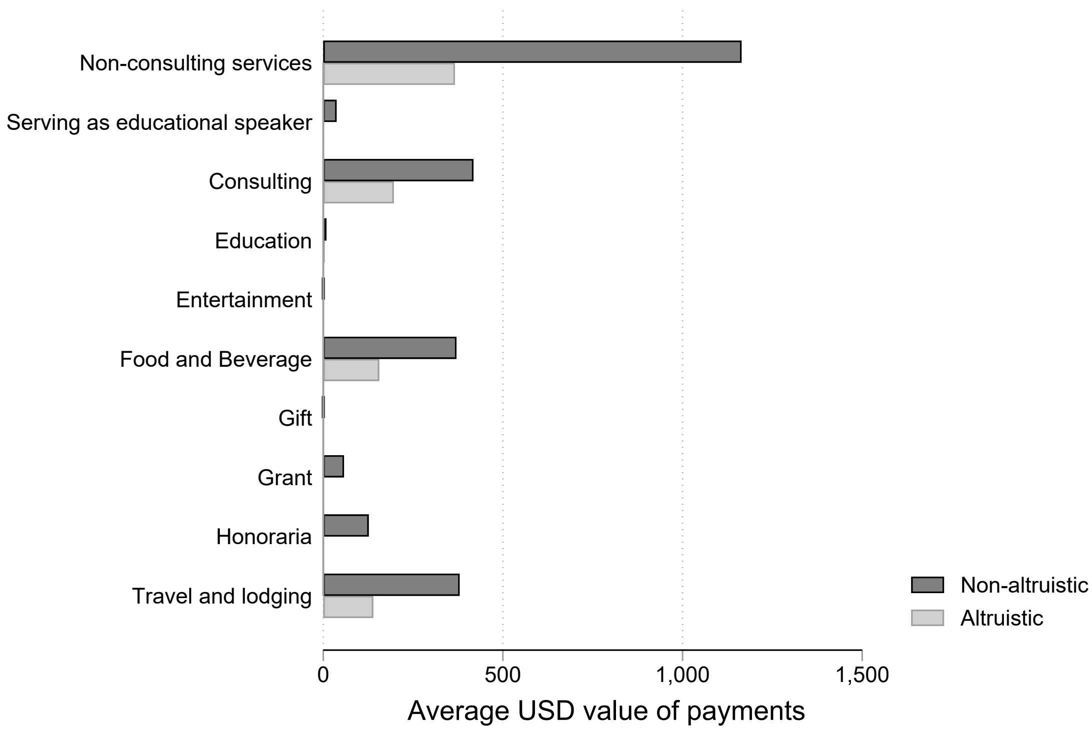
	Mean	Std. dev.	Min.	Median	Max.	Obs.
A: Physician characteristics						
Altruism parameter α	0.61	0.25	0.00	0.57	1.00	280
Altruistic	0.17	0.38	0.00	0.00	1.00	280
Any payment, all years	0.79	0.41	0.00	1.00	1.00	280
Total USD value of payments, all years[a]	14,391.92	57,255.64	0.00	460.00	575,250.00	280
Log (Total USD value of payments, all years + 1)	5.54	3.62	0.00	6.12	13.26	280
Female	0.39	0.49	0.00	0.00	1.00	280
Age below 39	0.30	0.46	0.00	0.00	1.00	280
Age 40-49	0.33	0.47	0.00	0.00	1.00	280
Age 50-59	0.22	0.42	0.00	0.00	1.00	280
Age above 60	0.16	0.36	0.00	0.00	1.00	280
Cardiology	0.34	0.47	0.00	0.00	1.00	280
Nonprofit hospital	0.16	0.37	0.00	0.00	1.00	280
Academic medical center	0.59	0.49	0.00	1.00	1.00	280
Physician-owned practice	0.25	0.43	0.00	0.00	1.00	280
Practice size: 1–35	0.16	0.36	0.00	0.00	1.00	280
Practice size: 36–350	0.48	0.50	0.00	0.00	1.00	280
Practice size: 351–1600	0.36	0.48	0.00	0.00	1.00	280
B: Industry payments and total drug prescribing						
Any payment	0.52	0.50	0.00	1.00	1.00	1,616
USD value of payments[b]	2,262.56	10,809.20	0.00	14.00	215,100.00	1,616
Log (USD value of payments + 1)	3.16	3.40	0.00	2.63	12.28	1,616
Number of claims[a]	2,834.62	3,387.60	10.00	1,580.00	28,110.00	1,616
Share of brand drug claims	0.20	0.06	0.00	0.19	0.54	1,616
Drug costs[a]	219,262.40	275,702.59	120.00	133,160.00	3,287,350.00	1,616
Per claim costs	84.89	64.28	5.61	72.73	1,122.73	1,616
Log per claim costs	4.30	0.49	1.72	4.29	7.02	1,616
Altruistic: Any payment	0.47	0.50	0.00	0.00	1.00	286
Altruistic: USD value of payments[a]	860.40	5,276.09	0.00	0.00	71,320.00	286
Altruistic: Number of claims[a]	3,017.45	3,138.52	10.00	1,980.00	16,780.00	286
Altruistic: Share of brand drug claims	0.19	0.05	0.05	0.18	0.48	286
Altruistic: Per claim costs	82.03	75.66	12.25	72.75	866.79	286
C: Patient pool characteristics						
Average patient risk score	1.47	0.48	0.60	1.42	4.10	1,616
Average patient age	71.17	4.22	34.52	71.84	83.69	1,616
Share of female patients	0.58	0.13	0.22	0.56	1.00	1,508
Share of non-white patients	0.30	0.23	0.00	0.23	1.00	1,496
Share of dual-recipient patients	0.28	0.20	0.00	0.22	1.00	1,342
Share of patients below age 65	0.18	0.13	0.00	0.15	1.00	1,155
Share of patients above age 84	0.12	0.05	0.00	0.11	0.38	901
Share of low-income patients	0.35	0.24	0.00	0.28	1.00	1,574

[a] To ensure anonymity, the median, minimum, and maximum are rounded to the nearest 10.
[b] To ensure anonymity, the median is rounded to the nearest integer, and minimum and maximum are rounded to the nearest 10.

In Figure 1, we explore average yearly payments categorized by the nature of payment, separately for non-altruistic and altruistic payments. Notably, non-altruistic physicians receive larger average payments than altruistic physicians within each individual payment category.[13]

In both groups of physicians, the highest average payments are associated with non-consulting services (frequently involving sponsored speaking engagements), consulting and travel, followed by transfers related to food and beverage. These categories highlight the importance of privately beneficial interactions with the pharmaceutical industry, including sponsored talks, as well as direct-to-physician marketing strategies, such as meals purchased by company representatives.

Figure 1: USD value of payments over nature of payment, by altruistic or non-altruistic preferences



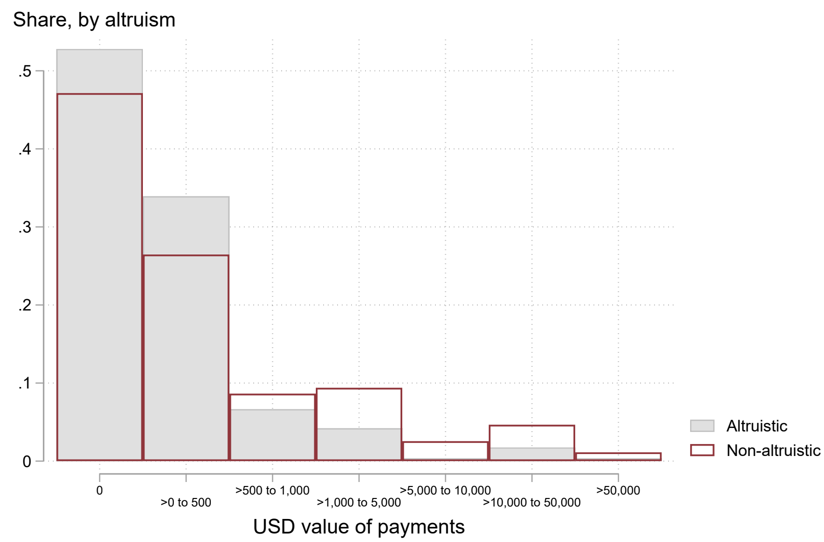
We next explore differences in the distribution of payment receipts between altruistic and non-altruistic physicians in Figure 2a. Figure 2a shows the distribution of payment values over a number of payment categories, separately for physicians with altruistic preferences and physicians with non-altruistic preferences. Figure 2 shows the corresponding kernel density estimate for log payments. We group together physicians with impartial and physicians with selfish preferences, for whom a Kolmogorov–Smirnov test does not reject equality of the distribution of payments ($D = 0.0414, p = 0.667$). Figure 6 in Appendix C.1 shows an overall

[13] In Appendix C.2, we show that the difference in payments by altruism is driven by physicians who are in their early- to mid-careers, between eleven and twenty years after graduation.

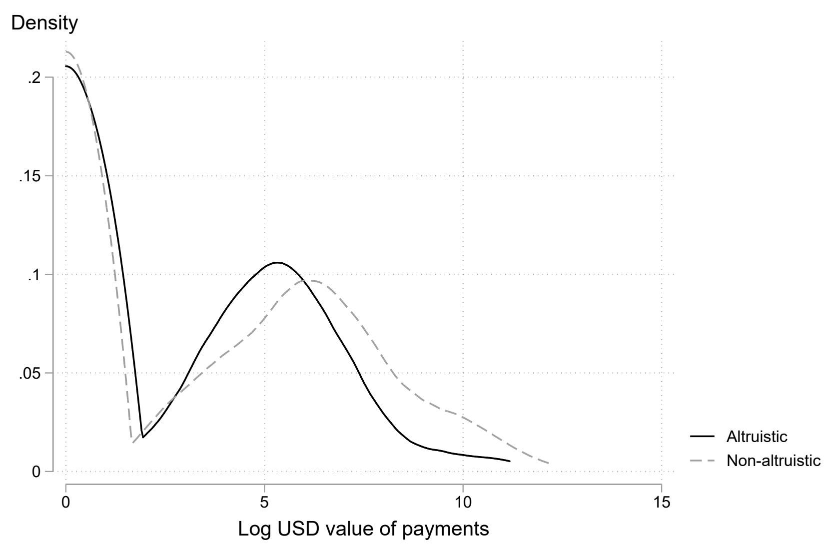
positive relationship between the raw continuous measure of altruistic preferences α and log payments in a scatter plot. Physicians with altruistic preferences receive lower payments compared to non-altruistic physicians throughout most of the distribution. The difference in distributions is significant on the 1% level.

Figure 2: Payments for physicians with altruistic compared to non-altruistic preferences

(a) Distribution over level payments, by category of payment value



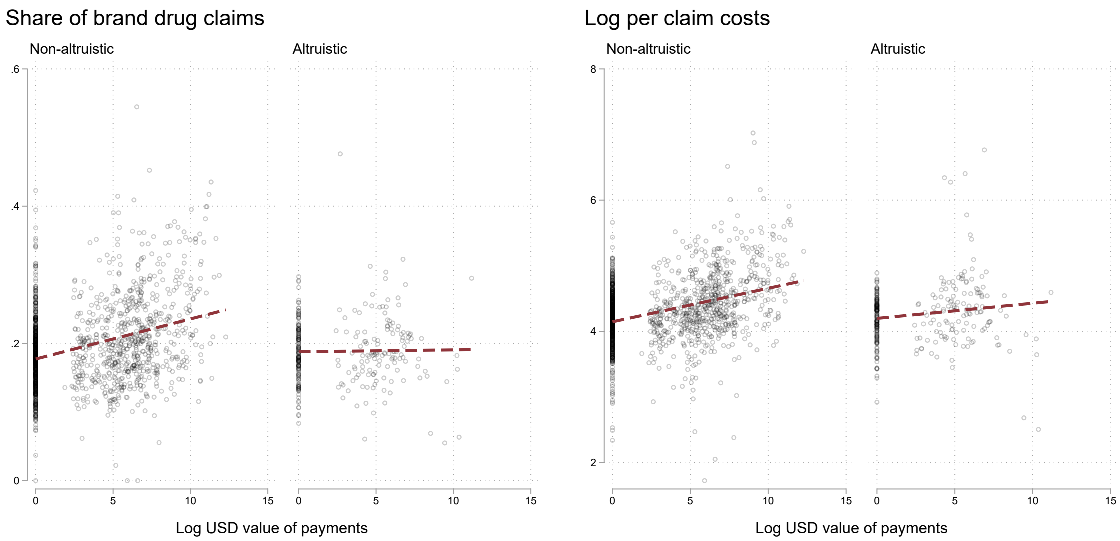
(b) Distribution over log-transformed payments, kernel density estimate



Notes: Figure 2a shows the share of observations for each category of payment values, separately for altruistic and non-altruistic physicians. Figure 2 presents a kernel density estimate of payment values given by the natural logarithm of (USD payments + 1). Kolmogorov–Smirnov tests reject equality of the distribution of payments for physicians with altruistic (not selfless) preferences compared to non-altruistic (selfless or impartial) preferences on a 1% significance level ($D = 0.1345, p < 0.001$).

Figure 3 shows scatter plots of the relationship between log industry payments and drug prescribing by altruistic compared to non-altruistic social preferences. Both in terms of brand shares in prescribing as well as costs, the concurrent increase in prescribing and payments is steeper for non-altruistic physicians than for altruistic physicians.

Figure 3: Scatter plots of payments and prescribing, by altruistic or non-altruistic preferences



Notes: These Figures plot the relationship between prescribing and payments, separately for non-altruistic and altruistic physicians. Each point represents a physician-year. Prescribing is measured by the share of brand drug claims in the left panel, and by the natural logarithm of costs per claim in the right panel. Payments are measured by the natural logarithm of (USD value of payments + 1). The dashed line represents a simple regression between prescribing and payments.

4 Empirical framework

4.1 Altruism and payments

In the first step of the empirical analysis, we study whether altruistic preferences are associated with physicians' receipt of industry payments. Our stylized model predicts that a non-altruistic physician accepts payments at least as often as an altruistic physician.

We hypothesize that non-altruistic physicians accept transfers from pharmaceutical firms associated with higher financial benefits on average. To test this prediction, we estimate the following regression equation:

$$\log E[pit] = \beta Non\text{-}altruistic_i + \delta x_{it} + \varepsilon_{it}, \quad (4)$$

where p_{it} denotes the value of industry payments that physician i receives in year t, $Non\text{-}altruistic_i$ is an indicator for non-altruistic preferences, x_{it} is a vector of individual- and time control variables including a constant term, and ε_{it} is the error term. β is a parameter and δ is a vector of parameters associated with the control variables.

Our preferred estimate of the marginal effect of altruism on the mean payment is based on estimating Equation 4 as a generalized linear model with the gamma distribution and log link, where the outcome variable is the USD value of payments. We additionally estimate Equation 4 on a subsample with any positive payments, in order to test whether non-altruistic preferences are related to the level of payments given any transfers, thus the intensive margin of payments.

As an alternative approach to modeling overall payments, we employ a linear specification with log-transformed payments as the outcome variable. We further estimate linear specifications for log payments conditional on any payment to capture the intensive margin, and any payment as the outcome variable to reflect the extensive margin.[14]

To measure physician altruism, we use an indicator variable for non-altruistic preferences, as opposed to altruistic preferences. Our parameter of interest is β, which is informative about whether industry transfers differ between altruistic and non-altruistic physicians. A positive value of β indicates that physicians with non-altruistic preferences obtain higher industry payments on average than altruistic physicians.

As our preferred set of control variables x_{it}, we include the age and gender of the physician (individual controls), characteristics of the physician practice (institutional controls), as well as year and state indicators in all regressions. In Section 5, we discuss specifications with alternative sets of controls, where results are similar to our main specifications. We cluster standard errors on the physician-level, the level of variation for altruistic preferences.

Table 2 shows results from estimating Equation 4. Column (1) of Table 2 shows the estimated average marginal effect of altruism along with coefficient estimates from estimating a generalized linear model of payments. Our analysis implies that physicians with non-altruistic preferences receive, on average, 2,184 USD (95% CI: 979.3–3,388.5) more industry payments per year than altruistic physicians, who receive 860 USD on average. The point estimate associated with non-altruistic preferences is 1.133 and statistically significant (1%).

As an alternative, widely used specification, we also estimate a linear model on the natural logarithm of (1 + payments) by OLS. Column (2) of Table 2 shows results when we use log-transformed payments as the outcome variable. The point estimate associated with non-altruistic preferences is 0.751, implying that payments are $(100 * (exp(0.751) - 1)) \approx 111.91\%$ higher compared payments to physicians with altruistic preferences. This estimate corresponds to a difference in payment levels by 968.37 USD per year at the

[14]For the linear specifications, we estimate the following corresponding regression equation:

$$\tilde{pit} = \beta Non\text{-}altruistic_i + \delta x_{it} + \varepsilon_{it}, \tag{5}$$

where $\tilde{pit}$ either denotes log-transformed payments or an indicator for any payment.

average payment of 860.39 USD to an altruistic physician. Thus, the implied marginal effect of non-altruistic preferences is below but close to the 95% confidence interval of 979.3–3,388.5 USD from our main specification. Mullahy and Norton (2022) discuss how marginal effects are often incorrect when estimated by OLS on a log-transformed outcome variable that is non-negative, right-skewed, and has a mass at zero. We interpret the estimates from a linear specification with log-transformed payments as a lower bound but reflective of the general relationship between payments and altruism.

Columns (3) and (4) of Table 2 test whether altruistic preferences are associated with payments in the subset of physician-years that are associated with any payment, thus reflecting the intensive margin of payments. Column (3) shows results for the generalized linear model, and Column (4) shows results for the linear specification with log-transformed payments conditional on any payment. The estimates from both specifications indicate that non-altruistic physicians also receive higher-valued transfers conditional on receiving any payments. The coefficient estimates are lower than for our main specifications on overall payments, indicating that altruistic payments may be related to both, whether and how high, payments are that physicians obtain.

In Column (5) the dependent variable is an indicator for any payment receipt, thus reflecting the extensive margin of payments. While we do not find that altruism is a statistically significant predictor of any receipt of industry transfers, the point estimate indicates that physicians with non-altruistic preferences are also more likely to receive any transfer in a given physician-year.

4.2 Altruism and prescribing

We next investigate how altruistic preferences shape physicians' prescribing practices. We first discuss the potential direct effects of altruism on drug prescribing and then focus on how altruistic preferences could interact with industry transfers to affect prescribing behavior.

Our stylized model implies that a more altruistic physician places more weight on the societal net benefit of a drug compared to a less altruistic physician. However, prescription decisions can be affected by direct-to-physician marketing. As our results on the relationship between altruism and payments indicate, there can be differential selection into engaging with the pharmaceutical industry or targeting by drug firms, depending on the altruistic preferences of physicians. Without accounting for industry transfers, we do not find that altruism is directly related to drug prescribing on any standard level of statistical significance.[15]

However, apart from any direct effects on prescribing, altruism might predict prescribing by acting as a moderating factor in the relation between payments to physicians and physicians' prescribing behavior.

[15]Table 9 in Appendix C.3 shows OLS estimation results from regressing drug prescribing on the indicator for non-altruistic preferences.

Table 2: Association between industry payments and altruism

	Payments		Int. margin		Ext. margin
	USD[a]	Log (1 + USD)[b]	USD[a]	Log USD[b]	Any pay[b]
	(1)	(2)	(3)	(4)	(5)
Marginal effects					
Altruism					
Non-altruistic	2183.886***		2350.872**		
	(614.591)		(983.844)		
Coefficient estimates					
Altruism					
Non-altruistic	1.133***	0.751**	0.752*	0.682**	0.074
	(0.324)	(0.325)	(0.386)	(0.300)	(0.049)
Individual controls					
Age below 39 (omitted)	-	-	-	-	-
Age: 40–49	0.881**	0.556	0.739**	0.536*	0.059
	(0.364)	(0.359)	(0.319)	(0.317)	(0.052)
Age: 50–59	-0.012	0.785**	-0.156	0.136	0.123**
	(0.327)	(0.332)	(0.313)	(0.303)	(0.052)
Age above 60	1.345***	0.949**	0.611	-0.025	0.187***
	(0.489)	(0.460)	(0.400)	(0.388)	(0.058)
Female	-1.539***	-0.946***	-1.393***	-0.923***	-0.090**
	(0.302)	(0.286)	(0.264)	(0.241)	(0.043)
Specialty: Other (omitted)	-	-	-	-	-
Specialty: Cardiology	2.146***	3.072***	1.121***	1.400***	0.363***
	(0.324)	(0.379)	(0.351)	(0.298)	(0.049)
Specialty: Family medicine	-0.077	0.260	-0.473	0.076	0.031
	(0.423)	(0.388)	(0.329)	(0.321)	(0.061)
Institutional controls					
Ownership: Other (omitted)	-	-	-	-	-
Ownership: Academic medical center	-0.290	-1.617***	0.339	-0.327	-0.236***
	(0.418)	(0.491)	(0.395)	(0.380)	(0.061)
Ownership: Physician-owned	0.487	-0.465	0.549	-0.289	-0.025
	(0.531)	(0.569)	(0.523)	(0.466)	(0.074)
Practice size: 1–36 (omitted)	-	-	-	-	-
Practice size: 36–350	-0.432	-0.125	-0.245	0.412	-0.096
	(0.421)	(0.497)	(0.425)	(0.443)	(0.076)
Practice size: 351–1600	0.417	0.254	0.550	0.517	-0.030
	(0.488)	(0.526)	(0.441)	(0.406)	(0.080)
Constant	4.860***	2.469***	6.089***	4.547***	0.520***
	(0.656)	(0.713)	(0.586)	(0.559)	(0.107)
Year controls	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	860.398	2.575	1,822.769	5.442	0.472
Observations	1,616	1,616	838	838	1,616

This table presents the results from estimating Equations (4) and (4). Columns (1) and (2) report results with overall payments as the outcome variable. Columns (3) and (4) show results for payments measured on the intensive margin when restricting the sample to any payment. Column (5) shows results for payments measured on the extensive margin, with an indicator for any payment as the outcome variable. Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors for average marginal effects are calculated using the delta method.

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

[a] Generalized linear models with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares.

[b] Linear models estimated by Ordinary Least Squares.

Our stylized model predicts that the decision to choose a brand drug over cheaper alternatives is affected by payments.[16] Prescribing decisions from both more and less altruistic physicians can be affected by interacting with the pharmaceutical industry. Our model predicts that a given level of payment shifts less altruistic physicians' drug prescribing decisions more easily toward a brand alternative than it would do for more altruistic physicians. Physicians with altruistic preferences and physicians with non-altruistic preferences might thus respond differently to any given payment level, in addition to accepting different levels of payments.

Therefore, we test whether altruistic preferences predict the relationship between industry payments to physicians and their drug-prescribing behavior. We estimate the following regression equation:

$$b_{it} = \gamma(\mathit{Non\text{-}altruistic}_i \times log(p_{it})) + \tilde{\delta}\tilde{x}_{it} + \nu_{it}, \tag{6}$$

where b_{it} measures physician i's drug prescribing practices in year t, $\mathit{Non\text{-}altruistic}_i$ indicates that physician i has non-altruistic preferences, p_{it} denotes industry payments to physician i in year t, $\tilde{x}_{it}$ is a vector of control variables, and ν_{it} is the error term. γ and $\tilde{\delta}$ denote parameters.

In Equation 6 our parameter of interest is γ, associated with the interaction between non-altruistic preferences and the amount of industry payments that a physician receives. The parameter γ thus captures whether social preferences moderate the relationship between industry payments and physicians' prescribing practices. A positive value of γ indicates that drug prescribing from physicians with non-altruistic preferences is more sensitive to payments from pharmaceutical firms and payments are more effective when targeted to non-altruistic physicians.

Table 3 shows OLS estimation results for Equation 6, controlling for physicians' individual and institutional characteristics, as well as indicators for calendar year and state. In addition, we include indicators for the quartile of patient pool characteristics in order to account for differences in prescribing due to patient differences. Standard errors are clustered on the physician-level.

In Columns (1) – (3) in Table 3, we investigate how drug prescribing, measured by the share of brand drug claims, is associated with the interaction between altruistic preferences and industry payments. Column (1) shows the association of brand prescribing with the log USD value of all payments, by altruistic preferences. Columns (2) and (3) focus on the interaction of altruistic preferences with the intensive and the extensive margin margin of payments, respectively. The interaction term between altruistic preferences and payments is statistically significant on at least the 5% significance level in all specifications and fully accounts for the positive association between payments and a higher share of brand drug claims. Our point estimate in Column (1) indicates that for a non-altruistic compared to an altruistic physician, a 1% increase in the USD

[16] Table 10 in Appendix C.4 shows that brand prescribing, as well as drug spending, are positively correlated with industry payments.

value of payments is on average associated with a 0.005 percentage points higher increase in the Share of brand claims.[17] At an average brand share of 18.86% among altruistic physicians in our sample, this estimate corresponds to an increase of 0.027% in the brand share.

In Columns (4) – (6) of Table 3, we investigate the relation between drug costs measured by log per claim drug costs and the interaction between altruism and industry transfers. Column (4) shows that the association between drug costs and total payments is estimated to be larger for physicians with non-altruistic preferences than for altruistic physicians by 2.4%. However, this difference by altruism is not statistically significant. Column (5) shows that given any payments, costs per claim are higher by 5.8% for a 1% increase in payments among non-altruistic physicians than among altruistic physicians and that this difference by altruism on the intensive margin is statistically significant on the 10% level. In Column (6), we observe for drug costs a positive, statistically insignificant, interaction between altruism and the extensive margin of receiving any payments. In all cases, no positive correlation between payments and drug costs remains once we account for the interaction between altruistic preferences and payments.

4.3 Interpretation of the regression estimates

Our regression estimates help to roughly assess the potential average financial savings if it was possible to improve physicians' compliance with professional norms of altruism. Comparing non-altruistic and altruistic physicians, the difference in the relationship between log payments and the share of brand claims is reported in Column (1) in Table 3 by a coefficient of 0.005. Similarly, the difference in the relationship between payments and log per claim drug costs by altruistic preferences is reported in Column (4) of Table 3 by a coefficient of 0.024. We estimate a difference in log payments by altruistic preferences of 0.751 in Column (2) of Table 2. We consider this estimate a lower bound and assume that, on average, payments are $(100 * (\exp(0.751) - 1)) \approx 111.91\%$ higher for non-altruistic physicians than for altruistic physicians. As discussed above, our main specification in Column (1) of Table 2 implies an even larger difference in payment levels.

Using the estimates above, we can next perform back-of-the-envelop calculations in order to evaluate how modifying physicians' altruism could affect drug prescribing and drug costs through their interaction with industry payments. We consider a non-altruistic physician at the mean and ask how brand prescribing and yearly drug costs would decrease if that physician were altruistic instead.

Regarding brand prescribing, we use the linear-log specification of Column (1) in Table 3 to predict that a non-altruistic physician, if she was altruistic instead, prescribes a brand share which is lower by

[17] The estimate implies a change in brand prescribing by 0.005/100 units, given the linear-log specification of our model. As brand prescribing is a share between 0 and 1, a 1% increase in payments corresponds to a change by $0.005/100 * 100 = 0.005$ percentage points.

Table 3: Drug prescribing and the interaction between industry payments and altruism

	Share of brand drug claims			**Log per claim drug costs**		
	(1)	(2)	(3)	(4)	(5)	(6)
Payments by altruism						
Non-altruistic × Log (1 + USD)	0.005***			0.024		
	(0.002)			(0.017)		
Non-altruistic × Log USD, given any payment		0.010***			0.058*	
		(0.004)			(0.032)	
Non-altruistic × Any payment			0.020**			0.092
			(0.009)			(0.091)
Payments						
Log (1 + USD)	-0.000			0.021		
	(0.001)			(0.016)		
Log USD, given any payment		-0.004			0.010	
		(0.004)			(0.030)	
Any payment			-0.001			0.101
			(0.008)			(0.087)
Altruism						
Non-altruistic	-0.010	-0.047**	-0.005	-0.052	-0.303*	-0.016
	(0.006)	(0.023)	(0.006)	(0.045)	(0.181)	(0.045)
Individual controls						
Age below 39 (omitted)	-	-	-	-	-	-
Age: 40–49	-0.004	-0.003	-0.003	0.037	0.023	0.048
	(0.006)	(0.010)	(0.006)	(0.053)	(0.083)	(0.055)
Age: 50–59	-0.004	-0.007	-0.003	0.024	-0.026	0.032
	(0.006)	(0.009)	(0.006)	(0.051)	(0.084)	(0.051)
Age above 60	-0.005	-0.008	-0.005	0.088	0.036	0.094
	(0.007)	(0.009)	(0.008)	(0.059)	(0.082)	(0.063)
Female	-0.000	-0.004	-0.004	0.060	0.131	0.029
	(0.007)	(0.011)	(0.007)	(0.066)	(0.102)	(0.068)
Specialty: Other (omitted)	-	-	-	-	-	-
Specialty: Cardiology	0.019**	0.022**	0.026***	0.108*	0.149*	0.177***
	(0.008)	(0.010)	(0.008)	(0.065)	(0.077)	(0.066)
Specialty: Family medicine	-0.005	-0.006	-0.004	-0.105**	-0.076	-0.092*
	(0.006)	(0.008)	(0.006)	(0.048)	(0.066)	(0.049)
Institutional controls						
Ownership: Nonprofit hospital (omitted)	-	-	-	-	-	-
Ownership: Academic medical center	-0.001	-0.003	-0.003	0.016	-0.025	-0.007
	(0.009)	(0.011)	(0.009)	(0.064)	(0.074)	(0.070)
Ownership: Physician-owned	-0.035***	-0.030**	-0.035***	-0.272***	-0.272***	-0.279***
	(0.010)	(0.013)	(0.010)	(0.077)	(0.102)	(0.083)
Practice size: 1–36 (omitted)	-	-	-	-	-	-
Practice size: 36–350	0.009	0.014	0.010	0.109	0.215*	0.119
	(0.009)	(0.013)	(0.009)	(0.088)	(0.112)	(0.092)
Practice size: 351–1600	-0.013	-0.014	-0.012	-0.094	-0.041	-0.078
	(0.009)	(0.013)	(0.009)	(0.079)	(0.099)	(0.082)
Constant	0.189***	0.208***	0.187***	4.009***	4.051***	3.995***
	(0.017)	(0.031)	(0.017)	(0.140)	(0.256)	(0.143)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes
Quartiles of patient pool characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	0.189	0.190	0.189	4.257	4.343	4.257
Observations	1,616	838	1,616	1,616	838	1,616

This table presents the results from estimating Equation 6, and captures the relationship between prescribing and payments by altruistic preferences. In Columns (1)–(3), prescribing is measured by the share of claims for brand drugs over all drug claims. In Columns (4)–(6), prescribing is measured by the natural logarithm of average per claim costs. Estimation by OLS. Standard errors in parentheses are clustered on the physician level.

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

$0.005 * \log([100 + 111.91]/100) = 0.0038$ units. This difference corresponds to $0.0038 * 100 = 0.38$ percentage points, or 1.91% at an average brand share of 19.65% among non-altruistic physicians. Regarding costs, we use the log-log specification of Column (4) in Table 3 and predict that per claim costs for a non-altruistic physician are $\exp(0.024 * \log((100 + 111.91)/100)) = 1.0182$ times the average claim cost among altruistic physicians. Thus, imposing altruistic preferences would correspond to a decrease of $(1.0182 - 1) * 100 = 1.82\%$, or 1.56 USD at an average claim cost of 85.51 USD among non-altruistic physicians. For an average number of 2,795.3 claims per year, our estimates suggest that a non-altruistic physician would impose 4361 USD lower drug costs per year if she complied with altruistic norms instead.

5 Additional analysis

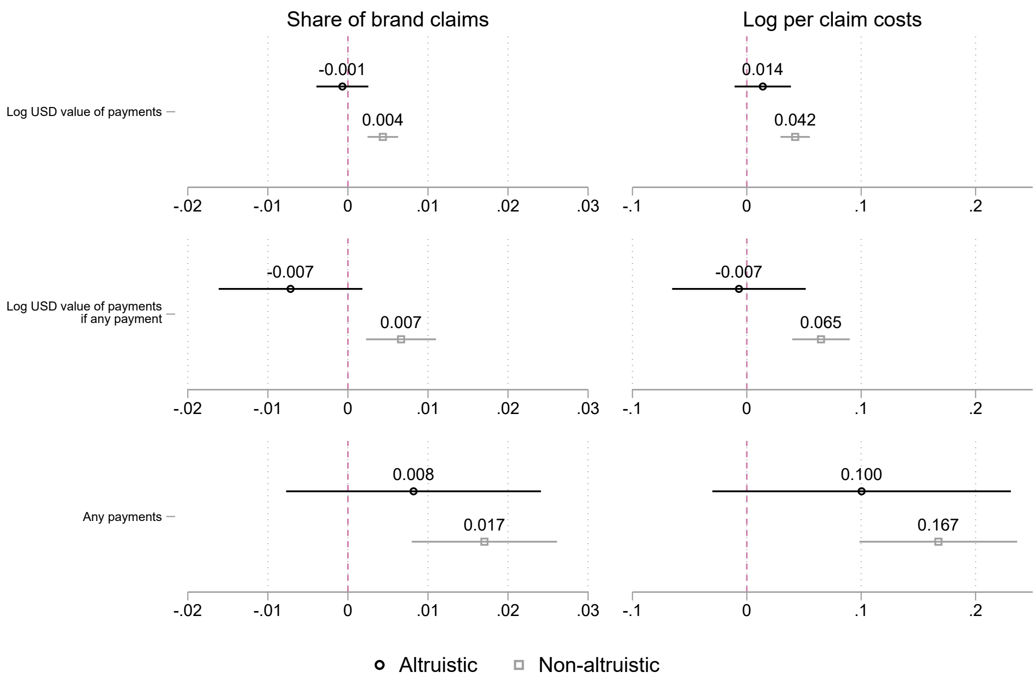
5.1 Sensitivity of the econometric specification

We next discuss potential threats to our econometric analysis of the relationship between altruism and payments, as well as possible extensions.

Stratified models. In order to allow coefficient estimates to vary flexibly by altruism, we estimate stratified regressions of drug prescribing on payments including either altruistic or non-altruistic physicians. Figure 4 shows results from these regressions. The results demonstrate that the positive relation between any measure of payments and prescribing is driven entirely by non-altruistic physicians, whereas there is no statistically significant relation between payments and prescribing for altruistic physicians. The point estimates indicate that a 1% increase in the USD value of payments is associated with an average increase in the share of brand claims by approximately 0.004 percentage points and an increase in per claim drug costs by approximately 0.042% among non-altruistic physicians, compared to an average increase by -0.001 percentage points in the brand share and 0.015% in the per claim drug costs among altruistic physicians (not statistically significant on the 5% level). The results from estimating stratified regressions are similar to our main estimates from Table 3.

Alternative sets of control variables. We perform estimations of our main regression models for payments (Equations 4 and 5) and prescribing (Equation 6) with different sets of control variables. Results are presented in Tables 11 and 12 in Appendix D.1. Table 11 shows that, for payments, the estimates associated with altruism are generally consistent with our main results, but lose precision when we reduce the set of control variables. Table 12 indicates that, for both brand prescribing and costs, the estimated coefficient associated with the interaction between payments and altruism remains essentially unchanged when changing the set of control variables.

Figure 4: Association between drug prescribing and industry payments, by altruistic and non-altruistic preferences



Notes: The figures show estimated coefficients from regressing the Share of brand drug claims (left) and Log per claim prescribing costs (right) on payments, separately for physicians with experimentally estimated altruistic or non-altruistic preferences. Each panel represents regression results estimated by Ordinary Least Squares with observations separated by altruistic or non-altruistic preferences. Results are based on different measures of industry payment. The upper panels show payments measured by log (1 + USD), the middle panels show log payments conditional on any payment, and the lower panels show any payment. All regressions include individual controls, institutional controls, patient pool heterogeneity, state controls, and calendar years. Lines represent the 95% confidence intervals. Robust standard errors are clustered on the physician-level.

Aggregated payments and prescriptions. We show results for payments and prescriptions aggregated on the physician-level in Tables 13 and 14 in Appendix D.2. The estimates are generally consistent with our main estimates, but the extensive margin of payments appears to matter more for aggregate payments.

Alternative econometric models. We test whether our results are sensitive to the econometric model chosen, and in particular to the way payments enter in the model.

Our main results for industry payments imply, as point estimates, that non-altruistic physicians obtain industry payments higher by 2,184 USD in our preferred generalized model specification, or 968.37 USD in the linear regression model based on log-transformed payment values as dependent variables. We present from two additional alternative estimation strategies in Table 4. First, we estimate a two-part model that accommodates statistical mass at zero payments (Belotti et al. 2015), with results shown in Column (1) of Table 4. We specify the two-part model as a generalized linear model with the log link, which 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 estimated marginal effect indicates that payments to non-altruistic physicians are on average 1,340 USD higher than payments to altruistic physicians, in between the marginal effect estimates of our main specifications. The overall coefficient of *Non-altruistic* is jointly significant in both parts of the model at a 10%-significance level, with standard errors clustered on the physician-level. Second, we estimate an OLS regression on the USD value of payments, with results shown in Column (2) of Table 4. The estimated coefficient associated with *Non-altruistic* is significant at a 10% level and indicates higher payments to non-altruistic physicians by 1,822 USD, again in line with our main results. These alternative specifications allow us to recover marginal effects that are robust to concerns associated with log-transformed outcome variables and zero value observations (Mullahy and Norton 2022). Our alternative specifications thus suggest the same qualitative results as our main analysis and yield coefficient estimates which are consistent with our main estimates.

In addition, we test our conclusions regarding the different strength by altruistic preferences in the relationship between drug prescribing and industry payments is sensitive to the model specification. As robustness check, we estimate two alternative models. First, we estimate the regression model in Equation 6, but instead of log-transformed payments we use a inverse hyperbolic sine transformation. Second, we estimate a specification interacting an indicator for non-altruistic preferences and log-transformed payments with zero replacing missing values, where we also include an indicator for no payments as a control variable. The results are presented in 15 in Appendix D.3, and show that the estimates are essentially unchanged compared to those in our main specifications.

Causal effects of physician altruism. We do not impose a causal link between physician altruism and payments in our empirical analysis. Nonetheless, we note that a reversed causal effect of payments on

Table 4: Association between industry payments and altruism

	USD payments	
	(1) Two-part model	(2) Linear
Marginal effects		
Altruism		
Non-altruistic	1340.174***	1822.022*
	(508.760)	(988.526)
Probit		
Altruism		
Non-altruistic	0.209	
	(0.161)	
GLM		
Altruism		
Non-altruistic	0.752**	
	(0.374)	
Wald-test: Non-altruistic[a]	$\chi^2(2) = 5.71$	
	$(p = 0.057)$	
State controls	Yes	Yes
Individual controls	Yes	Yes
Institutional controls	Yes	Yes
Altruistic: Mean outcome	860.398	860.398
Observations	1,616	1,616

This table presents estimation results of overall payments 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 based on the full model is reported. Column (2) reports results from a linear model estimated using Ordinary Least Squares. Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors for the average marginal effect in the two-part model are calculated using the delta method.

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

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

physician altruism is unlikely and that a relation between altruism, payments, and prescribing is present even if we restrict our analysis to observations from 2019, the year in which the experiment was conducted.[18]

In addition, we discuss the role of unobserved confounders which might threaten a conclusion that less altruistic preferences increase payments to physicians. We compute the robustness value, a sensitivity statistic developed by Cinelli and Hazlett (2020), which can be implemented in linear models estimated by OLS. The robustness value diagnoses how strongly an omitted variable would have to be correlated with altruism, *as well as* with payments, in order to eliminate the link between altruism and payments. In our OLS specification shown in Column (2) of Table 2, an omitted variable orthogonal to the covariates in the model would have to explain at least 12.91% of the residual variances in both altruism and payments to eliminate the association between altruism and payments. Using this framework, we also compute how including a potential confounding variable benchmarked against an observed control variable would change the estimated association between altruism and payments. We use as a benchmark the indicator for cardiologist, the strongest predictor of physician payments besides state controls. We observe that if we were to include a confounder three times as strong as Cardiology, our estimate of altruism would only decrease to 0.640 and hence change little from our original estimate of 0.751.[19] Moreover, we observe little correlation between altruism and any of our observable physician characteristics apart from a weak association with practice size.[20] Therefore, although we cannot rule out that unobserved factors may violate conditional independence between altruism and payments, our sensitivity statistics suggest it is unlikely that any such confounding factor would be strong enough to alter our main conclusions about a link between non-altruistic preferences and higher industry payments. Our results suggest that professional norms, such as altruism, may shape the physician-industry relationship in ways that extend beyond observable physician traits.

Skewed payments. We observe that industry payments are right-skewed, with few physicians obtaining highly valued transfers in only some years. To trace the source of variation better, we analyze quartiles of payments. In separate regressions, we dichotomize payments into indicators of receiving payments in the upper three quartiles, above median, or the upper quartile. We observe that altruism is most strongly associated with selection into the upper quartile of payments. Non-altruistic preferences are associated with an 11.6 percentage points increase (1% significance level) in the probability to obtain payments in the upper quartile, where received payments amount to at least 437 USD per year. Non-altruistic physicians still drive

[18]We show details in Tables 16 in Appendix D.4.

[19]The sensitivity statistics established in Cinelli and Hazlett (2020) provide upper limits in the case of multiple, possibly non-linear, confounders. Our sensitivity statistics are conservative and based on standard errors clustered on the physician-level, using 279 degrees of freedom, and the `sensemakr` package (Cinelli et al. 2020). We show the full set of sensitivity statistics in Table 18. In addition, we show additional regressions of altruism on various sets of covariates, including Cardiology, in Table 17 in Appendix D.5, in order to establish correlations between altruism and the covariates in the payment regressions. We used conservative estimates from pooled OLS with clustered standard errors on the physician-level for our benchmark analysis.

[20]Table 17 in Appendix D.5 shows that altruism is, in particular, not correlated with physician age, gender, specialty, or clinic ownership, which are important predictors of payments as shown in Table 2 of the main text.

sizeable correlation between between prescribing of brand drugs and payments in the upper quartile. At other quartiles, our estimates associated with altruism are numerically smaller or not statistically significant. However, we note that our main effects are in general not driven by individual outliers, but rather by statistical mass at the upper quartile. For example, our estimates are numerically similar or qualitatively consistent when we run regressions with payments winsorized at the 95th percentile.[21]

Continuous measure of altruism. We use a binary measure of physician altruism based on a cutoff of 0.5 as the utility weight that a physician places on their own benefits compared to the benefits of others. By defining altruistic physicians as those who place less weight on their own benefits than on others, we both allow for a natural interpretation of physician altruism and avoid making assumptions about the representativeness of our sample of physicians compared to the general population of physicians. Nonetheless, we show results based on a continuous measure of altruistic preferences in Appendix D.8. For interpretation, we standardize the value of α elicited in the experiment within our sample. Results from these specifications are generally consistent with our main conclusions on the relationship between altruism and payments but lose precision substantially. Our results on the interaction between altruistic preferences and prescribing are driven by physicians with selfless preferences, which we categorize as altruistic based on the binary measure of altruism. They do not replicate with a continuous measure of altruistic preferences that is standard-normalized in our sample. However, excluding physicians with impartial preferences ($\alpha = 0.5$ cannot be rejected) yields results in line with our main estimates, indicating that our results may be driven by larger contrasts in altruistic preferences and a power issue.

5.2 Drug-level analysis

We replicate our main analysis on the drug-physician-year observation level. That is, we investigate whether altruistic preferences predict a physician's receipt of payments for a given drug, and whether accepting such a payment increases prescriptions for *that drug*. The analysis on a drug level helps strengthen the direct link between payments and prescriptions, and physician altruism in relation to this link.

We measure payments in relation to a specific drug using information on industry interactions provided in the Open Payments database. Up to five products can be recorded in one interaction. To compute the value of a single transfer associated with a specific drug, we take the total USD value of the interaction and divide it by the number of products mentioned. We then construct our payment variables as in the main analysis, by aggregating transfers on a yearly level. In addition, we consider again the intensive margin of payments, that is payments related related to a drug given any positive payment, and the extensive margin, whether

[21]We show main regression results with indicator variables for payment quartiles in Table 19, and for payments winsorized at the 95th percentile in Table 20 in Appendix D.7.

any payment is observed related to a given drug.

To investigate prescribing for a given drug, we analyze the relative number of claims, measured by the Share of total claims, as well as relative costs, measured by Log drug costs relative to total claims. We compute the Share of total claims for a drug by the total number of a physician's claims for a given drug and year, divided by the total number of all claims the physician makes in that year. To measure costs, we take the natural logarithm of 1 + a drug's per claim costs in each physician-year weighted by the share of claims for that drug among all of the physician's claims in that year.[22] We focus on prescribing relative to the total number of claims in order to account for differences in overall prescribing intensities, for example due to patient differences.

We consider all drugs that have been associated with at least one payment during our sample period in the analysis, which selects on drugs with any marketing efforts and reduces matching errors due to spelling discrepancies. We exclude all transfers related to non-drug products by focusing on medicinal prescriptions with an Anatomical Therapeutic Chemical (ATC) code. From the full sample of 280 physicians, 277 physicians claim enough prescriptions of individual drugs in order to be included in the drug-specific Medicare public use files. The final data set is balanced at the physician-year-drug level. Our analysis includes drug fixed effects to account for between-drug differences in industry transfers or prescriptions. These fixed effects also account for differences in the relationship between payments and prescribing due to variation in the propensity to prescribe a given drug in the Medicare system.

Table 5 shows results on the relation between altruistic preferences and payments on the drug level. We obtain marginal effects estimates from Poisson pseudo-maximum likelihood regressions, which ensures that the estimation procedure converges given many fixed effects. We replicate a similar qualitative direction as in the main analysis but, given that we analyze drug-specific payments, at lower levels. For the drugs included in the analysis, our estimates imply that non-altruistic physicians obtain, on average, 8 USD more than altruistic physicians while accounting for the full set of control variables as well as drug-specific fixed effects. Compared to our main analysis, the analysis on a drug level cannot account for any transfers that are specified as generic payments or where no product name is mentioned. In addition, the drug level analysis does not account for indirect spillovers from industry interactions onto products that are not listed as Open Payment entries.

Table 6 shows that our main results are consistent with the estimated relationship between altruism, payments, and prescribing on the drug level. Columns (1) – (3) shows that payments related to a given drug are associated with a stronger increase of relative claims for that given drug for non-altruistic physicians compared to physicians with altruistic preferences, and Columns (4) – (6) shows weaker but positive estimates

[22]Formally, we compute log(1 + (Total costs for a drug / Total number of claims)).

Table 5: Association between drug-specific industry payments and altruism

	Payments		Int. margin		Ext. margin
	USD[a]	Log (1 + USD)[b]	USD[a]	Log USD[b]	Any pay[b]
	(1)	(2)	(3)	(4)	(5)
Marginal effects					
Altruism					
Non-altruistic	7.588***		363.146***		
	(2.929)		(125.470)		
Coefficient estimates					
Altruism					
Non-altruistic	2.017***	0.026*	1.579**	0.238*	0.007
	(0.741)	(0.014)	(0.776)	(0.125)	(0.004)
Constant	-1.525	0.099**	3.541***	3.236***	0.033***
	(1.330)	(0.039)	(1.025)	(0.209)	(0.012)
Drug fixed effects	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	1.018	0.043	76.116	3.180	0.013
Observations	221,392	221,392	3,991	3,991	221,392

This table presents the results from estimating Equations (4) and (4) on the physician-year-drug level, including drug fixed effects. Columns (1) and (2) report results with overall drug-specific payments as the outcome variable. Columns (3) and (4) show results for payments measured on the intensive margin when restricting the sample to any payment for a given drug. Column (5) shows results for payments measured on the extensive margin, with an indicator for any payment for a given drug as the outcome variable. Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors for average marginal effects are calculated using the delta method.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.
[a] Generalized linear model estimated by poisson pseudo-maximum likelihood.
[b] Linear models estimated by Ordinary Least Squares.

when we measure prescribing by costs spent for a given drug. We no longer observe that altruism by itself drives the relationship between payments and prescribing except when restricting the sample to any drug-physician-year observation with any payments in Columns (3) and (6). However, our estimated effect sizes of the interaction between altruism and payments are still meaningful compared to mean levels of prescribing. For example, based on our estimates from Column (1), the correlation between payments for a given drug and the share of prescriptions for that drug is twice as high for a non-altruistic physician compared to an altruistic physician. Our drug-specific estimates thus confirm our main results regarding substantial differences in the association between drug-specific payments and prescribing by altruism.

Table 6: Drug-specific prescribing and the interaction between industry payments and altruism

	Share of total claims			**Log drug costs relative to total claims**		
	(1)	(2)	(3)	(4)	(5)	(6)
Payments by altruism						
Non-altruistic × Log (1 + USD payments, drug level)	0.001**			0.036		
	(0.000)			(0.028)		
Non-altruistic × Log USD payments given any payment, drug level		0.003***			0.099**	
		(0.001)			(0.050)	
Non-altruistic × Any payment			0.002*			0.111
			(0.001)			(0.093)
Payments						
Log (1 + USD payments, drug level)	0.001***			0.099***		
	(0.000)			(0.025)		
Log USD payments given any payment, drug level		0.001			0.033	
		(0.001)			(0.046)	
Any payment			0.003***			0.324***
			(0.001)			(0.082)
Altruism						
Non-altruistic	-0.000	-0.007**	0.000	-0.003	-0.251	-0.002
	(0.000)	(0.003)	(0.000)	(0.005)	(0.172)	(0.005)
Constant	0.000*	-0.009**	0.000*	0.062***	-0.131	0.060***
	(0.000)	(0.004)	(0.000)	(0.013)	(0.205)	(0.013)
Drug fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes
Quartiles of patient pool characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	0.001	0.005	0.001	0.064	0.523	0.064
Observations	211,939	3,934	211,939	211,939	3,934	211,939

This table presents the results from estimating Equation 6 on the physician-year-drug level, and captures the relationship between drug-specific prescribing and payments by altruistic preferences. In Columns (1)–(3), prescribing is measured by the share of prescription claims for a given drug over the total number of claims a given physician prescribes in a year. In Columns (4)–(6), prescribing is measured by the natural logarithm of (1 + total costs for a given drug over the total number of claims in a year). Observations are on the drug-physician-year level. Estimation by OLS. Standard errors clustered on the physician-level in parentheses.
* p<0.10, ** p<0.05, *** p<0.01..

In Appendix E, we provide additional findings from analyzing two drug classes separately: cardiovascular drugs, which are the most commonly prescribed drug class, and blood thinners, which have the highest number of payments. Our results reveal differences between these classes, which may be attributed to the varying availability of generics. Specifically, physicians have access to both common generic alternatives and branded options for cardiovascular drugs, including statins such as Atorvastatin (branded as Lipitor), beta-blockers like Carvedilol (branded as Coreg), and ACE inhibitors such as Lisinopril (branded as Zestril). This higher availability of generic options may increase the role of altruism in physicians' treatment decisions when considering branded cardiovascular drugs. In contrast, blood thinners are a relatively new drug class, with many brands still under patent protection (such as Xarelto, Pradaxa, or Eliquis, as illustrated in Table 8 in Appendix B). Payments for these drugs may contain higher informative value and may limit the room for physicians to substitute expensive treatments with more cost-conscious options based on their altruistic preferences.

5.3 The role of patient risk

Finally, we investigate whether the composition of the patient pool attenuates industry ties among non-altruistic physicians. For example, it could be that non-altruistic physicians place a higher weight on their own benefit than altruistic physicians but still take their patients' financial or social circumstances into account. Alternatively, pharmaceutical firms might be less likely to target non-altruistic physicians whose patient pools are more vulnerable.

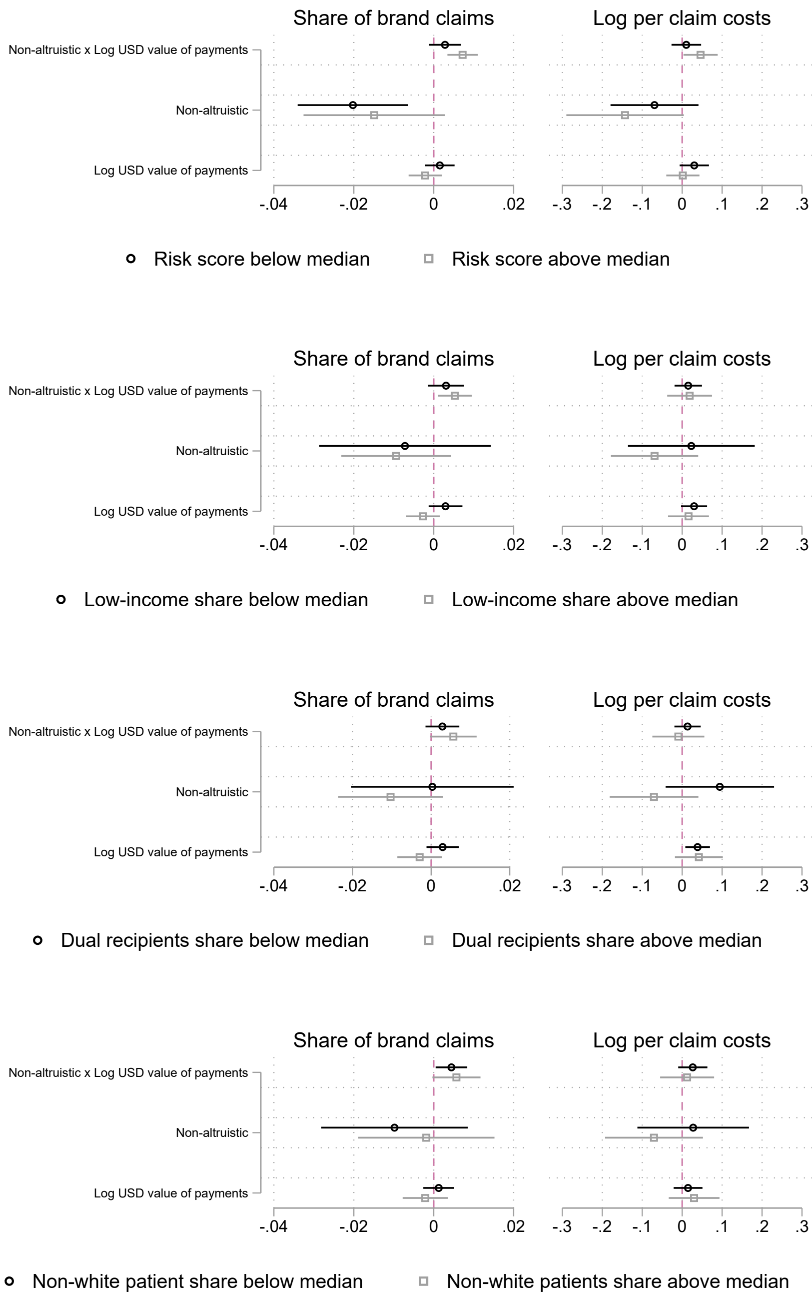
We find some evidence that patient pool vulnerability interacts with physician altruism. Figure 9 in Appendix F shows that non-altruistic preferences no longer predict higher industry payments among physicians who treat higher-risk patients, or when the share of low-income patients, dual recipients of Medicare and Medicaid, or non-white patients is high. Our results on higher payments to non-altruistic physicians thus appear to be driven by those physicians whose patient pools are less vulnerable.

If non-altruistic physicians consider their patients' circumstances even when accepting industry payments, we would expect that a stronger payment-prescribing relationship for non-altruistic physicians is driven only by physicians who treat low-risk patients. In that case, we might no longer find a positive relation between payments and prescribing for non-altruistic physicians with vulnerable patient pools. However, Figure 5 shows that stratifying by differences in patient pools affects little the estimated relationship between industry payments and prescribing of non-altruistic physicians. While prescribing is in general less responsive to industry payments when physicians treat more vulnerable patient pools, non-altruistic preferences in physicians offset the lower responsiveness to payments in more vulnerable patient pools.[23] Across various dimensions of patient pool heterogeneity, we observe differences between altruistic and non-altruistic physicians' prescribing practices in relation to industry payments. If patient pool heterogeneity matters at all, the interaction between non-altruistic preferences and industry payments increases brand prescribing and drug costs slightly

[23]Figure 10 in Appendix F shows that for non-altruistic physicians, the estimated association between payments and prescribing is similar in more vulnerable patient pools as the overall estimates and across patient characteristics. In contrast, for altruistic physicians, the association between payments and prescribing in more vulnerable patients is weaker than in the overall sample or even becomes negative. Figure 11 shows the same regressions but compares the first and the last quartile of each patient pool characteristic, with similar results.

stronger when patients have an above-median risk score or are lower-income. Our findings thus indicate that patient characteristics interact with physicians' altruistic preferences in the receipt of payments through the way pharmaceutical firms target physicians, rather than changing how much payments matter when non-altruistic physicians prescribe drugs.

Figure 5: Altruism and the association between drug prescribing and industry payments, by different groups of patients



Notes: The figures show estimated coefficients from regressing Total log drug prescribing costs (left) or Share of brand drug claims (right) on industry payments interacted with an indicator variable for altruistic preferences, separately for physicians with patient pools at the median characteristic or above (above median) and for physicians with patient pools below the median characteristic (below median). Each panel represents OLS regression results with observations separated by a different characteristic. All regressions include individual controls, institutional controls, patient pool quartiles, state controls, and calendar years. Lines represent the 95% confidence intervals. Robust standard errors are clustered on the physician-level.

6 Conclusion

To forgo personal gains for patient and societal benefit is a social norm among physicians. However, pharmaceutical companies often involve controversial direct-to-physician marketing practices that benefit physicians privately. Our results reveal that altruistic preferences, even if typically unobserved, are an essential determinant of the strength of physician-industry ties. We therefore provide first empirical evidence for the role of professional norms in the practice of medicine under potential conflicts of interest.

Although our set-up assumes that physicians' altruistic preferences are intrinsic and do not change within our observational period, we do not exclude the possibility that physician preferences or behaviors can be affected in the long run. For example, different social norms in medicine might form as a result of changes in the education of medical professionals, resulting in generational differences (Li et al. 2022). Altruistic preferences of medical students have been found to change throughout their training rather than to stay fixed since they begin their studies (Attema et al. 2022). In addition, policymakers can influence physicians' treatment decisions by adapting the market structure in which physicians operate and thus changing altruistic motives and competitive incentives (Byambadalai et al. 2019). Our work demonstrates that if professional norms about physicians' social preferences were modified, drug prescribing decisions might shift away from brand-name drugs, such that aggregate drug costs decrease.

Even if altruistic preferences were immutable, physician behavior could be affected by the institutional framework. Policies can directly target social preferences and other non-pecuniary motives to improve health care quality. For example, interventions have aimed at intrinsic incentives to perform well by informing physicians about their quality in relation to peers (Kolstad 2013). Similarly, transparency or disclosure policies can hold physicians accountable to their professional norms and change prescription behavior by increasing compliance (Chao and Larkin 2022). More generally, the degree to which non-pecuniary motives drive physician behavior can interact with the regulatory and competitive environment (Jack 2005; Hennig-Schmidt et al. 2011; Scott and Sivey 2022). Our findings suggest that there is room for policymakers, the public, and the medical profession to weaken financial links between the pharmaceutical industry and physicians, for example by reinforcing norms expected of physicians or by changing incentives in healthcare markets.

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A Comparative statics of the optimal brand prescribing propensity

We denote the optimal brand prescribing propensity by $b^*(\alpha)$ and the utility level at the optimum by U^*.

As discussed in more detail in the main text, we place assumptions on the relationship between brand prescribing and benefits and costs to patients and society, on the relationship between payments and the private value of brand prescribing, and on the relationship between private returns to brand prescribing and the propensity of brand prescriptions. For convenience, we reprint these assumptions below.

The marginal health benefit increases at a slower rate than the marginal societal costs of additional brand drug use:

$$\frac{\partial^2 H_o}{\partial b^2} < \frac{\partial^2 C_o}{\partial b^2}. \tag{7}$$

The private value from brand prescribing is weakly increasing in payments:

$$\frac{\partial \pi_s}{\partial p} \geq 0. \tag{8}$$

The private returns to a higher brand prescribing propensity are positive but decreasing:

$$\frac{\partial \pi_s}{\partial b} > 0, \quad \frac{\partial^2 \pi_s}{\partial b^2} < 0. \tag{9}$$

Then, we can use the implicit function theorem to characterize the level of optimal brand prescribing $b^*(\alpha)$. The first order condition with respect to the brand prescribing propensity 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, $\frac{\partial b^*}{\partial p} = -\frac{\partial U^*}{\partial p} / \frac{\partial U^*}{\partial b}$:

$$\frac{\partial b^*}{\partial p} = -\frac{\alpha \overbrace{\frac{\partial \pi_s}{\partial p}}^{\geq 0 \text{ by } (8)}}{(1-\alpha)\underbrace{\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}_{<0 \text{ by } (7)} + \alpha \underbrace{\frac{\partial^2 \pi_s}{\partial b^2}}_{<0 \text{ by } (9)}}$$

$\Rightarrow \frac{\partial b^*}{\partial p} \geq 0$. Thus, optimal brand prescribing propensity moves up with higher payments. We can then examine the relationship between brand prescribing propensity, payments, and altruism, by taking the partial derivative with respect to physicians' weight on private benefits, α:

$$\frac{\partial^2 b^*}{\partial p \partial \alpha} = -\frac{\overbrace{\frac{\partial \pi_s}{\partial p}}^{\geq 0 \text{ by (8)}} \overbrace{\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}^{<0 \text{ by (7)}}}{\left((1-\alpha)\underbrace{\left(\frac{\partial^2 H_o}{\partial b^2} - \frac{\partial^2 C_o}{\partial b^2}\right)}_{<0 \text{ by (7)}} + \alpha \underbrace{\frac{\partial^2 \pi_s}{\partial b^2}}_{<0 \text{ by (9)}}\right)^2}.$$

$\Rightarrow \frac{\partial^2 b^*}{\partial p \partial \alpha} \geq 0$ for $\alpha > 0$. Thus, the optimal brand prescribing propensity moves up faster with increasing payments for physicians with a higher level of α, i.e. who place a higher weight on their private benefits.

B Additional information on drug classes and drugs

Table 7: Most commonly prescribed drugs

Generic name	**ATC codes (level 2)**	**Drug class name**	**Share of all claims**
atorvastatin calcium	c10	Lipid modifying agents	7.01%
lisinopril	c03, c09	Diuretics, Agents acting on the renin–angiotensin system	4.85%
amlodipine besylate	c08, c09	Calcium channel blockers, Agents acting on the renin–angiotensin system	4.70%
levothyroxine	h03	Thyroid therapy	4.03%
metoprolol succinate	c03, c07	Diuretics, Beta blocking agents	3.49%
simvastatin	c10	Lipid modifying agents	2.88%
losartan potassium	c03, c09, r05	Diuretics, Agents acting on the renin–angiotensin system, Cough and cold preparations	2.79%
furosemide	c03	Diuretics	2.71%
metoprolol tartrate	c03, c07	Diuretics, Beta blocking agents	2.48%
omeprazole	a02	Drugs for acid related disorders	2.42%
metformin	a10	Drugs used in diabetes	2.35%
hydrochlorothiazide	c03	Diuretics	2.18%
carvedilol	c07	Beta blocking agents	2.12%
pravastatin	c10	Lipid modifying agents	1.59%
rosuvastatin calcium	c10	Lipid modifying agents	1.50%
gabapentin	n03	Antiepileptics	1.48%
warfarin	b01	Antithrombotic agents	1.48%
clopidogrel bisulfate	b01	Antithrombotic agents	1.42%
apixaban	b01	Antithrombotic agents	1.37%
atenolol	c07	Beta blocking agents	1.32%
potassium chloride	a12, b05, r05	Mineral supplements, Blood substitutes and perfusion solutions, Cough and cold preparations	1.25%
hydrocodone acetaminophen	r05	Cough and cold preparations	1.17%

Table 8: Drugs with highest transfers

Brand name	**ATC codes (level 2)**	**Drug class name**	**Generic approved before 2020**	**Generic name**	**Total value of transfers**
eliquis	b01	Antithrombotic agents	no	apixaban	$ 448,440.90
xarelto	b01	Antithrombotic agents	no	rivaroxaban	$ 251,633.00
pradaxa	b01	Antithrombotic agents	no	dabigatran etexilate mesylate	$ 151,042.70
repatha	c10	Lipid modifying agents	no	evolocumab	$ 132,453.80
adempas	c02	Antihypertensives	no	riociguat	$ 112,824.40
entresto	c09	Agents acting on the renin–angiotensin system	no	sacubitril and valsartan	$ 108,694.80
crestor	c10	Lipid modifying agents	yes (2016)	rosuvastatin	$ 78,382.71
brilinta	b01	Antithrombotic agents	yes (2019)	ticagrelor	$ 56,319.88
corlanor	c01	Cardiac therapy	no	ivabradine	$ 52,646.32
savaysa	b01	Antithrombotic agents	no	edoxaban	$ 49,488.85
northera	c01	Cardiac therapy	no	droxidopa	$ 32,918.81
praluent	c10	Lipid modifying agents	no	alirocumab	$ 22,492.44
bydureon	a10	Drugs used in diabetes	no	exenatide	$ 20,976.10
tanzeum	a10	Drugs used in diabetes	no	albiglutide	$ 19,134.96
farxiga	a10	Drugs used in diabetes	no	dapagliflozin	$ 16,645.79
invokana	a10	Drugs used in diabetes	no	canagliflozin	$ 13,685.44
multaq	c01	Cardiac therapy	no	dronedarone	$ 12,436.12
effient	b01	Antithrombotic agents	yes (2017)	prasugrel	$ 12,312.04
uptravi	b01	Antithrombotic agents	no	selexipag	$ 9,904.71
toujeo	a10	Drugs used in diabetes	no	insulin glargine	$ 5,254.06
victoza	a10	Drugs used in diabetes	no	liraglutide	$ 4,207.29
norvasc	c08, c09	Calcium channel blockers, Agents acting on the renin–angiotensin system	yes (2007)	amlodipine	$ 3,375.00
jardiance	a10	Drugs used in diabetes	no	empagliflozin	$ 3,233.18
tresiba	a10	Drugs used in diabetes	no	insulin degludec	$ 2,877.35

C Additional descriptive results

C.1 Additional plots of the relationship between altruism and payments

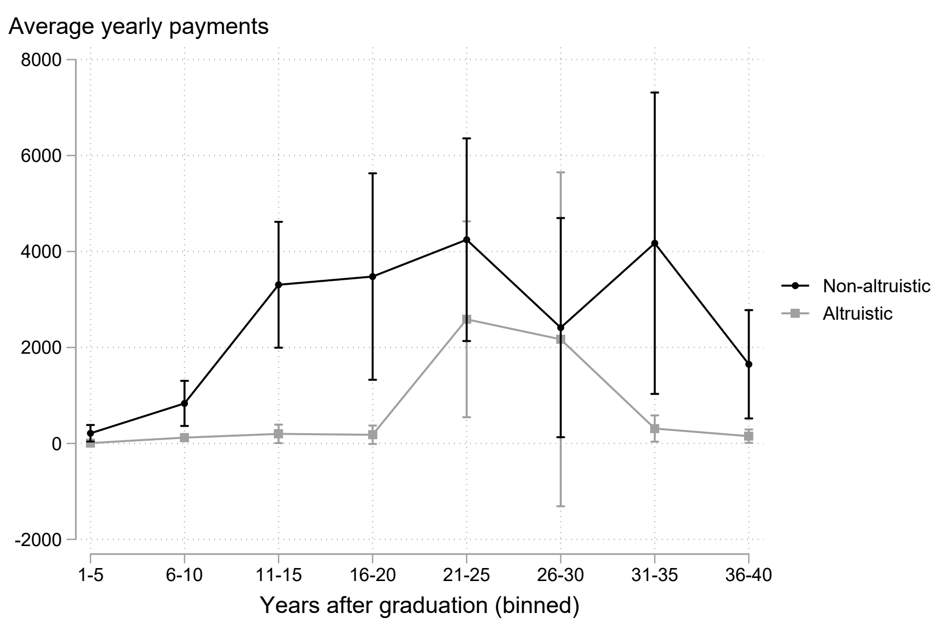
C.2 Evolution of payments over physicians' careers

Figure 7 traces how industry payments evolve over physicians' careers, separately for physicians with and without altruistic preferences. At the beginning of the career, industry transfers are on average higher for physicians without than physicians with altruistic preferences, but the difference is not statistically different and the level of average payments is low. The difference in payments by altruism is largest for mid-career physicians, between eleven and twenty years after graduation. For non-altruistic preferences, payments are similar between mid-career and experienced physicians. In comparison, payments to physicians with altruistic preferences evolve slower but reach similar levels as payments to physicians with non-altruistic preferences during the course of their careers.

Figure 6: Scatter plot of estimated altruism parameter (α) and log payments

Notes: This figure plots the relationship between payments and altruistic preferences. Each point represents a physician-year. Altruistic preferences are measured by parameter α from Equation 3. Higher values of α correspond to more weight on private benefits (higher selfishness). Payments are measured by the natural logarithm of (USD value of payments + 1). The dashed line represents a simple regression of payments on α.

Figure 7: Payments over physician careers, by altruistic or non-altruistic preferences



Notes: Each point represents the estimated mean payment over all physician-year observations in a given bin of years after graduation. Lines represent the 95% confidence interval of the estimated mean.

C.3 Correlation between prescribing and altruism

Table 9 shows OLS estimation results from regressing drug prescribing on the indicator for non-altruistic preferences. In Column (1) drug prescribing is measured by the share of brand drug claims. In Column (2) drug prescribing is measured by log per claim drug costs. Our estimates indicate that there is no statistically significant relationship between altruism and drug prescribing.

Table 9: Association between drug prescribing and altruism

	Share of brand drug claims	**Log per claim drug costs**
	(1)	(2)
Altruism		
Non-altruistic	0.005	0.039
	(0.005)	(0.052)
Constant	0.185***	4.053***
	(0.016)	(0.151)
Year controls	Yes	Yes
Individual controls	Yes	Yes
Institutional controls	Yes	Yes
State controls	Yes	Yes
Quartiles of patient pool characteristics	Yes	Yes
Altruistic: Mean outcome	0.189	4.257
Observations	1,616	1,616

This table presents the results from regressions of prescribing on altruism, controlling for the full set of control variables. In Column (1), prescribing is measured by the share of claims for brand drugs over all drug claims. In Column (2), prescribing is measured by the natural logarithm of average per claim costs. Estimation by OLS. Standard errors in parentheses are clustered on the physician level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

C.4 Correlation between prescribing and payments

Table 10 shows that drug prescribing and brand prescribing are positively correlated with industry payments. Columns (1) – (3) show a positive correlation between brand prescribing and payments. Columns (4) – (6) show a positive correlation between drug costs and payments. Payments are measured by log payments, log payments given any payment (the intensive margin), or any payment (the extensive margin).

Table 10: Association between payments and prescribing

	Share of brand drug claims			Log per claim drug costs		
	(1)	(2)	(3)	(4)	(5)	(6)
Payments						
Log (1 + USD)	0.042***			0.004***		
	(0.006)			(0.001)		
Log USD, given any payment		0.062***			0.005**	
		(0.012)			(0.002)	
Any payment			0.180***			0.017***
			(0.033)			(0.004)
Constant	3.931***	3.954***	3.780***	0.174***	0.177***	0.162***
	(0.132)	(0.140)	(0.187)	(0.016)	(0.016)	(0.025)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes
Quartiles of patient pool characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	4.257	4.343	4.257	0.189	0.190	0.189
Observations	1,616	838	1,616	1,616	838	1,616

This table presents the results from regressions of prescribing on payments, measured by log-transformed payments, log payments given any payment, or any payment, and controlling for the full set of control variables. In Columns (1)–(3), prescribing is measured by the share of claims for brand drugs over all drug claims. In Columns (4)–(6), prescribing is measured by the natural logarithm of average per claim costs. Estimation by OLS. Standard errors in parentheses are clustered on the physician level.
* p<0.10, ** p<0.05, *** p<0.01.

D Sensitivity of main results

D.1 Varying set of control variables

Tables 11 and 12 show estimation results of our main regression models for payments (Equations 4 and 5) and prescribing (Equation 6) with different sets of control variables. Columns (1)–(3) demonstrate that, for overall payments as the outcome variable, the marginal effect estimate of non-altruistic preferences in the generalized linear model increases and standard errors decrease when expanding the set of control variables. Columns (4)–(6) show that the point coefficient estimated in the linear model remains similar across specifications. Overall, expanding the set of control variables improves the precision of our results while implying similar effect sizes.

D.2 Aggregated payments and prescribing

Tables 13 and 14 show results for payments and prescriptions aggregated on the physician-level for our period of observation from 2014–2019. The estimates are consistent with our main results, but the extensive margin of payments (Any payment) appears to matter more than in our main specifications.

Table 11: Association between industry payments and altruism, varying sets of control variables

	USD payments[a]			Log (1 + USD payments)[b]		
	(1)	(2)	(3)	(4)	(5)	(6)
Marginal effects						
Altruism						
Non-altruistic	1686.987*	1444.775**	2052.607***			
	(897.565)	(718.841)	(588.970)			
Coefficient estimates						
Altruism						
Non-altruistic	1.078	0.688	1.070***	0.713	0.637*	0.730**
	(0.750)	(0.435)	(0.335)	(0.433)	(0.360)	(0.323)
Constant	6.914***	5.204***	5.248***	2.702***	1.493***	2.632***
	(0.651)	(0.406)	(0.631)	(0.404)	(0.429)	(0.653)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	No	Yes	Yes
Institutional controls	No	No	Yes	No	No	Yes
State controls	No	No	No	No	No	No
Altruistic: Mean outcome	860.398	860.398	860.398	2.575	2.575	2.575
Observations	1,616	1,616	1,616	1,616	1,616	1,616

This table presents the results from estimating Equations (4) and (4) with overall payments as the outcome variable, and different sets of control variables. Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors of average marginal effects are calculated using the delta method.
* p<0.10, ** p<0.05, *** p<0.01.
[a] Generalized linear models with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares.
[b] Linear models estimated by Ordinary Least Squares.

Table 12: Drug prescribing and the interaction between industry payments and altruism, varying sets of control variables

	Share of brand drug claims				Log per claim drug costs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Payments by altruism								
Non-altruistic × Log (1 + USD)	0.005***	0.006***	0.006***	0.006***	0.031	0.035	0.036*	0.033
	(0.002)	(0.002)	(0.002)	(0.002)	(0.022)	(0.022)	(0.021)	(0.021)
Payments								
Log (1 + USD)	0.000	-0.002	-0.001	-0.001	0.023	0.003	0.008	0.010
	(0.001)	(0.001)	(0.001)	(0.002)	(0.021)	(0.021)	(0.020)	(0.021)
Altruism								
Non-altruistic	-0.009	-0.011*	-0.013**	-0.012**	-0.062	-0.081	-0.086*	-0.092*
	(0.007)	(0.007)	(0.006)	(0.006)	(0.056)	(0.055)	(0.049)	(0.047)
Constant	0.206***	0.215***	0.235***	0.221***	4.003***	4.048***	4.147***	3.994***
	(0.006)	(0.009)	(0.011)	(0.013)	(0.052)	(0.067)	(0.082)	(0.096)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Institutional controls	No	No	Yes	Yes	No	No	Yes	Yes
State controls	No	No	No	Yes	No	No	No	Yes
Quartiles of patient pool characteristics	No	No	No	No	No	No	No	No
Altruistic: Mean outcome	0.189	0.189	0.189	0.189	4.257	4.257	4.257	4.257
Observations	1,616	1,616	1,616	1,616	1,616	1,616	1,616	1,616

This table presents the results from estimating Equation 6 with varying sets of control variables. In Columns (1)–(3), prescribing is measured by the share of claims for brand drugs over all drug claims. In Columns (4)–(6), prescribing is measured by the natural logarithm of average per claim costs. Estimation by OLS. Standard errors in parentheses are clustered on the physician level.
* p<0.10, ** p<0.05, *** p<0.01.

Table 13: Association between industry payments aggregated from 2014-2019 and altruism

	Payments, all years		**Int. margin, all years**		**Ext. margin, all years**
	USD[a]	Log (1 + USD)[b]	USD[a]	Log USD[b]	Any pay[b]
	(1)	(2)	(3)	(4)	(5)
Marginal effects					
Altruism					
Non-altruistic	11759.557***		9965.951**		
	(3476.194)		(4588.083)		
Coefficient estimates					
Altruism					
Non-altruistic	0.992***	1.147**	0.684*	0.568	0.142**
	(0.358)	(0.451)	(0.383)	(0.368)	(0.066)
Constant	6.736***	3.834***	7.409***	6.362***	0.583***
	(0.676)	(0.972)	(0.670)	(0.657)	(0.127)
Year controls	No	No	No	No	No
Individual controls	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	7862.884	4.705	11331.803	6.775	0.694
Observations	280	280	221	221	280

This table presents estimation results based on overall payments aggregated on the physician level as outcome variables. Columns (1) and (2) report results with overall payments as the outcome variable. Columns (3) and (4) show results for payments measured on the intensive margin when restricting the sample to any payment. Column (5) shows results for payments measured on the extensive margin, with an indicator for any payment as the outcome variable. Heteroskedasticity-robust standard errors of coefficient estimates are in parentheses. Standard errors of average marginal effects are calculated using the delta method.

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

[a] Generalized linear models with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares.

[b] Linear models estimated by Ordinary Least Squares.

Table 14: Drug prescribing and the interaction between total industry payments and altruism, aggregated over all years from 2014-2019

	Share of brand drug claims, all years			**Log per claim drug costs, all years**		
	(1)	(2)	(3)	(4)	(5)	(6)
Payments by altruism						
Non-altruistic × Log (1 + Total USD, all years)	0.004**			0.006		
	(0.002)			(0.021)		
Non-altruistic × Log total USD given any payment, all years		0.004			-0.043	
		(0.005)			(0.042)	
Non-altruistic × Any payment, all years			0.022*			-0.012
			(0.014)			(0.133)
Payments						
Log (1 + Total USD, all years)	0.000			0.020		
	(0.002)			(0.020)		
Log total USD given any payment, all years		0.003			0.109***	
		(0.005)			(0.041)	
Any payment, all years			-0.010			-0.020
			(0.012)			(0.111)
Altruism						
Non-altruistic	-0.023**	-0.021	-0.015	-0.039	0.238	0.029
	(0.009)	(0.033)	(0.010)	(0.087)	(0.262)	(0.093)
Constant	0.156***	0.132***	0.163***	4.256***	3.522***	4.363***
	(0.022)	(0.041)	(0.023)	(0.239)	(0.344)	(0.223)
Year controls	No	No	No	No	No	No
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes
Quartiles of average patient pool characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	0.191	0.192	0.191	4.323	4.352	4.323
Observations	280	221	280	280	221	280

This table presents estimation results based on measures of prescribing aggregated on the physician level as outcome variables, and captures the relationship between prescribing and aggregated payments by altruistic preferences. In Columns (1)–(3), prescribing is measured by the share of claims for brand drugs over all drug claims. In Columns (4)–(6), prescribing is measured by the natural logarithm of average per claim costs. Estimation by OLS. Standard errors in parentheses are clustered on the physician level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

D.3 Alternative econometric specifications for drug prescribing

In Table 15, we test whether altruism affects the relationship between payments and prescribing based on two alternative econometric models. In Columns (1) and (3), we estimate the regression model in Equation 6, but instead of log-transformed payments we use a inverse hyperbolic sine transformation. In Columns (2) and (4), we estimate a specification where our coefficient of interest is associated with the interaction between an indicator for non-altruistic preferences and log-transformed payments with zero replacing missing values, and we additionally include an indicator for no payments as a control variable. The results are essentially unchanged compared to our main specifications.

Table 15: Drug prescribing and the interaction between altruism and industry payments, alternative econometric models

	Share of brand drug claims		**Log per claim drug costs**	
	(1)	(2)	(3)	(4)
Payments by altruism				
Non-altruistic × Arcsinh USD	0.004***		0.021	
	(0.001)		(0.015)	
Non-altruistic × Log USD		0.004***		0.020
		(0.002)		(0.018)
Payments				
Arcsinh USD	-0.000		0.019	
	(0.001)		(0.015)	
Log USD		0.002		0.046**
		(0.002)		(0.021)
No payment		0.017		0.164**
		(0.010)		(0.068)
Altruism				
Non-altruistic	-0.010	-0.009	-0.051	-0.048
	(0.006)	(0.006)	(0.045)	(0.046)
Constant	0.189***	0.175***	4.005***	3.871***
	(0.017)	(0.021)	(0.140)	(0.156)
Year controls	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	0.189	0.189	4.257	4.257
Observations	1,616	1,616	1,616	1,616

This table presents estimation results of prescribing, capturing the relationship between prescribing and aggregated payments by altruistic preferences, for alternative econometric model specifications or measures of payments. Prescribing is measured by the share of claims for brand drugs over all drug claims in Columns (1)–(2), and by per claim costs in Columns (3)–(4). In Columns (1) and (3), payments are inverse hyperbolic sine transformed. In Columns (2) and (4), payments are log-transformed with zero replacing missing values, and an indicator for no payments is included as control variable. Estimation by OLS. Standard errors in parentheses are clustered on the physician level.

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

D.4 Contemporaneous altruism, payments, and prescribing

We restrict the analysis to data from 2019, the year of the experiment, such that our outcomes of payments and prescribing are measured contemporaneous with physicians' social preferences. Table 16 shows that the estimates to our main estimations in the restricted sample.

Table 16: Contemporaneous data

	Payments, prescribing, and altruism in 2019			
	Payments		Brand share	Claim costs
	USD[a]	Log (1 + USD)[b]		
	(1)	(2)	(3)	(4)
Payments by altruism				
Non-altruistic×Log (1 + USD)			0.005**	0.004
			(0.002)	(0.024)
Altruism				
Non-altruistic	1.595***	0.669*	-0.009	-0.056
	(0.427)	(0.373)	(0.008)	(0.074)
Payments				
Log (1 + USD)			0.001	0.049**
			(0.002)	(0.025)
Constant	5.822***	2.676***	0.137***	4.533***
	(0.735)	(0.841)	(0.023)	(0.266)
Individual controls	Yes	Yes	Yes	Yes
Institutional controls	Yes[c]	Yes	Yes	Yes
Quartiles of average patient pool characteristics	No	No	Yes	Yes
State controls	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	1861.325	2.931	0.164	4.481
Observations	274	274	274	274

This table presents the results from estimating Equations (4) and (4) with overall payments as the outcome variable, and from estimating Equation 6, on data from the year 2019, when the experiment was conducted. Standard errors of coefficient estimates in parentheses are clustered on the physician level.
* p<0.10, ** p<0.05, *** p<0.01.
[a] Generalized linear models with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares.
[b] Linear models estimated by Ordinary Least Squares.
[c] To achieve convergence, this specification does not include the practice ownership indicators as control variables.

D.5 Sensitivity statistics

Table 17 reports all estimates that are needed in order to calculate the Sensitivity Statistics as introduced by Cinelli and Hazlett (2020). Column (1) reproduces our main regression results on the physician-year level from Column (1) of Table 2, where we regressed log payments on an indicator for non-altruistic preferences and our preferred set of observable control variables. Column (2) shows estimates of the association between the indicator for non-altruistic preferences as well as observable characteristics, including the indicator for cardiologist. Column (3) reproduces results from the physician level regression as in Column (1) of Table 13, and Column (4) shows estimates from regressing the indicator for non-altruistic on observable characteristics.

Estimates from Column (1) of Table 2 inform about the Robustness Value and the Partial R^2 for the estimated association between payments and altruism using physician-year level observations, while the estimates from Column (2) associated the indicator for cardiologist are required for the benchmark exercise. Equivalently, Columns (3) and (4) of Table 2 are informative about the Sensitivity Statistics for the association between payments and altruism based on regressions on the physician level. In both cases, we use 280 degrees of freedom.

We show the Sensitivity Statistics for both the physician-year level and the physician level regression estimate of the association between payments and altruism. Table 18 shows the Robustness Values and the Partial R^2s. Figure 8 shows results from a benchmark exercise, using cardiologist as a benchmark. The benchmark exercise informs about changes in the association between payments and altruism by introducing unobserved confounders which have one, two, or three times the explanatory strength with payments and altruism as the indicator for cardiologist.

D.6 Payment quartiles

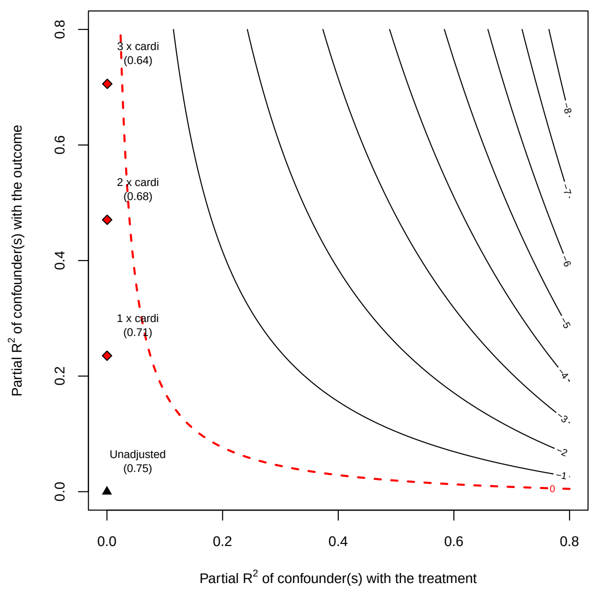
Table 19 shows results from regressions of dichotomized payments, separately for the upper three quartiles of payments. In each regression, we measure payments by an indicator of receiving payments above the 25th, 50th (median), or 75th percentile.

Table 17: Sensitivity statistics: Regressions of payments and regressions of altruism

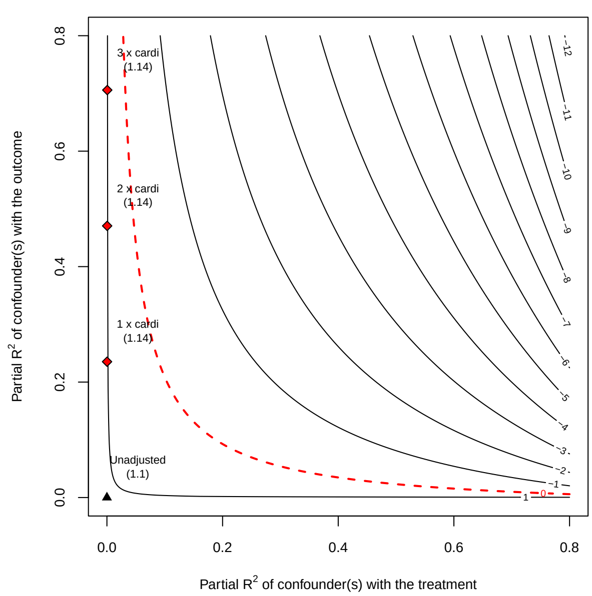
	Physician level		**Physician-year level**	
	Log (1 + USD payments) (1)	Non-altruistic (2)	Log (1 + USD payments) (3)	Non-altruistic (4)
Altruism				
Non-altruistic	0.751**		1.147**	
	(0.325)		(0.451)	
Individual controls				
Age below 39 (omitted)	-	-	-	-
Age: 40–49	0.556	-0.040	0.883*	-0.042
	(0.359)	(0.062)	(0.489)	(0.062)
Age: 50–59	0.785**	-0.057	0.707	-0.058
	(0.332)	(0.067)	(0.483)	(0.067)
Age above 60	0.949**	0.011	1.369**	0.008
	(0.460)	(0.071)	(0.568)	(0.072)
Female	-0.946***	0.019	-0.942**	0.013
	(0.286)	(0.055)	(0.402)	(0.054)
Institutional controls				
Specialty: Other (omitted)	-	-	-	-
Specialty: Cardiology	3.072***	0.014	3.332***	0.001
	(0.379)	(0.059)	(0.452)	(0.060)
Specialty: Family medicine	0.260	-0.026	0.174	-0.017
	(0.388)	(0.071)	(0.522)	(0.070)
Ownership: Nonprofit hospital (omitted)	-	-	-	-
Ownership: Academic medical center	-1.617***	-0.061	-0.986*	-0.070
	(0.491)	(0.073)	(0.563)	(0.073)
Ownership: Physician-owned	-0.465	-0.131	-0.083	-0.140
	(0.569)	(0.100)	(0.706)	(0.101)
Practice size: 1–36 (omitted)	-	-	-	-
Practice size: 36–350	-0.125	0.220*	-0.320	0.207*
	(0.497)	(0.117)	(0.750)	(0.115)
Practice size: 351–1600	0.254	0.177	0.153	0.155
	(0.526)	(0.112)	(0.755)	(0.110)
Constant	2.469***	0.720***	3.834***	0.752***
	(0.713)	(0.118)	(0.972)	(0.115)
Year controls	Yes	Yes	No	No
State controls	Yes	Yes	Yes	Yes
Mean outcome	3.161	0.823	5.551	0.825
Observations	1,616	1,616	280	280
Mean outcome	10.276	0.610	11.065	0.613
Mean controls	0.232	0.829	0.230	0.829
# Observations	4264	4264	4264	4264

This table presents linear regressions of log-transformed payments or a binary indicator of non-altruistic preferences as outcome variable. Columns (1)–(2) show results for a regression of aggregated payments on the physician-level, with heteroskedasticity-robust standard errors in parentheses. Columns (3)–(4) show results for physician-year level regressions, with standard errors clustered on the physician level

Figure 8: Sensitivity Statistics: Benchmark exercise



(a) Physician-year level



(b) Physician level

Notes: These figures show results from a benchmark exercise of the association between payments and altruism, based on work by Cinelli and Hazlett (2020). We use cardiologist as a benchmark. The benchmark exercise places bounds on changes in the association between payments and altruism by introducing unobserved confounders which have one, two, or three times the explanatory strength with payments and altruism as the indicator for cardiologist. The calculations are based on regression results as shown in Table 17.

Table 18: Sensitivity statistics for the relationship between payments and altruism

	Physician-year level	**Physician level**
Robustness value	0.129	0.140
Partial R^2	0.019	0.022

This table shows two sensitivity statistics developed by Cinelli and Hazlett (2020), the Robustness Value and the Partial R^2, for the regression of log payments on altruism. We calculate the sensitivity statistics on the physician-year level for the estimate associated with altruism from our preferred specification shown in Column (1) of Table 2 (also reported in Column (1) of Table 17), where we regress the Log USD value of payments on an indicator for Non-altruistic, individual controls, institutional controls, year fixed effects and state fixed effects, where standard errors clustered on the physician level. The sensitivity statistics on the physician level are based on estimates from the corresponding regression using physician-level observations, shown in Column (1) of Table 13 (also reported in Column (3) of Table 17). The Robustness Level defines the minimal strength of association that unobserved confounders need to have with both altruism and log payments in order to set the estimated association between altruism and log payments to zero. The Partial R^2 is a measure of robustness to confounding of the point estimate associated with altruism in an extreme scenario, where unobserved confounding explains 100 percent of the residual variance in payments. In this scenario, the Partial R^2 defines the minimal explanatory power that such extreme unobserved confounding needs to have with the residual variance in altruism in order to set the estimated association between altruism and log payments to zero.

Table 19: Industry payments in the 25th, 50th, or 75th percentile

	Payment above 25th percentile				**Payment above median**				**Payment above 75th percentile**			
	Any pay		Brand share	Claim costs	Any pay		Brand share	Claim costs	Any pay		Brand share	Claim costs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Payments by altruism												
Non-altruistic × Payment above 25th percentile			0.020**	0.092								
			(0.009)	(0.091)								
Non-altruistic × Payment above median							0.026***	0.102				
							(0.009)	(0.091)				
Non-altruistic × Payment above 75th percentile											0.037***	0.276***
											(0.011)	(0.103)
Altruism												
Non-altruistic	0.074	0.352	-0.005	-0.016	0.072	0.346	-0.007	-0.019	0.116***	1.089**	-0.004	-0.037
	(0.049)	(0.272)	(0.006)	(0.045)	(0.049)	(0.273)	(0.006)	(0.044)	(0.042)	(0.445)	(0.005)	(0.050)
Payments												
Payment above 25th percentile			-0.001	0.101								
			(0.008)	(0.087)								
Payment above median							-0.006	0.108				
							(0.008)	(0.086)				
	(0.086)											
Payment above 75th percentile											-0.005	0.037
											(0.010)	(0.090)
Constant	0.520***	0.273	0.187***	3.995***	0.478***	0.023	0.191***	3.998***	0.192*	-2.157***	0.187***	4.053***
	(0.107)	(0.618)	(0.017)	(0.143)	(0.107)	(0.582)	(0.017)	(0.143)	(0.105)	(0.800)	(0.016)	(0.142)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartiles of average patient pool characteristics	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Altruistic: Mean outcome	0.472	0.472	0.189	4.257	0.451	0.451	0.189	4.257	0.150	0.150	0.189	4.257
Observations	1,616	1,616	1,616	1,616	1,616	1,616	1,616	1,616	1,616	1,601	1,616	1,616
Model	Linear[a]	Logit[b]	Linear[a]	Linear[a]	Linear[a]	Logit[b]	Linear[a]	Linear[a]	Linear[a]	Logit[b]	Linear[a]	Linear[a]

This table presents results based on payments above the 25th, 50th, or 75th percentile. Columns (1)–(2), (5)–(6), and (9)–(10) show results for 'Any pay' as outcomes, measured by indicator variables of receiving payments in the 25th, 50th, or 75th percentile, and specified as linear or logit model, respectively. In Columns (3), (7), and (11), prescribing is measured by 'Brand share', referring to the share of brand claims over all drug claims. In Columns (4), (8), and (12), prescribing is measured by 'Claim costs', referring to the natural logarithm of average per claim costs. Standard errors clustered on the physician-level in parentheses.

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

[a] Estimation by Ordinary Least Squares.

[b] Estimation by Maximum Likelihood

D.7 Winsorized payments

Table 20 shows results from regressions of payments winsorized at the 95th percentile and the 90th percentile.

Table 20: Industry payments winsorized at the 95th or 90th percentile

	Winsorized at 95th percentile				Winsorized at 90th percentile			
	Payments		Brand share	Claim costs	Payments		Brand share	Claim costs
	USD[a]	Log (1 + USD)[b]			USD[a]	Log (1 + USD)[b]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Payments by altruism								
Non-altruistic × Log (1 + USD)			0.005***	0.023			0.005***	0.020
			(0.002)	(0.017)			(0.002)	(0.017)
Altruism								
Non-altruistic	0.945***	0.712**	-0.010	-0.048	0.567**	0.628**	-0.009	-0.036
	(0.296)	(0.315)	(0.006)	(0.045)	(0.268)	(0.300)	(0.006)	(0.044)
Payments								
Log (1 + USD)			-0.000	0.022			-0.000	0.025
			(0.002)	(0.016)			(0.002)	(0.016)
Constant	4.671***	2.557***	0.189***	3.999***	4.826***	2.685***	0.188***	3.985***
	(0.555)	(0.698)	(0.017)	(0.140)	(0.496)	(0.678)	(0.017)	(0.141)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartiles of patient pool characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Altruistic: Mean outcome	427.766	2.555	0.189	4.257	239.110	2.518	0.189	4.257
Observations	1,616	1,616	1,616	1,616	1,616	1,616	1,616	1,616

This table presents the results from estimating Equations (4) and (4) with overall payments as the outcome variable, and from estimating Equation 6, where payments are winsorized. Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors for average marginal effects are calculated using the delta method.
* p<0.10, ** p<0.05, *** p<0.01.
[a] Generalized linear models with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares.
[b] Linear models estimated by Ordinary Least Squares.

D.8 Standardized and continuous measure of altruism

Table 21: Standard-normalized continuous measure of altruism

	Full sample				Excluding impartial preferences			
	Payments		Brand share	Claim costs	Payments		Brand share	Claim costs
	USD	Log (1 + USD)			USD	Log (1 + USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Payments by altruism								
Log (1 + USD) × Standardized α			0.000	0.002			0.001*	0.005
			(0.001)	(0.006)			(0.001)	(0.006)
Altruism								
Standardized α	0.296**	0.201	-0.002	-0.013	0.370**	0.271*	-0.003	-0.014
	(0.118)	(0.151)	(0.003)	(0.019)	(0.163)	(0.148)	(0.003)	(0.021)
Payments								
Log (1 + USD)			0.007***	0.066***			0.002	0.046***
			(0.002)	(0.013)			(0.002)	(0.017)
Constant	5.852***	2.970***	0.179***	3.973***	5.131***	3.354***	0.189***	4.081***
	(0.684)	(0.667)	(0.016)	(0.128)	(0.352)	(0.785)	(0.016)	(0.149)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Quartiles of average patient pool characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Mean outcome	860.398	2.575	0.189	4.257	860.398	2.575	0.189	4.257
Observations	1,616	1,616	1,616	1,616	1,131	1,131	1,131	1,131

This table presents the results from estimating Equations (4) and (4), and from estimating Equation 6, with a continuous measure of altruism replacing the indicator for non-altruistic preferences. The continuous measure is standard-normalized within the sample of 280 physicians, with higher values indicating higher weight on private returns, or less altruistic preferences. Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors for average marginal effects are calculated using the delta method.
Estimation by OLS. Standard errors clustered on the physician-level in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

E Analysis for cardiovascular drugs and blood thinners

We further study whether drug class specific factors affect the relationship between altruism, prescribing, and payments, by examining blood thinners (antithrombotic agents) and cardiovascular drugs separately. We construct our analysis sample based the list of drugs with Anatomical Therapeutic Chemical code (ATC) code B01 (antithrombotics) or ATC code C (cardiovascular drugs) as included in the FDA Orange Book until 2017, appended by more recent drug approvals as listed in the KEGG DRUG Database. We consider only physicians who are active prescribers of a given drug class and exclude physicians if they prescribe fewer than 50 claims in total and receive no transfers within that drug class. Table 22 provides additional information on drug classes.

Table 23 in Appendix E indicates that altruistic preferences are more strongly associated with the receipt of industry transfers for cardiovascular drugs compared to blood thinners. Table **??** indicates that for physicians with non-altruistic preferences, drug payments are associated with a substitution towards more costly brand alternatives within the class of cardiovascular treatments. However, this is not the case for blood thinners. Within the treatment class of blood thinners, prescribing and the receipt of industry payments are not related differentially by altruism.

These differences between cardiovascular drugs and blood thinners could be explained by limited availability of lower-cost alternatives for patients who require antithrombotic medications. As a result, industry payments for blood thinners would not differentially affect brand shares or costs of blood thinners for altruistic compared to non-altruistic physicians. In contrast, in the case of cardiovascular drugs, there are few differences between non-altruistic and altruistic physicians in accepting industry transfers, but only drug decisions for non-altruistic physicians differ with tighter relationships with industry, indicating that non-altruistic physicians might substitute cardiovascular for expensive treatments more often.

Table 22: Prescriptions and payments by drug classes

ATC	**Drug class name**	**Claims share**	**Costs share**	**Share of physicians**		
				with >50 claims	**with any pay**	**excluded**
b	Drugs affecting the blood and blood forming organs	6.92%	25.29%	90.25%	38.27%	7.22%
c	Cardiovascular drugs	52.78%	28.09%	98.56%	36.46%	1.44%
a10	Drugs used in diabetes	5.01%	15.58%	67.15%	36.10%	21.30%
b01	Antithrombotic agents	5.47%	24.51%	89.17%	38.27%	7.94%
c03	Diuretics	23.11%	6.40%	98.19%	6.14%	1.81%
c07	Beta blocking agents	10.20%	3.69%	96.39%	10.83%	3.61%
c09	Agents acting on the renin–angiotensin system	15.81%	5.23%	97.47%	25.63%	2.53%
c10	Lipid modifying agents	14.42%	10.58%	96.75%	29.60%	3.25%

Table 23: Separate analysis for selected drug classes

	Cardiovascular drugs				Blood thinners			
	Payments		Brand share	Claim costs	Payments		Brand share	Claim costs
	USD[a]	Log (1 + USD)[b]			USD[a]	Log (1 + USD)[b]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marginal effects								
Altruism								
Non-altruistic	478.036*				291.999			
	(258.605)				(245.854)			
Payments by altruism								
Non-altruistic × Log (1 + USD payments)			0.004**	0.061**			0.006	0.007
			(0.002)	(0.024)			(0.010)	(0.042)
Altruism								
Non-altruistic	2.393***	0.219	0.004	-0.024	0.976	0.476**	0.044	0.153
	(0.560)	(0.176)	(0.004)	(0.082)	(0.768)	(0.221)	(0.035)	(0.157)
Payments								
Log (1 + USD payments)			-0.001	0.008			-0.000	0.026
			(0.002)	(0.021)			(0.010)	(0.039)
Constant	1.126	0.870*	0.055***	3.321***	1.767*	1.428***	0.021	3.244***
	(0.706)	(0.482)	(0.013)	(0.204)	(1.015)	(0.525)	(0.100)	(0.373)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Institutional controls	Yes[c]	Yes	Yes	Yes	Yes[c]	Yes	Yes	Yes
Quartiles of patient pool characteristics	No	No	Yes	Yes	No	No	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Altruistic: Mean outcome	48.989	0.895	0.024	0.024	79.243	1.114	0.329	0.329
Observations	1,616	1,616	1,523	1,523	1,616	1,616	1,179	1,179

This table presents the results from estimating Equations (4) and (4) with overall payments as the outcome variable, and from estimating Equation 6, separately for cardiovascular drugs (ATC C) and blood thinners (ATC B01). Standard errors of coefficient estimates in parentheses are clustered on the physician level. Standard errors for average marginal effects are calculated using the delta method.

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

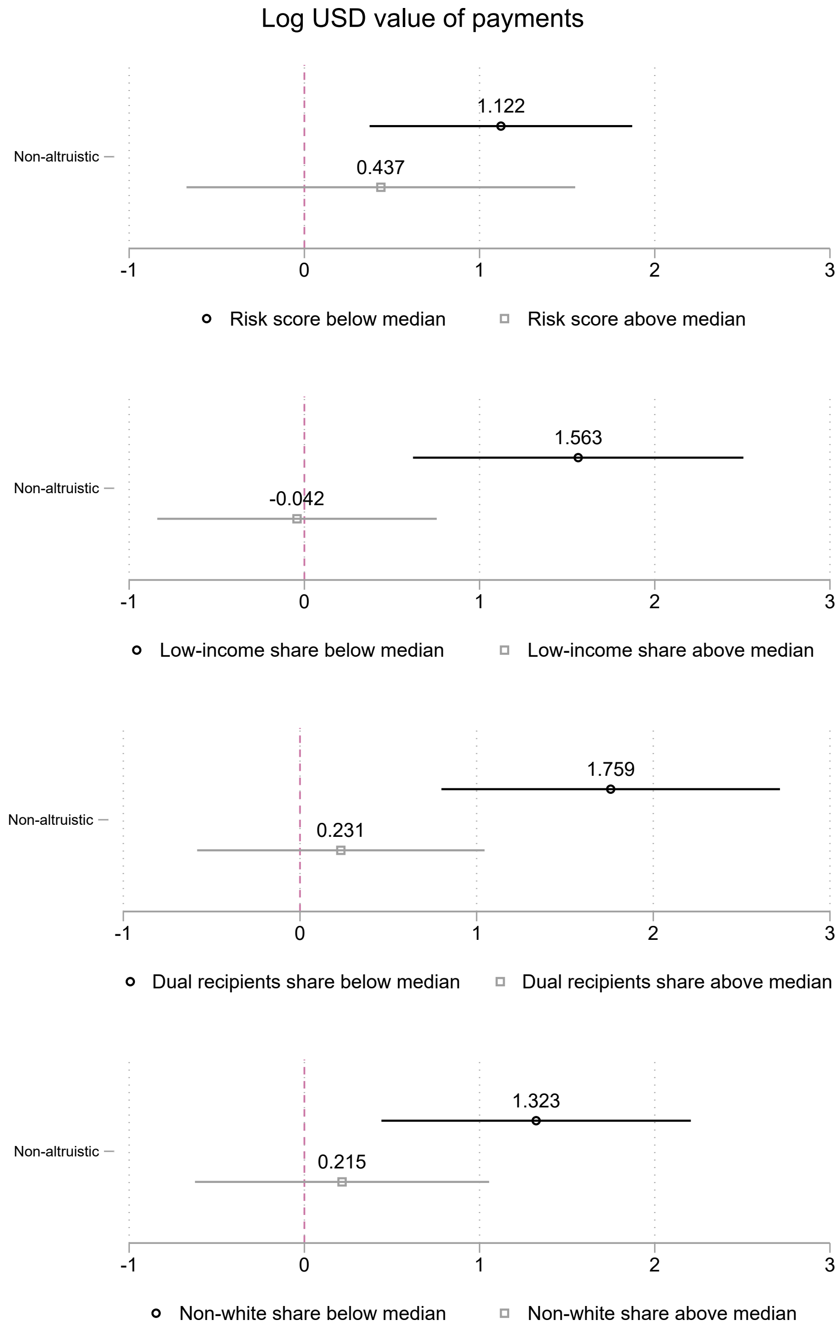
[a] Generalized linear models with a log link and gamma family distribution, estimated by Iterated Reweighted Least Squares. Specifications with a restricted set of controls in order to achieve convergence.

[b] Linear models estimated by Ordinary Least Squares.

[c] To achieve convergence, this specification does not include the practice ownership indicators as control variables.

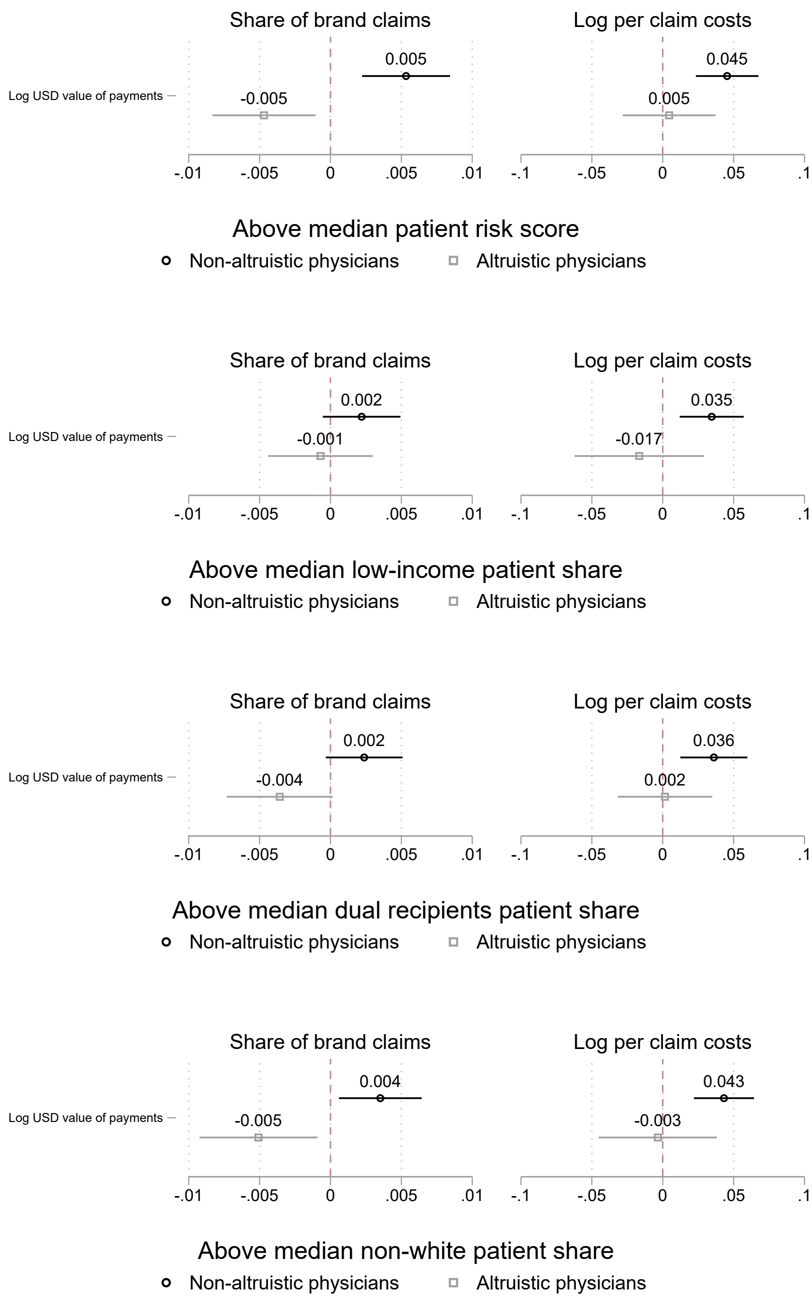
F Patient heterogeneity

Figure 9: The association between altruism and industry payments, by different groups of patients



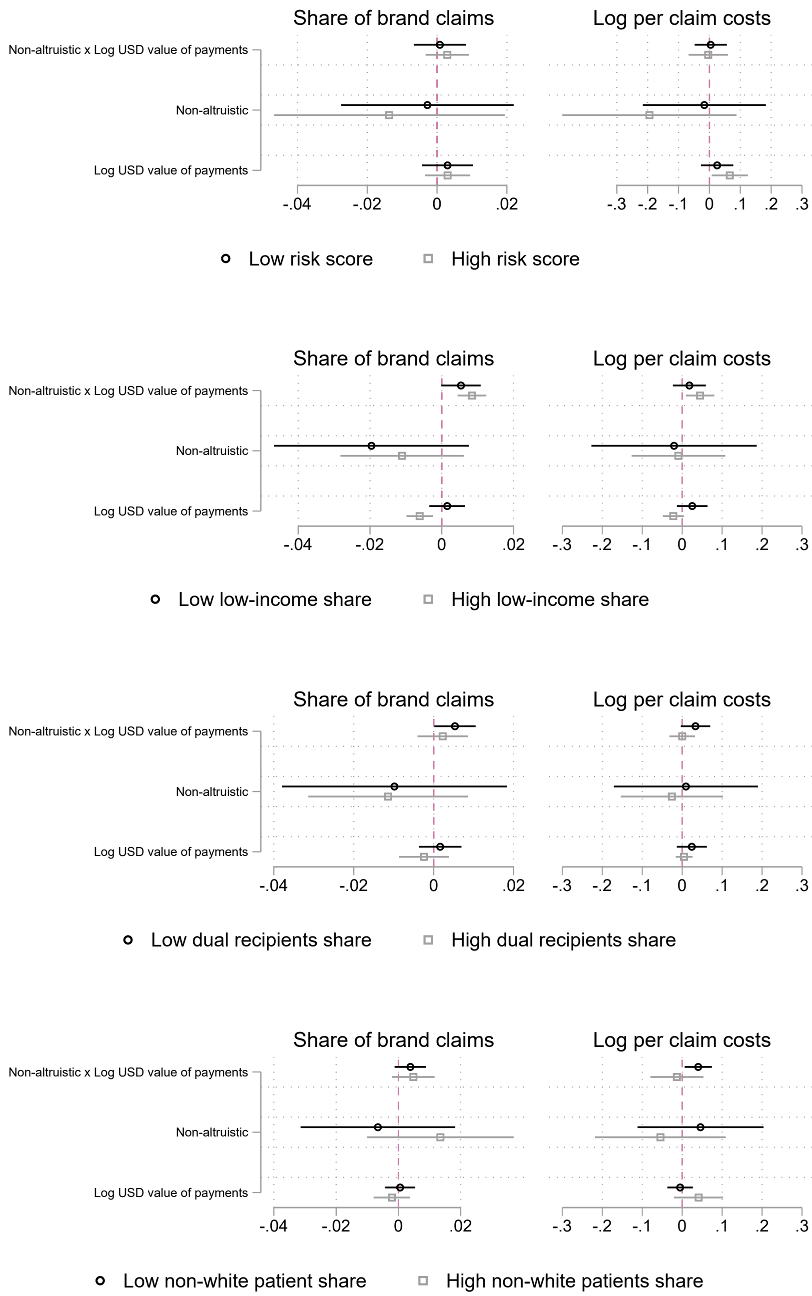
Notes: The figures show estimated coefficients from regressing Log USD value of payments on an indicator variable for altruistic preferences, separately for physicians with patient pools at the median characteristic or above (above median) and for physicians with patient pools below the median characteristic (below median). Each panel represents OLS regression results with observations separated by a different characteristic. All regressions include individual controls, institutional controls, patient pool quartiles, state controls, and calendar years. Lines represent the 95% confidence intervals. Robust standard errors are clustered on the physician-level.

Figure 10: Altruism and the association between drug prescribing and industry payments, for patients with above mean risks



Notes: The figures show estimated coefficients from regressing Total log drug prescribing costs (left) or Share of brand drug claims (right) on industry payments interacted with an indicator variable for altruistic preferences, separately for altruistic and non-altruistic physicians with vulnerable patient pools. Each panel represents OLS regression results with a different subset of physicians by patient pool characteristics and observations separated by altruistic or non-altruistic physicians. All regressions include individual controls, institutional controls, patient pool quartiles, state controls, and calendar years. Lines represent the 95% confidence intervals. Robust standard errors are clustered on the physician-level.

Figure 11: Altruism and the association between drug prescribing and industry payments, by groups of patients in the lowest/highest quartile of a characteristic



Notes: The figures show estimated coefficients from regressing Total log drug prescribing costs (left) or Share of brand drug claims (right) on industry payments interacted with an indicator variable for altruistic preferences, separately for physicians with patient pools in the lowest/highest quartile of a characteristic. Each panel represents OLS regression results, with observations separated by a different characteristic. All regressions include individual controls, institutional controls, patient pool quartiles, state controls, and calendar years. Lines represent the 95% confidence intervals. Robust standard errors are clustered on the physician-level.