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The effect of institutional characteristics and social norms on corruption in healthcare

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Abstract

Corruption in healthcare is widespread and consequential. Informal payments (IPs) are a common form of petty corruption, especially in low- and middle-income countries. Using data from the Life in Transition Survey encompassing 33 countries across Europe and Central Asia, I analyze the prevalence and reasons behind IPs made to public health providers. In addition to individual- and system-level factors often used in literature, I also introduce a latent measure of social norms related to high levels of corruption. These are associated with a significantly higher prevalence of paying informally. This paper also bridges a gap between the corruption literature and health-related research by introducing a typology of IPs based on why they were made. I find that the association between health system characteristics and IPs prevalence differs based on the reason for payment. This difference is further exacerbated by the existence of corruption-related social norms. The results of this analysis highlight the need to revisit existing anti-corruption policies and align them to the underlying social norms.

1 | INTRODUCTION

Corruption is defined as the "misuse of public office for private gain" (Rose-Ackerman, 2003). Healthcare-related corruption is widespread (Vian, 2008) and costly, estimated to cost $455 billion annually (National Academies of Sciences et al., 2018). It affects adversely patients' satisfaction with the service provision (Habibov, 2016), their trust in providers (Schaaf & Topp, 2019) and is associated with worse health outcomes (Mavisakalyan et al., 2021). Informal payments (IPs) from patients to providers are among the most common forms of corruption in healthcare (Lewis, 2000). Due to the ambiguous and covert nature of the exchange, defining an informal payments (IP) has been challenging (Cherecheş et al., 2013). I adopt the definition provided by Lewis (2000, p. 1)—"payments to individual and institutional providers, in kind or in cash, that are made outside official payment channels".

By borrowing from the health policy and the general corruption literature I categorize IPs into four main types, according to what motivates them. Firstly, there are gratuity payments which patients customarily make in order to express their gratitude for receiving treatment (Kornai, 2000). Secondly, IPs can be "greed" payments which are initiated by a patient to obtain something on top of the basic entitlements - for example, faster or better treatment (Bauhr, 2017). Thirdly, IPs correspond to "need" payments - a form of extortion requested by a provider which will be paid by the patient to obtain a service they are entitled to for free (Bauhr, 2017). Finally, patients can also make IPs to conform to their belief - which may or may not be correct - that IPs are expected or necessary. I will refer to the these as an "implicit expectation" payment (Vian & Burak, 2006). I build on the existing literature which has considered types of IPs (Habibov et al., 2021) by expanding the typology of IPs, estimating the likelihood of making each type and their association with socioeconomic characteristics.

Describing these four types of IPs is not only of interest in itself, but it is also critical when designing policy solutions that can effectively reduce IPs, as each calls for a different type of remedy. Gaál et al. (2010) lay out some of the policies which have been adopted across Eastern Europe. These include physician-targeted incentives which also correspond to traditional anti-corruption policy design (Rose-Ackerman, 1975) and increased health spending. While the authors discuss the success of such instruments in some places, they also detail their ineffectiveness elsewhere. This discrepancy can partially be attributed to the mismatch between the type of IP prevalent in a country and the policy used to address it. Increasing wages might reduce the number of IPs initiated as extortion by providers ("need" payments) but have no effect on the expectations of patients or their willingness to express gratitude. On the other hand, these could be reduced by an intervention designed to address patients' beliefs about others' behaviors (Köbis et al., 2022).

There is little evidence of the prevalence and determinants of the different types in the health literature. This has mostly focused on the predictive role of individual characteristics on the prevalence and size of IPs. Health-related studies have demonstrated that being a woman (Baji et al., 2012), older (Balabanova & McKee, 2002), less educated (Burak & Vian, 2007), from a lower socio-economic background, or in urban areas (Tomini and Maarse (2011)) increases the probability of paying IPs. Moreover, when breaking down IPs into types, separate likelihoods were not estimated but rather used as a determinant of patient outcomes (e.g., Habibov et al., 2021).

Whilst important, this focus neglects the role of other potentially important drivers, which become more obvious if one considers the different types of IPs. Two factors are particularly important. First, institutional health system factors, such as government spending (Williams &

Horodnic, 2015) or the degree of financial protection of patients (Vian & Burak, 2006), have been highlighted in the corruption literature as determinants of the prevalence of IPs. While theoretically these systemic factors are expected to mitigate IPs, the empirical evidence is mixed. Increasing health insurance coverage do not necessarily lead to a reduction in IPs (Liu et al., 2020). Formalizing IPs by introducing out-of-pocket-payments has had limited effects in Bulgaria (Balabanova & McKee, 2002) or Georgia (Belli et al., 2004).

Limited evidence of such reforms have led some authors to consider another set of structural factors, in the form of norms, in particular the existence of social norms around IPs and patients' beliefs about such norms (Gaál et al., 2010). Bicchieri (2016) shows how individuals' actions are driven by the influence of descriptive social norms. If someone thinks that people in similar socioeconomic, geographical or demographic groups to theirs make IPs to healthcare providers, they are likely to follow a similar behavior. There is no empirical evidence documenting how the existence of such norms might influence the likelihood of IPs in healthcare.

In this paper, I address these different gaps in the literature on IPs in healthcare. Firstly, I present a theoretical overview of IPs. Then, I use a detailed dataset on IPs and their types to describe their prevalence and variety across several European and Central Asian countries. Next, I analyze in a unified framework the predictive power of individual characteristics, institutional factors and social norms. Finally, I assess the extent to which these associations vary by the type of IPs.

2 | THEORETICAL OVERVIEW

2.1 | What are informal payments

Defining IPs in healthcare is complex due to the ambiguity of the exchange (Ledeneva, 2018). There are a number of dimensions along which IPs can be defined. Lewis (2000) provides a comprehensive definition encompassing in-kind and cash exchanges outside official payment channels. Chereches et al. (2013)'s review of how the health-related literature has defined IPs highlights the weight place on intention. This is of particular interest when differentiating between gratitude and need or greed payments. While gratitude payments are seen as a benign cultural trait (Yang, 2016), the latter payments aimed at influencing the quality of treatment receive harsher judgment. This distinction illustrates the emphasis on intention as the driving differentiating factor within the health policy literature. On the other hand, theoretical approaches grounded in anthropology (Mauss, 1925) and sociology (Smart, 1993) provide evidence on the importance of impact rather than intention. Whether a gift or monetary exchange is made without any clear intention of seeking reciprocity and favoritism, these are a likely outcome. Currie et al. (2013) find that even a small gift can generate social networks and negative externalities for those who cannot participate in them, often exacerbating inequalities in the standard of care received by various patient groups. This more consequentialist view is also reflected in some recent investigations on the topic of health-related IPs (Dallera et al., 2022; Hunt, 2010; Mavisakalyan et al., 2021). For the purpose of this study, I will consider all types of IPs comparable to petty corruption due to the outcome of creating ingroup and outgroup network externalities for payers and payees regardless of any gratitude-related intentions.

2.2 | What drives and deters informal payments

2.2.1 | A neoclassical economics perspective

The standard economics reading of corruption centers around profit-maximization. If the private benefits of choosing against the public interest are higher than the corresponding costs, economic agents are expected to act in their own benefit, or in this case initiate or accept bribes. Becker and Stigler (1974) and (Rose-Ackerman, 2013), among others, model bribery through a principal agent framework. This approach links the prevalence of bribes to poor incentives—insufficient wages to public officials, low monitoring capacity of the principal affecting the probability of being and a low resulting penalty for those being caught costs are higher than the potential benefits of acting corruptly. However, as pointed out by Rothstein (2010), the principal agent framework loses its explanatory appeal and policy appeal when considering countries with high corruption levels and effectively no functioning sanctioning authorities. Moreover, it assumes uniformity in the behavior of people within the same institutional environment, which is naturally not the case—people have different responses to such incentives.

More recent literature has pictured corruption as a frequency-dependent phenomenon subject to strategic complementarities, the control of which depends on the incentives embedded in existing laws (Tucker, 2007). As a result of these complementarities, societies or sectors which reach some critical level of corruption can fall into a corruption trap, which is difficult to escape. Similar to a poverty trap this would necessitate a big-push which by definition has to be top-down in nature. This turns the problem of corruption from an individual maximization problem into a collective action one (Kurer, 2001; Persson et al., 2013; Tucker, 2007). Creating incentives for one of the parties involved in bribery to self-report could lead to a reduction in this tendency.

Neoclassical economic literature underscores incentives—both in terms of payments and sanctions—as a driver of the decision to engage in corruption. Interpreting it as a collective action problem comes closer to conceptualizing extrinsic and intrinsic drivers. An alternative to this framework is provided by institutional economics (Hogdson & Jiang, 2007; Ostrom, 2011). An institutional theoretical approach can help incorporate mechanisms from social psychology and economic anthropology to way bribery and IPs are modeled (Bicchieri, 2016). It incorporates unwritten rules which show how individual norms are affected by and affect the wider formal institutional climate.

2.2.2 | Institutional theory and social psychology

North (1991) argues against a standard economics approach lacking a consideration of institutions and their role in interpreting the effect of incentives on human behavior. These encompass the formal and informal coordination equilibria, norms, or rules as well as their enforcement mechanisms (Crawford & Ostrom, 1995). Institutional theory considers the interactions between formal and informal institutions as well as their effect on social capital, social cohesion and well-being (Briefs, 1957) which can have a direct effect on the normalization and prevalence of corrupt practices. A standard economics approach argues that formal institutions, that is, sanctions or incentives, can drive and deter corruption. On the other hand, institutional theory recognizes that the effectiveness of these formal rules is often a function of their alignment to informal institutions (Amini et al., 2022; Helmke & Levitsky, 2004).

Lauth (2004) describes the interactions that can occur between the two as either complementary, substitutive or conflicting.

Formal and informal institutions act as complements if the latter create and strengthen the incentives to comply with the former - thus enhancing their efficiency (Tonoyan et al., 2010). On the other hand, they are substitutive when they are functionally equivalent. The two are seen as conflicting when they are completely incompatible. As discussed by Tonoyan et al. (2010) this is especially the case when formal institutions exhibit operational voids, which has continuously been the case in post-communist countries (Pejovich, 1999).

Pejovich (1997) presents a conceptual theory of the interaction between formal and informal institutions in the context of transitioning countries in Eastern Europe. The central proposition of his framework is grounded in the notion that the imposition of new formal rules which were misaligned with the prevailing informal institutions in Eastern Europe has created incentives for rent-seeking and corruption. The author also discusses the role of these coalitions in creating a hybrid economic and political system in the region which remains in perpetual political transition making the strengthening of formal institutions harder (Pejovich, 1999). To understand why and how certain formal institutional characteristics affect the prevalence of bribery, it is necessary to understand how these interact with informal institutions, that is, social norms and conventions. Interdisciplinary approaches in corruption studies linking institutional theory and economics with underlying social norms have become influential due to their ability to encompass wide-ranging theoretical and methodological instruments (Lambsdorff et al., 2004).

More recently, Bicchieri (2005) has put forward a framework of social norms detailing how they affect individual behavioral choices. In this approach, informal institutions in the form of social norms are used to smooth out interactions between group members. As such, they require an individual to them think about their beliefs about how others from the group behave (first-order or descriptive norms) and what others from the group approve or disapprove of (second-order injunctive norms). Bicchieri's framework guides the empirical analysis of this paper and informs the methodological steps taken in measuring how informal institutions, or social norms, affect the prevalence of IPs.

3 | DATA AND METHODOLOGY

3.1 | Survey data and analytical sample

The main source of data for this study is the third round of the Life in Transition survey (LITS) conducted at the end of 2015 and start of 2016 (EBRD, 2016). Undertaken in 34 countries, this survey includes a nationally representative sample of households and covers a range of socio-economic and attitudinal questions, including on corruption perceptions. I use this round because it is both the most recent version of the LITS and because it includes detailed information about IPs and views of respondents regarding corruption in different public administrative branches.

The third wave of LITS is designed to use a multi-stage random probability stratified clustered sampling. The survey employs a list of 75 primary selection units (PSUs) per country. Depending on the country, two different procedures for selecting households were used. These could be directly selected from a list of addresses or a register of individuals. Alternatively, enumerators adopted a random walk sampling approach. Data was collected using face-to-face interviews with a member of the household using Computer-assisted Personal Interviewing

(CAPI) software which assisted in automatically selecting a member of the household to be interviewed.

The focus of the LITS is to trace social developments in post-communist countries in Eastern Europe and Central Asia. However, the round used in this analysis also includes a number of countries which do not fall under this umbrella but are used for comparative purposes—Cyprus, Germany, Greece, Italy and Turkey. I exclude Kosovo for which health system-level data is unavailable. In total, the analysis is done on 33 countries, as shown in Table 1A in the Appendix.

Finally, I restrict the analytical sample to people who have had contact with the health care system. Specifically, those who have used it in the 12 months prior to taking part in the survey in order to capture differences between patients who paid informally and those who did not. Appendix Table 1A describes some of the characteristics of the 33 national level samples.

3.2 | Outcomes

I am interested in two types of outcomes: (i) whether an IP took place and (ii) why the patient made it, allowing me to define the type of the IP following the typology presented in introduction.

First, to determine whether the respondent or someone from their household made some IP when receiving medical treatment, I use the survey question asking: "*Did you or any member of your household make an unofficial payment or gift when using these services over the past 12 months?* ".

Next, to categorize the different types of IPs, I use the detailed information requested from respondents in the survey regarding the reason for paying informally. Figure 1 illustrates the survey flow and relevant questions for the restricted sample. Respondents who made an IP were asked to declare the reason for payment. These are mutually exclusive and can be linked to the four types of payments described in the introduction: "need", "implicit expectation", "greed" and "gratitude".

3.3 | Determinants of IPs

3.3.1 | Individual-level factors

The LITS study includes a broad range of individual characteristics used in this analysis. To guide the choice of covariates, I followed previous investigations of individual-level drivers of IPs in the literature as discussed in the previous section (e.g., Williams & Horodnic, 2015) and included the following ones: relative income level, self-assessed health status, education, gender, age and whether the respondent lives in an urban or rural area.

Notably, due to the survey design and question formulation it is important to consider the possibility that respondents were not sharing their own experience with IPs but this of other members of their household.[1] For the purpose of the analysis I assume that most respondents are likely to share their own experience rather than this of other household members due to misreporting and recall bias (UNODC, 2018). In the case of the former, they might not be aware of any informal exchanges between physicians and members of their household since they happen behind closed doors. Recall bias might be even higher when talking about others' experience.

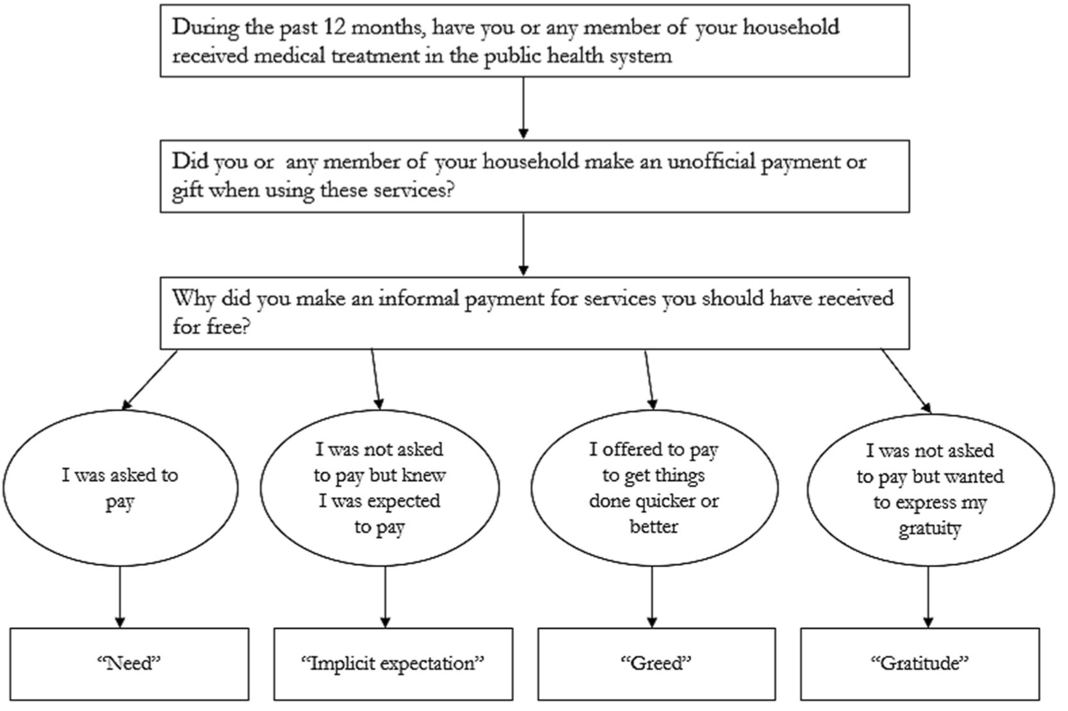

FIGURE 1 Structure of life in transition survey and informal payments-related questions used in the analysis.

3.3.2 | Descriptive social norms

The novel contribution in this part of the analysis is the inclusion of expectations about corruption in public service provision (i.e., how widespread they think IPs are in different sectors). These are used to construct a variable measuring a descriptive corruption norm.

To examine the role of social norms related to corruption, I construct a binary latent class binary index measuring the presence of a descriptive corruption norm. Following the theoretical discussion of Bicchieri and Mercier (2014) I use a composite measure of the respondents' expectations about the frequency of IPs paid by people from their country when interacting with a number of public services. These include civil courts, road police, license issuing agencies, public health care, education, unemployment and social benefits bureaus. The LITS survey includes a series of questions formulated as a vignette.[2] Bicchieri and Mercier (2014) discuss the importance of reference groups, that is, the group an individual might consider vis a vis their expectations. This survey question allows us to understand the norm by pointing to a reference group which respondents can easily identify with.

To compute a measure of corruption-related norms, I use Latent Class Analysis (LCA) to categorize respondents into homogeneous groups. Latent Class Analysis is a probabilistic form of cluster analysis used to identify specific subgroups in a population that share some common response patterns (Lagarde, 2013). Through the LCA, I predict the posterior probability of each respondent's membership in each class.

LCA methodology

To compute a measure of individuals' norms related to corruption, I use LCA to identify qualitatively different subgroups within populations who often share certain underlying traits. The main assumption of LCA is that membership in unobserved groups/classes can be estimated through patterns of scores across scales, such as survey questions. Here, I used responses to vignette-type questions regarding expectations about IPs during interaction with the public sector to uncover people's agreement with some underlying norms about corruption. The number of classes is determined by using goodness-of-fit statistics (Akaike information criterion [AIC] and Bayesian Information Criteria [BIC]). In this study the classes will indicate subgroups with varying corruption-related norms. Let $i = 1,..., N$ denote the respondents. I utilized the responses of each individual to 8 survey questions related to beliefs about others' interactions with public administration representatives and service providers were used to construct a measure of norms about corruption. Respondents were asked *"In your opinion, how often do people like you have to make unofficial payments or gifts in these situations?"* in reference to the following scenarios:

- Interact with the road police;
- Request official documents (e.g., passport, visa, birth or marriage certificate, land register, etc.) from authorities;
- Go to courts for a civil matter;
- Receive public education (primary or secondary);
- Receive public education (vocation);
- Receive medical treatment in the public health system;
- Request unemployment benefits;
- Request other social security benefits.

Respondents were asked to assess this likelihood on a five-point Likert scale from never to always. For the LCA, I recoded these 8 categorical variables into binary ones. For each question denoted $k = 1,..., 8$, $Y_{ik} = 0$ if individual i chose "never" for question k in the original five-point scale and $Y_{ik} = 1$ otherwise.

Table 1 shows the AIC and BIC tests results which are conventionally used to determine the optimal number of classes. Although the three-class model has a lower BIC, AIC and L^2 values, the %-reduction in all measures represents a relatively little improvement when switching between the 2 and 3 class models. A similar approach to determining the optimal dimensionality is adopted by Hooghe et al. (2016). Therefore, a 2-LC solution was used for this analysis.

LCA results

The results of the statistical analysis suggest that individuals' expectations broadly fall into two groups, corresponding to two distinct norms: a ***low-corruption*** norm, corresponding to respondents who believe that no bribery will be necessary when interacting with public systems, and a ***high-corruption*** norm, whereby there is an underlying expectation that bribery is necessary when receiving a public service.

I estimated the posterior probability for each individual belonging in a class and the one associated with a higher probability was assumed to be the true class of the respondent (Lagarde, 2013). Based on this I constructed a binary norm variable which was used to determine the prevalence of both types of corruption norms. It ranges between 4.47% (Germany) and 43.7% (Kyrgyzstan) of patients with an average of 21.3%. Appendix Table 2A presents the prevalence of the norm across all countries in the sample. I used the norm variable to calculate

TABLE 1 Akaike's information criterion and Bayesian information criterion.

Model	N	L^2 (null)	L^2 (model)	df	AIC	BIC
1 class	48,943	.	−170,736.7	8	341,489.3	341,559.7
2 class	48,943	.	−112,396.7	17	224,827.4	224,976.9
3 class	48,943	.	−105,659.3	26	211,370.7	211,599.4

Note: BIC uses N = number of observations.

the predicted probabilities of paying informally at different levels of the national-level variables for each of the latent classes. To ensure the robustness of the LCA strategy I present an alternative specification excluding the health-related question. The results of this analysis are reported in Table 2A in the Appendix. Moreover, I performed a paired *t*-test of the difference in means and found that there is no significant difference between the two sets of LCA results, signifying the robustness of this approach.

To ensure robustness of the results I also estimate the prevalence of the high-corruption norm when the assignment rule changes. In the sample there are 74 observations which have posterior probability close to 0.5, that is, the probability of belonging to one class is not substantially different from belonging to another. Given that most observations are in the extremes (around 0 and 1) small changes to the threshold could affect overall results. Therefore, I perform two sensitivity analyses and recalculate the mean prevalence of the high-corruption norm across countries. I look at the following cases - if individuals are assigned to the high-corruption norm class given a posterior probability of belonging to this class (1) higher than 0.45 or (2) higher than 0.55. I present these estimates in Table 2A of the Appendix and demonstrate that the country-level prevalence estimates are robust to changes in class assignment thresholds.

To account for the underlying levels of corruption on the country-level, I also compare the results from the LCA to each country's 2016 Corruption Perception Index (CPI) value (Transparency International, 2016). The value of each country's CPI for 2016 is also presented in Table 2A and discussed further in relation to the measure of social norms in the Appendix is an aggregate index of the perceptions about public sector corruption of businesspeople and country experts. Higher levels of CPI are associated with lower perceived corruption. Notably, in contrast to the corruption norm measure I construct, the CPI reflects the views of a specific subgroup of the population rather than a representative sample. Also, it does not represent the reference group for the LITS sample where people are asked to assess the behaviors of *others like them*. Lastly, I also use the country-level CPI score as an independent variable in the main regression analysis to rest for overall corruption.

3.3.3 | Health system factors

To determine the role of institutions, I consider three characteristics of healthcare systems linked to financing and resource availability. These are the share of GDP spent on healthcare and the number of physicians per 1000 people. These features signal the financial protection and resource availability within the health system. The data were obtained through the World Bank Open Data platform (World Bank, 2023). The data used is for 2015 since it reflects the state of the health system during the 12 months prior to participating in the survey (which is the period under consideration in the survey questions, see Figure 1). If the country-year observation was missing from the World Bank dataset, then it was replaced with the one from 2014. It is assumed that these institutional capacity factors are quite sticky and take time to adjust.

3.4 | A multilevel statistical analysis

To analyze the influence of the different types of predictors, I use a two-level random intercept logistic regression model (Rodriguez and Goldman (1995); Hox et al. (2017)). The two levels will be given by individuals (Level 1) nested in countries (Level 2). If data of hierarchical nature is analyzed using a single-level methodology, the obtained estimator values would be biased and overestimated (Snijders, 2011).

I include a number of socioeconomic and demographic characteristics that will be taken into account in accordance with the literature. These include self-reported health status, gender, age, urban or rural place of living, level of formal education, income and corruption norm class. These covariates are represented by vector $X_n = X_1 + X_2 + \ldots + X_N$. Equation (1) shows the estimated reduced form equation,

$$\log \frac{\pi_{ik}}{1-\pi_{ik}} = y_{ik} = \beta_0 + \sum^{N} \beta_n X_{nik} + \gamma z_k + \epsilon_k \tag{1}$$

where π_{ik} reflects the probability of making an IP for individual i in country k. β_0 is the common country-invariant intercept and β_n represents the regression coefficient for each individual-level variable x_{ik}. ϵ_k represents the country random effect, or the country-specific deviation from the fixed intercept. The residual term is assumed to have zero mean and constant variances $\sigma^2_{\epsilon_k}$. z_k represents each national-level variable which will be controlled for in the second part of the analysis and γ is the relevant regression coefficient. When I focus on individual-level characteristics only, its coefficient γ is 0. The same regression equation will be estimated for each payment reason.

3.5 | Research hypotheses

The main research hypotheses I will consider in this paper are as follows:

1. Individual characteristics identified in previous studies (being a woman, older, less educated, with a lower socioeconomic status and living in urban areas) have a positive association with IPs prevalence.
2. Social descriptive norms linked to corruption have a positive association with IPs prevalence.
3. Institutional characteristics (lower overall health spending as share of GDP and lower physician density) have a positive association with IPs prevalence.
4. The associations between IPs and individual and institutional characteristics or social norms depend on the reason for payment, that is, the type of IP.

4 | RESULTS

4.1 | Estimating an empty multilevel model

Snijders (2011) discusses the grounds for statistical bias in cases when hierarchical data is not analyzed in a multilevel framework. Namely, the dependence of the observations at the lower level can lead to Type 1 error when trying to test for statistical significance of the relationship between covariates. In order to check whether the choice of a multilevel structure is appropriate, a likelihood ratio test is carried out comparing an empty (null) two-level model to a single-level one. The reduced form of this baseline empty model is given by:

$$\log\left(\frac{\pi_{iq}}{1-\pi_{iq}}\right) = y_{iq} = \beta_0 + \epsilon_q \tag{2}$$

where π_{iq} reflects the probability of making an IP for individual i in country q. β_0 is the common country-invariant intercept. ϵ_q represents the country random effect, or the country-specific deviation from the fixed intercept. The residual term is assumed to have zero mean and constant variances $\sigma^2_{\epsilon_q}$. Figure 2 presents a caterpillar diagram of the 95% confidence intervals of the country-specific effects. The figure illustrates that the intervals for only a small number of the countries cross the 0-line (Montenegro, Greece, Serbia, Slovak Republic and Turkey) while all other countries exhibit country effects which are significantly different from 0.

Lastly, I also estimate the interclass correlation coefficient (ICC). This measure provides information on the percentage of the total variance in the probability of making an IP that is attributable to the country level, or a statistic of clustering of odds of making IPs in the same

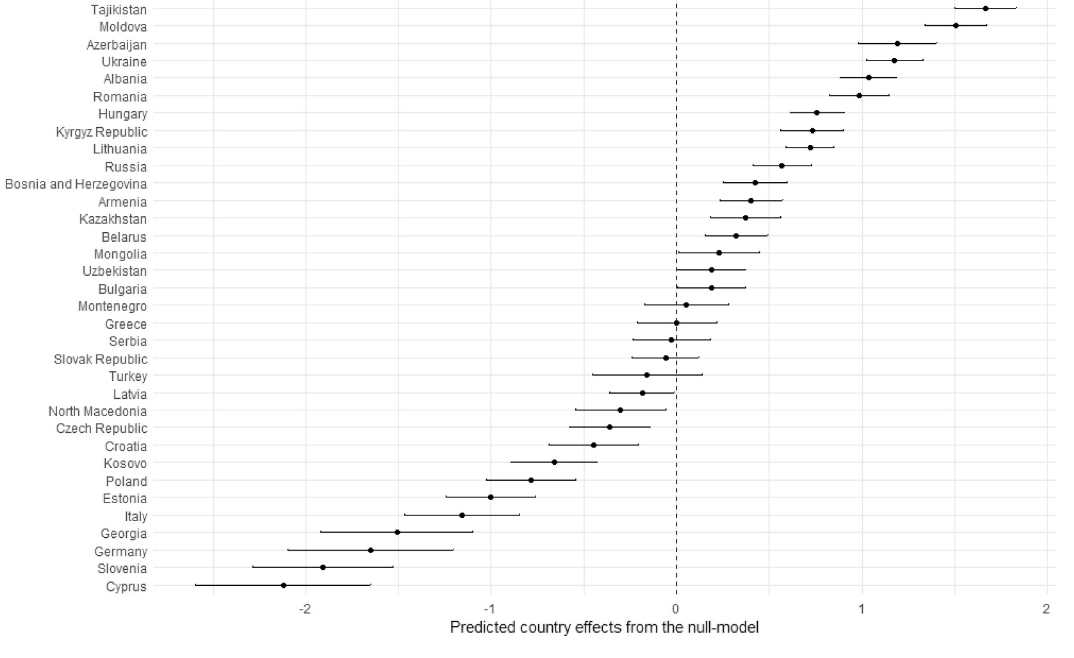

FIGURE 2 Caterpillar diagram of predicted country effects.

country. The analysis uses a logit multilevel regression, and the ICC accounts for the logistic distribution of individual error terms assumed in such regression models and its approximate variance of $\frac{2\pi}{3}$. It is therefore adapted from the linear ICC formula which involves individual-level error terms as:

$$\rho_{\text{logit}} = \frac{\widehat{\sigma^2_{\epsilon_q}}}{\widehat{\sigma^2_{\epsilon_q}} + \frac{2\pi}{3}} \tag{3}$$

Using the equation above, I estimate the ICC for the null model to be 0.213. This means that 21.3% of the total variance is attributed to between-country variance. Following the relevant methodological literature (see for example Amini & Douarin, 2020; Snijders, 2011), this result is sufficient to substantiate the choice of multilevel regressions.

4.2 | Prevalence and types of informal payments

I first describe the sample used in the analysis based on whether the respondents paid informally when using the public health system. Overall, 15.8% of the respondents who used the public healthcare system in the 12 months prior to taking part in the survey reported that they or a member of their family paid informally. The share is lowest in Slovenia (2.1%) and highest in Tajikistan (45.7%). Table 1A in the Appendix lists the share of patients who paid informally in all countries in the sample.

95% of all those who reported an IP declared the reason for making the payment. The most common type of payment in the sample is “gratuity” (30.83%) followed by “implicit expectation” (26.30%), “greed”′ (19.65%) and “need” (18.37%). The remaining 4.85% of patients who paid informally either refused to provide a reason for it or did not know what the reason for the IP was.

4.2.1 | Individual characteristics and social norms

Firstly, to test the effect of individual-level characteristics, I regressed the binary outcome indicating whether a patient has paid on a number of individual-level covariates. As discussed in Section 1 there is mixed evidence of the association between personal characteristics and the likelihood of making IPs. In this sample, I find that age, gender, health status and income are significantly associated with a change in the odds of paying informally. The regression results are reported in detail in Table 2. Female (OR 1.10; p-value <0.01) and younger (OR 0.99; p-value <0.01) patients have higher odds of making IPs. The largest changes in the odds of paying informally are linked to health status and income. Patients who report average (OR 1.36; p-value <0.01) or very bad health (OR 1.71; p-value <0.01) status are more likely to make IPs compared to those who would describe it as very good.

Patients who are not in the poorest quartile in their respective country are also significantly less likely to pay informally than those who are. Additionally, as patients climb up the national income ladder the relative odds of paying informally increase. For example, those who are in the top 25% have significantly higher odds of paying informally than those at the bottom (OR

TABLE 2 Multilevel regression results with individual variables, social norms and institutional characteristics.

	(1)			(2)			(3)		
	Odds ratios	**Std. Error**	***p***	**Odds ratios**	**Std. Error**	***p***	**Odds ratios**	**Std. Error**	***p***
Fixed effects									
(Intercept)	0.08	0.02	**<0.001**	0.47	0.34	0.289	1.46	0.88	0.530
Age	1.00	0.00	**0.004**	1.00	0.00	**0.005**	1.00	0.00	**0.007**
Gender (female)	1.10	0.04	**0.022**	1.10	0.04	**0.014**	1.10	0.04	**0.014**
Urbanity (urban)	0.98	0.04	0.648	0.99	0.04	0.784	0.99	0.04	0.782
Health status (average)	1.36	0.06	**<0.001**	1.38	0.07	**<0.001**	1.38	0.07	**<0.001**
Health status (very bad)	1.71	0.11	**<0.001**	1.72	0.11	**<0.001**	1.72	0.11	**<0.001**
Education (primary)	1.16	0.22	0.444	1.13	0.23	0.554	1.13	0.23	0.535
Education (secondary)	1.29	0.24	0.163	1.25	0.24	0.249	1.26	0.24	0.237
Education (higher)	1.36	0.26	0.103	1.32	0.27	0.163	1.33	0.27	0.151
2nd income quartile	1.22	0.07	**<0.001**	1.22	0.07	**0.001**	1.22	0.07	**0.001**
3rd income quartile	1.43	0.08	**<0.001**	1.43	0.08	**<0.001**	1.44	0.08	**<0.001**
4th income quartile	1.50	0.09	**<0.001**	1.52	0.09	**<0.001**	1.53	0.09	**<0.001**
Descriptive norm (high-corruption norm)	1.53	0.07	**<0.001**	1.51	0.07	**<0.001**	1.51	0.07	**<0.001**
Physician density (per 1000 people)				0.81	0.10	0.082	0.89	0.08	0.195
% Of GDP spent on health				0.86	0.07	0.078	0.94	0.06	0.396
Corruption perceptions index 2016							0.95	0.01	**<0.001**

(Continues)

TABLE 2 (Continued)

	(1)			(2)			(3)		
	Odds ratios	**Std. Error**	***p***	**Odds ratios**	**Std. Error**	***p***	**Odds ratios**	**Std. Error**	***p***
Random effects									
σ^2	3.29			3.29			3.29		
$\tau_{00\ \text{country}}$	0.92			0.77			0.42		
ICC	0.22			0.19			0.11		
N_{country}	34			33			33		
Observations	22,799			21,957			21,957		
Marginal R^2/Conditional R^2	0.020/0.234			0.060/0.238		s	0.152/0.247		

Note: The outcome variable is a binary measure of whether an IP was made or not in the 12 months prior to taking the survey. Coefficients reported as odds ratios. In the case of categorical variables, the base level was omitted. These are Gender (Male), Urbanity status (rural), Health Status (Very good), Education (none), 1st Income Quartile (lowest) and Descriptive norm (low-corruption norm). The table presents robust standard errors. Statistically significant *p*-values are in bold.

1.50; p-value <0.01). Notably, patients who exhibit the high-corruption descriptive norm have significantly higher odds of making an IP compared to those in the low-corruption norm class (OR 1.53; p-value <0.01). This analysis provides sufficient evidence to support Research Hypotheses 1 and 2.

The random effects of the model demonstrate that the variance within countries (σ^2) is 3.29 while the variance between the random intercepts (τ_{00}) is 0.92. The latter measures how much the average outcome measure varies from one country to another. Lastly, the ICC shows that 22% of the total variance is attributable to differences between countries.

4.2.2 | System-level characteristics

Next, I analyze the extent to which key country-level characteristics predict the likelihood of paying informally, by using multilevel logistical regressions. The results reported in Table 2 highlight the importance of institutional factors to understand the in prevalence of IPs. A higher % of GDP spent on healthcare has a significant negative association with the odds of an IP (OR 0.86, p-value = 0.08). Lastly, physician density, measured by the number of physicians per 1000 people, is linked to a lower likelihood of paying informally (OR 0.81, p-value = 0.08). This suggests that competitive pressure may be reducing the occurrence of IPs. Overall, the relationship between institutional effects and the odds of paying informally confirm the link between improved resource availability and decreased probability of IPs, providing evidence in support of Research hypothesis 3.

The results of the regression analyses using both individual and health-system level characteristics hold even after I control for the underlying country-levels of corruption as measured by the CPI (see the third column in Table 2). The lower the CPI, the higher corruption is in the country and vice versa. The results of my analysis also demonstrate that higher CPI is significantly associated with lower odds of making an IP (OR 0.95, p-value <0.01).

The predicted probability of making an IP for respondents of each norm-type at different levels of GDP spent on healthcare and physician density are reported in Table 3A in the Appendix.

The variance within countries remained unchanged while the variance between the random intercepts is 0.77. The latter measures how much the average outcome measure varies from one country to another. Lastly, the ICC shows that 19% of the total variance is attributable to differences between countries.

4.2.3 | Interaction terms

Next, I implement interaction terms between socioeconomic level variables and the measure for descriptive norms similar to Amini and Douarin (2020). This allows me to test whether the effect attributed to high-corruption norms is driven by differences in other factors such as income, education and gender. I report the detailed results in the Appendix (see Table 5A). Overall, most of the interaction terms are insignificant. The only exception to this is the interaction term between the high corruption norm and the highest income group (OR 1.26, p-value = 0.06). This shows that the social norms effect is particularly strong effect for the richest quartile in each country. However, this becomes insignificant once institutional variables (physician density and % of GDP spent on health) are controlled for.

4.3 | Relationship between norms and types of payments

Next, I break down the outcome variable into 4 categories and run a separate regression for each category. Rather than looking at whether a patient has made a payment, I considered the reason as described by the payer. Each of the four reasons (see Figure 1) is considered as a separate outcome variable. I investigated the association of each of these reasons to the corruption norm while controlling for both individual- and system-level characteristics. The results of this analysis are reported in Table 3 and a detailed regression output can be found in Table 4A in the Appendix.

Three of the payment types (need, greed, expectations) follow a trend mirroring the general dynamic described above. Belonging to the high-corruption norm class rather than the low-corruption one is positively associated with making these three payments. However, the opposite is true for patients who made a "gratitude" payment. The high-corruption norm class is associated with significantly lower odds of making an IP of this type (OR 0.87; *p*-value = 0.027). When considering the effect of country-level characteristics on predicted odds, results are mixed. Higher health expenditure as % of GDP is associated with higher odds of making need, implicit expectation, and gratitude payments. Notably, it is also linked to a significant decrease in the odds of making greed payments (OR 0.88, *p*-value = 0.03). Physician density has no significant association with the likelihood of making any of the payment types. It is linked to a decrease in the odds of making need and implicit expectation payments, and an increase in the odds of making greed and gratitude payments. The detailed output including institutional characteristics is included in Table 4A in the Appendix.

The random effects differ substantially across payment types. Especially, the variance in random intercepts in the case of need and gratitude payments are much higher than these for greed and implicit expectation payments. A similar difference can be seen in the case of the ICC.

4.4 | Robustness checks

4.4.1 | LPM with country-level fixed effects

To test the robustness of the results presented above with respect to model specification, I estimated a single level linear probability model (LPM) with a country fixed effects. This robustness check reflects the literature and the estimation strategies used in other studies looking at bribery in Eastern Europe (Ivlevs & Hinks, 2018). The model is specified as an Ordinary Least Squares regression and takes the following form:

$$Y_i = \beta_0 + \sum_N \beta_i * X_i + \gamma_k + \epsilon_i$$

The outcome variable is whether or not the individual made an IP and the independent variables are all individual -level characteristics and the corruption norm measure. γ_k represents the country-level effects. The results are reported in Table 4 (**Basic LPM).** Although the coefficients cannot be compared to the odds ratios in terms of magnitude and direct interpretation, the direction of the association and significance follow the same trend as the results obtained in the multilevel analysis. This shows that the results obtained in the multilevel analysis are robust to changes in model specification.

TABLE 3 Regression results for payment types.

	Need			Implicit expectation			Greed			Gratitude		
	Odds ratio	**SE**	***p***	**Odds ratio**	**SE**	***p***	**Odds ratio**	**SE**	***p***	**Odds ratio**	**SE**	***p***
Fixed effects												
(Intercept)	0.31	0.16	**0.024**	0.23	0.10	**0.001**	0.19	0.11	**0.003**	0.51	0.23	0.133
Age	1.00	0.00	0.130	1.00	0.00	0.334	0.99	0.00	**0.010**	1.01	0.00	**0.010**
Gender (female)	1.00	0.10	0.965	0.98	0.08	0.810	0.90	0.08	0.243	1.09	0.09	0.268
Urbanity (urban)	1.07	0.11	0.522	0.96	0.08	0.644	1.06	0.10	0.525	0.94	0.08	0.494
Health status (average)	0.93	0.11	0.550	1.01	0.10	0.905	1.18	0.12	0.111	0.87	0.08	0.160
Health status (very bad)	1.01	0.15	0.965	1.05	0.13	0.697	1.35	0.19	**0.032**	0.72	0.09	**0.011**
Education (primary)	0.91	0.41	0.827	1.06	0.43	0.890	1.41	0.73	0.509	0.84	0.34	0.670
Education (secondary)	0.82	0.35	0.651	1.26	0.49	0.560	1.29	0.65	0.608	0.78	0.30	0.514
Education (higher)	0.71	0.32	0.445	1.12	0.45	0.782	1.29	0.66	0.621	0.94	0.37	0.868
2nd income quartile	0.84	0.11	0.187	0.99	0.11	0.901	1.18	0.16	0.220	1.02	0.12	0.862
3rd income quartile	0.79	0.11	**0.094**	1.01	0.12	0.909	1.21	0.16	0.160	1.01	0.12	0.929
4th income quartile	0.65	0.10	**0.004**	1.02	0.13	0.847	1.34	0.19	**0.034**	1.04	0.13	0.752
Descriptive norm (high-corruption norm)	1.03	0.10	0.778	1.06	0.09	0.514	1.15	0.11	0.119	0.83	0.07	**0.027**
Random effects												
σ^2	3.29			3.29			3.29			3.29		
$\tau_{00\ country}$	1.35			0.27			0.26			0.71		
ICC	0.29			0.08			0.07			0.18		
$N_{country}$	34			34			34			34		

(Continues)

TABLE 3 (Continued)

	Need			Implicit expectation			Greed			Gratitude		
	Odds ratio	**SE**	***p***	**Odds ratio**	**SE**	***p***	**Odds ratio**	**SE**	***p***	**Odds ratio**	**SE**	***p***
Observations	3444			3444			3444			3444		
Marginal R^2/Conditional R^2	0.006/0.296			0.002/0.078			0.012/0.084			0.009/0.185		

Note: The outcome variable is a binary measure of whether an IP was made or not in the 12 months prior to taking the survey. Coefficients reported as odds ratios. In the case of categorical variables, the base level was omitted. These are Gender (Male), Urbanity status (rural), Health Status (Very good), Education (none), 1st Income Quartile (lowest) and Descriptive norm (low-corruption norm). The table presents robust standard errors. Statistically significant p-values are in bold.

TABLE 4 Regression output from the LPM and Heckman correction models.

				Heckman selection models					
	Basic LPM			Car ownership			House ownership		
Predictors	**Estimates**	**SE**	***p***	**Estimates**	**SE**	***p***	**Estimates**	**SE**	***p***
(Intercept)	0.04	0.03	0.089	0.42	0.08	**<0.001**	0.05	0.18	0.781
Age	−0.0004	0.0001	**0.007**	0.02	0.009	**<0.001**	0.001	0.008	0.529
Gender (female)	0.011	0.005	**0.022**	−0.01	0.01	0.076	0.01	0.01	0.367
Urbanity (urban)	−0.001	0.005	0.813	0.001	0.01	0.834	−0.001	0.01	0.788
Health status (average)	0.04	0.01	**<0.001**	−0.003	0.01	0.736	0.04	0.02	0.056
Health status (very bad)	0.06	0.01	**<0.001**	−0.01	0.02	0.48	0.06	0.04	0.079
Education (primary)	0.01	0.02	0.486	0.01	0.02	0.652	0.01	0.02	0.508
Education (secondary)	0.02	0.02	0.217	0.02	0.02	0.198	0.02	0.02	0.226
Education (higher)	0.03	0.02	0.134	0.02	0.02	0.325	0.03	0.02	0.15
2nd income quartile	0.02	0.01	**<0.001**	−0.003	0.01	0.65	0.02	0.01	0.113
3rd income quartile	0.04	0.01	**<0.001**	−0.0002	0.01	0.984	0.04	0.02	0.05
4th income quartile	0.05	0.01	**<0.001**	−0.01	0.01	0.643	0.05	0.03	0.077
Descriptive norm (high-corruption norm)	0.06	0.01	**<0.001**	0.03	0.01	**0.004**	0.06	0.02	**0.001**

(Continues)

TABLE 4 (Continued)

Predictors	Basic LPM			Heckman selection models					
				Car ownership			House ownership		
	Estimates	SE	*p*	Estimates	SE	*p*	Estimates	SE	*p*
IMR				−0.34	0.07	**<0.001**	−0.01	0.16	0.969
Observations	22,799			22,799			22,756		
R^2/R^2 adjusted	0.091/0.089			0.092/0.090			0.091/0.089		
Selection probit models (coefficients reported as risk ratios)									
Car ownership			1.15	0.02	**<0.001**				
House ownership							0.94	0.02	**0.001**
Other controls			YES				YES		
Observations			39,867				39,761		
R2 nagelkerke			0.05				0.047		

Note: The outcome variable is a binary measure of whether an IP was made or not in the 12 months prior to taking the survey. In the case of categorical variables, the base level was omitted. These are Gender (Male), Urbanity status (rural), Health Status (Very good), Education (none), 1st Income Quartile (lowest) and Descriptive norm (low-corruption norm). The table presents robust standard errors. Statistically significant *p*-values are in bold.

Abbreviation: LPM, linear probability model.

4.4.2 | Heckman correction

The main analysis reported is based on a subsample of respondents who could have been affected by bribery in healthcare. As presented in Figure 1, the filtering question related to the use of healthcare excludes non-users. This could lead to a selection issue given that the sample is not drawn from a random distribution (Wooldridge, 2002). To avoid this bias, I use an extension of the original Heckman correction model which allows for discrete dependent variables (Heckman, 2013). This model requires an identification variable which would be associated with the probability of having contact with the public healthcare system but not with the probability of paying a bribe. Following the literature which has also utilized the LITS survey for studying bribery in public services and healthcare specifically, I use binary variables pointing to house and car ownership for this identification (Ivlevs & Hinks, 2015, 2018; Mavisakalyan et al., 2021). The selection models demonstrate that both identification variables (car and house ownership) are significant and follow the same directions as reported in previous studies (Ivlevs & Hinks, 2015; Mavisakalyan et al., 2021), whereby car ownership is associated with higher usage of health and home ownership with lower. Using these selection models, I calculated the Inverse Mill's Ratio (IMR) and included it as an independent variable in the two linear probability regressions estimating the probability of making IPs. The Heckman correction model is often applied to linear models rather than logistic ones (Ivlevs & Hinks, 2018). Therefore, I apply the correction to the results obtained from the LPMs above given the similarity in direction and significance they exhibit to the main model specification.

Only the IMR calculated from the car ownership model is statistically significant indicating the presence of a selection bias. It is also negative (−0.34), implying an omitted variable(s) which has an opposite effect on using the public healthcare system and making an IP (Ivlevs & Hinks, 2015). A possible explanation suggested by Ivlevs and Hinks (2015) is general accessibility of public services. In the case of healthcare this can include distance to the closest public clinic, working hours, availability of specialists.[3] People who find it difficult to access healthcare for various reasons might try to avoid using it, but they might be more likely to make an IP when they do. Another potential explanation is private insurance coverage. Individuals who have private insurance might be less likely to use public healthcare. However, when they do they might be more likely to make IPs to ensure they get the same benefits as they do from private providers.

5 | DISCUSSION

This is the first study to quantitatively compare different types of IPs. Moreover, it is the first study to introduce a descriptive corruption norm measure bridging the gap between recent trends in the general corruption literature and the health-focused studies about IPs. By utilizing LCA to measure norms I introduce a theory grounded approach to measuring the associations between corruption norms and IPs while still controlling for individual- and national-level characteristics.

This analysis demonstrates the complexity of IPs. Firstly, on an individual level I find that patients who are younger, female, richer and in worse health have significantly higher odds of making IPs. Additionally, those who exhibit a high-corruption norm are also more likely to pay informally. After including national-level characteristics, I found that a lower share of GDP spent on health is significantly linked to higher odds of making IPs. These results hold even after introducing a measure of underlying country-level corruption as the CPI. An important contribution of this analysis is understanding that not all payment types have the same association with these characteristics.

The results of this analysis have important consequences for measuring IPs and designing policy instruments to mitigate them. Implementing social norms into the study of IPs opens the door for a new set of policy tools which could mitigate the practice. Targeted public information campaigns and behavioral instruments have been studied as a way of changing norms. These can complement larger reforms. Importantly, rather than highlighting the negative impacts of corruption, campaigns can instead focus on addressing the underlying norms of the population. Köbis et al. (2022) find that exposing people to a poster campaign aiming to update their descriptive norms (i.e., their expectations about others' bribing behaviors) reduced the likelihood of bribery in a corruption game. Adapting this mechanism to healthcare could involve placing similar posters or leaflets addressing the expectations of patients and providers about how common IPs are.

The analysis of different types of IPs unveiled gratitude payments as an outlier in their relationship to institutional and social norms measures. One possible explanation is that even when institutional drivers of IPs are addressed, there is a path dependency in patients' behavior. Therefore, perhaps as systems improve IPs remain but are seen as a token of gratitude rather than an explicit barrier to care. However, these can still impact the equitable delivery of care negatively. Historically, Mauss (1925) discusses the importance of gift-giving, where repaying the gift in one way or another was always seen as an obligation. Mauss (1925) also investigates the role of gifts as the main form of transaction where the marketization of certain services was not well-developed. Given the dramatic political and economic transitions in Eastern Europe and Central Asia over the past 3 decades, these informal exchanges could substitute formal regulated channels (Ledeneva, 1998). As such, although given as gratuity, gifts trigger an obligation for repayment in the receiver (Bourdieu, 1977). Baez Camargo et al. (2017) implemented a field experiment aiming to reduce the negative network effects of gratitude IPs. They targeted individual physicians by nudging patients into donating the IP to the clinic and paying it anonymously rather than to the provider and saw a reduction. While their intervention relied on a different set of norms, namely injunctive social norms, their results also point to a reduction in gift-giving. Alternatively, individuals with high-corruption norm might be more willing to describe their behavior as a non-gratitude payment as the social sanction they might face is lower. If an individual believes that others like them (their reference group as per Bicchieri (2016) behave in the same way and normalize the behavior of making IPs, there is less of a cognitive dissonance or social desirability bias when sharing one's own experience. Liu et al. (2017) discuss the ability of decision-makers to rationalize their behavior when choosing to engage in bribery or not. Similarly, individuals who believe that their reference group does not engage in bribery or IPs might be more likely to think about their behavior as benign expression of gratitude. This means they are not deviating from the norm in any substantial ethical way and will not bear social sanctions as a result (Bicchieri, 2005). On the other hand, those who think corruption is common in their reference group, might be more likely to label their exchanges as corrupt as the potential social sanctions are lower given that they are conforming to the norm.

This analysis also has some limitations. When studying a practice such as IPs quantitatively, data is often unreliable. Although these payments are commonplace in many of the countries in our sample, there are social desirability concerns survey respondents might experience when answering questions on the topic. When analyzing IPs overall, this limitation is likely to lead to an underestimate of the true prevalence. However, in the case of IP types, it might be the case that underreporting occurs differently and would affect need payment more than gratitude payments, for example, It is possible that the data also suffers from some selection bias as indicated by one of the two Heckman selection models. Furthermore, when calculating the effects of various interaction terms in single-level logit and probit regressions, further corrections need to be implemented in order to avoid biases and type-1 errors (Ai & Norton, 2003). However, in the case of models using multilevel models, it is computationally challenging and there exist no statistical packages able to perform the same corrections (Sommet & Morselli, 2017). While this might result in some biases *sometimes* (but not always (Sommet & Morselli, 2017)), the literature has advocated for the use of the simple significance-of-the-product-term approach adopted in the analysis here. Lastly, existing literature has indicated the potential reverse causality which exists between an individual's health status and the probability of paying informally (Habibov & Auchynnikava, 2022; Mavisakalyan et al., 2021). My analysis demonstrates that as health status becomes worse, the likelihood of making an IP increases. However, it could also be the case that as the prevalence of IPs increases, individuals have less trust, willingness or ability to utilize the healthcare system resulting in worse health outcomes. Further research is needed to understand the true causal directionality of this relationship and in particular more reliable data across many time periods. Additionally, instead of self-assessed health status, other measures of healthcare utilization, relative quality and outcomes would be necessary.

6 | CONCLUSION

This analysis highlights the variety and complexity of IPs and aims to bridge a gap between the health economics and the wider corruption literature, which has acknowledged this diversity. Descriptive social norms, lower GDP spending are associated with higher odds of making need, greed, and implicit expectations IPs. However, this is not the case for gratitude IPs. Considering this, it is important to re-visit anti-corruption policies in healthcare and incorporate a more holistic view of IPs and their determinants. As laid out throughout this analysis, social norms must become a consideration of anti-corruption practitioners when designing policy tools. They can be used to understand the prevalence of health-related corruption as well as effective prevention mechanisms. This analysis also points to the necessity of thinking IPs as a heterogenous phenomenon. While reasons for payments are rarely included in large cross-sectional or nationally representative surveys, these results present an important consideration when thinking about why some anti-corruption policies have had such varied success across different regions. Understanding why patients pay informally can inform subsequent policy design due to the differential effectiveness of investing in health institutions as a mitigation strategy on its own.

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DATA AVAILABILITY STATEMENT

A dataset of all publicly available data used in the study is available from the corresponding author at i.parvanova@lse.ac.uk.

TRANSPARENCY DECLARATION

I affirm that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

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ENDNOTES

[1] `Did you or any member of your household make an unofficial payment or gift when using this service'

[2] `In your opinion, (how often) do people like you have to make unofficial payments or gifts when interacting with [*public service institution*]?'

[3] The physician density variable included in the analysis does not capture the differentials in physician availability based on type of care/specialization.

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