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Country Perceptions Shape Transnational Bribery and its Deterrence

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Abstract

Punishment is commonly believed to deter bribery. Yet, in transnational contexts with fragmented enforcement responsibility across countries, punishment effectiveness depends on public perceptions about the enforcing countries. We bridge behavioral experimentation and computational social science by combining an incentivized behavioral experiment across 20 countries (N = 4,081; 81,620 decisions) alongside a large-scale media sentiment analysis spanning 16 years. Participants' expectations about corruption and punishment in different countries predicted bribery behavior. These expectations aligned with media narratives portraying countries as more or less corrupt, revealing a close relationship between media discourse and bribery decisions. These findings suggest that anti-corruption efforts must address not only legal frameworks but also information environments influencing public perceptions, highlighting the complex interplay between enforcement credibility and media discourse in transnational bribery.

Global commerce is expanding, and with it, transnational bribery (*1*). While transnational corruption was once primarily associated with high-level political or corporate actors, it now increasingly affects ordinary citizens navigating international bureaucracies and markets (*2*). Bribery distorts fair competition, undermines public trust in democratic institutions (*3*, *4*), stifles development (*5*), and damages the environment (*6*, *7*). Although laws prohibiting transnational bribery exist, their enforcement remains inconsistent and fragmented. Thus, the central question is not whether bribery is illegal, but whether punishment is expected and, therefore, effective.

Critically, transnational anti-bribery enforcement is at risk because the current US administration has decided to strongly scale back its enforcement of the Foreign Corrupt Practices Act (FCPA; *8*). Since its enactment in 1977, the FCPA has become the backbone of global anti-bribery enforcement (*9*, *10*). With the current uncertainty surrounding the FCPA's role (*11*), international responsibility for punishing bribery is now dispersed across various actors. In this moment of transition, enforcement of transnational anti-bribery is increasingly critical.

Punishment is widely regarded as the primary remedy for corruption (*12*). A large body of behavioral research shows that sanctions can indeed deter unethical behavior (*13–15*) and, in particular, corruption (*16–18*), as they enforce social norms and induce fear (*19*), guilt aversion, or fairness concerns (*20*). Yet, punishment does not always work. In transnational settings, where various authorities govern interactions and enforcement is uncertain, subjective perceptions of enforcement probability may matter more than formal rules. Indeed, individuals are less likely to offer bribes when they expect officials to intervene, even if those expectations are inaccurate *(21)*. If people believe bribery will go unpunished, misconduct may rise, even when legal sanctions remain in place, because deterrence depends not only on legal design but also on expectations.

Recent policy reports have called for more behavioral insights into corruption (*22*), but, especially in the context of transnational bribery, such insights remain lacking. A nascent body of experimental work has begun to answer that call by simulating bribery in controlled, incentivized games across countries (*21*, *23*). In these studies, participants from across the world interact as citizens and public officials and decide whether to offer and accept “unofficial payments”. In line with canonical bribery games (*23*) as used here, offering and accepting such payments result in mutually beneficial outcomes for both parties involved but impose negative externalities on others. These experimental games offer a controlled method for measuring bribery and expectations regarding bribery, and their validity has been supported by real-life behavior (*24*). This behavioral approach to corruption enables researchers to compare the expected and actual frequencies of bribery across countries. To our knowledge, this is the first study to systematically link incentivized behavioral bribery data with large-scale computational media sentiment analysis across countries.

Moreover, behavioral corruption studies have shown that bribery is conditional (*25*): people are more likely to engage in it when they believe their counterpart comes from a “corrupt” country. These expectations about different countries are not only powerful but also shared, systematic, and often wrong (*23*). Yet, two key questions remain open: how do expectations about bribery and punishment shape people’s willingness to offer and accept bribes, and how does media portrayal of corruption correlate with these expectations?

Here, we present two preregistered studies that address these questions. First, we conducted a behavioral experiment across 20 countries (N = 4,081; total incentivized decisions = 81,620). Participants engaged in a transnational bribery game in which a “citizen” from one country sought a license and could offer a bribe to a "public official" from another country. The game featured a probabilistic punishment mechanism. The likelihood of detection was based on expert estimates of the public official's country-specific detection risk (see Fig. 1). All participants interacted with counterparts from each of the other 19 countries, as well as from their own country, in a fully crossed design. The selected countries account for 73% of global GDP (*26*) and 43% of transnational trade (*27*). This design enables us to examine not only whether punishment deters bribery but also how its effects vary across parties involved and with people's expectations.

Second, in an empirical investigation, we link these behavioral data with large-scale sentiment analyses of news reports and social media (drawing on approx. 4,000 media sources about 20 countries over 16 years). Drawing on machine-learning techniques, we constructed a novel indicator of country-specific media sentiment toward corruption, enabling us to systematically capture and quantify how corruption is portrayed across countries in global news and social media over time. We then test whether such media narratives can help explain shared country-specific expectations and bribery behavior. Together, these studies challenge the idea that law alone curbs bribery. Especially in fragmented enforcement landscapes, *perceptions* about bribery and punishment - which correlate with media sentiments - influence transnational bribery behavior.

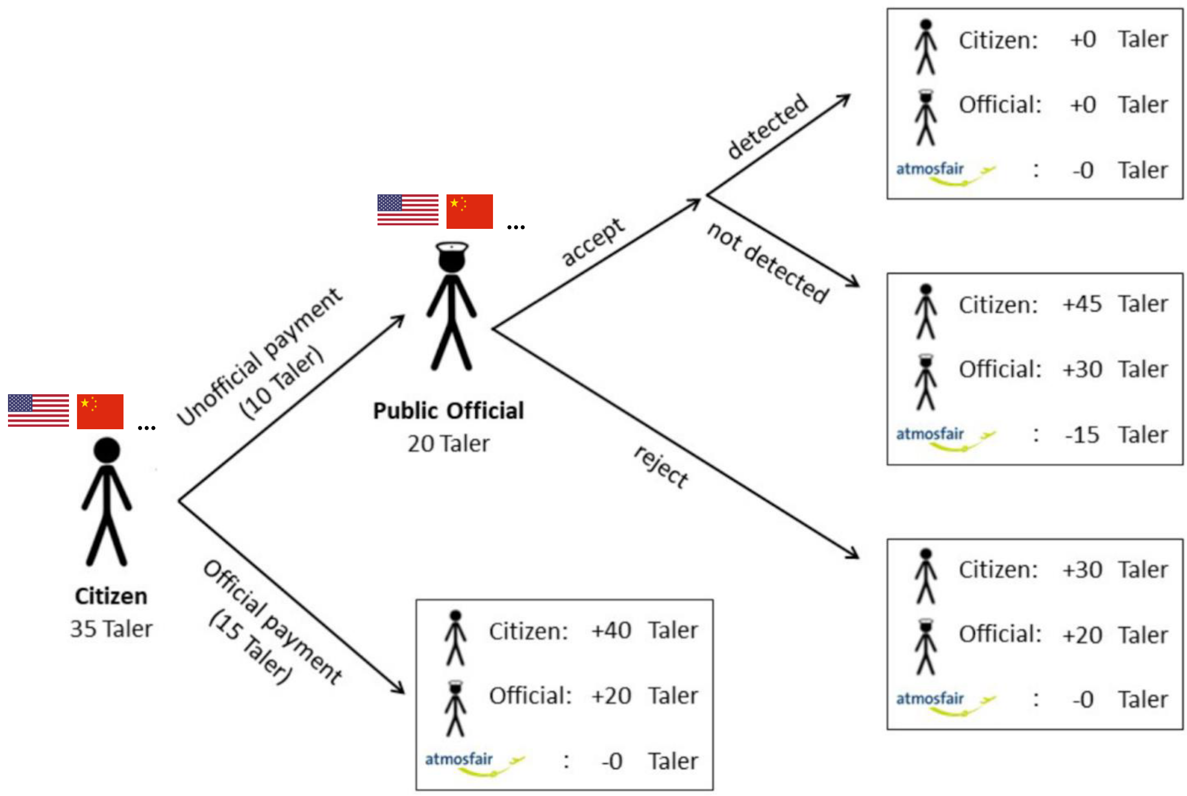

Fig. 1. Conceptual overview of the task. In a within-subject design, all participants assume both roles, starting with the citizen, and interact with public officials and citizens from all 20 countries (illustrated here with the USA and China). Citizens seek a license worth 20 Taler and can either make the official payment or offer an unofficial payment to the public official. Public officials can accept or reject this bribe. If accepted, the bribe is detected with a country-specific probability derived from corruption-expert ratings for the official's country. Detection results in both parties losing all earnings; if undetected, both receive the maximum payoff, at a financial cost to the external non-profit climate-protection organization "Atmosfair".

Results

Country Perceptions Drive Bribery Behavior

Our data show that bribe offers vary significantly across nations of bribe recipients (Fig. 2A; see supplementary materials, Fig. S1, for a complete overview). The vast majority of participants adjusted their decision to offer bribes based on their interaction partner's nationality (83%; Fig. 2B). Across all countries, only a minority of participants entirely abstained from offering bribes (15%) or offered bribes to all 20 countries (1%; see supplementary materials, Fig. S2, for an overview of these proportions across countries).

Individuals also differ in their expectations about the likelihood of punishment depending on *which* country is responsible for enforcing it (Fig. 2C). When estimating the probability that a bribe would be detected (i.e., punished) across the 20 countries, participants showed consistent expectations both within and across countries (all $ICC_{within} > 0$, significantly; $ICC_{across} = 0.56$, 95% CI [0.41, 0.73], $p < .001$; see supplementary materials, Table S1 and section S3.2 for further pre-registered analyses on additional hypotheses). For example, participants perceived detection as less likely in South Africa and India (45%) compared to the United States and Japan (53%).

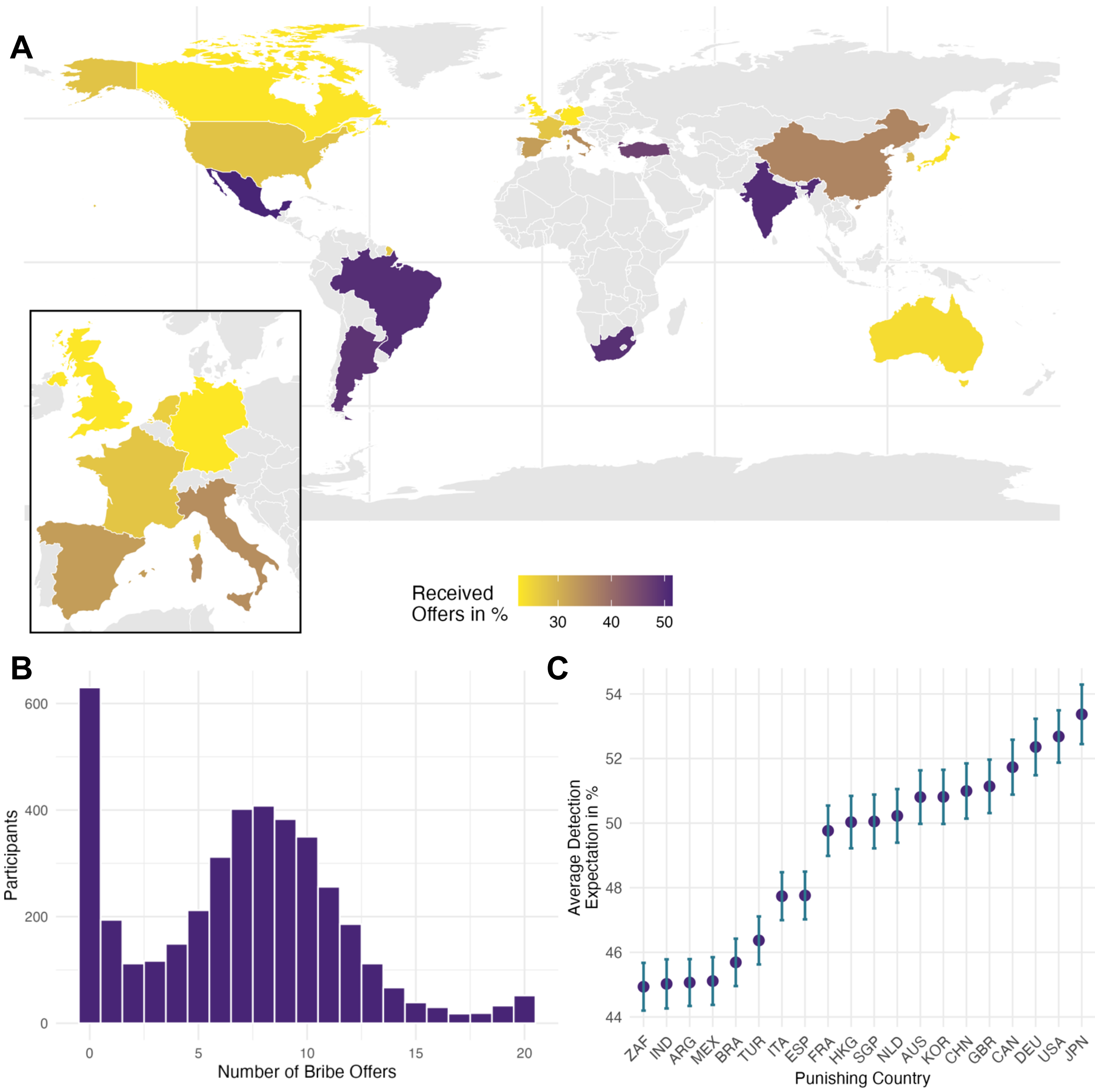

Fig. 2. (**A**) **Descriptive results of the average bribe offers each country received**. An enlarged view of European countries is shown at the bottom left. Darker colors represent more bribe offers; lighter colors represent fewer. (**B**) **Number of bribe offers per participant.** Bars represent the total number of participants offering a given number of bribes, ranging from 0 (= ppts did not offer any bribes) to 20 (= ppts offered bribes to all nations). Participants interacted with 20 countries and could therefore offer up to 20 bribes. (**C**) **Average detection expectations for each punishing country.** Dots indicate mean detection expectations, and error bars indicate 95% confidence intervals. ARG = Argentina;

AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; DEU = Germany; ESP = Spain; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; MEX = Mexico; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

These expectations can help explain why people selectively engage in bribery with specific nations. Namely, detection expectations about a country significantly predicted the likelihood of offering bribes (OR = 0.83, $p < .001$, 95% CI [0.76, 0.91]; see supplementary materials, Table S2). Beyond remaining undetected, a successful bribe also depends on the public official's acceptance of it. Here, we replicated previous findings (*23*) that acceptance expectations predicted bribe offers (OR = 1.56, $p < .001$, 95% CI [1.48, 1.65]; see supplementary materials, Table S3). Importantly, these two effects remained significant in a combined model (acceptance expectations: OR = 1.72, $p < .001$, 95% CI [1.64, 1.81]; detection expectations: OR = 0.71, $p < .001$, 95% CI [0.66, 0.76]; see supplementary materials, Table S4; Fig. S3). Furthermore, the results are robust to the inclusion of additional covariates (e.g., GDP per capita) and alternative model specifications (see supplementary materials, section S3.2.3). The importance of country-specific expectations was further underscored by open-ended responses about participants' thoughts while playing the bribery game: country perceptions were the second most relevant consideration, mentioned by 35%, surpassed only by game-strategic concerns (see supplementary materials, Table S5).

As a consequence, the effectiveness of punishment in reducing bribery is also related to country-specific expectations. A particularly concerning pattern emerges when considering where deterrence fails most severely. While punishment appears to reduce bribery overall (see supplementary materials, section S3.4.4; Fig. S4), its effect is weakest in countries where people expect bribery to go undetected—such as Argentina and South Africa (see supplementary materials, Fig. S5). Hence, punishment was least effective in countries that also rank among the most corrupt on Transparency International's Corruption Perceptions Index (see supplementary materials, Table S6), suggesting a troubling asymmetry: the countries most in need of effective deterrence are precisely those where it is least likely to work.

Media sentiments about corruption align with bribery expectations and behavior

Since direct interactions with people from other countries are rare, most individuals form impressions of foreign nations through the media (*28*). In other words, people may base their expectations about corruption in a given country on what they read in the news and on social media. Additionally, news and social media posts are likely influenced by both the true prevalence of bribery in a country as well as country-specific bribery expectations. To gain initial insights into whether there is a link between media portrayals and transnational bribery, we pair our behavioral data with international datasets of media sentiments regarding corruption.

Sentiment analysis extracts and quantifies opinions expressed in newspapers, blogs, and social media through machine learning (*29*). In our case, it measures daily how corrupt a specific country is portrayed in the media. Specifically, we utilize MarketPsych data, which draws on approximately 4,000 media sources, including Reuters, Twitter, and Reddit (see https://www.marketpsych.com). While sentiments have been validated in the context of financial markets (*30*–*33*) and for general corruption perceptions (*34*), we developed a novel time-weighted retention model of daily sentiments about each country from 2008 until the day before the collection of our behavioral data (for more information, see supplementary materials, Methods). The resulting sentiment indicators capture date-specific long-term perceptions of corruption of specific countries.

The results revealed that media sentiments were associated with both bribe offers and expectations of bribery and punishment. Namely, people perceived countries that were more frequently and strongly mentioned in connection with corruption as less likely to detect bribery (β = -0.06, $p < .001$, 95% CI [-0.06, -0.06]; see Fig. 3A; see supplementary materials, Table S7) and as more likely to engage in bribery (β = 0.15, $p < .001$, 95% CI [0.14, 0.15]; see supplementary materials, Table S8). Moreover, people offered more bribes to interaction partners from these countries (OR = 1.46, $p < .001$, 95% CI [1.43, 1.48]; see Fig. 3B; see supplementary materials, Table S9). This pattern emerged both for sentiments from newspaper texts and from social media sources (see supplementary materials, section S3.5.6). Further underlining the robustness, we found the effects in our new data, in previous data on transnational bribery (*23*; see supplementary materials, section S3.5.1), and when combining both datasets (see supplementary materials, section S3.3.1; for further robustness checks, see section S3.3.4). Additional preregistered analyses on media sentiments of trust and fear are reported in the supplementary materials (see sections S3.3.2 and S3.3.3).

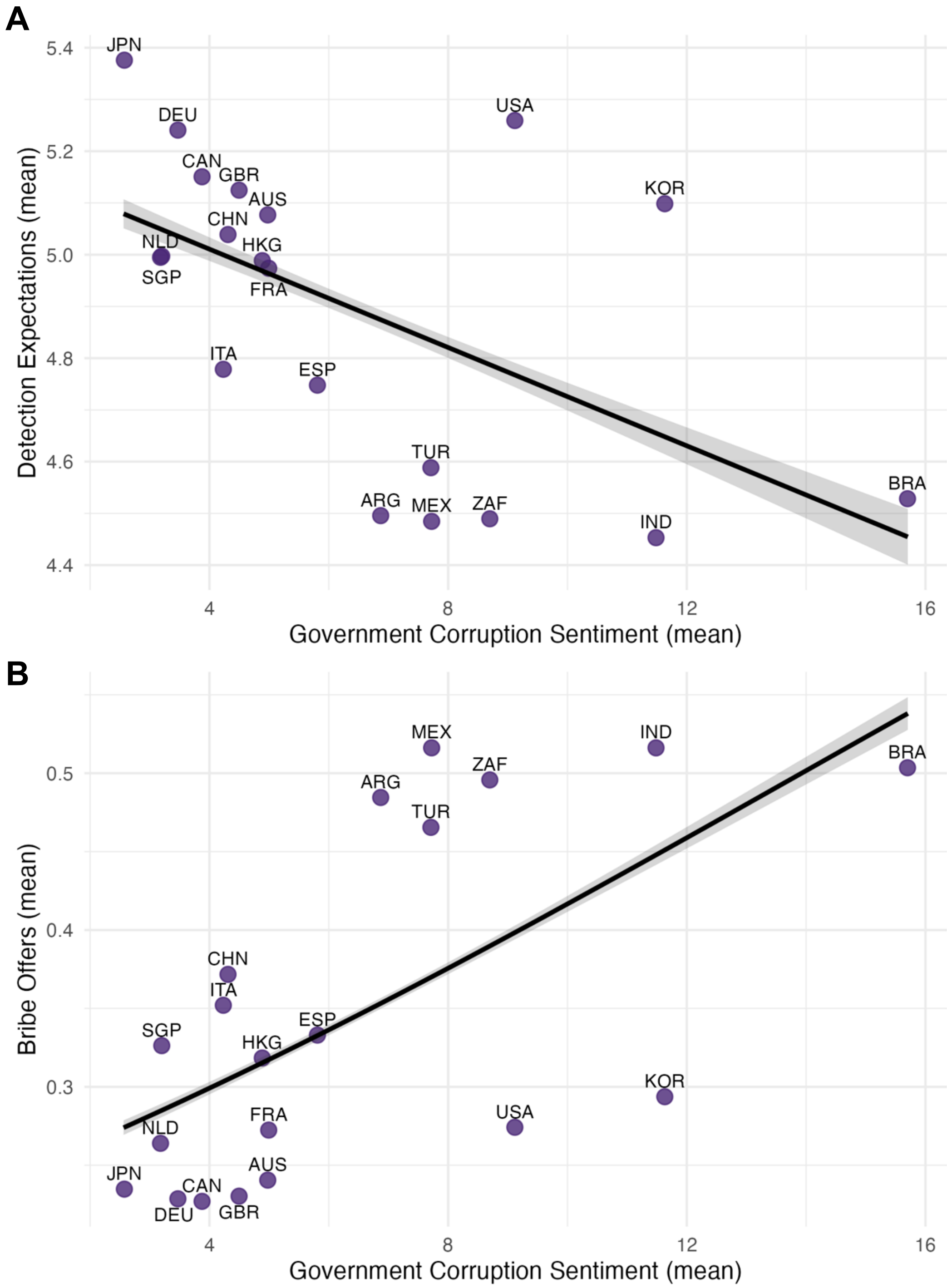

Fig. 3. Average corruption-sentiment indicators for all examined countries linked to average detection expectations (A) and bribe offers received (B). Detection expectations range from 1 to 10. Bribe offers range from 0 to 1, indicating relative frequencies. Black lines visualize predictions from a linear regression (A) and a logistic regression (B). Gray areas indicate 95% confidence intervals of the regressions. ARG = Argentina; AUS = Australia;

BRA = Brazil; CAN = Canada; CHN = China; DEU = Germany; ESP = Spain; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; MEX = Mexico; NLD = Netherlands; RUS = Russia; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

Correlational in nature, these results do not permit drawing causal conclusions about how media coverage influences bribery behavior (see supplementary materials, section S3.5.2, for further investigation). Exploratory analyses revealed that long-term sentiments yielded more robust predictions than short-term sentiments from 30 days and six months before data collection (see supplementary materials, section S3.5.3). This finding is consistent with the view that corruption perceptions are slow-moving constructs, shaped by accumulated exposure over years rather than recent news cycles. That pattern itself has implications for how quickly anti-corruption campaigns might realistically shift public expectations. Altogether, these findings suggest that people hold relatively stable impressions of corruption across countries that align with general media portrayals, which are not quickly updated in response to recent coverage.

Discussion

Anti-corruption strategies heavily focus on punishment (*35–38*). Yet, our results highlight an important complementary perspective: transnational bribery is strongly shaped by expectations intertwined with media narratives. In our large-scale experiment, people selectively offered bribes to countries they expected to engage in bribery but not to punish it. Deterrence thus depends not only on the presence of sanctions but on whom people interact with and what they believe about a country's willingness or ability to enforce anti-bribery laws. The transnational heterogeneity of punishment effectiveness resonates with prior work on antisocial punishment, which shows that punishment worldwide often deviates from classical predictions (*39*).

Here, we show that international perceptions of corruption are closely tied to media coverage. By combining global media sentiment with behavioral data, we show that news and social media narratives are linked not only to perceptions of a country's corruption but also to expectations about whether bribery will be detected. As a behavioral consequence, these sentiments correlate with the willingness to offer bribes in an incentivized bribery task. This finding may carry uncomfortable implications: a free and active press could initially backfire by amplifying perceptions of corruption and thereby increasing bribery attempts in international interactions (*40, 41*). In the longer term, however, sustained independent reporting remains essential for transparency and reform. At the same time, the results highlight the danger of misinformation about corruption, which might distort public perception and therefore create self-fulfilling prophecies.

Our study has some limitations. First, we implemented only a "sudden death" punishment that affected both involved actors equally, but does not account for the full complexity of anti-corruption enforcement. However, the experimental paradigm is well-suited to testing alternative sanctioning types, including asymmetric leniency provisions that target only one member of the corrupt dyad (*42*). It also provides a framework to evaluate other widely discussed international enforcement schemes for corruption, such as an International Anti-Corruption Court (IACC; *43*). Second, the novel indicator of country-specific media sentiments has constraints. Namely, the sentiment dataset did not distinguish among media outlets' national origins and relied exclusively on English sources until 2020, although it later expanded to 13 languages. Consequently, the sentiment measure captures how specific countries are portrayed globally, which may not reflect the specific media diet of individual participants.

For anti-corruption policy-making, our results offer clear implications. Deterrence requires visibility. Punishment mechanisms must not only exist but also be expected to curb transnational bribery. Critically, these expectations are linked to broader media sentiment, highlighting the potential relevance of combining legalistic approaches with policies targeting information environments. Our work can inspire further behavioral insights into how different types of coverage influence corruption expectations, how quickly people update these punishment expectations, and how they adjust their behavior in response. This matters especially in a moment when the enforcement of one of the most influential international regulations tackling transnational bribery – the FCPA – is being deliberately scaled back (*44*). Such a pause creates a dangerous informational vacuum. When a major enforcement regime recedes, global perceptions of punishment might shift with it.

Our results show that these perceptual shifts have tangible behavioral consequences. Participants were significantly more likely to offer bribes to officials from countries they believed were unlikely to enforce anti-bribery laws. Expectations of impunity, regardless of their actual legal accuracy, were associated with increased bribery in our experimental setting. This insight underscores a broader conclusion: anti-corruption efforts hinge not only on legal frameworks but on the expectations and narratives that shape how individuals interpret the credibility of enforcement across borders.

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Supplementary Materials

S1 Materials and Methods

The preregistration of the behavioral experiment can be found on the Open Science Framework. The media sentiment analysis and the retention model were also preregistered on the Open Science Framework before merging the sentiment data with the behavioral data (https://osf.io/yn9fw/overview?view_only=9a41b0f966dd45ae845cce054d423939). The term "beliefs" was used in the preregistration on the media sentiment, but for reasons of terminological consistency, we use the term "expectations" throughout this manuscript. The behavioral experiment was conducted online via Unipark (see https://www.unipark.com/). Study materials were initially translated using a large language model and later controlled by native speakers. Data were prepared and analyzed using R Version 4.4.2 (*45*) and Stata (*46*).

S1.1 Pre-survey with Corruption Experts

The bribery game in our experiment included country-specific detection probabilities of a bribe transaction. In order to define these probabilities realistically, we conducted a pre-survey with $N = 15$ corruption researchers (8 female, 6 male) from 13 different countries who had an average of $M = 9.60$ ($SD = 6.99$) years of experience with corruption research. Unfortunately, we could not reach our ambitious goal of $N = 100$ researchers. In randomized order, the corruption researchers estimated the probability that a bribery transaction, in the form of a bribe being paid to a public official, would be detected in each of the participating 20 countries. We also elicited the researchers' confidence (between 0% and 100%) in their estimate, following established practice (*47*). To determine country-specific detection probabilities in our main experiment, we calculated the weighted average probability:

$$Probability_{country} = \frac{\sum_{i=1}^{n} w_{country,i} \times p_{country,i}}{\sum_{i=1}^{n} w_{country,i}}$$

Here, $p_{country,i}$ is researcher *i*'s estimate of the detection probability for *country*, and $w_{country,i}$ is researcher *i*'s confidence in their estimate.

S1.2 Participants

For our main experiment, we selected 20 countries that varied strongly in how frequently bribery occurs in international transactions according to their scores on Transparency International's Bribe Payers Index of 2011 (BPI; *48*). For each country, we aimed to recruit a representative sample (according to age and sex for the adult population aged 18-65 years using age bins) of *N* = 200 participants. We recruited similar countries to previous research on transnational bribery without punishment (*23*) to ensure high comparability across studies, but slightly deviated in the country selection: We excluded Russia due to legal sanctions during the data collection (2023) forbidding transactions to Russian participants and we added Germany, Spain and Mexico to diversify our sample. Overall, our sample included the following countries: Argentina, Australia, Brazil, Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Mexico, Singapore, Spain, South Africa, South Korea, The Netherlands, Turkey, Great Britain, United States.

We conducted an *a priori* sensitivity analysis in G*Power (*49*) for a repeated-measurement mixed ANOVA as the closest pragmatic approximation for the cluster-corrected regression analysis we ran in our confirmatory analyses. The sensitivity analysis showed that with the estimated overall sample size of $N = 4000$, small effects of $f = .02$ can be detected with a power of $1-\beta = .95$ and a two-tailed $\alpha = .05$, assuming sphericity and a correlation of .50 among repeated measures. Note that the preregistration incorrectly stated $f = .10$ due to a transcription error. The correct G*Power calculation yields $f = .02$.

We collected data from $N = 4145$ participants via the online panel provider Toluna (https://de.toluna.com/). After excluding 64 participants who reported being from another country than their recruitment location (as is common in similar intercultural studies; *23*), our final sample included $N = 4081$ participants (2053 female). Participants' ages ranged from 18 to 65 ($M = 41.67$, $SD = 12.65$). We slightly deviated from the sample of $N = 200$ per country. In some countries, we oversampled because of multiple simultaneous submissions. In other countries, we did not reach $N = 200$ per country due to our data exclusion or recruitment difficulties. Country-specific sample sizes are reported in Table S10.

S1.3 Measures

S1.3.1 The Bribery Game

As a behavioral measure of bribery, we adapted the bribery game used in (*23*), adding a punishment mechanism (the game tree is depicted in the main text, Fig. 1). This incentivized game mimics a typical transaction between a public official and a citizen. The game currency "Taler" is converted to participants' national currency (1 Taler = 5 US Cents). Participants take both the role of a citizen and a public official. In the role of a citizen, participants decide how to obtain a license to use natural resources that is worth 20 Taler. They can either pay the public official a more expensive "official payment" or a cheaper "unofficial payment", i.e., a bribe. In the role of a public official, participants decide whether to "accept" or "reject" the unofficial payment from a citizen. If an unofficial payment is offered and accepted, the transaction is detected with a country-specific probability and the payoffs of citizens and public officials are reduced to 0 Taler. This probability depends on the public official's country and is based on experts' ratings, as described above (see section S1.1). If the transaction is not detected, the unofficial payment is mutually beneficial for both the citizen and the public official. However, these successful bribe transactions reduce an overall amount donated to the non-profit climate-protection organization “Atmosfair” as part of the study, reflecting the damage to the public good that corruption causes.

S1.3.2 Measures of Expectation

To assess expectations about the counterpart’s bribe offer behavior, we asked participants “What percent of participants from [interaction partner’s country; e.g., India] in the role of a citizen do you estimate offer the unofficial payment?” Correspondingly, we measured the expectation about the bribe acceptance behavior of the counterpart, by asking “What percent of participants from [interaction partner’s country; e.g., India] in the role of public officials do you estimate accept the unofficial payment?” Furthermore, we assessed detection expectations about the probability for each interaction partner’s country using the item “We asked experts to rate the probability that a transfer is detected. What is the experts’ rating for [interaction partner’s country; e.g., India]?” To assess detection expectations in their own country, we asked participants “What do you think, what is the probability that an unofficial transaction is detected in your country?” Participants answered all of these questions along ten categories, each indicating 10-percentage-point bins (i.e., 0-10%; 11-20%; 21-30%; 31-40%; 41-50%; 51-60%; 61-70%; 71-80%; 81-90%; 91-100%). As incentivization for these expectation measures, bribe offer and bribe acceptance expectations could lead to a bonus payment if they matched the actual average decision of participants from the respective country. Regarding detection expectations, participants could gain a bonus payment if they correctly estimated the detection probability based on the ratings of corruption researchers.

S1.3.3 Additional Questions

For exploratory purposes, we assessed additional measures related to the bribery decisions. Participants indicated how corrupt they perceive offering and accepting an unofficial payment on two separate Likert scales from 1 (“not at all corrupt”) to 7 (“very corrupt”). They also estimated the relative proportion of detected transactions identified through audits by independent official authorities versus reports filed by private individuals, on a continuous scale from “100% audits and 0% reports” to “0% audits and 100% reports”. On additional Likert scales, participants indicated how much they trust scientists, from 0 (“not at all”) to 10 (“a great deal of trust”), and their support for atmosfair, the climate-protection organization whose donation was reduced by successful bribe interactions, from 1 (“I don’t support it at all”) to 7 (“I support it very much”).

S1.4 Design and Procedure

We employed a 20 (own country) x 20 (target country) x 2 (role: citizen vs. public official) mixed design, with own country as a quasi-experimental between-subjects factor but target country and role as within-subjects factors. Participants first took the role of a citizen and then the role of a public official. Thus, they interacted with public officials as well as citizens from all 20 target countries. The order of countries that participants interacted with was randomized. The bribery game and the expectations were incentivized, using a strategy method: after participation, either one random decision from the bribery game or one expectation measure was selected to determine the bonus payment.

The study was conducted online. After giving informed consent, participants indicated their age and sex. Then, all components and possible consequences of the bribery game were explained. Instructions were only slightly modified (i.e., adding the detection mechanism) from a previous study (*23*) that had optimized the comprehensiveness of instructions using a semi-structured interview. To ensure that participants understood the bribery game, they had to answer four control questions correctly before they could proceed. Participants had multiple tries to pass the control questions. Following information about their interaction partners' countries and the incentivization, participants played the bribery game as a citizen with public officials from all 20 countries in randomized order. Next to their decision whether to pay an official or unofficial payment, they indicated bribe offer expectations and detection expectations for each country. Afterwards, participants took the role of a public official and decided whether to accept or reject unofficial payments from citizens from all 20 countries in randomized order. Here, they also indicated their acceptance expectations for each of the 20 countries.

Participants then indicated how corrupt they perceived offering a bribe as well as their detection expectations of unofficial transactions in their own country. Moreover, they guessed what percentages of detected unofficial transactions are detected through audits or through reports. Subsequently, participants indicated their support for the climate-protection organization atmosfair and their trust in scientists. Finally, participants stated their thoughts when making decisions in the bribery game. Participants received a base payment according to the guidelines of the panel provider and an additional bonus payment that ranged between $0 and $2.25, converted into their respective national currency.

S1.5 Media Sentiment Analysis

To model country perceptions conveyed through media, we used data on media sentiments provided by MarketPsych (see https://www.marketpsych.com/), which we transformed to long-term indicators that model the media perception of a country. We used these indicators as predictors for behavioral bribery data.

S1.5.1 The sentiment dataset

MarketPsych collects news and social media data with a machine learning algorithm that accounts for the specific linguistic complexity of different text sources, such as social media or financial news. The underlying dataset combines 4,000 relevant sources, including Reuters news, other mainstream news sources, and social media. Social media content began in 1998 with internet forums and message boards. LexisNexis social media content and tweets were added in 2008 and 2009, respectively. Using popularity rankings based on incoming links, this generally includes the top 20% of blogs and microblogs. The underlying dataset included only English-language content until February 2020. Subsequently, content in Arabic, Chinese, Japanese, Dutch, French, German, Indonesian, Italian, Korean, Russian, Spanish, and Portuguese has been added subsequently. MarketPsych excludes press releases, corporate websites, corporate filings, promotional content, and robot-generated content to ensure high-quality data.

Specifically, we utilized three different types of sentiments towards countries: a sentiment score regarding government corruption (hereafter, referred to as corruption), and two separate sentiment scores of trust and fear. For additional analysis, we also retrieved general sentiments which capture whether news reports about a given country tend to have a positive or negative tonality overall. Whenever the respective emotion or term (e.g., corruption) appears, directly or indirectly, alongside a specific country in the analyzed sources, a sentiment value is calculated for that day. These sentiment values range between -1 (e.g., low corruption) and 1 (e.g., high corruption). Furthermore, MarketPsych calculates a positive “buzz” value that captures the extent of media coverage on a specific day weighted by the sources’ relevance. For example, MarketPsych calculates the degree to which the media reports on India in relation to corruption on a specific day, as captured in the sentiment value (i.e., low corruption vs. high corruption). Following the example, the buzz value quantifies how many sources report on India in relation to corruption and how relevant these sources are (i.e., low buzz: few irrelevant sources; high buzz: many relevant sources).

S1.5.2 Models of sentiment indicators

We decided to model country perceptions as a function of daily media sentiments over a long period of time. Therefore, we included sentiment values from 2008 onwards, as social media data has been covered since then. Missing sentiment values on a given day were coded as 0. We employed a time-weighted retention rate model that accounts for the diminishing impact of past news events (*50*), assuming that news sentiment lying further in the past becomes less important over time. Furthermore, recent findings show that information retention is rather stable within the first 12 hours to 7 days, while, after 7 days, a linear forgetting curve is a reasonable estimate, especially for complex information (*51, 52*).

Based on these findings, we used a stable retention rate (weight = 1) for the 7 days before study participation and a linear forgetting curve for news lying more than 7 days in the past. The slope of the forgetting curve was equal across all participants, independent of their date of behavioral data collection. For the latest behavioral data collection date, the earliest relevant value from 2008 had a weight of 0. Thus, the weight of the earliest relevant sentiment value from 2008 was higher for individuals who participated earlier in the behavioral experiment. Our retention model resulted in a sentiment indicator (*sentiment)* for a country *i* at a time *t(p)* (date of behavioral data collection):

$$sentiment_{i,t(p)} = \sum_{t=1}^{t(p-1)} value_{i,t} \times weight_t \times \frac{buzz_{i,t}}{M(buzz_i)}$$

$value_{i,t}$ indicates the sentiment value for country *i* on a specific day *t*. *t*=1 is the first day in 2008 taken into account, *t(p-1)* is the day before participant *p* took part in the behavioral study.

Furthermore, we divided every buzz value $buzz_{i,t}$ by the average buzz of the respective country *i*, $M(buzz_i)$, to account for buzz differences between countries because the media generally reports more about some countries than about others. $weight_t$ indicates the retention weight at a date *t*. For dates that were $x \leq 7$ days prior to data collection $t(p)$, we defined $weight_t = 1$. For $x > 7$, the retention rate's weight for a date that was *x* days prior to $t(p)$ was:

$$weight_{t(p-x)} = 1 - \frac{x-7}{t(p_{last}-7) - t(start)}$$

Here, $t(p - x)$ counts the number of days going from 2008 ($t(start)$) to the day of study participation *p*. In this way, more recent sentiment values are weighted more strongly as they should have greater influence on country perception than sentiment values lying further in the past. p_{last} indicates the last date of data collection across all participants. Thus, the retention function stays the same across all participants. Put differently, the retention function for sentiment values lying more than 7 days in the past had the following slope:

$$slope = \frac{1}{t(p_{last}-7) - t(start)}$$

In conclusion, this model captures sentiments about a specific country that are most strongly influenced by recent media coverage (within the past week) while incorporating long-term sentiments (since 2008) and controlling for the country-specific extent of media coverage. These sentiment indicators were separately calculated for corruption, trust, fear and, for exploratory analyses, general sentiments.

S1.5.3 Behavioral data

To extend temporal generalizability, we combined the sentiment indicators not only with the present behavioral experiment but also with previous data on transnational bribery (*23*), hereafter referred to as TB-NP (transnational bribery with no punishment). Nevertheless, the regression analyses reported in the main text were based solely on behavioral data from the present study. We used sentiment indicators about the target country (i.e., the country the interaction partner in the bribery game was from) as predictors for bribe offers and bribery expectations. Intra-national interactions were excluded because we expected perceptions towards fellow citizens to depend on various experiences that go far beyond international news reporting. We included the complete samples from TB-NP (N = 5,582) and the present study (N = 4,081), resulting in a total sample size of N = 9,663 participants. Since every participant interacted with 17 foreign countries in TB-NP and 19 foreign countries in the present study, our dataset consisted of N = 172,433 participant-country pairings (N = 94,894 from TB-NP and N = 77,539 from the present study).

We ran an *a priori* sensitivity analysis for a repeated measures ANOVA within-subjects factors in G*Power (*49*) to approximate the mixed-effects models of our confirmatory tests. This analysis revealed that we could detect effects of f = .01 with our sample size of N = 9,663, a power of $1-\beta = .95$, $\alpha = .05$, and, most conservatively, 17 measurements per person.

S2 Supplementary Text: Hypotheses

S2.1 Hypotheses of the Behavioral Experiment

One aim of the present study was to replicate key findings from previous research on transnational bribery (*23*), reflected in H1-H5. To explain variation across countries, we used Transparency International's Bribe Payers Index from 2011 (BPI; *48*) as an indicator of the perceived likelihood of companies from different countries to pay transnational bribes. We preregistered the following hypotheses for our behavioral experiment that addressed both bribe acceptance expectations and bribe offers.

H1: Patterns of bribe offers toward different countries are shared within and across participating countries.

H2: The lower a country's rank on the BPI, the more bribes people offer to the country (lower ranks indicate higher perceived bribery).

H3: Country-specific expectations concerning bribe acceptance are shared within and across participating countries.

H4: People hold higher acceptance expectations about countries with a lower rank on the BPI.

H5: Bribe offers toward a given country increase with expected bribe acceptance rates in that country.

Beyond these replication hypotheses, we pre-registered several original hypotheses about the expected detection of bribes. First, we predicted that people would share similar expectations about which countries are more likely than others to detect bribery.

H6: Country-specific expectations concerning bribe detection are shared within and across participating countries.

Second, we expected these detection expectations to matter in that they determine whether people in the role of a citizen decide to offer a bribe to another country.

H7: Bribe offers toward a given country decrease with higher expected detection rates in that country.

When people in the role of a public official accept a bribe, the detection probability depends on their own country of residence. Therefore, we expected these detection expectations to influence bribe acceptance behavior.

H8: Bribe acceptance decreases with higher expected detection rates in one's own country.

Finally, we utilized the BPI as a country-level measure to explain in which countries people expect bribe detection to be more likely than in others.

H9: People expect bribe detection to be more likely in countries with a higher rank on the BPI (higher ranks indicate higher perceived bribery).

S2.2 Hypotheses of the Media Sentiment Analysis

We predicted the following hypotheses regarding the relationship between media sentiments and transnational bribery. First, we expected that media sentiments about corruption should reflect in people's expectations about that country. To operationalize general bribery expectations about a country, we averaged participants' bribe offer expectations and bribe acceptance expectations about a country.

H10: Bribery expectations about a country increase with higher corruption sentiments about that country.

In line with the effect of descriptive norms, previous findings show that people offer more bribes to groups that they expect to be more corrupt (*20, 23, 53*). Thus, we hypothesized that corruption sentiments influence whether people decide to offer a bribe to a foreign public official.

H11: Bribe offers to a country become more likely with increasing corruption sentiments about that country.

We derived competing hypotheses for the influence of trust on bribe offers. On the one hand, a particularized trust in the other party is necessary to offer them a bribe because a bribe payer must assume that the other party will not reject the offer. On the other hand, corruption is associated with low generalized trust in a country (*54, 55*):

H12a: Bribe offers to a country become more likely with increasing trust sentiments.

H12b: Bribe offers to a country become less likely with increasing trust sentiments.

However, on a level of nation-specific expectations, we predicted a high trust image of a country to be associated with less expected bribery.

H13: Bribery expectations about a country decrease with higher trust sentiments.

We included fear sentiments as another bribery-relevant emotion, especially regarding deterrence through punishment (*56, 57*). Among other reasons, participants refrain from unethical behavior because they fear being punished (*19*). Following this, we expected punishment to be more effective if people fear the punishment enforcing country. This hypothesis only applies to the present experiment, as TB-NP did not include punishment.

H14: Bribe offers to a country become less likely with increasing fear of that country (i.e., an increasing sentiment of fear towards that country).

Furthermore, we aimed to specify this relation of H14, in that the effect of fear was actually related to the punishment aspect. Following, we expected fear sentiments to be less important when punishment is impossible. Thus, we compared the present experiment, including punishment, with data from TB-NP that did not implement punishment.

H15: In the present experiment, fear sentiments towards another country have a stronger negative influence on bribe offers to that country compared to TB-NP.

Finally, we hypothesized that deterrence through fear should be more effective when people expect a high detection probability. In other words, if people think bribes will not be detected anyway, the fear of punishment should play a less important role. This hypothesis applied only to the present experiment, not to TB-NP.

H16: Fear sentiments towards another country have a stronger negative influence on bribe offers to that country as participants' detection expectations increase.

S3 Supplementary Text: Analysis

S3.1 Descriptive Results of the Behavioral Experiment

In interaction with which countries did people decide to engage in bribery? We found that some countries (e.g., India or South Africa) generally received more bribe offers than others (e.g., Japan or Canada; see Fig. S1A). However, these patterns varied across offering countries. We found similar results for bribe acceptance behavior (see Fig. S1B). For example, Chinese participants in the role of a citizen offered only 22.11% of bribes to public officials from China but 61.31% of bribes to public officials from Mexico. In contrast, Japanese participants in the role of a citizen offered 49.27% of bribes to public officials from China and 42.44% of bribes to public officials from Mexico. To give an example of bribe acceptance behavior, participants from Argentina in the role of a public official accepted 72.46% of bribes offered by Argentinian citizens but only 22.89% of bribes offered by Canadian citizens.

Overall, in 34.48% of 81,620 decisions, participants in the role of a citizen decided to offer a bribe to the public official. When taking on the role of a public official, participants accepted a bribe in 42.14% of opportunities. Interestingly, participants were selectively corrupt (see Main Text, Fig. 2B). This means that most of them offered bribes to specific countries but not to others. Likewise, most people selectively accepted bribe offers from specific countries but not from others. A substantial minority was generally uncorrupted and never offered a bribe (15.44%) or never accepted a bribe offer (14.75%), while only small fractions of participants always offered bribes (1.27%) or accepted all bribes (3.60%). Interestingly, this pattern of mostly selectively corrupt individuals generalizes across all 20 countries, with some variation (see Fig. S2).

S3.2 Confirmatory Analysis of the Behavioral Experiment

In Hypotheses H1, H3, and H6, we predicted that expectations about specific target countries and the tendency to offer bribes to countries to be shared both within and across countries. We tested these hypotheses using intraclass correlation coefficients (ICCs) and predicted ICCs to be significantly larger than zero, indicating systematic agreement. We calculated ICCs separately for each country of residence to assess whether participants from the same country showed consistent patterns in their bribe offers and expectations toward different target countries. To model agreement across countries, we calculated the means for participants' expectations and bribe offers for each country when interacting with each target country. We then calculated an ICC for these country-level means to assess whether different countries show similar patterns in their expectations and bribe offers.

All other models of the present experiment were analyzed using cluster-corrected bootstrapped standard errors (200 repetitions) at the national level. Specifically, we ran logistic regression models with cluster-corrected, bootstrapped standard errors for H2, H5, H7, and H8, and linear regression models with cluster-corrected, bootstrapped standard errors for H4 and H9. All continuous predictors were z-standardized. Demonstrating the robustness of our analysis, we replicated all results from regression models, using mixed-effects models.

S3.2.1 Replication Results

Overall, the findings confirm our hypotheses H1-H5 and therefore fully replicate previous key findings on transnational bribery (*23*). As predicted (H1), the tendency to bribe offers to specific countries was shared across participating countries (ICC = 0.83; 95% CI[0.73, 0.92], $F(19, 361) = 92.45$, $p < .001$) and within participating countries (all ICCs significantly larger than 0; see Table S1). Similarly, we find that expectations concerning bribe acceptance in specific countries are shared across countries (ICC = 0.78; 95% CI[0.66, 0.88]; $F(19, 361) = 70.11$, $p < 0.001$) as well as within (all ICC significantly larger than 0; see Table S1), supporting H3. These findings reveal a consistent pattern: which countries are offered more bribes and are expected to accept more than others.

These bribe acceptance expectations reflect in actual bribe offer behavior as a logistic regression showed: Participants in the role of a citizen were more likely to offer a bribe if they expected bribe acceptance rates to be higher in that country (OR = 1.56, $z = 16.37$, $p < .001$, 95% CI [1.48, 1.65]; see Fig. S3; see Table S3), supporting H5.

Besides, we expected the Bribe Payers Index (BPI) to explain which countries receive more bribes (H2) and which countries are expected to show higher bribe acceptance rates (H4). Indeed, participants in the role of a citizen offered more bribes to countries with a lower rank on the BPI, indicating higher perceived corruption rates, than to countries with a higher rank (OR = 0.71, $z = -17.62$, $p < .001$, 95% CI [0.68, 0.73]; see Table S11), as a logistic regression revealed. Moreover, in a linear regression, bribe acceptance expectations were negatively related to the BPI ($\beta = -0.16$, $t(19) = -18.04$, $p < .001$, 95% CI [-0.18, -0.14]; see Table S12). These results indicate that people are more likely to offer bribes to countries with a reputation for foreign bribery and also expect these countries to accept more bribe offers.

S3.2.2 Confirmatory Results of Bribe Detection

We predicted that country-specific expectations concerning bribe detection would be shared within and across participating countries (H6). In support, analyses of ICCs demonstrated agreement about detection expectations across countries (ICC = 0.56; 95% CI [0.41, 0.73]; $F(19, 361) = 26.1$, $p < .001$) and within countries (all ICCs significantly larger than 0). This implies that people across and within countries agree on which countries are likely to detect bribery and which are unlikely to do so. However, it must be noted that the within-country agreement, although significantly larger than zero, was small (see Table S1). These detection expectations influence bribe offer behavior as a logistic regression showed: Supporting H7, participants in the role of a citizen offered fewer bribes to countries where they expected a higher detection probability (OR = 0.83, $z = -4.12$, $p < .001$, 95% CI [0.76, 0.91]; see Fig. S3; see Table S2). Moreover, we expected participants in the role of a public official to accept fewer bribes when they expect bribe detection to be more likely in their own country, i.e., the punishing country (H8). Contrary, however, detection expectations about their own country were not negatively associated with bribe acceptance behavior (OR = 1.04, $z = 1.34$, $p = .179$, 95% CI [0.98, 1.10]; see Table S13), as shown by a logistic regression. This finding aligns with the exploratory result that the interaction partner's country better explains bribery behavior than the participants' own country (see section S3.4.3).

Finally, we expected detection expectations about a given country to be higher with an increasing rank on the Bribe Payers Index (BPI), indicating lower bribery rates (H9). This hypothesis was confirmed by a linear regression: Participants held higher detection expectations for countries with higher BPI ranks ($\beta = 0.06$, $t(19) = 5.79$, $p < .001$, 95% CI [0.04, 0.08]; see Table S14).

S3.2.3 Robustness checks

To examine the robustness of our confirmatory models, we conducted two robustness checks for all regression models (i.e., H2, H4, H5, H7, H8, H9). As a first preregistered robustness check, we reran all the confirmatory regression models but with additional covariates, including the difference in GDP between participants' country of residence and the target country, the support of atmosfair, as well as participants' age and sex. The models of H8 and H9, which analyzed detection expectations, additionally included trust in scientists because participants had to trust the researchers to implement detection probabilities accurately. Again, we used logistic and linear regression models with bootstrapped cluster-corrected standard errors. They replicated all previous confirmatory findings: the effects of H2, H4, H5, H7 and H9 remained significant beyond the covariates while the effect of H8 remained insignificant. For a full report of the models, see Tables S15-S20.

As a second robustness check, we repeated all confirmatory regression models but as either generalized linear mixed-effects models (H2, H5, H7, H8) or linear mixed-effects models (H4 and H9). We included random slopes and intercepts at both the country and participant levels. However, in cases of non-convergence, we sequentially removed random slopes first at the country level, then at the participant level, while keeping random intercepts at both levels. Again, we replicated all prior confirmatory findings with significant predictors in H2, H4, H5, H7, and H9 but not in H8 (see Tables S21-S26).

S3.3 Confirmatory Media Sentiment Analysis

The analyses of H10-H13 and H15 are based on data from both the present experiment and previous data of transnational bribery (TB-NP; *23*). Both studies used the same measures of bribery, although the bribery game in TB-NP slightly differed from the present one, mainly in excluding punishment. In our confirmatory analysis, we focused on bribe offers and bribery expectations, that is, the average of bribe offer expectations and bribe acceptance expectations for a country. All of the following hypotheses were analyzed in mixed-effects models including random intercepts for each participant and for participants' countries of residence (i.e., not the target country they interacted with). We consistently predicted bribe offers in generalized linear mixed-effects models (H11, H12, H14-H16) and bribery expectations using linear mixed-effects models (H10, H13). When models failed to converge, we used alternative optimization algorithms to achieve convergence without changing the model specification. All predictors included in interaction terms were centered at their mean. In linear mixed-effects models, degrees of freedom were calculated using the Satterthwaite method. In summary, H10-H15 were all confirmed, but H16 was rejected.

S3.3.1 Corruption Sentiments and Bribery

Confirming our hypotheses H10 and H11, corruption sentiments about a country were positively related to both bribery expectations ($\beta = 0.13$, $t(163{,}000) = 87.00$, $p < .001$, 95% CI [0.13, 0.14]; see Table S27) as well as bribe offers (OR = 1.44, $z = 61.86$, $p < .001$, 95% CI [1.42, 1.45]; see Table S28). This implies that people from countries portrayed as more corrupt in the media receive more offers and are expected to be more likely to engage in bribery.

S3.3.2 Trust Sentiments and Bribery

Furthermore, we derived competing hypotheses on the influence of trust sentiments toward a country on bribe offers to that country. We found that people offered fewer bribes to countries with higher trust sentiments (OR = 0.67, $z = -66.65$, $p < .001$, 95% CI [0.67, 0.68]; see Table S29). Thus, we confirm H12b but reject H12a, which predicted the opposite effect. This suggests that general trust might play a more important role than particularized trust in decisions about transnational bribe offers (*54*). In line with this, bribery expectations regarding a person from another country were negatively associated with trust sentiments about that country ($\beta = -0.14$, $t(162{,}900) = -93.94$, $p < .001$, 95% CI [-0.15, -0.14]; see Table S30). This supports hypothesis H13 and shows that people offer more bribes to countries the media portrays as untrustworthy.

S3.3.3 Fear Sentiments and Bribery

Beyond that, we expected bribe offers to a given country to become less likely as fear sentiment towards that country increased (H14). As TB-NP did not include punishment and this hypothesis was based on fear of the punishing country, this analysis included only behavioral data from the present experiment. Supporting our prediction, people offered fewer bribes to countries that are portrayed with higher fear sentiments in the media (OR = 0.93, $z = -8.73$, $p < .001$, 95% CI [0.91, 0.94]; see Table S31).

To further investigate whether this effect of fear could be traced to the implementation of punishment, we expected fear sentiments toward another country to have a stronger negative influence on bribe offers in the present experiment (with punishment) than in TB-NP (without punishment; H15). A significant interaction term of fear sentiments and the dummy-coded factor that differentiated the two studies confirmed this hypothesis (OR = 0.95, $z = -3.28$, $p < .001$, 95% CI [0.91, 0.98]; see Table S32).

Finally, we predicted that fear sentiments toward another country would have a stronger negative influence on bribe offers as individual detection expectations increase (H16). Data from TB-NP were excluded from this analysis because the bribery game in TB-NP lacked a detection mechanism. This hypothesis was not confirmed as indicated by a non-significant interaction term of fear sentiments and detection expectations (OR = 1.00, $z = 0.17$, $p = .864$, 95% CI [0.98, 1.02]; see Table S33). This suggests that the negative relation between fear sentiments and bribe offers is independent of participants' detection expectation.

S3.3.4 Robustness Checks for Media Sentiment Analyses

We conducted three robustness checks for all our confirmatory mixed-effects models on media sentiments. First, we compared all confirmatory models (as described above) with models that only missed the hypothesis-relevant fixed effect predictor in likelihood ratio tests. Here, we replicated all findings from our confirmatory analyses as likelihood-ratio tests reached significance (all $p < .002$), except for H16 (see Table S34).

Second, we reanalyzed all the mixed-effects models, including the general sentiment about the target country as an additional predictor. The general sentiment indicates the general tonality in that the media reports about a country, i.e., negative (-1) to neutral (0) or positive (1). Interestingly, the relevant predictors remained significant for models of H10-H14 (all $p < .001$) but not for H15. This means that, when controlling for the general sentiment towards a country, fear sentiments showed no stronger influence on bribe offers in the present experiment than in TB-NP (OR = 1.00, $z = 0.23$, $p = .821$, 95% CI [0.97, 1.04]). All results are reported in Tables S35-S41.

We found that country-specific bribery expectations increased with corruption sentiments (confirmed H10) and decreased with trust sentiments (confirmed H13). Here, bribery expectations were calculated as the average of bribe offer expectations and acceptance expectations. As a third robustness check, we tested whether these effects (H10 and H13) held for both the measures of bribe offer expectations and bribe acceptance expectations separately. In fact, our findings remained robust. Corruption sentiments predicted both bribe offer expectations ($\beta = 0.11$, $t(163{,}100) = 67.07$, $p < .001$, 95% CI [0.11, 0.12]; see Table S42), and bribe acceptance expectations ($\beta = 0.13$, $t(163{,}100) = 77.37$, $p < .001$, 95% CI [0.12, 0.13]; see Table S43). Similarly, trust sentiments predicted bribe offer expectations ($\beta = -.12$, $t(162{,}900) = -72.69$, $p < .001$, 95% CI [-0.13, -0.12]; see Table S44), as well as bribe acceptance expectations ($\beta = -0.13$, $t(162{,}900) = -83.19$, $p < .001$, 95% CI [-0.13, -0.14]; see Table S45).

S3.3.5 Limitations of the Sentiment Measure of Fear

An important limitation concerning the fear sentiments must be noted. When we preregistered our hypotheses, we aimed to use fear sentiments as a measure of whether a country is feared (i.e., is threatening). However, after careful reconsideration and after the preregistration, we concluded that fear sentiments only partly measure whether a country is feared. Critically, the sentiment data operationalized to what extent a country was mentioned in association with terms related to fear. Thus, the fear sentiment values did not distinguish whether a country is feared or whether it is fearful. This distinction is crucial to our hypothesis that expected fear sentiments influence bribery due to a fear of deterrence imposed by a specific country. Consequently, our results regarding fear sentiments (H14-H16) should be interpreted cautiously.

S3.4 Exploratory Analysis of the Behavioral Experiment

For exploratory tests, we applied a Bonferroni-corrected alpha error level to each set of tests addressing the same exploratory research question.

S3.4.1 The Accuracy of Expectations

We tested whether participants' average expectations about specific countries matched the average bribe offer and acceptance behavior in those countries, using Pearson’s r correlation tests. We applied Bonferroni correction to control for multiple testing (k = 3 tests) and therefore evaluated all reported p-values against the threshold of $\alpha_{corrected} = .017$. Acceptance rates in a country are not correlated with expectations about that country ($r(18) = 0.16$, $p = .498$, 95% CI [-0.30, 0.56]) and the same holds true for bribe offer expectations and bribe offer rates ($r(18) = -.11$, $p = .648$, 95% CI [-0.53, 0.35]). A similar previous study (*23*) found bribery expectations about specific countries to be systematically wrong, but with our set of countries (and hence relatively low power) we could not replicate these significant negative correlations.

Moreover, we tested whether participants could accurately estimate detection probabilities. Here, participants' expectations about detection probabilities across countries aligned closely with the detection probabilities we calculated from expert ratings (see section S1.1). This was shown by a strong correlation ($r(18) = 0.84$, $p < .001$, 95% CI [0.63, 0.94]).

S3.4.2 Heterogeneity of Expectations

To compare agreement in different kinds of bribery-related expectations across countries, we averaged expectations for each combination of two countries and calculated ICCs with bootstrapped confidence intervals (1000 resamples). A confidence interval overlap test indicated that bribe offer expectations (ICC = 0.76, 95% CI [0.66, 0.82]) and acceptance expectations (ICC = 0.78; 95% CI [0.66, 0.85]) are more homogeneous than detection expectations (ICC = 0.56; 95% CI [0.45, 0.63]). Agreements on bribe offer and acceptance expectations did not differ. This indicates that people from different countries generally agree on whether people in other countries offer and accept bribes. However, they show less agreement about whether bribes will be detected across countries.

S3.4.3 Effects of One's Own and the Other Country

Furthermore, we were interested in whether bribery behavior depends more strongly on the country a person is from or on the country a person interacts with. Thus, we set up two logistic regression models predicting bribe offers. One model used the country of residence as a predictor; the other used the target country as a predictor. A comparison of AIC values indicated that the target country a person interacted with (AIC = 101161) influences bribe offer behavior stronger than the country a person is from (AIC = 104922). Additionally, we found similar results for bribe acceptance behavior: the interaction partner's country where the bribe comes from (AIC = 108446) is a better predictor for bribe acceptance than the country of residence (AIC = 110283). Fig. S1 visualizes these results. Panel A shows particularly strong variation in bribe offers across rows which indicate the interaction partner's country. In turn, in panel B, bribe acceptance rates vary more strongly across columns which indicate the interaction partner's country here. These findings reflect the conditionality of bribery: people adapt their bribery behavior to the country they interact with. In other words, decisions to engage in bribery are driven more by the national background of the interaction partner than by people's own national background.

S3.4.4 The Effect of Punishment

As preregistered, we compared bribery rates in 17 common countries between the present experiment with punishment and the previous study on transnational bribery without punishment (TB-NP; *23*). We applied Bonferroni correction to control for multiple testing (k = 2 tests), and thus evaluated all reported p-values against the threshold of $\alpha_{corrected}$ = .025. In a logistic regression with a dummy-coded study factor, we found a statistically significant but small difference in bribe offers (see Fig. S4). The present experiment showed slightly lower bribe offers than TB-NP (OR = 0.99, z = -2.57, p = .010, 95% CI [0.98, 0.997]; see Table S46). In another logistic regression, we found that fewer bribe offers were accepted in the present experiment compared to TB-NP (OR = 0.97, z = -5.76, p < .001, 95% CI [0.96, 0.98]; see Table S47). Put differently, bribe offer rates declined from 35.23% in TB-NP to 34.58% in the present study, a relative decline of 1.85%. Bribe acceptance rates declined by 3.44% (from 43.94% to 42.42%). Although significant, the modest reduction suggests that the risk of punishment alone might be insufficient to curb transnational bribery.

These effects must be interpreted with caution as they stem from a cross-study comparison that may introduce temporal confounds. Yet, the replication of key findings (see section S3.2.1), the use of large and demographically similar samples, and the stability of Corruption Perception Index scores (Mdn change = 2.7%; see Table S6) support comparability.

S3.4.5 Country-Specific Effect of Punishment

We ran country-specific tests to compare bribery rates between the previous experiment without punishment (TB-NP; *23*) and the present experiment (with punishment) for all the target countries participants interacted with. We used chi-squared tests to compare both the bribe offer and acceptance rates between the two studies. As we analyze each comparison across 17 countries we conduct $k = 34$ tests, we evaluate all p values against a threshold of $\alpha_{corrected} = .00147$. As explained before (see section S3.4.4), these cross-study comparisons must be interpreted cautiously.

Overall, bribe offer and acceptance rates decreased modestly in the present experiment compared to TB-NP. When looking at specific target countries, participants in the role of a public official accepted significantly fewer bribes from citizens from Australia ($p = .001$), China ($p = .001$), France ($p < .001$), and the United States ($p < .001$) in the present experiment than in TB-NP. Complete results are reported in Table S48. Turning to study differences in bribe offers, participants offered significantly more bribes to Argentina in the present experiment than in TB-NP ($p = .001$). For the other target countries, bribe offers did not differ significantly between the two studies (see Table S49, for complete report). Due to the very small reduction of bribe offers between studies (see section S3.4.4) it is not surprising that most country-specific bribe offer differences do not reach significance after a strict Bonferroni correction for 17 tests ($\alpha_{corrected} = .003$). Yet, descriptively, we can still find a pattern (see Fig. S5): We consistently observe a decrease in both bribe offer and bribe acceptance rates across countries that are targeted less frequently with bribes. In contrast, bribe offer and bribe acceptance rates towards countries that are targeted more frequently with bribes descriptively increase or remain relatively stable across the two studies. Although exploratory in nature, this pattern generalizes for both bribe offer and acceptance behavior.

When comparing the results of TB-NP to the present study, we observed the expected deterrence effect of punishment in interactions with some punishment enforcing countries, but not with others. Specifically, bribe offer rates remained stable or even increased for Turkey, Argentina, South Africa, Brazil, and India in the current study (with punishment) compared to TB-NP. This pattern is replicated in bribe acceptance rates and may reflect people's perception that punishment in these countries is very unlikely (see Main Text, Fig. 2C). Alternatively, the increase in bribe offers to some countries may be due to crowding-out, where introducing punishment shifts decision-making from moral to strategic reasoning (*54*). Overall, punishment appears more effective for countries that receive fewer bribes (e.g., Canada, Great Britain, the USA) than for those that are bribed more frequently and are perceived as more corrupt (e.g., Argentina, South Africa). This heterogeneity challenges the assumption of universal deterrence effects, instead highlighting the importance of tailoring interventions to local expectations.

S3.4.6 Content Analysis of Text Fields

We conducted a content analysis using a large language model to identify the most relevant topics participants considered when making their decisions in the bribery game. In an open-ended text field at the end of our study, participants wrote about their decision-making processes. We prompted ChatGPT Pro 5.1 to identify general topics mentioned in the text fields and to count how often they occur.

We used the following prompt with a bribery game tree and the text data attached:

"Here is a list of descriptions of what people thought when they offered or accepted a bribe as a citizen or public official in an experimental economic bribery game with incentivization. Attached is the game tree. People played this game with 20 different nations and in both roles in a completely crossed within-subject design (so 40 decisions for each participant). So all participants played both roles: the public official and the citizen. There was also a punishment mechanism based on a country-specific detection probability – when detected, both the citizen and the public official lose all their bonus payment. The citizen can decide to either offer an unofficial payment (a bribe) or an official payment. The public official can decide to either accept or reject the unofficial payment. In the text field participants indicated their thoughts behind their bribery behavior. These are in different languages. Please consider all comments in the attached csv in all languages and analyze the content of all the comments. Please extract specific topics that are mentioned most often in the comments. Count how often these topics are mentioned in percent and give me a table for the most relevant topics. Please also indicate what percentage of answers is useless, i.e., participants who clearly did not answer the question seriously."

The most common topic, mentioned by 47.2%, was game strategic reasoning related to the outcome. The second most common topic (34.7%) was perceptions of different countries, for example, their corruption or trustworthiness. Also, moral attitudes of being uncorrupt (33.8%) or prosocial motives (17.5%) were relevant topics that participants indicated to have thought about. Full results are reported in Table S5.

S3.5 Exploratory Media Sentiment Analysis

In our exploratory media sentiment analysis, we focused on corruption sentiments because their effects on transnational bribery are most relevant for this project and straightforward to interpret. Accordingly, we did not further investigate trust sentiments and fear sentiments that were part of the confirmatory analyses reported above (see section S3.3). We applied a Bonferroni-corrected alpha error level for each set of tests addressing the same exploratory research question. Unless otherwise stated, we ran linear mixed-effects models to predict bribery expectations and generalized linear mixed-effects models to predict bribe offers. Furthermore, all mixed-effects models included two random intercepts: one at the participant level and one at the country level. All predictors included in interaction terms were centered at their mean.

S3.5.1 Analysis of Corruption Sentiments in Different Studies Separately

While corruption sentiments showed robust effects in the combined dataset of both the present experiment and previous data on transnational bribery without punishment (TB-NP; *23*; see section S3.3.1), we tested these effects for both studies separately. We applied Bonferroni correction to control for multiple testing (k = 4 tests) and we thus evaluated all reported p-values against the threshold of $\alpha_{corrected} = .013$.

As reported in the main text, corruption sentiments predicted significantly which countries received bribe offers (OR = 1.46, z = 43.95, p < .001, 95% CI [1.43, 1.48]; see Table S9) and which countries were expected to be more likely to engage in bribery (β = 0.15, t(73,460) = 59.97, p < .001, 95% CI [0.14, 0.15]; see Table S8) when only analyzing the present experiment. Likewise, in TB-NP data only, corruption sentiments predicted bribe offers (OR = 1.41, z = 43.76, p < .001, 95% CI [1.39, 1.43]; see Table S50) and bribery expectations (β = 0.12, t(89,310) = 59.97, p < .001, 95% CI [0.11, 0.12]; see Table S51). These results demonstrate the temporal robustness of sentiment effects. Corruption sentiment indicators could predict bribery expectations and bribe offer behavior in two contexts, more than two years apart, one with punishment and one without.

S3.5.2 Comparison of Past and Future Sentiments

Because our hypothesis tests are correlational, we cannot claim causality. To at least approximate possible causal directionality, we compared our indicators that model sentiments from past media reports (before behavioral data collection) with indicators modelling future sentiments (after behavioral data collection). Of course, future sentiments cannot influence behavior retroactively. Thus, if they predict behavior equally well or better than past sentiments, this would suggest that both reflect stable country perceptions rather than media causally influencing behavior, as we assumed.

For future sentiment indicators, we reversed the linear retention function so that sentiments occurring shortly after behavioral measurement were given more weight than sentiments occurring long after the measurement. We compared both indicators of past and future sentiments in combined mixed-effects models. We applied Bonferroni correction to control for multiple testing (k = 5 tests), and thus evaluated all reported p-values against the threshold of $\alpha_{corrected}$ = .010.

We first compared long-term past sentiment indicators that we used for our main analyses with future sentiment indicators. Although bribery expectations could be explained by both past sentiments (β = 0.12, t(170,000) = 55.05, p < .001, 95% CI [0.11, 0.12]) and future sentiments (β = 0.03, t(171,400) = 11.31, p < .001, 95% CI [0.02, 0.04]), past sentiments had a stronger effect, as indicated by non-overlapping confidence intervals (see Table S52). The analysis of bribe offers in a combined model revealed even clearer effects in support of the past sentiment indicator: Past sentiments predicted bribe offers significantly (OR = 1.43, $z = 46.00$, $p < .001$, 95% CI [1.41, 1.45]), whereas future sentiments did not (OR = 1.01, $z = 0.69$, $p = .488$, 95% CI [0.99, 1.03]; see Table S53).

However, the past sentiment indicators included much more data points (from 2008 to the behavioral data collections in 2021 and 2023) than the future sentiment indicators (from 2021 or 2023 to 2025). Therefore, the asymmetric time spans may introduce differential measurement precision, with longer periods potentially reducing noise through aggregation. This makes it difficult to disentangle whether observed differences reflect genuine temporal precedence or artifacts of differential sampling periods. To address this concern, we matched the temporal windows at 499 days (the period between the last behavioral data collection and final sentiment data collection in 2025). Accordingly, we considered sentiment data from 499 days before individual behavioral data collection for past sentiments and sentiment data from 499 days after behavioral data collection for future sentiments.

Here, past sentiments ($\beta = 0.17$, $t(162{,}994) = 29.12$, $p < .001$, 95% CI [0.16, 0.18]) remained a stronger predictor for bribery expectations than future sentiments ($\beta = 0.13$, $t(165{,}473) = 20.91$, $p < .001$, 95% CI [0.12, 0.15]; see Table S54). However, past sentiments (OR = 1.11, $z = 11.02$, $p < .001$, 95% CI [1.09, 1.13]) were less strongly associated with bribe offers than future sentiments (OR = 1.21, $z = 18.55$, $p < .001$, 95% CI [1.18, 1.23]; see Table S55). Notably, these past and future sentiments with equal time spans were highly correlated ($r(172{,}431) = 0.79$, $p < .001$, 95% CI [0.78, 0.79]).

These analyses yield mixed evidence regarding causal directionality. For bribery expectations, past sentiments consistently outperformed future sentiments, supporting the hypothesis that media coverage shapes expectations. For bribe offers, results were inconsistent: past sentiments were superior predictors when using the full dataset since 2008 but not when time spans were matched. However, the high correlation between past and future sentiment indicators makes it difficult to isolate the individual effects of different predictors.

Furthermore, the strong correlation suggests that media portrayals of country corruption are highly stable over time rather than fluctuating rapidly. This stability creates a fundamental challenge for causal inference: if country perceptions change little over months to years, comparing slightly offset time windows provides limited leverage to approximate temporal causality. Overall, no causal inference can be made and findings must be interpreted as correlational. Definitive causal claims would require experimental manipulation of media coverage or natural variations through external shocks.

S3.5.3 Comparison of Long-Term and Short-Term Sentiments

We assumed that country perceptions are shaped over a long period and change rather slowly than quickly. That is why we used *long-term* sentiment indicators that span more than 13 years of daily sentiment data for our analyses. Since, to our knowledge, we are the first to combine long-term sentiment indicators with behavioral data, we compared our indicators with two *short-term* corruption sentiment indicators. For short-term indicators, we selected a 6-month period, as preregistered, and 30-days period before individual behavioral data collection. First, we tested univariate short-term models, without including long-term sentiments, to predict bribery expectations and bribe offer behavior. Second, we tested whether short- or long-term sentiments showed stronger and more robust effects in combined models that included both predictors. Again, we applied Bonferroni correction to control for multiple testing (k = 8 tests), and evaluated all reported p-values against the threshold of $\alpha_{corrected}$ = .006.

The univariate models of short-term corruption sentiments replicate our main results: short-term sentiments over six months predicted both bribery expectations (β = 0.04, t(163,000) = 24.44, p

$< .001$, 95% CI [0.04, 0.04]; see Table S56) as well as bribe offers (OR = 1.07, $z = 12.32$, $p < .001$, 95% CI [1.06, 1.09]; see Table S57). Even the more immediate sentiments over 30 days showed small positive associations with bribery expectations ($\beta = 0.01$, $t(162{,}800) = 11.24$, $p < .001$, 95% CI [0.01, 0.02]; see Table S58) and bribe offers (OR = 1.02, $z = 2.86$, $p = .004$, 95% CI [1.01, 1.03]; see Table S59).

Importantly, however, these effects of short-term sentiments were not as strong and robust as the effects of long-term sentiments. This was demonstrated by four mixed-effects models, each combining one type of short-term sentiments (30 days vs. 6 months) with long-term sentiments. When predicting bribery expectations, the predictor of short-term sentiments switched direction from positive to negative (in comparison to the univariate model) or showed no significant effect after Bonferroni correction, indicating low robustness (six months: $\beta = -0.004$, $t(162{,}900) = -2.29$, $p = .022$, 95% CI [-0.01, 0.00]; 30 days: $\beta = -0.02$, $t(162{,}800) = -11.90$, $p < .001$, 95% CI [-0.02, -0.02]). At the same time, the positive relationship between long-term sentiments and bribery expectations remained robust (see Tables S60 and S61). Furthermore, we found the same result in generalized linear mixed-effects models predicting bribe offer behavior: the effect of long-term sentiments remained robust while short-term sentiments predictors changed their directions in comparison to univariate models (six months: OR = 0.96, $z = -7.38$, $p < .001$, 95% CI [0.94, 0.97]; 30 days: OR = 0.92, $z = -14.06$, $p < .001$, 95% CI [0.91, 0.93]; see Tables S62 and S63).

To summarize, the long-term sentiment indicators used in our confirmatory analysis reliably outperformed two different short-term sentiment indicators in explaining behavioral bribery data. This could be due to the fact that country perceptions are conveyed by the media over a long period. This would suggest that media reports influence country perceptions months and even years after their release, and that country perceptions do not change easily in response to the most recent coverage. Alternatively, the relatively small effect of immediate media coverage might also speak for the opposite direction of causality that a relatively constant bribery rate in a country drives both media coverage and expectations.

S3.5.4 Bribe Acceptance and Corruption Sentiments

Beyond that, we investigated whether corruption sentiments can predict whether participants in the role of a public official tend to accept or reject bribe offers depending on the country the bribe comes from. In a generalized linear mixed-effects model, corruption sentiments significantly predicted bribe acceptance behavior (OR = 1.36, $z = 51.90$, $p < .001$, 95% CI [1.35, 1.38]; see Table S64). This means people are more likely to accept bribe offers when they come from countries portrayed as more corrupt in the media.

S3.5.5 General Sentiments and Bribery Expectations

Additionally, we analyzed the relation of bribery expectations and general media sentiment, which indicate the general tonality in that the media reports about a country, i.e., negative (-1) to neutral (0) or positive (1). The general media sentiment towards a country was negatively associated with bribery expectations ($\beta = -0.10$, $t(162{,}800) = -62.35$, $p < .001$, 95% CI [-0.10, -0.09]; see Table S65). Interestingly, this effect for general sentiments even holds when including corruption sentiments in the model as a fixed effect covariate ($\beta = -0.03$, $t(162{,}782) = -18.38$, $p < .001$, 95% CI [-0.04, -0.03]; see Table S35). This suggests that, beyond news reports about corruption, people from countries that the news reports negatively about are expected to be more corrupt than people from countries that receive a more positive media coverage.

S3.5.6 Differences Between Different Media Sources

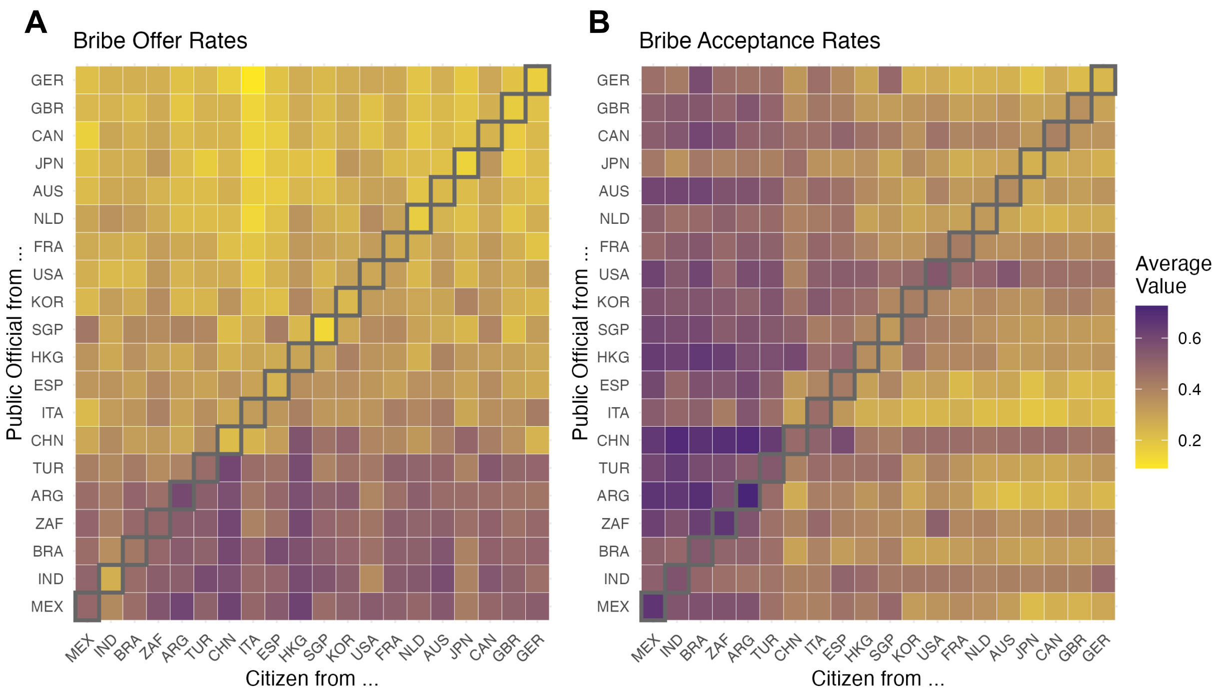
MarketPsych calculates sentiment values from various media sources. We decided to use the combined dataset of news and social media sources for our main analysis, as this contained the most data points. However, we found that our main findings generalized across three different datasets: newspaper texts only, social media texts only (including blog posts)b, and news headlines only. To control for multiple testing (k = 8 tests), we applied Bonferroni correction, and thus evaluated all reported p-values against the threshold of $\alpha_{corrected} = .006$.

Namely, in separate univariate models, bribery expectations increased with higher corruption sentiments in news texts ($\beta = 0.14$, $t(163{,}000) = 88.19$, $p < .001$, 95% CI [0.13, 0.14]; see Table S66), in social media texts ($\beta = 0.11$, $t(163{,}300) = 68.45$, $p < .001$, 95% CI [0.10, 0.11]; see Table S67) and in news headlines ($\beta = 0.08$, $t(162{,}800) = 53.22$, $p < .001$, 95% CI [0.08, 0.08]; see Table S68). Similarly, bribe offers were positively associated with corruption sentiments extracted from news data (OR = 1.45, $z = 63.65$, $p < .001$, 95% CI [1.43, 1.47]; see Table S69), social media data (OR = 1.30, $z = 44.93$, $p < .001$, 95% CI [1.29, 1.31]; see Table S70) as well as news headline data (OR = 1.26, $z = 40.34$, $p < .001$, 95% CI [1.24, 1.27]; see Table S71).

Additionally, we ran two models with corruption sentiments from all three data sources as predictors to compare their predictive value. Interestingly, news sentiments proved to be the best predictor for both bribery expectations (see Table S72) and bribe offers (see Table S73). In contrast, social media and headline sentiments were less robust, losing statistical significance or changing direction of their effects compared to the univariate models. Generally, it must be noted that sentiment indicators from different sources were correlated. For example, news and social media sentiments were strongly associated ($r(172{,}431) = 0.82$, $p < .001$, 95% CI [0.82, 0.82]). This limits the possibility to isolate the individual effects of different predictors.

S4 Supplementary Figures

Figure S1: Bribe Offer and Bribe Acceptance Rates across Country Pairings

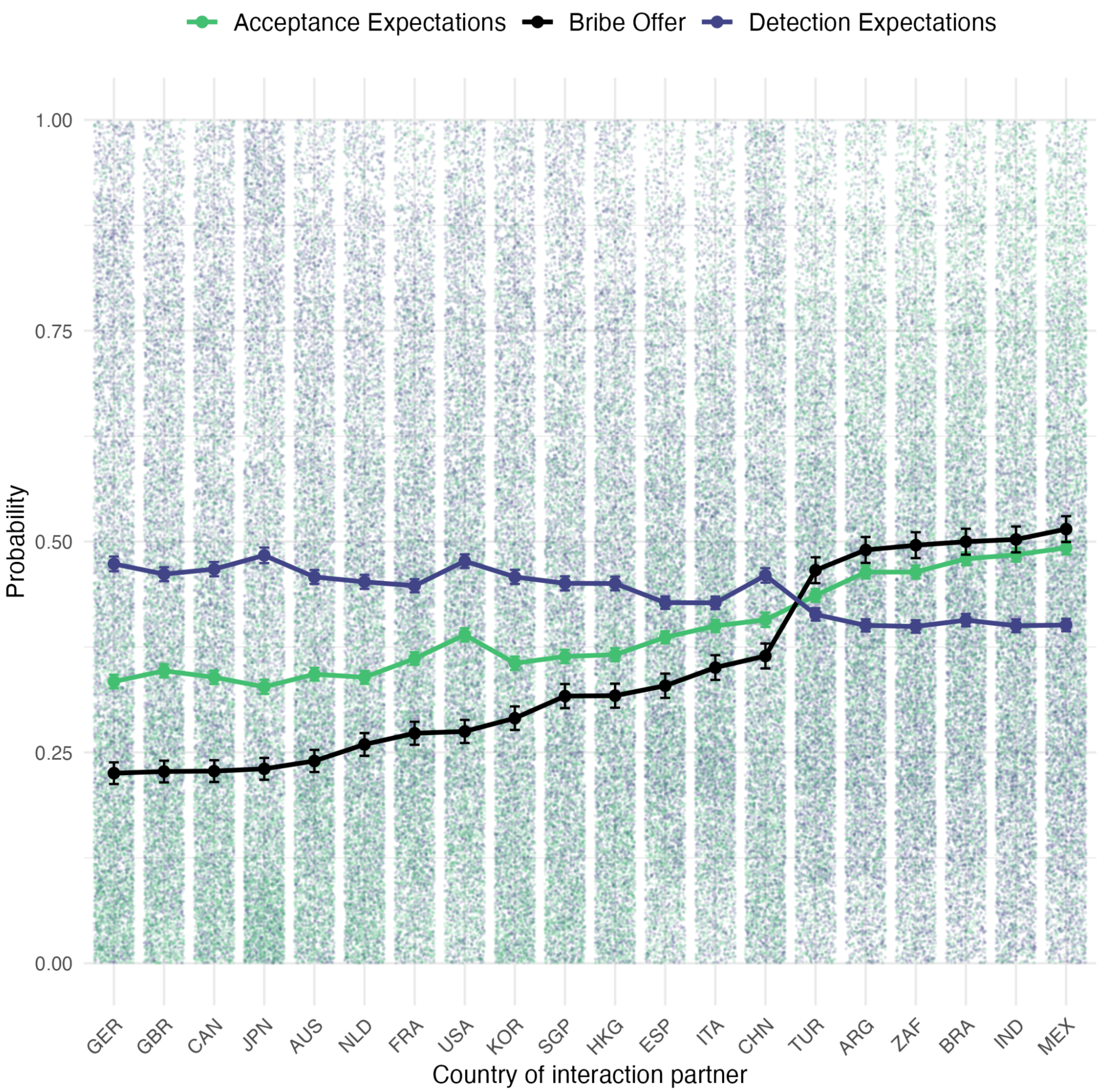


Note. (**A**) Bribe offer rates of participants in the role of a citizen to public officials from different countries. (**B**) Bribe acceptance rates of participants in the role of a public official when interacting with citizens from different countries. Yellow fields indicate low bribery rates, and purple fields indicate high bribery rates. Pictures with gray margins indicate within-country interactions. ARG = Argentina; AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; DEU = Germany; ESP = Spain; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; MEX = Mexico; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

Figure S2: Amount of Bribe Offers and Bribe Acceptances per Participant and Country

Note. Country codes indicate participants' countries of residence. Purple bars represent the number of participants who offered bribes to a certain number of countries. Green bars represent the number of participants who accepted bribes from a certain number of countries. Participants interacted with 20 countries and could therefore offer and accept up to 20 bribes. ARG = Argentina; AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; DEU = Germany; ESP = Spain; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; MEX = Mexico; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

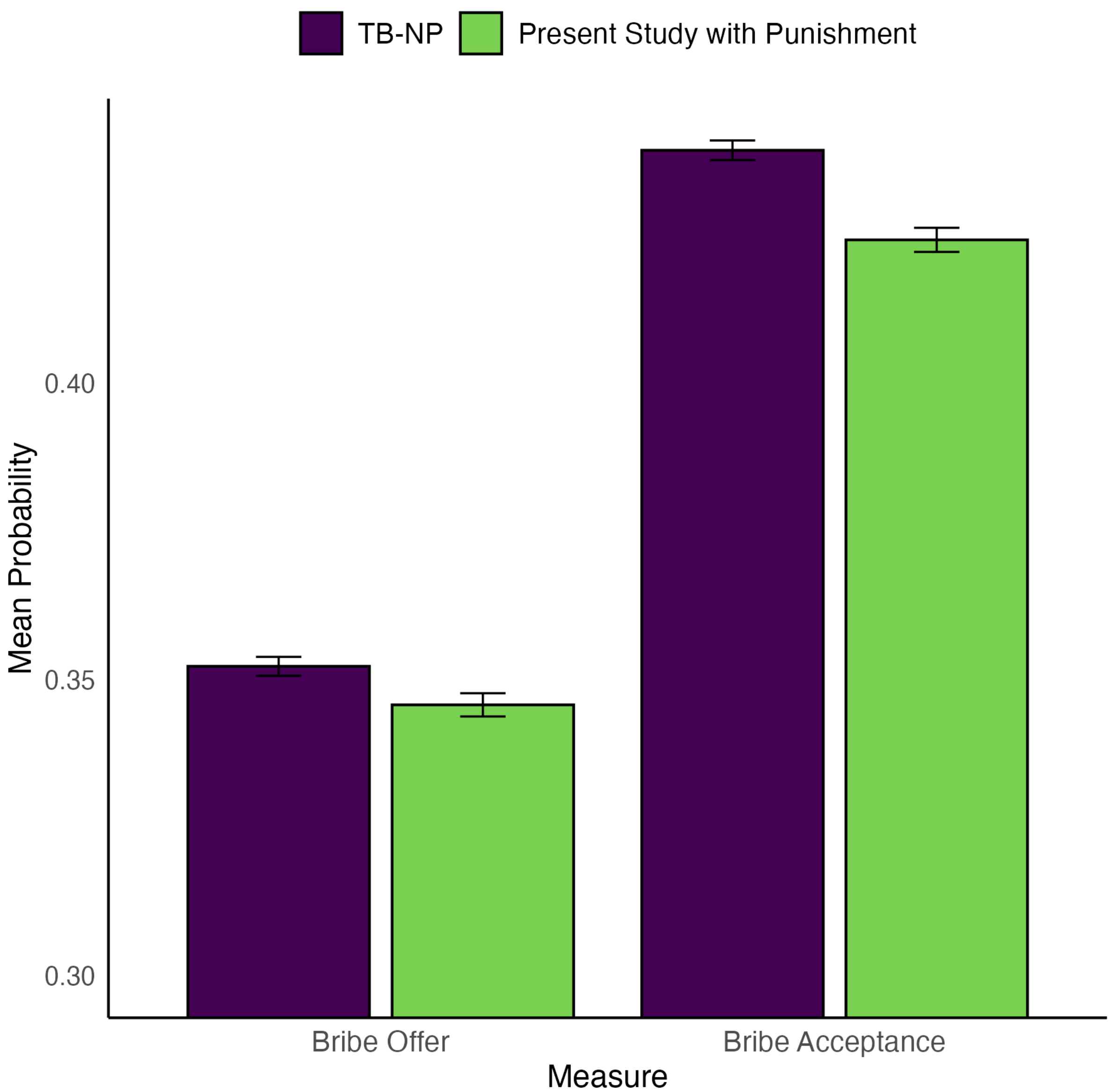
Figure S3: Relationship Between Bribery Behavior and Expectations across Countries



Note. Average bribe offer rates (black), acceptance expectations (green), and detection expectations (purple) are shown for each country of the interaction partner. All measures were transformed into probability scores between 0 and 1. Error bars show 95% confidence intervals. Scattered points show data points across all participants. ARG = Argentina; AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; DEU = Germany; ESP = Spain; FRA = France;

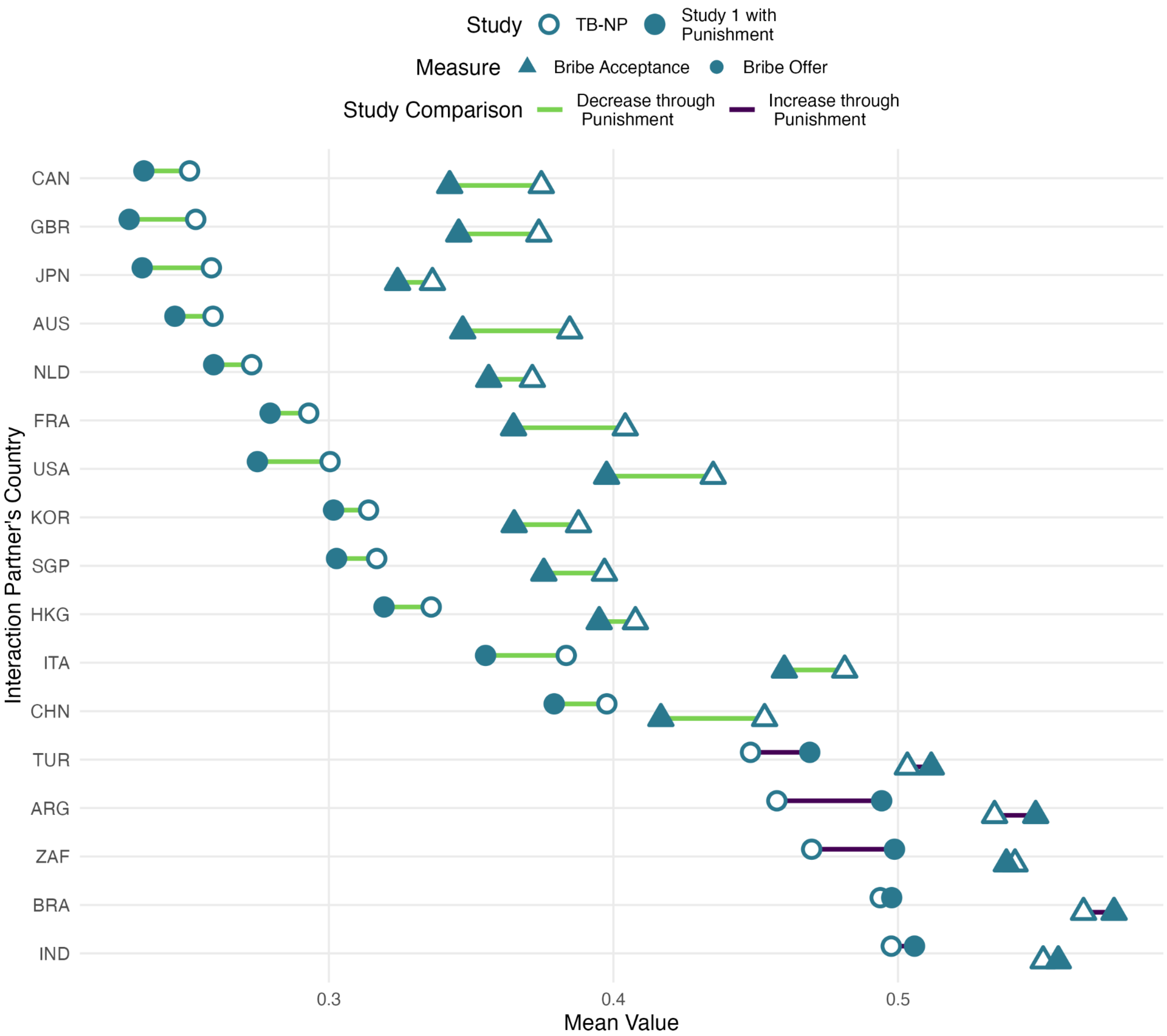
GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; MEX = Mexico; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

Figure S4: The Effect of Punishment on Bribery Rates



Note. The probability of offering and accepting bribes, comparing previous transnational data without punishment (TB-NP; *23*) with the present Study. The probability ranges from 0 to 1. Error bars indicate 95% confidence intervals.

Figure S5: Country-Specific Punishment Effect



Note. Bribe offer and acceptance rates in the present study and compared to previous transnational data without punishment (TB-NP). Behavioral values are averaged on a scale from 0 (no offer; no acceptance) to 1 (offer; acceptance). A green line indicates a lower value in the present study compared to TB-NP, showing a decrease through punishment. A purple line indicates a higher value in TB-NP, suggesting an increase when punishment is introduced. Countries on the y-axis indicate the interaction partner's country that bribes were offered to (points) and bribes were accepted from (triangles). Only countries included in both TB-NP and the present study are reported. ARG = Argentina; AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa. Data for TB-NP stems from (*22*).

S5 Supplementary Tables

Table S1.
Intraclass Correlations within Countries.

Nation	ICC nation-specific bribe offers [CI] (H1)	ICC nation-specific expectations about frequency of bribe acceptance [CI] (H3)	ICC nation-specific expectations about frequency of bribe detection [CI] (H6)
Argentina	0.10 [0.06, 0.20]	0.19 [0.12, 0.34]	0.08 [0.05, 0.16]
Australia	0.08 [0.05, 0.16]	0.10 [0.06, 0.19]	0.03 [0.02, 0.07]
Brazil	0.04 [0.02, 0.09]	0.10 [0.06, 0.19]	0.01 [0.002, 0.02]
Canada	0.05 [0.03, 0.10]	0.05 [0.03, 0.10]	0.03 [0.01, 0.06]
China	0.15 [0.09, 0.27]	0.12 [0.07, 0.22]	0.16 [0.10, 0.30]
France	0.05 [0.03, 0.11]	0.07 [0.04, 0.14]	0.02 [0.01, 0.06]
Germany	0.08 [0.05, 0.16]	0.16 [0.09, 0.28]	0.003 [0.00, 0.01]
Great Britain	0.08 [0.05, 0.17]	0.12 [0.07, 0.23]	0.03 [0.01, 0.06]
Hong Kong	0.10 [0.06, 0.20]	0.13 [0.08, 0.25]	0.03 [0.02, 0.07]
India	0.02 [0.01, 0.04]	0.02 [0.01, 0.05]	0.02 [0.01, 0.05]
Italy	0.11 [0.07, 0.21]	0.16 [0.10, 0.29]	0.02 [0.01, 0.06]
Japan	0.07 [0.04, 0.15]	0.13 [0.08, 0.25]	0.00 [0.001, 0.02]
Mexico	0.07 [0.04, 0.14]	0.14 [0.08, 0.25]	0.03 [0.01, 0.06]
Singapore	0.09 [0.05, 0.17]	0.14 [0.09, 0.27]	0.03 [0.02, 0.07]
South Africa	0.04 [0.02, 0.09]	0.11 [0.06, 0.21]	0.03 [0.02, 0.07]
South Korea	0.06 [0.03, 0.12]	0.09 [0.05, 0.18]	0.01 [0.01, 0.03]
Spain	0.10 [0.06, 0.19]	0.12 [0.07, 0.23]	0.07 [0.04, 0.15]
The Netherlands	0.09 [0.05, 0.18]	0.14 [0.09, 0.26]	0.05 [0.03, 0.11]
Turkey	0.08 [0.05, 0.17]	0.09 [0.06, 0.19]	0.01 [0.002, 0.02]
USA	0.03 [0.02, 0.07]	0.03 [0.01, 0.06]	0.02 [0.01, 0.05]

Note. ICC = intraclass correlation coefficients. CI = 95% confidence intervals [lower bound, upper bound].

Table S2.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Effect of Detection Expectations on Bribe Offers (H7).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.52	0.027	[0.50, 0.55]	-24.29	< .001
Detection Expectations	0.83	0.046	[0.76, 0.91]	-4.12	< .001

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. *N* = 4,081 (81,620 observations).

Table S3.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Effect of Acceptance Expectations on Bribe Offers (H5).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.51	0.03	[0.48, 0.54]	-23.39	< .001
Acceptance Expectations	1.56	0.03	[1.48, 1.65]	16.37	< .001

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. *N* = 4,081 (81,620 observations).

Table S4.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Combined Effect of Detection and Acceptance Expectations on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.50	0.03	[0.47, 0.54]	-21.19	< .001
Detection Expectations	0.71	0.04	[0.66, 0.76]	-9.44	< .001
Acceptance Expectations	1.72	0.03	[1.64, 1.81]	21.33	< .001
Detection Expectations × Acceptance Expectations	0.99	0.02	[0.95, 1.03]	-0.50	.615

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. *N* = 4,081 (81,620 observations).

Table S5.
Content Analysis of Text Fields by Artificial Intelligence.

Topic	Share of comments mentioning this topic (%)	*N* comments
Game strategy / numerical reasoning - talking about official vs. unofficial payment, payoffs, expected value, detection probabilities, role differences, "best option", etc.	47.2%	1,926
Perceived (un)trustworthiness / corruption of countries - stereotypes or beliefs about how corrupt/honest specific countries are, how developed/underdeveloped they are, whether their institutions can be trusted, etc.	34.7%	1,416
Anti-corruption, morality, honesty, lawfulness - explicit references to being honest, following rules/the law, rejecting corruption as morally wrong, wanting to "do the right thing", integrity, etc.	33.8%	1,377
Prosocial motives / public good - concern for society, citizens, the community or "the country", helping others, not harming third parties, public welfare.	17.5%	715
Self-interest / maximizing own payoff - focusing on getting more money/benefit, "what is best for me", maximizing gains, personal advantage.	13.8%	563
Personal experience with (anti-)corruption - references to own or close others' experiences with corruption/bribery, or how things are usually done in their country/region.	13.3%	543
Punishment risk / detection probability - mentioning risk of being caught, probability of detection, losing the bonus, sanctions, prison, fines, etc.	10.3%	421
Confusion / randomness / no idea - saying they didn't really know what to do, didn't understand, guessed, answered randomly.	6.8%	279
Charity / environment / atmosfair - explicitly mentioning atmosfair, donations, environment, CO_2, climate, etc., as a reason for their choices.	6.2%	253
Non-serious answers - obvious spam / "love love love…", chatty unrelated messages, very short off-topic entries, or purely "I didn't understand anything" without any task-related reasoning.	1.5%	60

Table S6.
Change of CPI Scores over Years between the Present Experiment and Previous Data on Transnational Bribery without Punishment.

Country	CPI 2021	CPI 2023	CPI change in percent (positive)
Argentina	38	37	2.63
Australia	73	75	2.74
Brazil	38	36	5.26
Canada	74	76	2.70
China	45	42	6.67
France	71	71	0.00
Great Britain	78	71	8.97
Hong Kong	76	76	0.00
India	40	39	2.50
Italy	56	56	0.00
Japan	73	73	0.00
Singapore	85	83	2.35
South Africa	44	41	6.82
South Korea	62	63	1.61
Netherlands	82	79	3.66
Turkey	38	34	10.53
USA	67	69	2.99

Note. Data of the present experiment was collected in 2023. Previous data on transnational bribery without bribery stems from 2021. CPI = Transparency International's Corruption Perception Index. Change in percent indicates the relation of CPI 2023 / CPI 2021 as a positive percent value.

Table S7.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Detection Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.89	0.08	0.00	0.03	[-0.06, 0.06]	65.12	< .001	18.96
Corruption Sentiments	-0.16	0.01	-0.06	0.00	[-0.06, -0.06]	-24.06	< .001	73460.01
Random Effects								
σ^2	3.30							
$\tau_{00\ \mathrm{participant}}$	3.43							
$\tau_{00\ \mathrm{country}}$	0.10							
ICC	0.52							
$N_{\mathrm{participant}}$	4,081							
N_{country}	20							
Observations	77,539							
Marginal R^2 / Conditional R^2	0.004 / 0.518							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S8.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribery Expectations, only Using Data from the Present Experiment.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	3.75	0.05	0.00	0.02	[-0.05, 0.05]	70.11	< .001	18.97
Corruption Sentiments	0.10	0.00	0.15	0.00	[0.14, 0.15]	63.27	< .001	73461.09
Random Effects								
σ^2	2.21							
$\tau_{00\ \text{participant}}$	2.81							
$\tau_{00\ \text{country}}$	0.04							
ICC	0.56							
$N_{\text{participant}}$	4,081							
N_{country}	20							
Observations	77,539							
Marginal R^2 / Conditional R^2	0.022 / 0.573							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S9.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Offers, only Using Data from the Present Experiment.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.37, 0.44]	-22.12	< .001
Corruption Sentiments	1.46	0.01	[1.43, 1.48]	43.95	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	1.99				
$\tau_{00\ \text{country}}$	0.02				
ICC	0.38				
N participant	4,081				
N country	20				
Observations	77,539				
Marginal R^2 / Conditional R^2	0.026 / 0.395				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S10.
Sample Sizes per Country of Residence.

Country	Number of Participants
Argentina	201
Australia	206
Brazil	216
Canada	204
China	199
France	201
Germany	201
Hong Kong	199
India	216
Italy	212
Japan	205
Mexico	220
Singapore	201
South Africa	212
South Korea	203
Spain	192
The Netherlands	198
Turkey	199
Great Britain	199
United States	197

Table S11.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Effect of BPI Scores on Bribe Offers (H2).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.52	0.03	[0.49, 0.54]	-26.35	< .001
BPI	0.71	0.02	[0.68, 0.73]	-17.62	< .001

Note. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. N = 4,081 (81,620 observations).

Table S12.
Linear Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Effect of BPI Scores on Bribe Acceptance Expectations (H4).

Predictors	std. Beta	SE	CI	*t*	*p*	df
(Intercept)	0.00	0.00	[0.00, 0.00]	-1.06	.305	19
BPI	-0.16	0.01	[-0.17, -0.14]	-18.04	< .001	19

Note. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). std. = standardized. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. N = 4,081 (81,620 observations).

Table S13.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Effect of Detection Expectations in One's Own Country on Bribe Acceptance Behavior (H8).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.73	0.05	[0.67, 0.80]	-7.04	< .001
Detection Expectation (own country)	1.04	0.03	[0.98, 1.10]	1.34	.179

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. *N* = 4,081 (81,620 observations).

Table S14.
Linear Regression with Cluster-Corrected Bootstrapped Standard Errors Predicting the Effect of BPI Scores on Detection Expectations (H9).

Predictors	std. Beta	SE	CI	*t*	*p*	df
(Intercept)	0.00	0.00	[0.00, 0.00]	0.67	.513	19
BPI	0.06	0.01	[0.04, 0.08]	5.79	< .001	19

Note. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). std. = standardized. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. N = 4,081 (81,620 observations).

Table S15.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Including Additional Covariates as a Robustness Check for H2, Predicting the Effect of BPI Scores on Bribe Offers

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.51	0.03	[0.49, 0.54]	-22.92	< .001
BPI	0.69	0.02	[0.66, 0.73]	-15.78	< .001
GDP Difference	1.11	0.02	[1.06, 1.17]	4.60	< .001
Sex	0.94	0.02	[0.91, 0.98]	-3.28	.001
Age	0.92	0.02	[0.88, 0.95]	-4.39	< .001
Valuation Charity	0.90	0.02	[0.86, 0.94]	-4.46	< .001

Note. Sex is a factor, coded as 1 for male and as 2 for female. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. GDP Difference = gross domestic product of the interaction partner's country subtracted from the gross domestic product of participant's country of residence. Valuation Charity = valuation of the charity "Atmosfair". *N* = 4,081 (81,620 observations).

Table S16.
Linear Regression with Cluster-Corrected Bootstrapped Standard Errors Including Additional Covariates as a Robustness Check for H4, Predicting the Effect of BPI Scores on Acceptance Expectations.

Predictors	std. Beta	SE	CI	*t*	*p*	df
(Intercept)	0.00	0.00	[0.00, 0.00]	-0.84	.411	19
BPI	-0.16	0.01	[-0.18, -0.14]	-15.93	< .001	19
GDP Difference	0.05	0.01	[0.03, 0.07]	5.38	< .001	19
Sex	-0.03	0.01	[-0.05, 0.00]	-2.03	.056	19
Age	-0.08	0.02	[-0.11, -0.05]	-5.34	< .001	19
Valuation Charity	0.00	0.01	[-0.02, 0.02]	-0.04	.966	19

Note. Sex is a factor, coded as 1 for male and as 2 for female. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). std. = standardized. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. GDP Difference = gross domestic product of the interaction partner's country subtracted from the gross domestic product of participant's country of residence. Valuation Charity = valuation of the charity "Atmosfair". *N* = 4,081 (81,620 observations).

Table S17.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Including Additional Covariates as a Robustness Check for H5, Predicting the Effect of Acceptance Expectations on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.51	0.03	[0.48, 0.54]	-22.11	< .001
Acceptance Expectations	1.56	0.03	[1.48, 1.64]	17.06	< .001
GDP Difference	1.05	0.02	[1.01, 1.09]	2.66	.008
Sex	0.96	0.02	[0.92, 0.99]	-2.33	.020
Age	0.95	0.02	[0.91, 0.99]	-2.60	.009
Valuation Charity	0.90	0.02	[0.85, 0.94]	-4.51	< .001

Note. Sex is a factor, coded as 1 for male and as 2 for female. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. GDP Difference = gross domestic product of the interaction partner's country subtracted from the gross domestic product of participant's country of residence. Valuation Charity = valuation of the charity "Atmosfair". *N* = 4,081 (81,620 observations).

Table S18.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Including Additional Covariates as a Robustness Check for H7, Predicting the Effect of Detection Expectations on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.52	0.03	[0.49, 0.55]	-23.49	< .001
Detection Expectations	0.83	0.04	[0.77, 0.90]	-4.71	< .001
GDP Difference	1.06	0.01	[1.03, 1.09]	3.93	< .001
Sex	0.94	0.02	[0.91, 0.97]	-3.70	< .001
Age	0.91	0.02	[0.88, 0.95]	-4.52	< .001
Valuation Charity	0.92	0.02	[0.88, 0.96]	-3.93	< .001

Note. Sex is a factor, coded as 1 for male and as 2 for female. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. GDP Difference = gross domestic product of the interaction partner's country subtracted from the gross domestic product of participant's country of residence. Valuation Charity = valuation of the charity "Atmosfair". *N* = 4,081 (81,620 observations).

Table S19.
Logistic Regression with Cluster-Corrected Bootstrapped Standard Errors Including Additional Covariates as a Robustness Check for H8, Predicting the Effect of Detection Expectation in One's Own Country on Bribe Acceptance.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.73	0.05	[0.67, 0.79]	-7.19	< .001
Detection Expectation (own country)	1.03	0.03	[0.98, 1.09]	1.27	.203
GDP Difference	1.13	0.04	[1.05, 1.22]	3.13	.002
Sex	0.96	0.03	[0.90, 1.02]	-1.22	.221
Age	0.88	0.02	[0.84, 0.92]	-5.37	< .001
Valuation Charity	0.94	0.03	[0.89, 0.99]	-2.21	.027
Trust in Scientists	0.96	0.02	[0.93, 1.00]	-2.08	.037

Note. Sex is a factor, coded as 1 for male and as 2 for female. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. GDP Difference = gross domestic product of the interaction partner's country subtracted from the gross domestic product of participant's country of residence. Valuation Charity = valuation of the charity "Atmosfair". *N* = 4,081 (81,620 observations).

Table S20.
Linear Regression with Cluster-Corrected Bootstrapped Standard Errors Including Additional Covariates as a Robustness Check for H9, Predicting the Effect of BPI Scores on Detection Expectations.

Predictors	std. Beta	SE	CI	*t*	*p*	df
(Intercept)	0.00	0.00	[0.00, 0.00]	0.50	.622	19
BPI	0.07	0.01	[0.05, 0.08]	7.05	< .001	19
GDP Difference	-0.03	0.02	[-0.06, 0.00]	-2.00	.060	19
Sex	-0.04	0.02	[-0.07, 0.00]	-2.09	.050	19
Age	-0.04	0.01	[-0.06, -0.01]	-2.96	.008	19
Valuation Charity	0.06	0.02	[0.03, 0.09]	3.66	.002	19
Trust in Scientists	0.06	0.01	[0.04, 0.09]	4.69	< .001	19

Note. Sex is a factor, coded as 1 for male and as 2 for female. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). std. = standardized. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. GDP Difference = gross domestic product of the interaction partner's country subtracted from the gross domestic product of participant's country of residence. Valuation Charity = valuation of the charity "Atmosfair". *N* = 4,081 (81,620 observations).

Table S21.
Generalized Linear Mixed-Effects Model as a Robustness Check for H2, Predicting the Effect of BPI Scores on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.38	0.01	[0.35, 0.41]	-24.65	< .001
BPI	0.63	0.01	[0.61, 0.64]	-35.60	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	62.54				
$\tau_{00\ \text{country}}$	0.02				
$\tau_{11\ \text{participant.BPI}}$	0.93				
$\rho_{01\ \text{participant}}$	-0.98				
ICC	0.95				
$N_{\text{participant}}$	4,081				
N_{country}	20				
Observations	81,620				
Marginal R^2 / Conditional R^2	0.003 / 0.950				

Note. Due to non-convergence, the random slope was excluded from the country level. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S22.
Linear Mixed-Effects Model as a Robustness Check for H4, Predicting the Effect of BPI Scores on Acceptance Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	0.00	0.02	0.00	0.02	[-0.04, 0.04]	0.04	.965	81615.00
BPI	-0.16	0.00	-0.16	0.00	[-0.16, -0.15]	-64.71	< .001	81615.00
Random Effects								
σ^2	0.48							
$\tau_{00\ \mathrm{participant}}$	0.49							
$\tau_{00\ \mathrm{country}}$	0.01							
ICC	0.51							
$N_{\mathrm{participant}}$	4,081							
N_{country}	20							
Observations	81,620							
Marginal R^2 / Conditional R^2	0.025 / 0.517							

Note. Due to non-convergence, the random slope was excluded from both the participant level and the country level. Degrees of freedom are calculated using the Satterthwaite method. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S23.
Generalized Linear Mixed-Effects Model as a Robustness Check for H5, Predicting the Effect of Acceptance Expectations on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.42	0.01	[0.40, 0.45]	-26.74	< .001
Acceptance Expectation	2.22	0.10	[2.03, 2.42]	17.82	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	6.28				
$\tau_{00\ \text{country}}$	0.10				
$\tau_{11\ \text{participant.acceptance\_expectation}}$	0.21				
$\tau_{11\ \text{country\_acceptance\_expectation}}$	0.00				
$\rho_{01\ \text{participant}}$	-0.83				
$\rho_{01\ \text{country}}$	-0.97				
ICC	0.66				
$N_{\text{participant}}$	4,081				
N_{country}	20				
Observations	81,620				
Marginal R^2 / Conditional R^2	0.062 / 0.681				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S24.
Generalized Linear Mixed-Effects Model as a Robustness Check for H7, Predicting the Effect of Detection Expectations on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.44	0.02	[0.40, 0.48]	-17.27	< .001
Detection Expectations	0.66	0.02	[0.62, 0.70]	-13.75	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	11.49				
$\tau_{00\ \text{country}}$	0.03				
$\tau_{11\ \text{participant.detection\_expectations}}$	0.37				
$\rho_{01\ \text{participant}}$	-0.90				
ICC	0.78				
$N_{\text{participant}}$	4,081				
N_{country}	20				
Observations	81,620				
Marginal R^2 / Conditional R^2	0.012 / 0.780				

Note. Due to non-convergence, the random slope was excluded from the country level. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S25.
Generalized Linear Mixed-Effects Model as a Robustness Check for H8, Predicting the Effect of Detection Expectations in One's Own Country on Bribe Acceptances.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	0.42	0.01	0.00	0.02	[-0.05, 0.05]	36.08	< .001	81615.00
Detection Expectation (own country)	0.01	0.00	0.01	0.01	[0.00, 0.03]	1.42	.156	81615.00
	Random Effects							
σ^2	0.18							
$\tau_{00\ participant}$	0.06							
$\tau_{00\ country}$	0.00							
ICC	0.27							
N $_{participant}$	4,081							
N $_{country}$	20							
Observa-tions	81,620							
Marginal R^2 / Conditional R^2	0.000 / 0.266							

Note. Due to non-convergence, the random slope was excluded from both the participant level and the country level. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S26.
Linear Mixed-Effects Model as a Robustness Check for H9, Predicting the Effect of BPI Scores on Detection Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	0.00	0.03	0.00	0.03	[-0.05, 0.05]	0.00	.998	81615.00
BPI	0.06	0.00	0.06	0.00	[0.06, 0.07]	25.45	< .001	81615.00
Random Effects								
σ^2	0.49							
$\tau_{00\ \text{participant}}$	0.49							
$\tau_{00\ \text{country}}$	0.01							
ICC	0.51							
$N_{\text{participant}}$	4,081							
N_{country}	20							
Observations	81,620							
Marginal R^2 / Conditional R^2	0.004 / 0.511							

Note. Due to non-convergence, the random slope was excluded from both the participant level and the country level. Degrees of freedom are calculated using the Satterthwaite method. BPI = Transparency International's Bribe Payers Index (regarding the interaction partner's country). SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S27.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribery Expectations (H10).

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	3.85	0.06	0.00	0.03	[-0.06, 0.05]	60.69	< .001	19.87
Corruption Sentiments	0.09	0.00	0.13	0.00	[0.13, 0.14]	87.00	< .001	163036.54
Random Effects								
σ^2	2.13							
$\tau_{00\ \text{participant}}$	3.11							
$\tau_{00\ \text{country}}$	0.08							
ICC	0.60							
$N_{\text{participant}}$	9,663							
N_{country}	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.606							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S28.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Offers (H11).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.21	0.01	[0.19, 0.23]	-29.69	< .001
Corruption Sentiments	1.11	0.00	[1.11, 1.12]	61.86	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.23				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.41				
$N_{\text{participant}}$	9,663				
N_{country}	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.023 / 0.423				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S29.
Generalized Linear Mixed-Effects Model Predicting the Effect of Trust Sentiments on Bribe Offers (H12).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.39	0.02	[0.36, 0.44]	-18.31	< .001
Trust Sentiments	0.67	0.00	[0.67, 0.68]	-66.65	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.24				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.41				
$N_{\text{participant}}$	9,663				
N_{country}	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.027 / 0.426				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S30.
Linear Mixed-Effects Model Predicting the Effect of Trust Sentiments on Bribery Expectations (H13).

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.58	0.06	0.00	0.03	[-0.06, 0.06]	71.55	< .001	19.77
Trust Sentiments	-0.02	0.00	-0.14	0.00	[-0.15, -0.14]	-93.93	< .001	162874.30
Random Effects								
σ^2	2.12							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.020 / 0.609							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S31.
Generalized Linear Mixed-Effects Model Predicting the Effect of Fear Sentiments on Bribe Offers (H14).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.77	0.06	[0.66, 0.90]	-3.20	.001
Fear Sentiments	0.97	0.00	[0.97, 0.98]	-8.73	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	1.86				
$\tau_{00\ country}$	0.02				
ICC	0.36				
$N_{participant}$	4,081				
$N_{country}$	20				
Observations	77,539				
Marginal R^2 / Conditional R^2	0.001 / 0.365				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S32.
Generalized Linear Mixed-Effects Model Predicting the Effect of Fear Sentiments on Bribe Offers Depending on the Implementation of Punishment (H15).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-17.28	< .001
Fear Sentiments	0.99	0.00	[0.98, 0.99]	-4.22	< .001
Study-id	1.08	0.04	[1.01, 1.16]	2.16	.031
Fear Sentiments × Study-id	0.99	0.00	[0.98, 0.99]	-3.28	.001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.09				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.39				
$N_{\text{participant}}$	9,663				
N_{country}	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.001 / 0.394				

Note. Study-id is a factor (1 = previous data on transnational bribery without punishment; 2 = present experiment). SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S33.
Generalized Linear Mixed-Effects Model Predicting the Effect of Fear Sentiments on Bribe Offers Depending on Detection Expectations (H16).

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.41	0.02	[0.37, 0.44]	-20.97	< .001
Fear Sentiments	0.98	0.00	[0.97, 0.98]	-7.80	< .001
Detection Expectations	0.86	0.00	[0.85, 0.86]	-34.10	< .001
Fear Sentiments × Detection Expectations	1.00	0.00	[1.00, 1.00]	0.17	.864
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.02				
$\tau_{00\ \text{country}}$	0.03				
ICC	0.38				
$N_{\text{participant}}$	4,081				
N_{country}	20				
Observations	77,539				
Marginal R^2 / Conditional R^2	0.031 / 0.403				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S34.
Likelihood Ratio Tests Comparing Confirmatory Models of Sentiment Hypotheses with Respective Null Models.

Model	Formula	Chi^2	df	*p*
H10 Null Model	Bribery expectations ~ (1 | Participant) + (1 | Country)			
Model H10	Bribery expectations ~ Corruption sentiments + (1 | Participant) + (1 | Country)	7397.47	1	< .001
H11 Null Model	Bribe offers ~ (1 | Participant) + (1 | Country)			
Model H11	Bribe offers ~ Corruption sentiments + (1 | Participant) + (1 | Country)	3825.63	1	< .001
H12 Null Model	Bribe offers ~ (1 | Participant) + (1 | Country)			
Model H12	Bribe offers ~ Trust sentiments + (1 | Participant) + (1 | Country)	4489.13	1	< .001
H13 Null Model	Bribery expectations ~ (1 | Participant) + (1 | Country)			
Model H13	Bribery expectations ~ Trust sentiments + (1 | Participant) + (1 | Country)	8593.06	1	< .001
H14 Null Model	Bribe offers ~ (1 | Participant) + (1 | Country)			
Model H14	Bribe offers ~ Fear sentiments + (1 | Participant) + (1 | Country)	74.89	1	< .001
H15 Null Model	Bribe offers ~ Fear sentiments + Study-id + (1 | Participant) + (1 | Country)			
Model H15	Bribe offers ~ Fear sentiments * Study-id + (1 | Participant) + (1 | Country)	10.48	1	.001
H16 Null Model	Bribe offers ~ Fear sentiments + Detection expectations + (1 | Participant) + (1 | Country)			
Model H16	Bribe offers ~ Fear sentiments * Detection expectations + (1 | Participant) + (1 | Country)	0.03	1	.866

Note. Chi-squared tests compare confirmatory models with respective null models that only lack the hypothesis-relevant predictor or interaction term. Study-id is a factor (1 = previous data on transnational bribery without punishment; 2 = present experiment). Country = participant's country of residence.

Table S35.
Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H10, Predicting the Effect Corruption Sentiments on Bribery Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	69.57	< .001	19.86
Corruption Sentiments	0.27	0.00	0.12	0.00	[0.11, 0.12]	62.77	< .001	163013.87
General Sentiments	-0.08	0.00	-0.03	0.00	[-0.04, -0.03]	-18.38	< .001	162781.97
Random Effects								
σ^2	2.13							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.607							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S36.
Generalized Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H11, Predicting the Effect of Corruption Sentiments on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.39	0.02	[0.36, 0.44]	-18.15	< .001
Corruption Sentiments	1.34	0.01	[1.32, 1.36]	42.30	< .001
General Sentiments	0.88	0.01	[0.87, 0.89]	-18.67	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.24				
$\tau_{00\ country}$	0.05				
ICC	0.41				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.025 / 0.425				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S37.
Generalized Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H12, Predicting the Effect of Trust Sentiments on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-18.36	< .001
Trust Sentiments	0.67	0.01	[0.66, 0.68]	-45.83	< .001
General Sentiments	1.01	0.01	[0.99, 1.03]	1.17	.243
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.24				
$\tau_{00\ country}$	0.05				
ICC	0.41				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.027 / 0.426				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S38.
Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H13, Predicting the Effect of the Effect Trust Sentiments on Bribery Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.60	0.06	0.00	0.03	[-0.06, 0.06]	71.77	< .001	19.76
Trust Sentiments	-0.03	0.00	-0.16	0.00	[-0.17, -0.16]	-70.33	< .001	163256.89
General Sentiments	0.06	0.01	0.03	0.00	[0.02, 0.03]	11.04	< .001	163188.02
Random Effects								
σ^2	2.12							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.021 / 0.609							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S39.
Generalized Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H14, Predicting the Effect of Fear Sentiments on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.41	0.02	[0.37, 0.44]	-22.50	< .001
Fear Sentiments	0.86	0.01	[0.84, 0.87]	-17.09	< .001
General Sentiments	0.72	0.01	[0.70, 0.73]	-36.58	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	1.95				
$\tau_{00\ \text{country}}$	0.02				
ICC	0.37				
$N_{\text{participant}}$	4,081				
N_{country}	20				
Observations	77,539				
Marginal R^2 / Conditional R^2	0.021 / 0.387				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S40.
Generalized Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H15, Predicting the Interaction Effect of Fear Sentiments and the Implementation of Punishment on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.36	0.02	[0.32, 0.39]	-19.49	< .001
Fear Sentiments	0.80	0.01	[0.78, 0.82]	-18.21	< .001
Study-id	1.29	0.05	[1.20, 1.38]	6.76	< .001
General Sentiments	0.71	0.00	[0.71, 0.72]	-53.55	< .001
Fear Sentiments × Study-id	1.00	0.02	[0.97, 1.04]	0.23	.821
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.18				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.40				
$N_{\text{participant}}$	9,663				
N_{country}	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.019 / 0.415				

Note. Study-id is a factor (1 = previous data on transnational bribery without punishment; 2 = present experiment). SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S41.
Generalized Linear Mixed-Effects Model Including General Sentiments as a Robustness Check for H15, Predicting the Interaction Effect of Fear Sentiments and Detection Expectations on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.37, 0.43]	-21.04	< .001
Fear Sentiments	0.87	0.01	[0.85, 0.88]	-15.67	< .001
Detection Expectations	0.87	0.00	[0.86, 0.87]	-31.64	< .001
General Sentiments	0.73	0.01	[0.72, 0.74]	-34.31	< .001
Fear Sentiments × Detection Expectations	1.00	0.00	[0.99, 1.01]	-0.32	.749
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.08				
$\tau_{00\ \text{country}}$	0.03				
ICC	0.39				
$N_{\text{participant}}$	4081				
N_{country}	20				
Observations	77539				
Marginal R^2 / Conditional R^2	0.046 / 0.419				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S42.
Linear Mixed-Effects Model as a Robustness Check for H10, Predicting the Effect of Corruption Sentiments on Bribe Offer Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.52	0.06	0.00	0.02	[-0.05, 0.05]	74.93	< .001	19.88
Corruption Sentiments	0.29	0.00	0.11	0.00	[0.11, 0.12]	67.07	< .001	163142.11
Random Effects								
σ^2	3.18							
$\tau_{00\ participant}$	3.29							
$\tau_{00\ country}$	0.07							
ICC	0.51							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.013 / 0.520							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S43.
Linear Mixed-Effects Model as a Robustness Check for H10, Predicting the Effect of Corruption Sentiments on Acceptance Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.26	0.07	0.00	0.03	[-0.06, 0.05]	61.28	< .001	19.61
Corruption Sentiments	0.33	0.00	0.13	0.00	[0.12, 0.13]	77.37	< .001	163090.54
Random Effects								
σ^2	3.02							
$\tau_{00\ \mathrm{participant}}$	3.63							
$\tau_{00\ \mathrm{country}}$	0.09							
ICC	0.55							
$N_{\mathrm{participant}}$	9,663							
N_{country}	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.016 / 0.559							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S44.
Linear Mixed-Effects Model as a Robustness Check for H13, Predicting the Effect of Trust Sentiments on Bribe Offer Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.52	0.06	0.00	0.02	[-0.05, 0.05]	76.07	< .001	19.95
Trust Sentiments	-0.31	0.00	-0.12	0.00	[-0.13, -0.12]	-72.70	< .001	162918.53
Random Effects								
σ^2	3.16							
$\tau_{00\ \text{participant}}$	3.26							
$\tau_{00\ \text{country}}$	0.07							
ICC	0.51							
$N_{\text{participant}}$	9,663							
N_{country}	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.015 / 0.520							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S45.
Linear Mixed-Effects Model as a Robustness Check for H13, Predicting the Effect of Trust Sentiments on Acceptance Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.26	0.07	0.00	0.03	[-0.06, 0.06]	59.19	< .001	19.45
Trust Sentiments	-0.35	0.00	-0.13	0.00	[-0.14, -0.13]	-83.19	< .001	162895.19
Random Effects								
σ^2	3.00							
$\tau_{00\ participant}$	3.65							
$\tau_{00\ country}$	0.10							
ICC	0.56							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.563							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S46.
Logistic Regression Predicting the Difference in Bribe Offers between the Present Experiment and Previous Data on Transnational Bribery without Punishment.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.54	0.00	[0.53, 0.54]	-114.09	< .001
Study-id	0.99	0.01	[0.98, 1.00]	-2.57	.010

Note. Study-id is a factor (1 = previous data on transnational bribery without punishment; 2 = present experiment). Only common countries included in both studies were considered. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. *N* = 8,748 (148,716 observations).

Table S47.
Logistic Regression Predicting the Difference in Bribe Acceptances between the Present Experiment and Previous Data on Transnational Bribery without Punishment.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.76	0.00	[0.76, 0.77]	-51.24	< .001
Study-id	0.97	0.01	[0.96, 0.98]	-5.76	< .001

Note. Study-id is a factor (1 = previous data on transnational bribery without punishment; 2 = present experiment). Only common countries included in both studies were considered. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. N = 8,748 (148,716 observations).

Table S48.
Chi-Squared Tests on the Difference in Bribe Acceptance Rates between the Present Experiment and Previous Data on Transnational Bribery without Punishment, Depending on the Country the Bribe Came from.

Country	χ^2	df	*p*
ARG	1.56	1	.211
AUS	10.78	1	.001
BRA	0.93	1	.335
CAN	7.68	1	.006
CHN	10.14	1	.001
FRA	12.20	1	< .001
GBR	5.74	1	.017
HKG	0.89	1	.345
IND	0.21	1	.643
ITA	3.51	1	.061
JPN	0.85	1	.357
KOR	3.75	1	.053
NLD	1.54	1	.214
SGP	3.58	1	.058
TUR	0.61	1	.435
USA	10.93	1	< .001
ZAF	0.06	1	.810

Note. ARG = Argentina; AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

Table S49.
Chi-Squared Tests on the Difference in Bribe Offer Rates between the Present Experiment and Previous Data on Transnational Bribery without Punishment, Depending on the Country the Bribe was Offered to.

Country	χ^2	df	*p*
ARG	10.68	1	.001
AUS	1.53	1	.216
BRA	0.04	1	.849
CAN	2.37	1	.123
CHN	2.38	1	.123
FRA	1.65	1	.200
GBR	5.33	1	.021
HKG	2.22	1	.136
IND	0.41	1	.520
ITA	6.72	1	.010
JPN	5.36	1	.021
KOR	1.23	1	.267
NLD	1.43	1	.232
SGP	1.75	1	.186
TUR	3.38	1	.066
USA	6.29	1	.012
ZAF	6.96	1	.008

Note. ARG = Argentina; AUS = Australia; BRA = Brazil; CAN = Canada; CHN = China; FRA = France; GBR = Great Britain; HKG = Hong Kong; IND = India; ITA = Italy; JPN = Japan; KOR = South Korea; NLD = Netherlands; SGP = Singapore; TUR = Turkey; USA = United States; ZAF = South Africa.

Table S50.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Offers, only Using Previous Data on Transnational Bribery without Punishment.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.03	[0.36, 0.46]	-13.46	< .001
Corruption Sentiments	1.41	0.01	[1.39, 1.43]	43.76	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.40				
$\tau_{00\ \text{country}}$	0.07				
ICC	0.43				
$N_{\text{participant}}$	5,582				
N_{country}	18				
Observations	94,894				
Marginal R^2 / Conditional R^2	0.020 / 0.440				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S51.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribery Expectations, only Using Previous Data on Transnational Bribery without Punishment

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.40	0.09	0.00	0.04	[-0.07, 0.08]	51.62	< .001	16.98
Corruption Sentiments	0.28	0.00	0.12	0.00	[0.11, 0.12]	59.97	< .001	89312.82
Random Effects								
σ^2	2.07							
$\tau_{00\ participant}$	3.32							
$\tau_{00\ country}$	0.12							
ICC	0.62							
$N_{participant}$	5,582							
$N_{country}$	18							
Observations	94,894							
Marginal R^2 / Conditional R^2	0.014 / 0.630							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S52.
Linear Mixed-Effects Model Predicting Bribery Expectations, Comparing the Effects of Past Sentiments and Future Sentiments.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	68.40	< .001	19.81
Corruption Sentiments (past)	0.27	0.00	0.12	0.00	[0.11, 0.12]	55.05	< .001	169955.32
Corruption Sentiments (future)	0.07	0.01	0.03	0.00	[0.02, 0.04]	11.32	< .001	171364.07
Random Effects								
σ^2	2.13							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.606							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S53.
Generalized Linear Mixed-Effects Model Predicting Bribe Offers, Comparing the Effects of Past Sentiments and Future Sentiments.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-18.12	< .001
Corruption Sentiments (future)	1.01	0.01	[0.99, 1.03]	0.69	.488
Corruption Sentiments (past)	1.43	0.01	[1.41, 1.45]	46.00	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.23				
$\tau_{00\ country}$	0.05				
ICC	0.41				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.023 / 0.422				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S54.
Linear Mixed-Effects Model Predicting Bribery Expectations, Comparing the Effects of Past Sentiments and Future Sentiments, Using Equal Time Windows for All Indicators.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	69.69	< .001	19.88
Corruption Sentiments (past)	0.17	0.01	0.07	0.00	[0.07, 0.08]	29.12	< .001	162994.07
Corruption Sentiments (future)	0.13	0.01	0.06	0.00	[0.05, 0.06]	20.91	< .001	165472.98
Random Effects								
σ^2	2.16							
$\tau_{00\ participant}$	3.13							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.015 / 0.603							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S55.
Generalized Linear Mixed-Effects Model Predicting Bribe Offers, Comparing the Effects of Past Sentiments and Future Sentiments, Using Equal Time Windows for All Indicators.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-17.87	< .001
Corruption Sentiments (past)	1.11	0.01	[1.09, 1.13]	11.02	< .001
Corruption Sentiments (future)	1.21	0.01	[1.18, 1.23]	18.55	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.18				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.40				
$N_{\text{participant}}$	9,663				
N_{country}	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.013 / 0.412				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S56.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments from the Past Six Months on Bribery Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.07	0.00	0.03	[-0.06, 0.06]	67.42	< .001	19.81
Corruption Sentiments (6 months)	0.09	0.00	0.04	0.00	[0.04, 0.04]	24.44	< .001	162985.06
Random Effects								
σ^2	2.22							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.59							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.001 / 0.590							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S57.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments from the Past Six Months on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.41	0.02	[0.37, 0.45]	-18.08	< .001
Corruption Sentiments (6 months)	1.07	0.01	[1.06, 1.09]	12.32	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.09				
$\tau_{00\ country}$	0.05				
ICC	0.39				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.001 / 0.395				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S58.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments from the Past 30 Days on Bribery Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.07	0.00	0.03	[-0.06, 0.06]	67.07	< .001	19.80
Corruption Sentiments (30 days)	0.04	0.00	0.02	0.00	[0.01, 0.02]	11.24	< .001	162794.58
Random Effects								
σ^2	2.23							
$\tau_{00\ participant}$	3.10							
$\tau_{00\ country}$	0.08							
ICC	0.59							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.000 / 0.588							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S59.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments from the Past 30 Days on Bribe Offers.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.41	0.02	[0.37, 0.45]	-18.01	< .001
Corruption Sentiments (30 days)	1.02	0.01	[1.01, 1.03]	2.86	.004
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.09				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.39				
N participant	9,663				
N country	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.000 / 0.394				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S60.
Linear Mixed-Effects Model Predicting Bribery Expectations, Comparing the Effects of Short-Term Corruption Sentiments from the Past Six Months and Long-Term Corruption Sentiments since 2008.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	69.53	< .001	19.86
Corruption Sentiments (6 months)	-0.01	0.00	0.00	0.00	[-0.01, 0.00]	-2.28	.022	162871.94
Corruption Sentiments	0.31	0.00	0.13	0.00	[0.13, 0.14]	83.37	< .001	162932.54
Random Effects								
σ^2	2.13							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.606							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S61.
Linear Mixed-Effects Model Predicting Bribery Expectations, Comparing the Effects of Short-Term Corruption Sentiments from the Past 30 Days and Long-Term Corruption Sentiments since 2008.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	69.73	< .001	19.86
Corruption Sentiments (30 days)	-0.04	0.00	-0.02	0.00	[-0.02, -0.02]	-11.90	< .001	162796.13
Corruption Sentiments	0.32	0.00	0.14	0.00	[0.14, 0.14]	87.09	< .001	163038.91
Random Effects								
σ^2	2.13							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.607							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S62.
Generalized Linear Mixed-Effects Model Predicting Bribe Offers, Comparing the Effects of Short-Term Corruption Sentiments from the Past Six Months and Long-Term Corruption Sentiments since 2008.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-18.09	< .001
Corruption Sentiments (6 months)	0.96	0.01	[0.94, 0.97]	-7.38	< .001
Corruption Sentiments (long-term)	1.46	0.01	[1.44, 1.47]	61.00	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.23				
$\tau_{00\ country}$	0.05				
ICC	0.41				
N participant	9,663				
N country	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.023 / 0.423				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S63.
Generalized Linear Mixed-Effects Model Predicting Bribe Offers, Comparing the Effects of Short-Term Corruption Sentiments from the Past 30 Days and Long-Term Corruption Sentiments since 2008.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-18.09	< .001
Corruption Sentiments (30 days)	0.92	0.01	[0.91, 0.93]	-14.06	< .001
Corruption Sentiments (long-term)	1.47	0.01	[1.45, 1.49]	63.13	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.24				
$\tau_{00\ country}$	0.05				
ICC	0.41				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.024 / 0.424				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S64.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Acceptances.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.58	0.05	[0.48, 0.69]	-6.00	< .001
Corruption Sentiments	1.36	0.01	[1.35, 1.38]	51.89	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	3.28				
$\tau_{00\ country}$	0.17				
ICC	0.51				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.014 / 0.519				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S65.
Linear Mixed-Effects Model Predicting the Effect of General Sentiments on Bribery Expectations.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.06]	68.21	< .001	19.82
General Sentiments	-0.22	0.00	-0.10	0.00	[-0.10, -0.09]	-62.35	< .001	162805.15
Random Effects								
σ^2	2.18							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.59							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.009 / 0.597							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S66.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribery Expectations, only Including Data from News Sources.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	69.59	< .001	19.85
Corruption Sentiments	0.31	0.00	0.14	0.00	[0.13, 0.14]	88.19	< .001	162995.68
Random Effects								
σ^2	2.13							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.018 / 0.607							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S67.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribery Expectations, only Including Data from Social Media Sources.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	69.07	< .001	19.88
Corruption Sentiments	0.25	0.00	0.11	0.00	[0.10, 0.11]	68.45	< .001	163333.56
Random Effects								
σ^2	2.17							
$\tau_{00\ \text{participant}}$	3.11							
$\tau_{00\ \text{country}}$	0.08							
ICC	0.60							
$N_{\text{participant}}$	9,663							
N_{country}	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.011 / 0.600							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S68.
Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribery Expectations, only Including Data from News Headlines.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.06]	67.53	< .001	19.79
Corruption Sentiments	0.19	0.00	0.08	0.00	[0.08, 0.08]	53.22	< .001	162773.34
Random Effects								
σ^2	2.19							
$\tau_{00\ participant}$	3.11							
$\tau_{00\ country}$	0.08							
ICC	0.59							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.007 / 0.595							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S69.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Offers, only Including Data from News Sources.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-18.15	< .001
Corruption Sentiments	1.45	0.01	[1.43, 1.47]	63.65	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.24				
$\tau_{00\ country}$	0.05				
ICC	0.41				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.024 / 0.424				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S70.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Offers, only Including Data from Social Media Sources.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-18.11	< .001
Corruption Sentiments	1.30	0.01	[1.29, 1.31]	44.93	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.16				
$\tau_{00\ country}$	0.05				
ICC	0.40				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.012 / 0.409				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S71.
Generalized Linear Mixed-Effects Model Predicting the Effect of Corruption Sentiments on Bribe Offers, only Including Data from News Headlines.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.40	0.02	[0.36, 0.44]	-17.80	< .001
Corruption Sentiments	1.26	0.01	[1.24, 1.27]	40.34	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ \text{participant}}$	2.14				
$\tau_{00\ \text{country}}$	0.05				
ICC	0.40				
$N_{\text{participant}}$	9,663				
N_{country}	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.009 / 0.406				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S72.
Linear Mixed-Effects Model Predicting Bribery Expectations, Comparing the Effects of Different Data Sources.

Predictors	Coef-ficients	SE	std. Beta	std. SE	std. CI	*t*	*p*	df
(Intercept)	4.39	0.06	0.00	0.03	[-0.06, 0.05]	70.77	< .001	19.89
Corruption Sentiments (news headlines)	-0.28	0.01	-0.12	0.00	[-0.13, -0.12]	-41.07	< .001	163340.41
Corruption Sentiments (social media)	0.00	0.01	0.00	0.00	[0.00, 0.01]	0.68	.495	163298.74
Corruption Sentiments (news)	0.55	0.01	0.24	0.00	[0.23, 0.24]	68.87	< .001	162858.88
Random Effects								
σ^2	2.11							
$\tau_{00\ participant}$	3.12							
$\tau_{00\ country}$	0.07							
ICC	0.60							
$N_{participant}$	9,663							
$N_{country}$	21							
Observations	172,433							
Marginal R^2 / Conditional R^2	0.023 / 0.611							

Note. Degrees of freedom are calculated using the Satterthwaite method. SE = standard error. std. = standardized. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.

Table S73.
Generalized Linear Mixed-Effects Model Predicting Bribe Offers, Comparing the Effects of Different Data Sources.

Predictors	Odds Ratios	SE	CI	*z*	*p*
(Intercept)	0.39	0.02	[0.36, 0.43]	-18.47	< .001
Corruption Sentiments (news headlines)	0.75	0.01	[0.73, 0.76]	-26.41	< .001
Corruption Sentiments (social media)	0.91	0.01	[0.89, 0.93]	-9.07	< .001
Corruption Sentiments (news)	2.02	0.03	[1.97, 2.07]	53.26	< .001
Random Effects					
σ^2	3.29				
$\tau_{00\ participant}$	2.27				
$\tau_{00\ country}$	0.05				
ICC	0.41				
$N_{participant}$	9,663				
$N_{country}$	21				
Observations	172,433				
Marginal R^2 / Conditional R^2	0.030 / 0.431				

Note. SE = standard error. CI = 95% confidence intervals [lower bound, upper bound]. ICC = intraclass correlation coefficient. Country = participant's country of residence.