BANDITS ON PATROL: AN ANALYSIS OF PETTY CORRUPTION ON WEST AFRICAN ROADS

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Abstract

This paper explores the spatial determinants of petty corruption on West African roads, employing a unique micro-dataset on bribes extorted from truck drivers by officials at various checkpoints. First, I use road traffic levels to predict the spatial distribution of corruption, finding a broadly inverted-U relationship. Secondly, I investigate how regional favouritism might affect this distribution. When a new president comes into power in Mali, bribe values in his birth region change. This change is heterogeneous: there are both winners and losers *within* his region. Finally, I critique my theoretical framework by finding an unusually large relationship between bribery and rainfall.

I am very grateful to Professor Kaivan Munshi for his valuable supervision and to the Borderless Alliance for providing the data.

I. INTRODUCTION

When the CEO of a successful Thai manufacturing firm hopes to be reborn as a customs official (Svensson, 2005: p.19), this is symptomatic of a problem of corruption that must be tackled in many developing countries. But how can this be done? Addressing this question, Olken and Pande (2012: p.481) suggest that there are "more questions to pose than concrete answers"; Svensson (2005: p.39) laments that answers "are often not clear-cut, and there are many issues about corruption we simply know too little about".

This paper attempts to bring greater insight into the determinants of petty corruption, motivated by the lack of cross-country analyses of specific, micro-level corruption (Svensson, 2005). I place particular focus on corruption's spatial distribution, which so far has received little attention, making use of a unique, rich micro-dataset that records 257,000 bribe values extorted by officials at various checkpoints on 11,000 truck journeys across six West African countries between 2006 and 2012.

I first attempt to predict the spatial distribution of this localised corruption. I use road traffic levels because they can be estimated at the same granularity as my dataset. Using gravity estimates of average traffic volumes and both parametric and semi-parametric methods, I find that corruption has a broadly inverted-U relationship with traffic. Controlling for various sources of heterogeneity, bribe values are moderate in low-traffic areas; as traffic increases, values increase until a turning point in medium-traffic areas; values then rapidly decrease to low levels in high-traffic areas. Understanding this distribution of bribery helps determine where best to target anti-corruption efforts.

Secondly, I explore the dynamics of corruption's spatial distribution. Supplementing a growing interest in the literature, I investigate regional favouritism's interaction with corruption in Mali, when an interim president comes into power. Using difference-in-differences and triple differences, I find some evidence of 'favouritism', although it is heterogeneously distributed across official groups: there exist both winners and losers *within* the president's birth region.

Finally, I evaluate my theoretical framework, which builds on Becker and Stigler's (1974) rational expected utility model. I do this by finding an unusually large relationship between bribe values and rainfall. Weather can have a psychological effect on decision-making in certain economic contexts (Busse et al., 2015; DellaVigna, 2009; Hirshleifer and Shumway, 2003). As behavioural economics deepens our understanding of development economics, future research should extend its application to corruption. Traditional models often struggle to explain certain idiosyncrasies.

The paper proceeds as follows: Section II reviews the literature, highlighting my contribution; Section III describes the data; Section IV presents my theoretical model; Section V discusses my empirical methodology and results; Section VI evaluates my model; Section VII concludes.

II. LITERATURE REVIEW

Corruption is inefficient and costly (Aidt, 2003; Olken and Pande, 2012). It is therefore crucial to understand its determinants in order to effectively reduce it. Olken and Pande (2012) emphasise the role of incentives, including compensation and monitoring; Schleifer and Vishny (1993) highlight market structure and industrial organisation. Nevertheless, whilst these factors are undoubtedly important, there remains much uncertainty about their precise effects. For example, the evidence on the impact of higher compensation is mixed (Aidt, 2003; Svensson, 2005).

In my opinion, this ambiguity is due to an over-generalisation of corruption. Whilst corruption is pervasive, it is also diverse and heterogeneous. If we really seek to understand it, general theories can only go so far. Lambsdorff (2006) argues that a distinction must be made between small-scale, petty corruption and larger-scale, institutional corruption. I suggest that we further distinguish between different types of petty corruption, given that it operates in a wide range of diverse contexts.

There has been some research on corruption in transport. Bribes and delays hinder trade (Freund and Rocha, 2011; Sequeira and Djankov, 2014) and distort agricultural investment decisions (Bromley and Foltz, 2011). However, few have explored the determinants of road corruption; most existing studies use the same dataset as this paper. Foltz and Bromley (2010) find evidence of price discrimination on truck characteristics by officials; Foltz and Opoku-Agyemang (2015) reveal that police salary raises in Ghana increased corruption; Cooper (2015) explores the interaction of extortion with election cycles. In this paper, I make a broader use of the dataset, focusing firstly on predicting the spatial distribution of corruption across the whole West African region, before narrowing in on dynamics as others have.

Generally, corruption's spatial distribution has received little attention. Olken and Barron (2009) touch on certain elements, with their similar Indonesian dataset. Political science literature alludes to the spatial distribution of rule of law and institutional quality. Bates (1983) and Herbst (2000) argue that state power in Africa diminishes with distance from the capital; Michalopoulos and Papaioannou (2013) confirm this empirically. I extend this analysis by focusing specifically on road corruption and by exploring ways to predict its distribution beyond distance from the capital, which is less relevant for decentralised processes.

There is also a dynamic relationship between corruption and the wider political economy, suggested by Schleifer and Vishny (1993) and analysed empirically in illegal logging in Indonesia (Burgess et al., 2012). My paper supplements a growing interest in the distributional consequences of regional and ethnic favouritism. Government leaders often treat those from their birth region (or co-ethnics) differently. This is evident in several forms: greater night-light intensity (Hodler and Rashcky, 2014); greater road provision (Burgess et al., 2015); and, improved health and education outcomes (Franck and Rainer, 2012; Kramon and Posner, 2014). Outcomes are not always positive (Kramon and Posner, 2013): intriguingly, across Africa, co-ethnic cash crop farmers face higher taxes (Kasara, 2007). I contribute to our understanding of regional favouritism by exploring its relationship with petty corruption. To my knowledge, this has not yet been studied. Furthermore, most studies implicitly assume a homogenous distribution of favouritism *within* recipient groups. I challenge this by analysing heterogeneity *within* the president's region.

Section VI emphasises potential behavioural determinants of corruption. Behavioural and psychological insights are increasingly applied to development economics (for example, Bernheim, Ray and Yeltekin, 2015). Only a few studies, however, relate these to corruption (Banerjee, Mullainathan, and Hanna, 2012; Foltz and Opoku-Agyemang, 2015; Lambsdorff, 2012). More must be done to integrate these two areas.

III. DATA

Bribes data

I use a unique dataset on petty road corruption collected by *USAID's West Africa Trade Hub* (provided by the *Borderless Alliance*). Running from 2006 to 2012, it surveys 11,000 cross-country truck journeys on common trade routes across Burkina Faso, Côte d'Ivoire, Ghana, Mali, Sénégal and Togo. It records information on illegal payments solicited by various officials (predominantly police, customs and military) at each checkpoint along a journey: **257,000 bribe opportunities**. In practice, at a checkpoint, an official stops a truck and asks the driver for his license and registration papers; the official may then refuse to return these until a bribe is received.

I convert Ghanaian bribe values into Franc CFA, the common currency for the other countries, and manually geo-code the checkpoints (Figure 1).

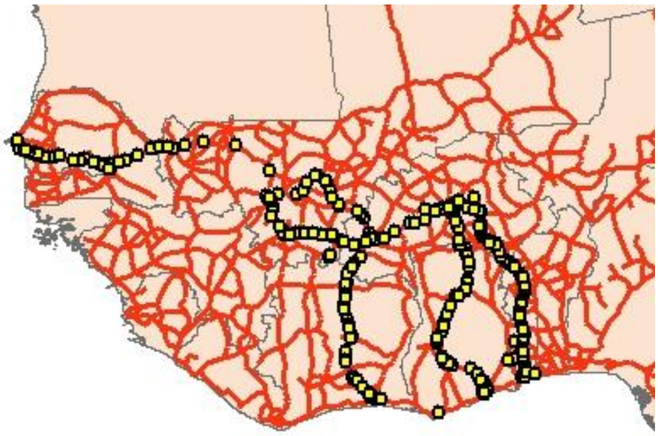

FIGURE 1. MAP OF CHECKPOINTS ON THE WEST AFRICAN ROAD NETWORK
Source: Author created; roads from Africa Infrastructure Country Diagnostic; borders from GADM.

<u>Is the data credible?</u>

Surveys are only given to drivers travelling across a whole trade route, and with papers and cargo in order (around one-third of trucks on these routes; Bromley and Foltz, 2011). By following the law, these drivers have little reason to bribe, and thus the data may represent a lower bound on bribe values.

The illegal nature of bribery may incentivise drivers to conceal their actions. However, road bribery is so common that it is not a taboo topic of discussion. Furthermore, truck-drivers have low social status and are often harassed by officials, and so welcome opportunities to voice their complaints. If anything, drivers may exaggerate their payments, which come out of their personal allowances. Regardless, since I focus on relative, rather than absolute, levels of bribery, these concerns do not affect my analysis[1]. Cooper (2015) and Foltz and Opoku-Agyemang (2015) make similar arguments.

Traffic data

The *Africa Infrastructure Country Diagnostic* (*AICD*) provides data on average traffic volumes on African roads. However, a significant number of roads are

[1] Trip/driver fixed effects also control for heterogeneity in exaggeration.

unmeasured. Therefore, I estimate average traffic flows at each checkpoint using a gravity model. Gravity models are commonly used to predict trade flows (Fujita, Krugman and Venables, 1999). They can also predict traffic (Jung, Wang and Stanley, 2008), and even counterfactual road networks (Burgess et al., 2015).

I compute gravity as:

$$Gravity_i = \sum_{n=1}^{N} \frac{Population_n}{e^{\beta distance(i,n)}}.$$

The gravity at checkpoint i is the population of city/town n, scaled by a decaying function of (road) distance between the checkpoint and the city/town, summed over all N cities/towns[2]. In each country analysed, I select the 20 largest cities/towns; I then add all other capital cities and cities with more than 10 million people in ECOWAS (West Africa).

Gravity is thus high at checkpoints in or close to large cities and low further away, as is traffic. I verify this intuitive relationship by regressing $\ln(traffic)$ from *AICD* (where available) on $\ln(gravity)$. The coefficient on $\ln(gravity)$ is 0.494 and is significant at the 0.1% level.

I compute gravity using the *Urban Network Analysis Toolbox for ArcGIS*. Geo-referenced cities/towns, with populations, are obtained from *GeoNames*; the road network is obtained from *AICD*.

I also compute distance from each checkpoint to its capital city.

Night-lights data

To proxy subnational GDP, I use night-lights data from the *National Centers for Environmental Information*. I aggregate average annual luminosity to the level of local administrative units (using maps from *GADM*).

[2] β=2.42 (Handy and Niemeier, 1997; Sevtsuk, Mekonnen and Kalvo, 2016).

Rainfall data

I use 0.05°x0.05° gridded daily precipitation data from *Climate Hazards Group InfraRed Precipitation with Station data*.

Summary statistics

TABLE 1 - SUMMARY STATISTICS

Variable	Mean	SD	Min	Max
Bribe value (Franc CFA)	1,406	2,689	0	450,000
Total paid in bribes per trip (Franc CFA)	32,175	25,677	1,196	494,000
Gravity	405,682	647,544	2,913	4,466,983
Distance to capital (km)	230	167	0	614
Average annual luminosity (1-63)	4.00	11.10	0	60.03
Daily rainfall (mm)	2.85	6.69	0	148.49

TABLE 2 - SOURCES OF VARIATION IN BRIBE VALUES

	Trip	Country	Checkpoint	Official
Within	2,423	2,635	2,486	2,666
Between	2,116	668	1,215	1,640

For context, Table 1 shows that bribe values average \$2.81. \$64.35 is paid per trip, which amounts to 1-5% of total trip costs (Foltz and Opoku-Agyemang, 2015). In Table 2[3], within-trip variation surpasses between-trip variation, indicating that drivers adjust payments by checkpoint; this justifies exploring the spatial distribution of bribery across the network. Nevertheless, higher variation within checkpoints than between checkpoints justifies also exploring the dynamics of this distribution.

[3] The sum of within and between variation does not equal total variation because the panels are unbalanced. This limits comparability across panel dimensions.

IV. THEORETICAL MODEL

I develop a theoretical model for road corruption, building on Becker and Stigler's (1974) model, although endogenising bribe values.

When an official stops a truck, he[4] chooses effort to extract a bribe, e, in order to maximise expected utility, U.

The official is punished for corruption with probability $p(e, \pi)$. The probability of punishment depends positively both on effort and the amount of monitoring, π.

When not punished, the official receives a bribe, $b(e, t)$, and supplements his wage, w. The bribe value depends positively and monotonically on effort and the volume of traffic, t, since there are more vehicles from which to discriminate.

When punished, the official is fired and receives outside option, $w_0 < w$.

Regardless of punishment, there is a cost, $c(e, t)$, to exerting each unit of effort. The opportunity cost also increases with traffic, as there is a greater volume of drivers on the road to stop and extort.

Assuming risk-neutrality, the official chooses e to maximise:

(1) $$U = [1 - p(e, \pi)][w + b(e, t)] + p(e, \pi)w_0 - c(e, t),$$

subject to b, $e \geq 0$. When $U < w$, no bribe is solicited (the constraints bind).

Otherwise, assuming U is concave in effort ($U''_{ee} < 0$), optimal e^* is derived from the first order condition:

(2) $$[1 - p(e, \pi)]b'_e(e, t) = p'_e(e, \pi)[w + b(e, t) - w_0] + c'_e(e, t).$$

Intuitively, e^* is chosen to equalise expected marginal benefit and expected marginal cost of effort. The marginal benefit of a higher bribe price when unpunished equals

[4] Most officials are male.

the inframarginal effect of a higher probability of punishment (where the official loses his wage and bribe, and receives his outside option) and the direct marginal cost of effort.

I abstract from heterogeneity in official bargaining power, and driver/truck-specific characteristics, which I control for empirically.

a) How might average traffic levels predict bribe values across the road network?

Traffic, t, directly enters the objective function: it denotes the volume of vehicles from which officials can discriminate; it also contributes to the opportunity cost of effort. Monitoring, π, also likely increases with the volume of traffic since more people observe extortion.

Thus, I re-write the first order condition, (2):

$$b'_e(e,t) = \frac{p'_e(e,\pi(t))[w + b(e,t) - w_0] + c'_e(e,t)}{1 - p(e,\pi(t))}. \quad (3)$$

Or:

$$MB(t) = MC(t). \quad (4)$$

I then make the following assumptions:

ASSUMPTION 1: $MB(t)$ is an increasing, concave function of traffic; $MB'(t) > 0, MB''(t) < 0$. A simple example explains this. Suppose that 10% of vehicles are high types (can be extorted for large amounts), and officials can stop only 50 vehicles in an hour at a given checkpoint due to capacity constraints. Suppose officials can perfectly observe and stop high types (Foltz and Bromley, 2010, show discrimination on observable truck characteristics). In a low-traffic area, 30 vehicles pass the checkpoint; therefore, 3 high types are extorted. In a medium-traffic area, 300 vehicles pass; 30 high types are extorted. In a high-traffic area, 600 vehicles pass; however, only 50 high types are extorted due to capacity constraints. $MB(t)$ is kinked at $t = 500$. In reality, the relationship is smoother, as checkpoint capacity increases with traffic but at a slower and diminishing rate (there is a limit to checkpoint size).

ASSUMPTION 2: $MC(t)$ is an increasing, convex function of traffic; $MC'(t) > 0, MC''(t) > 0$. Monitoring increases linearly with traffic, as more people observe corruption; this increases the probability of enforcement and the marginal effect of effort on this probability. Marginal opportunity cost increases convexly; this is explained by the capacity constraints example. In the low-traffic area there is no marginal opportunity cost of extortion, as only 30 cars pass. Only when traffic exceeds the capacity constraint of 50 will there be a marginal opportunity cost, which is increasing in traffic. Capacity increases with traffic, but at a slower and diminishing rate. In reality, capacity is only partly fixed; it is also endogenous to the effort exerted in each encounter. In high-traffic areas, every moment spent extorting more from a particular driver means that other drivers cannot be stopped.

The form of $MC(t)$ in (3) ensures convexity under these conditions, provided $p(e, \pi(t)) < 1$, which holds since bribery occurs at all checkpoints analysed[5] (when $p(e, \pi(t)) = 1$, no bribe is ever paid).

ASSUMPTION 3: In the lowest-traffic areas, $MB'(t_{min}) > MC'(t_{min})$. In these remote areas, the marginal opportunity cost of effort is negligible as discussed. There is also very little observation and monitoring.

ASSUMPTION 4: There exists a level of traffic, t^{**}, above which $MB'(t) < MC'(t)$. Eventually, $MC(t)$ increases more quickly than $MB(t)$.

Optimal e^* depends on the difference between $MB(t)$ and $MC(t)$, as e adjusts to equalise the two. For example, suppose that $MB(\tilde{t}) = MC(\tilde{t})$ when $e = \tilde{e}$. At other values of t, when $e = \tilde{e}$: if $MB(t) > MC(t)$, then $e^* > \tilde{e}$; if $MB(t) < MC(t)$, then $e^* < \tilde{e}$. Figure 2 illustrates this graphically.

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[5] Apart from one checkpoint with very few observations.

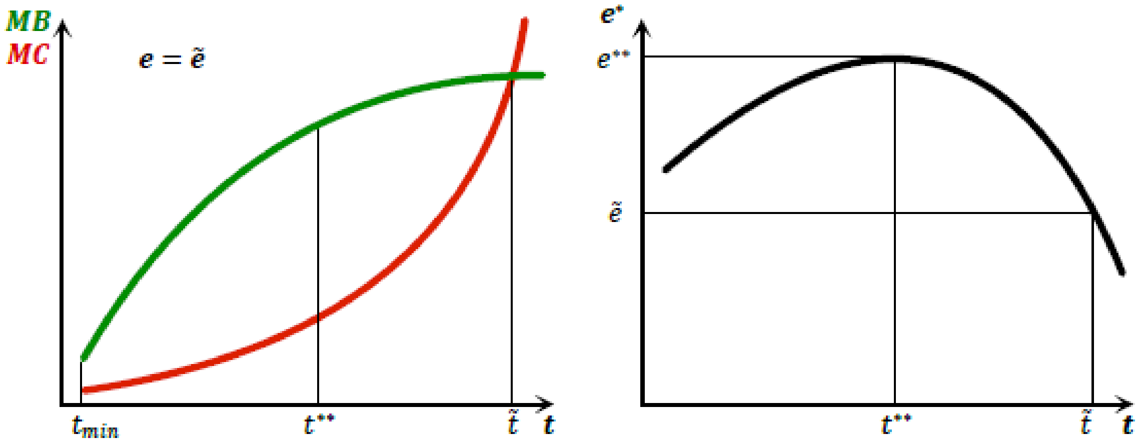

FIGURE 2. MOVEMENT OF MB, MC (LEFT) AND e* (RIGHT) WITH TRAFFIC

Ceteris paribus, optimal effort and bribe values (a positive monotonic function of effort) are highest at t^{**}, where the difference between MB and MC is greatest. There is an inverted-U relationship between bribe values and traffic.

b) How might regional favouritism affect bribe values in the president's region of birth?

Being in the president's birth region when he comes into power, r, affects optimisation through two channels. Firstly, the value of outside options, w_0, may increase, since economic activity may rise (Hodler and Raschky, 2014). This lowers the expected marginal cost of effort.

Secondly, monitoring may decrease. There may be patronage and local elite capture, a product of the decentralised nature of petty corruption (Bardhan and Mookherjee, 2000). The president may protect his region's officials, either altruistically (Franck and Rainer, 2012) or rationally. Padró i Miquel (2007) formalises a model where the incumbent rationally uses favouritism to maximise total rent extraction. Intriguingly, Kasara (2007) finds that across Africa co-ethnic cash crop farmers pay higher taxes; heads of state are better able to select, control and monitor local intermediaries in their own regions. Extortion could similarly be 'instrumentalised' to raise revenues (Cooper, 2015). Tax collection may further reinforce and be reinforced by patronage.

Conversely, if the president does not wish to support the officials (and perhaps sides with those negatively affected by their actions), monitoring may increase. This is again due to the president's greater control over his own region.

Thus, the first order condition, (2), can be re-written:

(5) $U'_e(e,r) = \left[1 - p\big(e,\pi(r)\big)\right]b'_e(e,t) - p'_e\big(e,\pi(r)\big)[w + b(e,t) - w_0(r)] - c'_e(e,t) = 0.$

Implicit function theorem demonstrates how optimal effort changes for officials in the president's region, when he comes into power, r[6]. Since expected utility is concave in effort ($U''_{ee} < 0$):

$$sign(e^{*\prime}(r)) = sign(U''_{er}(e,r)).$$

Differentiating (5) with respect to r:

(6) $$U''_{er}(e,r) = -\pi'(r)\left[p'_\pi\big(e,\pi(r)\big)b'_e(e,t) + p''_{e\pi}\big(e,\pi(r)\big)[w + b(e,t) - w_0(r)]\right] + {w_0}'(r)\left[p'_e\big(e,\pi(r)\big)\right],$$

where:

$$-\pi'(r)\left[p'_\pi\big(e,\pi(r)\big)b'_e(e,t) + p''_{e\pi}\big(e,\pi(r)\big)[w + b(e,t) - w_0(r)]\right]\begin{cases} < 0, when\ \pi'(r) > 0 \\ > 0, when\ \pi'(r) < 0 \end{cases}$$

due to changes in monitoring, and

$${w_0}'(r)\left[p'_e\big(e,\pi(r)\big)\right] > 0,$$

due to improved outside options.

Hence optimal effort and bribes values increase when $\pi'(r) < 0$ (monitoring decreases). Bribe values only decrease when both $\pi'(r) > 0$ and the effect of increased monitoring outweighs the effect of improved outside options.

[6] Implicitly differentiating $U'_e(e^*(r),r) = 0$ w.r.t. r gives $U''_{ee}\frac{de^*}{dr} + U''_{er} = 0$, implying $\frac{de^*}{dr} = -\frac{U''_{er}}{U''_{ee}}$. To enable differentiation, I assume r is continuous, rather than discrete.

V. EMPIRICAL METHODOLOGY AND RESULTS

a) How might average traffic levels predict bribe values across the road network?

Empirical specification

I use both parametric and semi-parametric methods. Using the whole dataset, I first estimate a multiple fixed effects regression for trip i at checkpoint j with official k in country l on date t:

$$\ln(expected\ bribe\ value_{ijklt} + 1) = \alpha + P(\ln(gravity_j)) + Q(dist.\ to\ capital_j) + \alpha_i + \alpha_{lkt} + \beta_{jl} + \theta_{jl} + \gamma foreign_{il} + \varepsilon_{ijklt}. \tag{7}$$

The dependent variable is formed by multiplying bribe values at checkpoint j by the proportion of total surveyed trucks that are stopped when passing checkpoint j during the month of date t. I use expected, rather than actual, bribe values since some checkpoints are more frequently occupied by officials than others. Furthermore, sometimes officials extort at unofficial, 'wildcat' locations rather than formal checkpoints (Foltz and Bromley, 2011). At low frequency checkpoints, stopping a driver is close to a one-off occasion. This may increase incentives to charge a higher bribe, just as incentives to cheat are higher in a one-stage game; there are fewer potential repercussions to extorting since the official is not more permanently based at the location. These incentives are driven by checkpoint-specific factors, rather than traffic. Therefore, bribe values at each checkpoint must weighted by their frequency, in order to accurately determine how traffic levels predict the extent of corruption across the whole road network[7].

$P(ln(gravity_j))$ is a 4^{th}-order polynomial, since my theory predicts a non-linear relationship. I control for distance to capital (as an 8^{th}-order polynomial),

[7] There is a significant (at the 1% level) broadly inverted-U relationship when actual bribe values are used, although results are biased upwards in below-average traffic areas where infrequently occupied checkpoints are more commonly found.

which may affect institutional quality (Bates, 1983; Herbst, 2000; Michalopoulos and Papaioannou, 2013). Polynomial orders are chosen iteratively. α_i is a trip-specific fixed effect to control for driver/truck-specific heterogeneity; α_{lkt} are country-official-month-year fixed effects to dynamically control for heterogeneity across countries and officials; β_{jl} and θ_{jl} fixed effects control for borders and truck terminals in each country; $foreign_{il}$ is a dummy for foreign trucks.

For visualisation, I then estimate this relationship semi-parametrically. Using the estimated coefficients in (7), I partial out from $\ln(expected\ bribe\ value_{ijkt} + 1)$ the effects of the controls and fixed effects. I then estimate a local polynomial regression of these partialled-out residuals on $\ln(gravity_j)$.

I assume the parameters and fixed effects in (7) are consistently estimated; the generally large number of observations within each fixed effect dimension circumvents the incidental parameters problem.

Exogeneity of traffic

Measurement error

Since I use gravity to estimate traffic, measurement error will attenuate coefficients[8]. Thus my results are a lower-bound estimate of the co-movement of corruption and traffic.

Omitted variable bias

There are omitted variables correlated with both traffic and corruption, such as monitoring. I do not intend, however, to isolate the true causal effect of traffic itself, but rather understand how it can be used to predict corruption. Traffic encompasses several important variables that are unavailable at such a granular, local level.

[8] Population data (in gravity computations) is also measured with error.

Simultaneity

West Africa's poor road conditions severely limit substitution opportunities; drivers cannot avoid roads with checkpoints. Petty corruption may marginally affect traffic by reducing trade (Freund and Rocha, 2011; Sequeira and Djankov, 2014). However, the magnitude of any potential effect is negligible compared to the large economic and demographic forces that drive traffic and the movement of people and goods. Moreover, even if this were problematic, my gravity model uses only population and distance, both of which are evidently exogenous. At worst, therefore, this analysis explores the predictive value of my gravity model itself, which is still useful for understanding the spatial distribution of corruption.

Results

Table 3 reports the coefficients of $P\left(ln(gravity_j)\right)$ in (7). Parameters are jointly significant at the 0.1% level (multicollinearity inflates individual standard errors). This significant relationship validates the use of semi-parametric methods for visualisation.

TABLE 3 - COEFFICIENT ESTIMATES OF THE GRAVITY POLYNOMIAL

Dependent variable: ln(expected bribe value + 1)				
ln(gravity)	ln(gravity)^2	ln(gravity)^3	ln(gravity)^4	$F(4,318)$
25.130	-3.409	0.204	-0.005	**5.06***
(19.461)	(2.575)	(0.149)	(0.003)	

Notes: R^2=0.422; N=256,635. Full specification in Equation (7). F-test of joint significance. Standard errors, clustered by checkpoint and trip, are reported in parentheses;
*** p≤0.01, ** p≤0.05, * p≤0.10.

Figure 3 illustrates how expected bribe values move with traffic, controlling for the sources of heterogeneity in (7). This almost matches my theoretical predictions of an inverted-U relationship. The confidence intervals are too narrow, as they do not account for clustering. Nevertheless, one can be confident that the patterns presented are significant, given the high joint significance of the parametric coefficients in Table 3 (accounting for two-way clustering).

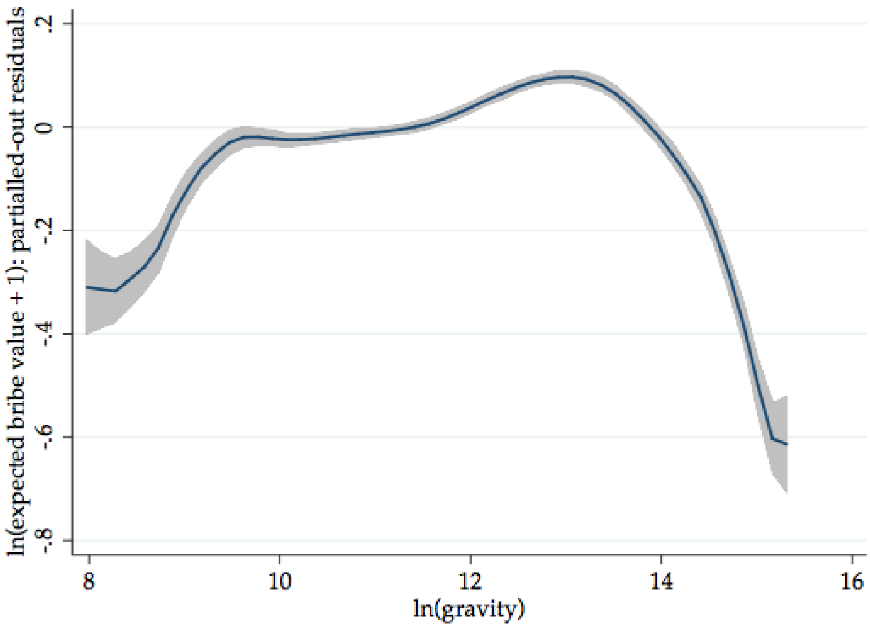

FIGURE 3. RELATIONSHIP BETWEEN EXPECTED BRIBE VALUES AND TRAFFIC

Notes: The effects of the controls and fixed effects in Equation (7) are partialled out of ln(expected bribe value + 1) to form the dependent variable. Third degree polynomial smooth. Rule-of-thumb bandwidth estimator used. Shaded 95% confidence intervals are too narrow, as they do not account for clustering.

However, the pattern is not as smooth as my theoretical prediction. This is perhaps because I assume outside options (w_0) to be constant in traffic. w_0 may actually increase with traffic since higher-traffic areas tend to have more economic activity. Subnational differences in activity can be proxied by night-lights data (Henderson, Storeygard and Weil, 2012; Hodler and Raschky, 2014; Michalopoulos and Papaioannou, 2013). I therefore add an 8^{th}-order polynomial of average annual luminosity to (7) to control for outside options local to each checkpoint, and follow the same semi-parametric procedure.

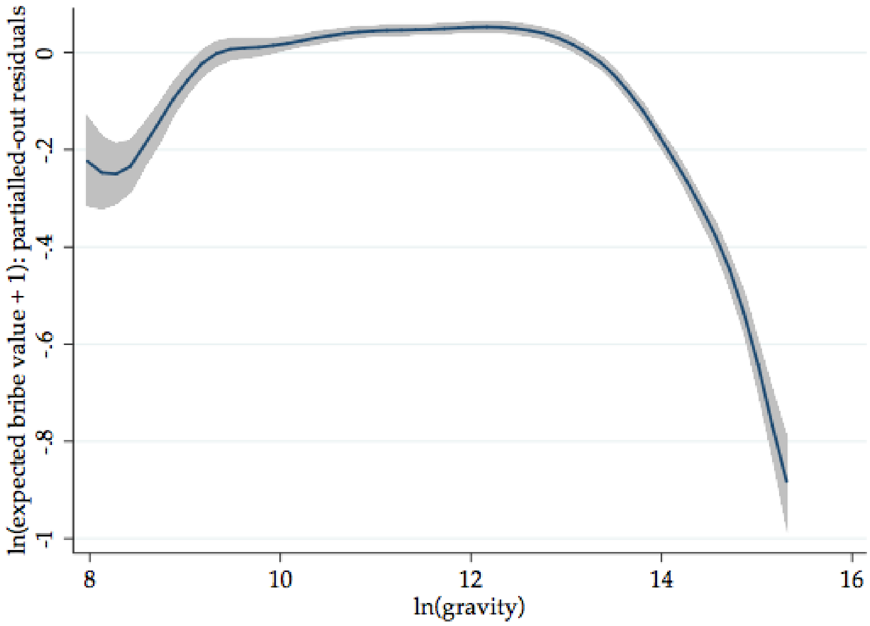

FIGURE 4. RELATIONSHIP BETWEEN EXPECTED BRIBE VALUES AND TRAFFIC, INCLUDING NIGHT-LIGHTS AS A CONTROL

Notes: The effects of the controls and fixed effects in Equation (7) and of a polynomial of average annual luminosity, are partialled out of ln(expected bribe value + 1) to form the dependent variable. Third degree polynomial smooth. Rule-of-thumb bandwidth estimator used. Shaded 95% confidence intervals are too narrow, as they do not account for clustering.

Figure 4's pattern is smoother and is parametrically significant at the 1% level. When compared to Figure 3, this suggests that a lower w_0 pushes down corruption levels in low-traffic areas, consistent with my theoretical framework (the expected marginal cost of effort is inversely related to w_0 in (2)).

However, Figure 4 must be interpreted cautiously. Economic activity and corruption may be jointly determined; therefore night-lights could be an endogenous control and conditional disturbances may thus be non-zero. Moreover, it appears that Figure 4's pattern is not robust to using Robinson's (1988) method to partial out the effects of the controls (de-meaned by the fixed effect dimensions) from $\ln(expected\ bribe\ value_{ijkt} + 1)$. Bias may be due to the incidental parameters problem when estimating fixed effects. Figure 3's pattern is highly robust to this alternative method.

Discussion

Figure 3, my preferred specification, broadly supports the theoretical predictions of an inverted-U relationship between traffic and corruption. Controlling for the frequency effect and other sources of heterogeneity, bribery is moderate in low-traffic areas. As traffic begins to increase, bribery generally increases due to the benefits of a greater pool of vehicles from which to discriminate. This continues until a turning point, after which bribery rapidly decreases to low levels in high-traffic areas. Here, the opportunity cost of marginal extortion is high, and so officials quickly charge smaller bribes from each vehicle in order to extort from as many as possible. They trade off price and volume, as suggested by Mookherjee and Png (1995) and Schleifer and Vishny (1993) in other contexts. Monitoring is also greater in high-traffic areas.

From a policymaker's perspective, these results may indicate that anti-corruption efforts should be targeted towards medium-traffic areas (medium-sized cities) on the road network, where corruption is highest but where effective monitoring may be more easily implemented than in more rural areas. There remains, however, much variation left unexplained by this static analysis (Table 2), leading me to explore the dynamics of corruption's spatial distribution.

b) How might regional favouritism affect bribe values in the president's region of birth?

Context

I explore regional favouritism in Mali. In March 2012, a military coup ended the 10-year presidency of a former military general (before entering civilian politics). The coup was condemned. As part of an internationally brokered agreement, the speaker of parliament was made interim president in April 2012 until elections could be held in August 2013.

Difference-in-differences

I explore changes in corruption at the checkpoint in Kati, the birth town of the interim president, once he comes into power; I compare it to a control group of five other Malian checkpoints, estimating a difference-in-differences (DD) regression for driver i at checkpoint j with official k on date t:

$$(8) \quad \ln(bribe\ value_{ijkt} + 1) = \beta_0 + \beta_1 Kati_j + \beta_2 In\ power_t + \beta_3 (Kati_j \times In\ power_t) + \alpha_i + \alpha_{kt} + \delta' truck_i + \varepsilon_{ijkt}.$$

I use actual bribe values for ease of interpretation since all checkpoints analysed are formal and frequently occupied by officials[9]. $Kati_j$ is a dummy for the interim president's region; $In\ power_t$ is a dummy for the interim presidency; α_i are driver fixed effects to control for driver-specific heterogeneity; α_{kt} are official-month-year fixed effects to dynamically control for heterogeneity between official groups; $truck_i$ is a vector of truck characteristic dummies. β_3 is the difference-in-differences estimate. I use data from 1 April 2010 to 30 September 2012 (when my sample ends).

[9] Conclusions are the same for expected bribe values.

Difference-in-difference-in-differences

Moving to a civilian president after 10 years of a former military president may affect the behaviour of military officials. They may opportunistically increase extortion (Cooper, 2015), as the new civilian leader may lack control over them compared to the previous military leader. Alternatively, with the president no longer 'one of their own', they may lose privileges and protection from punishment. This may also interact with regional favouritism, particularly if there is a response to the direct involvement of Kati military in the preceding coup.

I therefore investigate potential heterogeneity in favouritism between military and non-military officials in Kati, estimating a triple differences (DDD) regression:

$$
\begin{aligned}
(9) \qquad \ln\left(bribe\ value_{ijkt} + 1\right) = {} & \beta_0 + \beta_1 Kati_j + \beta_2 In\,power_t + \beta_3\left(Kati_j \times In\,power_t\right) \\
& + \beta_4 Military_k + \beta_5\left(Kati_j \times Mil._k\right) + \beta_6\left(In\,power_t \times Mil._k\right) \\
& + \beta_7\left(Kati_j \times In\,power_t \times Mil._k\right) + \alpha_i + \delta'\,truck_i + \varepsilon_{ijkt}.
\end{aligned}
$$

$Military_k$ ($Mil._k$) is a dummy for military officials. I exclude official-month-year fixed effects because of the $Military_k$ interaction terms. All other controls and fixed effects are as in (8). β_3 and $(\beta_3 + \beta_7)$ are the DD coefficients for non-military and military respectively.

The triple differences coefficient, β_7, directly tests for heterogeneous favouritism across Kati's official groups.

Baseline results

Baseline results (Table 4, Section A) suggest a significant effect of regional favouritism on bribery. In Column 1, bribe values increase by approximately 25% in the president's region relative to the control. However, this masks significant heterogeneity at the 1% level (Column 2). Whilst non-military bribe values in Kati rise by approximately 32% relative to control non-military, for military they fall by approximately 29% (32% - 61%) relative to control military[10].

TABLE 4 – DD AND DDD ESTIMATES OF REGIONAL FAVOURITISM

Dependent variable	ln(bribe value +1)			
	A. Baseline		B. Differential time trends	
	(1)	(2)	(3)	(4)
Kati	0.476***	0.481***	0.358***	0.424***
	(0.039)	(0.043)	(0.056)	(0.072)
In Power	1.027**	0.422**	1.285**	0.432
	(0.450)	(0.213)	(0.530)	(0.293)
Kati x In Power	**0.253*****	**0.315*****	0.119	**0.246***
	(0.074)	(0.096)	(0.118)	(0.142)
Military		-0.439***		-0.144
		(0.073)		(0.111)
Kati x Miltary		-0.007		-0.145
		(0.085)		(0.137)
In Power x Military		0.415**		0.755***
		(0.182)		(0.271)
Kati x In Power x Military		**-0.610*****		**-0.765*****
		(0.147)		(0.292)
Driver FE	Yes	Yes	Yes	Yes
Truck characteristics	Yes	Yes	Yes	Yes
Official-Month-Year FE	Yes	No	Yes	No
Differential time trends	No	No	Yes	Yes
R-squared	0.366	0.306	0.367	0.310
Observations	10,618	10,618	10,618	10,618

Notes: Differential time trends for the treatment and control are official-specific in (4). Truck characteristics include truck type, foreign truck and inland journey dummies. Standard errors, clustered by checkpoint-month and trip, are reported in parentheses; *** p≤0.01, ** p≤0.05, * p≤0.10.

[10] DD coefficients for non-military and military are significant at the 1% and 5% levels.

Validity of the difference-in-differences estimator

The key identifying assumption of difference-in-differences is common trends between the treatment and control groups in the absence of treatment. This is necessary for the control group to provide a valid counterfactual. Although this is fundamentally untestable, one can use past observations to test its plausibility.

I divide the sample into 5 six-month periods (there are six months of data with the interim president in power). Then, for the four periods before his presidency (April 2010 – March 2012), I estimate the following regression:

$$\text{(10)} \qquad \ln\left(bribe\ value_{ijkt} + 1\right) = \beta_0 + \beta_1 Kati_j + \sum_{p=2}^{p=4} \gamma_p Period\ p_t + \sum_{q=2}^{q=4} \lambda_q (Kati_j \times Period\ q_t) + \ \alpha_i + \alpha_{kt} + \delta'\ truck_i + \varepsilon_{ijkt}.$$

The $\sum_{q=2}^{q=4} \lambda_q (Kati_j \times Period\ q_t)$ dummies allow for differential behaviour in Kati, controlling for first-period differences with the control group. All fixed effects and controls are as in the baseline DD specification, (8).

TABLE 5 – PARALLEL TRENDS TEST: DIFFERENTIAL BRIBE VALUES IN KATI BEFORE THE COUP

	Oct. 2010 – Mar. 2011	Apr. 2011 – Sept. 2011	Oct. 2011 – Mar. 2012
Differential bribe values in Kati	0.015	**0.235*****	0.037
	(0.053)	(0.066)	(0.085)

Notes: Dependent variable is ln(bribe value + 1); R^2=0.368; N=9,592. Full specification in Equation (10). Standard errors, clustered by checkpoint-month and trip, are reported in parentheses; *** p≤0.01, ** p≤0.05, * p≤0.10.

Table 5 outlines the results. Bribe prices in Kati are approximately 24% higher during April – September 2011, controlling for initial differences. This appears to be a temporary shock without persistence, since there are no differences (beyond initial differences) in the other six-month periods[11]. The presence of the one-period shock,

[11] The same pattern also holds for both military and non-military individually.

however, calls into question whether the control group is a valid counterfactual to Kati.

The obvious alternative explanation for my baseline results is that another similar shock occurs in Kati after the coup, rather than regional 'favouritism'. It is impossible to rule this out with certainty, since the potential outcome in Kati without a Kati-born interim president is unobserved. This is always an issue with difference-in-differences, as even common past trends are never guaranteed to continue into the future (in the absence of treatment).

I argue, however, that there is still evidence of regional 'favouritism'. One way to deal with uncommon trends is to allow the treatment and control groups to follow different linear time trends (Table 4, Section B). Whilst this reveals an insignificant difference-in-differences estimate (Column 3), the triple differences results (Column 4) are consistent with the baseline: a significant increase for non-military (at the 10% level) and a significantly heterogeneous outcome for military (at the 1% level)[12]. However, using a linear trend here is imperfect, since divergence between Kati and the control does not follow a linear trend; it only occurs in one period. Therefore, this alone provides only limited additional support for regional 'favouritism'.

A more convincing argument comes from evaluating the nature of the pre-coup shock itself; specifically, the extent to which there is heterogeneity within Kati. To test this, I estimate a 'placebo' DDD regression: this replaces the "In Power" dummy in the baseline DDD, (9), with an "April – September 2011" (pre-coup shock) dummy, and ends the sample on 30 September 2011. I also estimate baseline and 'placebo' DD coefficients for both non-military and military.

[12] The -0.519 military DD coefficient is significant at the 5% level.

TABLE 6 – HETEROGENEITY WITHIN KATI DURING THE INTERIM PRESIDENCY AND DURING THE PRE-COUP SHOCK

	A. Baseline: Interim Presidency		B. 'Placebo': April – September 2011	
	Military	Non-military	Military	Non-military
DD Coeff.	**-0.295****	**0.315*****	**0.380****	0.070
	(0.119)	(0.096)	(0.185)	(0.109)
Difference: DDD Coeff.	**-0.610*****		0.310	
	(0.147)		(0.235)	

Notes: Dependent variable is ln(bribe value + 1). Controls and fixed effects in Equation (9). Standard errors, clustered by checkpoint-month and trip, are reported in parentheses; *** p≤0.01, ** p≤0.05, * p≤0.10.

Table 6 compares baseline estimates for the interim presidency to placebo estimates for the shock. During the pre-coup shock (Section B), both DD coefficients are positive, albeit to varying degrees. DDD estimates reveal no significant heterogeneity between the two official groups. This indicates a common, rather than idiosyncratic, shock; such is expected for a typical checkpoint-specific shock. By contrast, during the interim presidency (Section A), the difference between military and non-military officials is significant at the 0.1% level. Moreover, there is an unusually wide divergence in outcomes; the DD coefficients are of equal magnitude but in opposite directions.

The stark divergence and heterogeneity strongly suggest that bribe patterns in Kati during the interim presidency are fundamentally different in nature to patterns during the more typical pre-coup shock. This further strengthens the evidence supporting my baseline conclusion of heterogeneous regional 'favouritism' with a Kati-born president in power.

Discussion

These results show how regional 'favouritism' can affect corruption's spatial distribution. Both lower monitoring and better outside options can explain the increase in bribe values for non-military in Kati; the lack of sub-annual night-lights data prevents me from assessing the relative importance of these channels. Greater monitoring of and control over officials in the president's region (Kasara, 2007) likely explains the reduction for military in Kati, particularly since bribe values rise sharply for military at control checkpoints during the interim presidency (Table 4, Column 2). Monitoring may increase as punishment for the Kati military's direct involvement in the preceding coup. The divergence highlights that regional favouritism can have both winners and losers *within* the president's region.

Whilst Section IV provides illustrations of how favouritism might work, I have no evidence of the specific mechanism in this particular context. Therefore, there is no evidence to directly implicate the president or any other individuals. To draw direct conclusions, a much greater understanding is required of the political context and of the operations of the system of Malian officials. My results merely highlight that regional favouritism may help to explain some patterns in local corruption, as it can for public good allocation (see Section II).

Favouritism is also heterogeneous across countries and outcomes (Kramon and Posner, 2013). Therefore I cannot make general conclusions on regional favouritism's impact on corruption. External validity is also limited by the preceding coup, and noise is added by the Kati military's direct involvement in it. A further limitation is that my dataset ends within 6 months of the interim presidency. There exists an extension continuing until September 2013, the month after the subsequent presidential elections. Although I would be unable to investigate what happens after the Kati-born president leaves power, the extension would help verify whether my findings persist throughout the interim presidency. This could help rule out alternative explanations for my results, and hence show that the significant patterns only occur because Kati is the president's region. Unfortunately, I have been unable to access the extension.

Abadie and Gardeazabal (2003) develop a method to create a valid counterfactual where trends are uncommon. Their synthetic control group is a weighted combination of all potential control units; weights are determined by how well each control unit matches with the treatment unit, during the pre-treatment period. I create a synthetic control group, although its pre-coup bribe patterns do not match closely enough with Kati's to draw robust conclusions. Nevertheless, findings are qualitatively similar to those discussed.

VI. EVALUATION OF MODEL

The rational expected utility framework underlying my theoretical model usefully isolates certain determinants of corruption. Nevertheless, here I provide a brief example of its potential shortcomings.

Some aspects of petty corruption are arguably idiosyncratic and behavioural (Foltz and Opoku-Agyemang, 2015). I highlight this through the relationship between corruption and rainfall. Weather has been credibly shown to psychologically affect decision-making in certain economic contexts (Busse et al., 2015; DellaVigna, 2009; Hirshleifer and Shumway, 2003). I use high-resolution daily precipitation data to measure rainfall at checkpoint j on date t, estimating:

$$(11) \quad \ln\left(bribe\ value_{ijkt} + 1\right) = \beta_0 + \sum_{p=1}^{4} \beta_p Rainfall\ intensity\ p_{jt} + \alpha_i + \alpha_{jkt} + \varepsilon_{ijkt}.$$

$\sum_{p=1}^{4} \beta_p Rainfall\ intensity\ p_{jt}$ is a set of dummies for total rainfall on date t, at 24mm intervals; α_i are trip-specific fixed effects to control for driver/truck-specific heterogeneity; α_{jkt} are checkpoint-official-month-year fixed effects to dynamically control for seasonal fluctuations, and checkpoint and official heterogeneity.

TABLE 7 - ESTIMATED COEFFICIENTS ON RAINFALL DUMMIES

Dependent variable: ln(bribe value + 1)			
24 ≤ r < 48	48 ≤ r < 72	72 ≤ r < 96	96 ≤ r
0.000	-0.193	**1.662*****	**-0.689*****
(0.045)	(0.121)	(0.607)	(0.123)

Notes: R^2=0.555; N=253,559. r=rainfall (in mm). Full specification in Equation (11). Standard errors, clustered by checkpoint and trip, are reported in parentheses; *** p≤0.01, ** p≤0.05, * p≤0.10.

Relative to 0-24mm rainfall days[13], bribes are 427% higher ($e^{1.662} - 1$) on 72-96mm days and 50% lower ($e^{-0.689} - 1$) on 96+mm days (Table 7)[14]. The magnitude of these significant coefficients dwarfs many results in this paper[15].

My intention is not to propose a grand theory of weather and corruption, or to suggest that this finding cannot be reconciled through certain channels within or extensions to my traditional model[16]. 72+mm rainfall days are also too rare to draw robust conclusions. Nevertheless, given both the unexpected magnitude of these coefficients and weather's psychological effect on decision-making in other contexts (cited above), I merely wish to suggest that behavioural factors could perhaps explain certain idiosyncrasies of petty corruption. This should not be ignored in the future research agenda.

VII. CONCLUSION

In this paper, I explore the spatial determinants of corruption on West African roads. Petty corruption has a broadly inverted-U relationship with traffic: moderate in low-traffic areas, high in medium-traffic areas, and low in high-traffic areas. I also find some evidence of heterogeneous regional 'favouritism' in Mali; there are both winners and losers *within* the president's region. Finally, I argue for more research combining corruption and behavioural economics, after finding an unusually large relationship between bribe values and rainfall.

Although my findings provide some insight into the determinants of corruption, much remains to be explored. My partial equilibrium analysis does not consider substitution into other forms of corruption (Olken, 2007) or how corruption moves up the chain of officials (Basu, Bhattacharya, and Mishra, 1992). It would also be interesting to estimate spillovers between nearby checkpoints, using spatial

[13] Rain showers 10-50mm/hr are 'heavy' (UK Met Office).
[14] Coefficients are too large to use approximations.
[15] My other findings are robust to including rainfall dummies, since heavy rainfall is infrequent.
[16] Rainfall may affect traffic and monitoring, for example.

econometric techniques, as a test of self-reinforcing corruption models (see Aidt, 2003). This unique dataset provides a special opportunity to explore numerous questions on corruption in West Africa; I look forward to finding more answers.

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