DEVELOPMENTAL LEADERSHIP PROGRAM

Research Paper 52

Searching for Success: A Mixed Methods Approach to Identifying and Examining Positive Outliers in Development Outcomes

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April 2018

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DEVELOPMENTAL LEADERSHIP PROGRAM

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DLP's independent program of research is supported by the Australian aid program.

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Acknowledgements

This paper was produced as a part of *Investigating Islands of Integrity: Using a 'Positive Outlier' Approach to Understand How Corruption is Controlled*, a research project under the British Academy Global Challenges Research Fund Sustainable Development Programme (GF160007).

The authors wish to particularly thank Professor Heather Marquette and Dr Dieter Zinnbauer, who encouraged and supported us in this endeavour and participants in a workshop held at the British Academy used to discuss the statistical methodology and Stage 2 plans, as well as Dr Trevor Budhram at the University of South Africa and Mr Pius Gumisiriza at the Ugandan Management Institute, for their invaluable assistance in conducting the third stage of this research. Thanks also to Dr Niheer Dasandi at the University of Birmingham for his insightful review and comments on an earlier draft of this paper. Most importantly, we thank the many experts, researchers, journalists, government officials, police officers and health care workers in South Africa and Uganda who shared their time, expertise and experience in often challenging work environments.

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Summary

Increasingly, development scholars and practitioners are reaching for exceptional examples of positive change to better understand how developmental progress occurs. These are often referred to as 'positive outliers', but also 'positive deviants' and 'pockets of effectiveness'.

Studies in this literature promise to identify and examine positive developmental change occurring in otherwise poorly governed states. However, to identify success stories, such research largely relies on cases' reputations, and, by doing so, overlooks cases that have not yet garnered a reputation for their developmental progress.

This paper presents a novel three-stage methodology for identifying and examining positive outlier cases that does not rely solely on reputations. It therefore promises to uncover 'hidden' cases of developmental progress as well as those that have been recognised.

The utility of the methodology is demonstrated through its use in uncovering two country case studies in which surprising rates of bribery reduction occurred, though the methodology has much broader applicability. The advantage of the methodology is validated by the fact that, in both of the cases identified, the reductions in bribery that occurred were largely previously unrecognised.

Introduction

A growing literature has aimed to learn from exceptional examples of positive change in development. Such examples have variously been called 'positive outliers', 'positive deviants', 'pockets of productivity', 'pockets of effectiveness', 'islands of excellence' and 'islands of integrity'.[1] These cases buck the trend of their poor governance environment by doing better than the norm. They include successful public sector reforms in an otherwise poorly governed state (e.g. Andrews, 2013, 2015; Tendler, 1997), institutions that deliver goods and services much better than other organisations set in the same challenging governance environment (e.g. Roll, 2011; Naazneen et al., 2014); individual leaders who, unlike their peers, work effectively to encourage developmental reforms (e.g. Leonard, 1991; Melo et al., 2012); and surprisingly positive developmental outcomes, for instance when the income of the poor outpaces expectations based on the trajectory of national wealth (Donaldson, 2008).

Studies researching these cases have sought to understand how it is that 'some agents find better solutions to problems than their peers even though they have similar resources as their peers and face similar challenges and obstacles' (Andrews, 2015: 198). Each is also motivated by a desire to identify lessons that can be amplified, or 'scaled up', and applied to other institutions, and/or other countries, for greater effect (Ochieng, 2007: 458). According to Andrews (2015: 198), focusing on these surprising success cases has promoted 'learning about the strategies adopted to find and fit effective solutions' and as such has 'emerged as a way of identifying workable solutions to development's toughest problems'.

However, the vast majority of positive outlier studies also have in common a potential limitation, one that may have caused researchers to overlook the most surprising cases of developmental improvement. Most studies have relied on experts to identify the success cases that are scrutinised (Leonard, 1991; Grindle, 1997; Owusu, 2006; Roll, 2011; Melo et al., 2012; Andrews 2013, 2015; Naazneen et al., 2014). By relying on already established reputations, researchers risk overlooking surprising cases—cases where developmental improvement has occurred but has not already been recognised, or which, at times, have been dismissed by political opposition parties as pro-government or agency propaganda. Without identifying, and examining, these hidden cases, the effort to understand positive outliers misses valuable sources of data, and potentially some of the most surprising—and revealing—cases of successful reforms.

In this paper, we present a novel three-stage methodology for identifying positive outliers that promises to identify hidden and recognised cases of developmental progress. We present the methodology by describing each stage's general features, as well as detailing a specific example of its application—our use of the methodology to identify positive outliers of bribery reduction. While the methodology could be used to identify and examine a range of positive outliers in a broad array of areas, we demonstrate, through our case studies, that it successfully led to the identification of positive outliers that were otherwise 'hidden.'

In the methodology's first stage, potential positive outlying cases are identified as statistically significant outliers using simple regression analyses based on developmental outcome data. Our analyses—which relied on sector-specific bribery rates, drawn from Transparency International's Global Corruption Barometer (GCB)—identified potential positive outliers as sectors in which the respective sectoral bribery rate had reduced far more than expected, given the rate of change in bribery experienced by other sectors in the same country over the same period of time.

In a second stage, potential positive outliers are vetted through a review of the literature and preliminary consultations with in-country experts to assess whether a case, initially identified as a potential positive outlier, should be excluded from further scrutiny. This step is important because measurement errors in the quantitative data may lead to statistical tests identifying false positives as outlying cases. In our application of the methodology, we vetted five cases.

The third stage is used, as far as possible, to conclusively confirm or refute the remaining potential positive outlier cases, and to identify their often surprising causes. This is done through a rigorous qualitative appraisal, with potential cases investigated through in-country fieldwork. In our study, we conducted fieldwork in two cases—South Africa, examining a reduction in police-related bribery, and Uganda, looking at a reduction in health-related bribery.

By using statistical analyses of quantitative data on developmental outcomes to identify cases in the first instance, and then verifying or refuting these cases through a close qualitative examination, the methodology promises to identify cases of developmental progress that have not previously been celebrated or recognised.

In both our case studies—South Africa's police and Uganda's health sector—most close observers familiar with the cases were unaware that the sectoral bribery rate had significantly reduced. As such, neither case had been subject to previous research related to the potential reduction in bribery. The relatively unacknowledged nature of both cases demonstrates that the methodology is able to identify and interrogate positive outlying cases that are relatively 'hidden'.

1 This paper uses the term 'positive outlier' because the statistical methodology used to identify cases of surprising success relies on statistically significant outlying observations.

The remainder of this paper reviews the means by which previous studies in the positive outlier literature have identified cases and highlights the potential limitations of this earlier research that our approach seeks to address. It then describes the three-stage approach used in our methodology in more detail, including a discussion of the statistical modelling employed, the vetting of cases and the approaches utilised in the qualitative fieldwork. We next establish the methodology's usefulness in identifying 'hidden' positive outliers by demonstrating that the two positive outliers we uncovered, from our application of the methodology, were by and large previously under-recognised. By examining both the quantitative and the qualitative elements of our approach in detail, and the means by which this approach reveals new findings that depart from previous research, we hope to illuminate the strengths of this approach and its usefulness for future research.

Literature review: How positive outliers are selected

Almost all positive outlier research has been conducted in two phases. An identifying methodology is used to choose a case or cases as potential outliers to look at, and the qualitative research methods are used to examine how and why actors, institutions or reforms within the exceptional case(s) perform so well (Pascale et al., 2010: 7). Policy lessons are then drawn from what has been learnt. However, the lessons one can hope to eventually learn are dependent on the selection of cases and, therefore, the means by which they are identified. This is because the identifying methodology dictates the extent to which potential biases inform case selection, and such biases inherently shape what one might hope to learn from the cases themselves.

Despite the importance of the identification methodology, little attention is paid to the comparative benefits and limitations of the different approaches used to identify the cases that are eventually lauded.[2] In 2008, Leonard boldly attempted to inventory and review the positive outlier and related literatures (see also Leonard, 2010). His review focused on cataloguing 62 hypotheses from across the literature accounting for the emergence of various positive outliers. Surprisingly, however, little mention was made of the methodologies used to identify the cases reviewed.

Seminal pieces in this field that have followed Leonard's (2008) review, each offering its own reviews of the literature, have also failed to critically review or even summarise the methodologies used in the literature (e.g. Roll, 2013; Andrews, 2015). In the most recent published critical review of the literature, by Herrington and van de Fliert (2017), the criteria on which cases are selected, and the impact this selection process may or may not have had on the conclusions drawn, are not discussed at all.

More surprisingly, our own review of the literature found that many of the works failed to describe the methodology used for identifying the case(s) examined (see Roll, 2011; Hertog, 2014; Hout, 2014; Pogoson & Roll, 2014; Simbine et al., 2014; Strauss, 2014; Willis, 2014). Consequently, our focus on critically assessing the identification methodologies used in the wider literature, as well as offering a novel methodology for identifying potential positive outliers, makes an important contribution.

Selecting cases based on reputation

In the few works that describe their case selection criteria in detail, the most common methodology, by far, used to identify cases of surprising success is *reputational*, in which cases are selected because they are reputed to be successful performers (Leonard, 1991; Grindle, 1997; Tendler, 1997; Owusu, 2006; Roll, 2011; Melo et al., 2012; Andrews, 2013, 2015; Naazneen et al., 2014). For example, Naazneen, Huybens and Vinuela (2014) asked World Bank staff in 'fragile states' to point out successful institutions. And, Leonard (1991: 11) selected his cases of four developmental leaders based on the recommendation of 'many well-informed observers'.

There are at least two potential limitations that positive outlier research, reliant on reputational identification, may suffer from. First, as a reputational assessment is a subjective perception, a 'good reputation' may be misattributed and so may mask mediocre or even poor performance. When development agencies and organisations are involved, stories of developmental progress may be particularly susceptible to exaggeration (Berg, 2000; Carothers & de Gramont, 2013). Strong incentives exist to tell a good story about a programme's success. The professional reputations of the involved development bureaucrats are, to some extent, on the line when programmes are evaluated and their effects are communicated. Development agencies face pressures to tell optimistic stories so they can demonstrate to taxpayers, legislatures and other policy-makers that their work is good value for money (Mosse, 2005; Unsworth, 2009: 890).

2 It is beyond the scope of this paper to exhaustively review all studies that fall within the fences of the positive outlier and related literatures. Such a task would be a difficult undertaking; arguably any time a researcher examines an effective policy, leader or institution, in a country with 'weak governance', they are looking at a positive outlier. Leonard (2008: 9) calls this a problem of the boundaries to the study of 'pockets of productivity'. The review conducted for this paper resulted from an initial Google Scholar search for articles and books that refer to one of the following terms: 'positive outliers', 'positive deviants', pockets of productivity', 'islands of excellence' and 'islands of integrity', and we reviewed works that were referred to by others in the literature as belonging in the positive outlier literature.

The risk of relying on perceptions that misattribute success to a case can be overcome if a case's status as a 'positive outlier' can be convincingly supported by triangulating perception data with other sources. To the literature's credit, many studies using a reputational methodology describe additional steps taken to do this compellingly (e.g. Grindle, 1997; Tendler, 1997; Melo et al., 2012; Andrews, 2013, 2015; Naazneen et al., 2014). Naazneen et al. (2014: 16–17), for example, describe vetting cases initially identified by World Bank staff, through 'secondary research and a round of narrative-based interviews with individuals with first-hand experience with the institutions'. Somewhat similarly, Andrews (2015) started his search for outliers using a reputational approach by asking staff at Princeton University's Innovations for Successful Societies (ISS)—a programme that develops and banks case studies on successful reforms and developmental progress—to refer to him cases from ISS's repository of countries 'once considered fragile states' that have since generated 'sustained improvement in institutional performance and economic growth'. Forty cases were initially identified. Andrews then vetted the cases by having two graduate students rate each case against specific criteria. Thirty cases were ultimately selected.

Yet even the most convincing case-vetting may not overcome a second limitation of reputation-based case identification. When the universe of cases considered includes only those already thought to be successful, exceptionally performing cases that have not yet been identified as being successful are overlooked. Put differently, other and potentially more exceptional cases may fly under the radar of a reputational identification methodology. In these hidden, and perhaps highly unexpected, cases, developmental change may have not been recorded, or the records of such changes may have not received the same amount of publicity as cases more readily identified by observers, government actors or academics. A hidden positive outlier, for instance, may emerge in the performance of a highly specialised institution that the public (including observers trusted to give an assessment) is not equipped to assess. In other instances, it may be against the interest of certain influential groups to give credence to a story of success. Reluctance to acknowledge positive change may stem from a fear that a 'success' story will benefit political opponents, or that an acknowledgement of some progress may weaken the political commitments needed to encourage further progress.

Instances of developmental improvements that tend to go unacknowledged or to be suppressed may have different drivers, characteristics and/or unintended consequences than those that are more easily identified. If we fail to recognise and understand the achievements made in under-observed cases, we miss the opportunity to learn what has gone right in these surprising outliers, in what circumstances and at what costs. We limit ourselves to learning from more visible and obvious cases, and may therefore miss the opportunity to uncover the less obvious insights of their less visible counterparts. This may stunt our ability to understand what drives developmental change.

To our knowledge, only Donaldson (2008) has avoided using a reputational identification methodology. Inspired by the lauded one-to-one relationship that poverty reduction and economic growth had been generally found to have (Dollar & Kraay, 2001), Donaldson identified 'positive' and 'negative' outlier cases by first regressing the relationship between the change in the national incomes of the poor and growth in gross domestic product (GDP). He focused on the 27 country periods wherein income growth of the poor was significantly lower than the regression predicted—'negative outliers'—or significantly higher than what the regression predicted—'positive outliers.' By relying on the hypothesised relationship between GDP growth and income growth among the poor to identify outlying cases, Donaldson's study purposefully limited itself to focusing on why these 27 cases bucked this specific trend.

In our exercise of the methodology, we similarly use regression analyses to identify our pool of potential positive outliers. However, we focus only on sector-specific bribery data rather than on any other variables hypothesised to influence bribery or broader corruption patterns. This element of our methodology builds on the contribution that Donaldson (2008) made to the field. Donaldson purposefully identified cases that did not fit a hypothesised trend between two different indicators. By not initially relying on reputations or on a hypothesised relationship to explain why success may or may not be achieved, the identification methodology presented here promises to have the most potential for uncovering truly *surprising* successful cases—those that have not yet received acclaim *and* those that do not necessarily adhere to preconceived ideas of explaining why success may or may not occur in the first place.

Stage 1: Statistically identifying potential positive outliers in bribery reduction

The aim of the first stage of the methodology is to statistically identify *potential* positive outliers. The statistical analysis requires reliable and comparable cross-national development outcome data. An appropriate dataset would need to include measures of the extent to which an outcome changed over time, across subnational units within the countries included in the study.

As an example, in our application of the methodology, we sought to identify and research cases wherein bribery in specific sectors had unexpectedly reduced, and calculated country-level sector-specific bribery rates to do so. We relied on data from Transparency International's GCB, which has the largest geographic and temporal reach on individuals' responses to questions probing experiences with bribery, across multiple sectors (Peiffer, 2012). In the latest wave (2015), 162,136 adults were surveyed in 119 countries.

Using responses to questions on whether a bribe had been paid to specific sectors, we calculated nationally representative country-level sector-specific bribery rates for all sectors included in the last four waves of the GCB (2009, 2010/11, 2013 and 2015).[3] In each of these waves, questions were asked about bribes made to the medical, education, police, courts, utilities and permit (building and business) sectors. In all but the 2015 wave, questions were also asked about bribes made to the tax and land sectors. A single observation in this aggregated dataset, for example, is the estimated proportion of the Ugandan population in 2010 that had paid a bribe to receive health services.

Given our interest in identifying surprising cases of bribery reduction (i.e. a change in bribery over time), we necessarily focused our attention on those country-samples that were asked about their bribery patterns over at least two waves of the GCB. Table 1 shows the number of countries surveyed in different combinations of survey periods or wave pairs.

Table 1: Number of countries surveyed in at least two waves of the Global Corruption Barometer

	N
2015 and 2013	58
2015 and 2010/11	52
2015 and 2009	36
2015 and 2010/11	51
2015 and 2009	35

While in our exercise we used bribery rates across several sectors, the methodology's intuition could also be applied to identify positive outlying cases across demographic groups or geographic regions. For example, changes in subnational poverty rates in several different countries could be used to identify potential positive outlying regions wherein poverty decreased far more than what would be expected given the rate of change in poverty in other regions within the same country.

Structuring quantitative models

Positive outliers are identified as the subnational units (e.g. sectoral or regional units) within a country where there has been an improvement in the development outcome of interest, when stagnation or a worsening is predicted. Depending on the data, simple Ordinary Least Square (OLS) regression can be used to generate such predictions. In such analyses, the dependent variables are the changes in development outcome of interest (at a sectoral, regional or other subnational unit level).

In our exercise of the methodology, five OLS regressions were used to generate predictions, each representing one of the five pairs of GCB waves (Table 1). Our dependent variables were the changes in the sector-specific bribery rates between the earlier wave and the latest wave of data considered. We chose to treat all sectors together in the analyses, which is to say that, if six different sectors of data were available for a pair of GCB waves, the dataset was structured so that six different dependent variables for each country were specified. For example, for the analyses drawing on the 2009 and 2015 waves of data, there were six different dependent variables for each country examined, reflecting, respectively, changes in bribery rates related to health, education, permits, courts, police and utilities. The purpose of this structure was to identify outliers across sectors, that were not-sector specific (i.e. one set of potential health bribery-related positive outliers identified independently from another set of potential education bribery-related positive outliers).

We suggest that all analyses include an index or other measure that can reflect the rate of change in the outcome of interest, for all subnational units considered (e.g. other sectors, other regions), other than the subnational unit that inhabits the dependent variable position. We used principle component factor analysis (PCFA)—a statistical technique used to reduce a large number of variables into one or a few indices—to create our indices of wider changes in bribery rates.

As an example, if the dependent variable was the change in bribery for the education sector, we calculated its respective index of wider changes in bribery from the changes in bribery for all sectors, except for education. With such an index included, predictions about the change in the outcome of interest for each subnational unit are based, in part, on the rate of change of the outcome of interest for all other comparable subnational units, over the same time and in the same country.[4] Surprising cases, therefore, are those that have experienced changes that are not in step with their within-country comparators.

3 We restricted our analyses to those country samples reported to be nationally representative. We chose to exclude data from GCB waves prior to 2009 because there was little information available on the quality of the samples and many samples appeared too small to be trusted as reliable representations of the population (N below 500). As statistical outliers can arise as a result of errors in the data, a sincere effort was made to exclude questionable samples from the waves considered. Appendix A describes the samples that have been excluded and reasons for doing so.

4 All factor analyses performed produced one factor with an eigen value over 1.00.

Analyses should also control for a measure of the outcome of interest, at the start of the period scrutinised. This is a 'convergence' term; it is important because it accounts for the fact that potential improvement is a function of where an outcome started. For example, in our application, by including a convergence term, the model acknowledges that numerically small reductions in a bribery rate, from a relatively low bribery rate as a starting point, may be just as surprising, and therefore valuable to learn from, as cases that register numerically larger reductions but that start from a much higher sectoral-level bribery rate. Finally, in an examination of sector-specific outliers, where countries have in common the set of sectors considered, it may also be important to include dummy variables that represent the sectors scrutinised. Doing so accounts for what the dependent variable sector was (i.e. police, courts, health, permits, education, utilities, land). By including these variables, the models acknowledged that patterns in bribery changes may have sector-specific characteristics.

In our application, therefore, the resulting regressions use changes in bribery rates of all other sectors in the country to predict the change in bribery in the sector inhabiting the dependent variable position, while controlling for both the type of sector of the dependent variable and the bribery rate for the dependent variable sector at the start of the period scrutinised.[5]

The simplicity of the structure is intentional; if we were to include any other measures that we thought were linked to bribery patterns, the models would innately bias themselves towards a preconceived understanding of why it is that bribery rates increase or fall. By excluding all other potential factors from the analyses, the models are only able to identify when it is that a sectoral-level bribery rate falls out of sync with other sectoral-level bribery rates, in the same country and over the same period of time.[6]

Identifying potential positive outliers

Inspired by Donaldson (2008), potential positive outliers are determined statistically, by computing residuals, which is the distance between the regression line and each data point, and calculating the probability that the distance owes to random variation. Data points that are far away from the regression line—outliers—show that the regression model is less likely to explain its position. In our case, an outlying sectoral bribery rate reflects a sector that experienced a change in its bribery rate that is unexpected, given how bribery levels have changed in the other institutions in the country.

To calculate the residuals, we subtracted the change in sector-specific bribery rates predicted by the model (column 4 in Table 2 below) from the value reported by the GCB dataset (column 3). We record this residual value in column 5. Column 6 (labelled 'outlier') records the probability that the position of each case's corresponding value for its sectoral-level bribery rate is caused by random variation. This is estimated by calculating the P-values of the residual's Z-scores to determine the chance that the point's distance from the regression line is caused by random factors. As outliers exist along a continuum for how surprising they are, we flag observations as being outliers when there is an estimated 5% or less chance of occurring.[7]

For instance, as seen in Table 2 below, based on how bribery had changed in all other sectors measured, our analyses predicted that bribery to the health care sector in Uganda during the 2009 and 2013 period (first case listed) should have increased by 11.2%; the actual change over this period, according to the GCB, was a reduction of 5%—a difference of 16.2 percentage points. Since the likelihood that random error can explain this data point is less than 0.01%, Uganda's health care sector is considered a potential positive outlier in bribery reduction. Table 2 lists all identified potential positive outliers. While in some cases the reduction in bribery, according to the GCB, may seem small, the data suggests that these potential positive outliers are far from trivial. If we focus on just those four positive outliers identified from a comparison of the 2009 and 2013 waves of the GCB, the analyses suggest that 4.6 million fewer people were asked to pay a bribe to receive the basic services specified in Table 2 than what the model predicted.

5 The validity and reliability of cross-national bribery data has been questioned because, depending on context, people may have different ideas of what constitutes a bribe (Walton, 2015). By relying on within-country sector bribery rates to identify potential positive outliers, our analyses limit the extent to which different cross-national understandings of bribery influence case identification. Admittedly, our use of GCB data does to some extent assume there are shared national understandings of what constitutes a bribe, however. Others have argued that survey-based bribery data should not be trusted because people will be unwilling to admit to a strange enumerator that they have paid a bribe (Rose & Peiffer, 2015: 46). Many other scholars, however, have demonstrated that in many cultures the provision of bribes or associated gifts is not perceived to be shameful or taboo (Smart, 1993; de Sardan, 1999; Heyman and Smart, 1999; Hasty, 2005; Smart and Hsu, 2007). Consequently, concerns regarding the sensitivity of discussing bribery with informants often reflect Western norms more than the lived realities of many informants in non-Western countries, and perhaps should not be used to shape our expectations of how respondents will act in developing countries where bribery is thought to be more pervasive or normal (Tanzler et al., 2012). Further, to the extent that this is an issue across countries, rather than within countries, our methodology should still be appropriate to use.

6 As an example, an example of an analysis structure is described below for police from 2010 to 2015: *Δ bribery for police [bribery rate in 2015 – bribery rate 2010] = factor [Δ in bribery rates since 2010 for all other sectors] + convergence [bribery rate for police in 2010] + dummy variables for sector of interest (1 for police, 0 for education, 0 for courts…etc.).*

7 Specifically, we calculated studentised residuals. This is because standardised residuals can be vulnerable to a specific bias; if an outlying observation exerts a lot of 'leverage' in the model, it will actually shift the estimation of the relationships that it predicts outliers from.

Table 2: Statistical outliers in bribery reduction

Country	Sector	Δ	Predicted Δ	Residual	Outlier
		2009 to 2013			
Uganda	Health	-5.0	11.2	16.2	<0.01%
Lithuania	Health	-2.3	4.4	6.7	0.37%
Mongolia	Land	-2.2	4.1	6.3	0.71%
Malaysia	Police	-6.5	0.0	6.5	0.74%
		2010/11 to 2013			
El Salvador	Police	-18.5	-1.5	17	<0.01%
Uganda	Health	-17.3	-7.0	10.3	0.01%
Indonesia	Health	-2.7	5.0	7.7	0.32%
Thailand	Health	-7.1	0.0	7.1	0.39%
Hungary	Health	-7.4	-1.0	6.4	1.00%
		2010/11 to 2015			
Burundi	Health	-29.6	-16.7	12.9	0.01%
Azerbaijan	Health	-24.2	-15.5	8.7	1.00%
El Salvador	Police	-16.9	-9.2	7.7	2.20%
		2013 to 2015			
Liberia	Education	-28.8	-14.9	13.9	0.15%
South Africa	Police	-25.6	-15.6	10.0	4.24%
		2009 to 2015			
Azerbaijan	Health	-30.7	-13.1	17.6	<0.01%
Senegal	Permit	-27.5	-15.2	12.3	0.60%
Liberia	Education	-26.6	-17.2	9.4	2.32%
Sierra Leone	Education	-28.1	-18.8	9.3	3.70%

Stage 2: Triangulating statistical data

The second step in the identifying methodology is to vet potential positive outliers with the primary aim of assessing whether the positive developmental change recorded statistically is negated, *and demonstrably proven to be inaccurate,* by those with a deep familiarity with the identified case. Important to note is that the aim of this stage is not to confirm the findings of developmental progress reflected in the statistical data, but instead to uncover evidence that will exclude cases from further analysis. Moreover, cases are excluded in this stage only when evidence is presented to strongly suggest that the statistical data on the case was wrong. This is because, especially in the cases of 'hidden' or unacknowledged positive outliers, evidence confirming that positive developmental change occurred may be disproportionately difficult to come by, or supressed for various reasons. As such, if cases were excluded at this stage because confirmatory evidence was not found, the research could, once again, overlook examining 'hidden' positive outlying cases. This stage is particularly important to the identification methodology because measurement errors in quantitative data may lead to the statistical tests identifying false positives as outlying cases—cases where a positive developmental trend was recorded statistically but did not occur in reality.

In our examination of cases of potential bribery reduction, five of the eighteen statistically identified potential positive outliers were selected for further examination and vetting in Stage 2 (Table 3). The selection of the five cases reflected additional criteria—specific to our project—including whether the country was eligible for official development assistance (a stipulation of our research grant) and whether conducting further research in these countries was feasible, given how difficult, expensive and/or potentially unsafe it may be to eventually conduct fieldwork in each potential case.

Table 3: Cases vetted with desk research

Country	Sector	Outlier time period(s)
Uganda	Health	2009–2013 and 2010/11–2013
Indonesia	Health	2010/11–2013
Mongolia	Land	2009–2013
South Africa	Police	2013–2015
Sierra Leone	Education	2009–2015

Vetting methodologies

Both statistical and qualitative data can be consulted to vet potential positive outliers. For instance, in our case, an effort was made to triangulate the sector-specific bribery rates that were computed from GCB data in the five cases we focused on. Three of the five cases are African, and so, as we did with the GCB, we computed country-level sector-specific bribery rates for these countries using Afrobarometer data. Like the GCB, in many of its waves Afrobarometer has asked nationally representative samples of individuals whether they have paid a bribe for specific services in the past year. In all three African cases, while sometimes the bribery rates differed between the two surveys, a comparison with Afrobarometer data similarly suggested that the sector that was identified as a potential positive outlier in our statistical analyses had experienced a considerable reduction in bribery over a similar timeframe. Unfortunately, we were not aware of a similar dataset that could be used as a comparison for the Mongolia and Indonesia cases.

We also consulted experts familiar with the five country sectors. These experts were identified using a snowball sampling technique that started with contacts drawn from the larger research teams' personal networks of colleagues, former colleagues, academic contacts and friends, as well as emails to scholars in prominent area studies peer review journals who have published academic research on the cases. In total, we consulted fifty identified experts, across the five cases. The experts represented a cross-section of academics, development practitioners, government employees in the country identified, officials in foreign aid agencies and non-governmental organisation officers.

Correspondence with experts centred around whether they were aware of either supporting or countervailing evidence to suggest bribery had reduced in the sector (or indeed whether it had appeared to remain constant or to increase), and whether their experience within the sector indicated that a reduction in bribery may or may not have occurred. Gauging perceptions at this stage, rather than initially, ensured that reputational data alone was not used to qualify or disqualify a case from being considered as a potential positive outlier.

In our examination of potential bribery reduction, all five cases vetted in Stage 2 passed Stage 2's test—which is to say that we did not uncover any evidence to demonstrably prove that the underlying data, showing that bribery had reduced, was wrong. Our research budget required that we select only two of the five cases vetted in Stage 2 for the fieldwork of Stage 3. We selected South Africa and Uganda to research their police and health sectors, respectively, because our research team had generated a large network of relevant informants and we were confident that our research budget would support fieldwork in each case. It is important to reiterate, however, that each of the other cases could have been researched in Stage 3 because each passed Stage 2's vetting.

Stage 3: In-country case study fieldwork

The third and final stage of the methodology involves in-depth qualitative fieldwork. Two aims drive Stage 3—though only the first aim is related to the identification of positive outliers, which is our main focus here. This is to further vet the cases using data unearthed in the field. This is potentially important because evidence only accessible in the field may support or undermine the cases' 'positive outlier' status.

The second aim of Stage 3, which does not relate to the identification of a positive outlier, is to assess why and how positive developmental change occurred. It is hoped that the lessons learnt at this stage will help scholars and policy-makers better understand how positive developmental change happens, and the various knock-on effects such improvements may generate as a result. As this paper focuses on the methodology's utility in identifying positive outliers, we do not describe the specific assessments in our application of the methodology of how bribery reduced in each country sector. These examinations are described at length in forthcoming case study papers. However, a brief note is made of them here because they help explain why it is that the cases we identified may have eluded previous detection.

In both South Africa and Uganda, we conducted five to six weeks of fieldwork. We partially relied on snowball sampling, starting with the contacts of the extended research team developed through Stage 2. In both country sectors, we sought to engage academics and researchers, relevant government representatives and journalists, while concentrating mainly on the practitioners best placed to explain changes to bribery-related behaviours within the sectors examined—the South African police and Ugandan health workers.

South Africa

The GCB data on South Africa indicated a dramatic and unexpected reduction in bribery in the South African Police Service (SAPS) between 2013 and 2015 (Table 2), while Afrobarometer data suggested that the police bribery rate started to decline in 2011. Our additional analysis of Afrobarometer data, identifying the region of each respondent, showed that the decrease was likely most dramatic in one of the nation's rural provinces, Limpopo. In Limpopo, over this period of time, the police-related bribery rate reduced by nearly 15%, while in all other regions, according to the Afrobarometer data, the reductions in police-related bribery averaged at around 4%. During consultations with policing experts in Stage 2, few offered ideas as to why police bribery may have reduced, either nationally or in Limpopo. The experts consulted, however, were not able to present any evidence to suggest that bribery had not reduced. Consequently, we entered the field with a large pool of expert commentators with whom to consult but no strong leads on possible causes of a potential reduction.

Our research in South Africa led us to develop two hypotheses for why bribery to the police may have reduced. First, during the period scrutinised, a transformative policing technology—the Automated Vehicle Location (AVL) system—was introduced, which provided a new means to monitor the activities of road police. Our data indicates that, fearful of getting caught after implementation of this new technology, road police may initially have shown greater reluctance to request bribes. Second, in Limpopo, where bribery statistics showed the most significant reduction, a large-scale government crackdown on high-level corruption in the provincial government apparatus coincided with the period identified by the statistical data. During the crackdown, the province, most notably the capital of Polokwane, received an influx of high-level corruption investigators from Pretoria. The high visibility of these forces in the capital and across the province may have unintentionally reduced the extent to which ordinary police were willing to break the rules and ask for bribes during this extraordinary period for the province.

Uganda

In contrast with the South Africa case, following consultation with a broad range of experts on the health sector in Stage 2, we entered fieldwork ready to test and interrogate an already strong hypothesis of government-led reform. Several experts consulted in Stage 2 suggested that the activities of a relatively new Health Monitoring Unit (HMU) may have shaped bribery patterns in the sector.

In total, we interviewed 48 respondents in Uganda, including doctors, nurses, clinicians and administrators currently employed in the public health system; government officials from the health sector and other departments; employees of donor agencies engaged in health service delivery; and health care providers formerly employed in the public sector and now working in private practice; as well as academics, journalists and researchers.

In brief, the findings of the fieldwork conducted in Uganda over the course of five weeks enabled us to confidently conclude that bribery for health services had indeed reduced during the period noted. Most health workers we spoke with testified that they felt bribery had reduced. Our research highlighted the influential work of the HMU in generating a marked change in the behaviour of health sector workers. Through surprise audits, highly visible arrests of health sector workers and public shaming, the HMU's efforts to combat corruption in the sector is likely to have made health workers especially cautious of requesting bribes from patients.

Promise realised: Uncovering hidden 'positive outliers'

By not relying on reputational assessments in the first phase of the project, the presented methodology promises to enable researchers to identify and learn from cases of positive developmental change that may otherwise remain hidden. In our examinations of the police in South Africa and of health care in Uganda, the use of the presented methodology led us to uncover surprising instances of bribery reduction that had previously received little to no attention from academics or donors, or from policy-makers and the media, beyond those bureaucrats directly involved in the design and implementation of the programmes that likely contributed to the noted reduction.

In the South African policing case, the statistical reductions identified in police-related bribery nationally and in Limpopo province specifically were neither reported in the provincial or national media nor publicised by the South African chapter of Transparency International. In addition, no research or previous studies were identified at any of South Africa's excellent centres for crime and policing research.

Three main factors may account for the lack of acknowledgement of this case. First, one of the interventions that may have contributed to a reduction in the police-related bribery rate may have done so only unintentionally. The government corruption intervention in Limpopo targeted high-level corruption within the provincial government, and not members of the SAPS. Therefore, any impact it had on bribery rates among the police was neither intended nor monitored. Second, another likely factor—the introduction of the AVL system—has yet not been evaluated for its potential impact on bribery patterns, and so its effectiveness in this respect has not been documented. Third, there was a culture of criticism among actors and observers familiar with the case. The SAPS routinely receives a high degree of public criticism as a result of major failings in performance and management, and many of those interviewed—policing researchers and commentators, as well as the police themselves—were predisposed to critiquing the police, and were both unaccustomed and reluctant to investigate potential improvements in performance.

The reduction of bribery we uncovered in Uganda's health care system was also largely unacknowledged. The statistical reduction in the health-related bribery rate was similarly not publicised or acknowledged by the local Transparency International chapter. As noted earlier, we found that the activities of the president's HMU had likely influenced bribery patterns; however, organisations involved in monitoring and supporting public health were unaware of the impact of the unit in reducing the willingness of health care providers to request bribes. Further, while the activities of the HMU have received a great deal of domestic media coverage, to our knowledge no rigorous assessment of its effect on the behaviours of health workers has been undertaken.

A variety of factors specific to the Ugandan health care case contributed to preventing recognition of the reduction in bribery. First, government and media sources covering the successes of the HMU focused primarily on the unit's success in reducing drugs theft, rather than bribes requested at the point of service. The impact it was having on reducing bribery simply did not take centre stage. Second, the HMU is highly politicised. Supporters of the current presidential administration praise the HMU, while political opponents critique it for misdiagnosing the problems of the health sector and deflecting public attention from drug shortages and inadequate salaries for health workers. Consequently, many citizens dismiss claims of policy success as government propaganda. Finally, it is our assessment that health care service delivery has not improved as a result of or alongside the reduction in bribery.[8] The health sector in Uganda continues to suffer from many severe issues, such as a very low doctor to patient ratio, low investments in the health sector, drug shortages, poor-quality facilities and equipment and very low salaries for health workers (see forthcoming case study paper). The persistence and severity of these failures are likely to have eclipsed the noted reduction in bribes paid for health services, ensuring bribery within the health sector has remained a marginal issue.

Conclusion

Research on positive outliers promises to provide new insights into how development can be done better by focusing on those cases where developmental progress has occurred against the odds. To date, existing research on positive outliers has overlooked an array of cases that fall outside of the observations of narrowly defined groups of experts. The methodology presented in this paper, in contrast, promises to identify both types of positive outliers—those that have received recognition as well as those that have not. By using statistical analyses of developmental outcomes to identify potential positive outliers in the first instance, and then verifying or refuting these cases through a close qualitative examination, the presented methodology is able to recognise cases of developmental progress that have not previously been celebrated.

The cases we identified through the application of the presented methodology suggest that developmental 'success' stories can escape simple detection (i) when their 'success' is the unintended result of a policy intervention, (ii) when the case has not been deemed to be of sufficient political value to be monitored and 'claimed' as the success of a specific institution or organisation, (iii) when the policy arena is highly politicised and/or subject to a culture of criticism and/or (iv) when improvements in one area are not echoed by improvements in other areas.

Hidden cases are important to scrutinise as they may have different drivers, characteristics and unintended consequences than cases identified through reputational means. The lessons 'hidden' cases have to teach are just as valuable to our understanding of how developmental progress occurs as the lessons we learn from more obvious cases of developmental progress. Our research into bribery reduction in Uganda's health care sector, especially, teaches an unconventional lesson about developmental progress. In finding that health care service delivery has not improved as a consequence of an impressive reduction in bribery, the case demonstrates that some effective measures to control sector-specific bribery may do little to strengthen the sector as a whole, or contribute to supporting the sector's overarching mandate. The lesson is cautionary for those who advocate for, or otherwise support, all 'effective' anti-corruption efforts as the means by which the end of capacity-building can be achieved.

This paper focuses on the identification of potentially 'hidden' positive outliers, but it is only through the rigorous examination of these cases that we can hope to learn valuable lessons. It must therefore be acknowledged that the examination of potentially 'hidden' positive outliers presents unique challenges. Given the unrecognised nature of these cases, personal, professional and financial investments in fieldwork spent on these cases carry risk. As field researchers are tasked with the challenge of investigating a trend that few have considered or are aware of, it may be the case that little of value will be unearthed, or that the field researcher will uncover evidence in the field to prove that the identified case is not, as anticipated in the statistical data, a true success story. As some cases may be under-acknowledged because of the politicised nature of the developmental process, or may be politically volatile, field researchers may also confront the practical challenges of securing relevant permissions and interviews. However, the pursuit of these surprising cases is important—by not identifying and examining 'hidden' cases of exceptional developmental progress, we have naturally limited our understanding of what drives exceptional positive developmental change.

8 See our forthcoming paper

To the best of our knowledge, our examination of bribery reduction is the first application of the positive outlier approach to an investigation of corruption reduction. Importantly, however, given access to adequately comparable statistical data, our method promises to be of use in uncovering positive outliers in a broad array of areas. Relying on cross-national, subnational poverty data, it could be used, for example, to identify positive outlying regions where poverty has reduced far more than what would have been expected given shifting poverty trends elsewhere within the same country. Another application could lie in using the methodology, for instance, to interrogate cross-national data on public trust in different public sectors, to identify sectors for which public confidence has grown far more than would be expected given levels of trust in other sectors within the same country. It is our expectation that this method will contribute to enabling researchers to investigate much more fully the factors that contribute to the emergence of impressive and surprising developmental change—and to more rigorously interrogate the notions of success and failure that emerge as a result.

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Appendix: Excluded samples from pooled GCB dataset

This appendix summarises the country-samples that are included in the Global Corruption Barometer dataset, but are excluded from our analyses.

1. Data before the GCB 2009 wave is not included. This is because there is little information available on the quality of these samples and many country samples were too small to be trusted as being reliable representations of the population (i.e. N<500).
2. The patterns of responses to questions about religious corruption among Moroccan respondents for the 2010 GCB indicate that this country sample may be biased.
3. The GCB 2009 report notes that there were 'errors in the implementation of the survey' for the following countries: Armenia, Belarus, Cambodia, El Salvador and Georgia.
4. GCB 2013:
    a. Data from Azerbaijan, Lebanon and Russia were excluded from Transparency International reports because contact rates were lower or higher than what more realistic estimates would produce.
    b. Data from Albania, Brazil, Burundi, Fiji, France, Germany, Luxembourg, Malawi and Zambia were excluded from Transparency International reports because bribery rates were inconsistent with external data sources and/or previous GCB editions.
    c. Data from Ethiopia, Papua New Guinea, Solomon Islands, South Sudan and Sudan are excluded because computer-assisted telephone interviewing (CATI) was used but there is insufficient telephone coverage for the sampling method to return a nationally representative sample.
    d. CSPP discovered clear under-representation of segments of the national population in Chile, Democratic Republic of Congo, Cyprus, Egypt, Kyrgyzstan, India, Madagascar, Maldives, Mozambique, Nepal, Nigeria, Pakistan, Rwanda, Sierra Leone, Vanuatu and Yemen.
5. Urban only or otherwise non-nationally representative samples were excluded from the analyses.
6. Country samples of less than 500 were excluded.

Country	Year	Reason
Bolivia	2007	Urban only/not national sampling
Cameroon	2007	Urban only/not national sampling and sample too small
Colombia	2007	Urban only/not national sampling and sample too small
Dominican Republic	2007	Urban only/not national sampling and sample too small
Ecuador	2007	Urban only/not national sampling
Greece	2007	Urban only/not national sampling
Guatemala	2007	Urban only/not national sampling
India	2007	Urban only/not national sampling
Indonesia	2007	Urban only/not national sampling
Kosovo	2007	Urban only/not national sampling and sample too small
Malaysia	2007	Urban only/not national sampling
Panama	2007	Urban only/not national sampling and sample too small
Poland	2007	Urban only/not national sampling
Senegal	2007	Urban only/not national sampling and sample too small
Venezuela	2007	Urban only/not national sampling
Vietnam	2007	Urban only/not national sampling and sample too small
Armenia	2009	Admitted errors
Belarus	2009	Admitted errors
Bolivia	2009	Urban only/not national sampling
Cambodia	2009	Admitted errors and urban only
Cameroon	2009	Urban only/not national sampling and sample too small
Chile	2009	Urban only/not national sampling
Colombia	2009	Urban only/not national sampling and sample too small
El Salvador	2009	Admitted errors and urban only and sample too small
Georgia	2009	Admitted errors

Country	Year	Reason
Senegal	2010	Urban only/not national sampling
South Africa	2010	Urban only/not national sampling
Vanuatu	2010	Sample too small
Vietnam	2010	Urban only/not national sampling
DRC	2011	Urban only/not national sampling
Mozambique	2011	Urban only/not national sampling
Nepal	2011	Urban only/not national sampling
Rwanda	2011	Urban only/not national sampling
South Sudan	2011	Urban only/not national sampling
Sudan	2011	Urban only/not national sampling
Yemen	2011	Urban only/not national sampling
Zimbabwe	2011	Urban only/not national sampling
Albania	2013	Excluded from TI report
Azerbaijan	2013	Excluded from TI report
Brazil	2013	Excluded from TI report
Burundi	2013	Excluded from TI report
Chile	2013	Clear under-representation of segment of national population
Cyprus	2013	Clear under-representation of segment of national population
DRC	2013	Clear under-representation of segment of national population
Egypt	2013	Clear under-representation of segment of national population
Ethiopia	2013	CATI inappropriately used
Fiji	2013	Excluded from TI report
France	2013	Excluded from TI report
Germany	2013	Excluded from TI report
India	2013	Clear under-representation of segment of national population

Country	Year	Reason
Indonesia	2009	Urban only/not national sampling and sample too small
Iraq	2009	Urban only/not national sampling and sample too small
Kosovo	2009	Urban only/not national sampling
Morocco	2009	Urban only/not national sampling and sample too small
Panama	2009	Urban only/not national sampling and sample too small
Poland	2009	Urban only/not national sampling
Portugal	2009	Urban only/not national sampling and sample too small
Bangladesh	2010	Urban only/not national sampling
Bolivia	2010	Urban only/not national sampling
Cambodia	2010	Urban only/not national sampling
Chile	2010	Urban only/not national sampling
China	2010	Urban only/not national sampling
Greece	2010	Urban only/not national sampling
India	2010	Urban only/not national sampling
Iraq	2010	Urban only/not national sampling
Liberia	2010	Urban only/not national sampling and sample too small
Luxembourg	2010	Sample too small
Mexico	2010	Urban only/not national sampling
Morocco	2010	Suspicious response patterns
Peru	2010	Urban only/not national sampling

Country	Year	Reason
Kyrgyzstan	2013	Clear under-representation of segment of national population
Lebanon	2013	Excluded from TI report
Luxembourg	2013	Excluded from TI report and sample too small
Madagascar	2013	Clear under-representation of segment of national population
Malawi	2013	Excluded from TI report
Maldives	2013	Clear under-representation of segment of national population
Mozambique	2013	Clear under-representation of segment of national population
Nepal	2013	Clear under-representation of segment of national population
Nigeria	2013	Clear under-representation of segment of national population
Pakistan	2013	Clear under-representation of segment of national population
PNG	2013	CATI inappropriately used
Russia	2013	Excluded from TI report
Rwanda	2013	Clear under-representation of segment of national population
Sierra Leone	2013	Clear under-representation of segment of national population
Solomon Islands	2013	CATI inappropriately used and sample too small
South Sudan	2013	CATI inappropriately used
Sudan	2013	CATI inappropriately used
Vanuatu	2013	Clear under-representation of segment of national population and sample too small
Yemen	2013	Clear under-representation of segment of national population
Zambia	2013	Excluded from TI report

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