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An Axiomatic Approach to the Measurement of Corruption

Theory and Applications

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Abstract

In this paper we demonstrate that the axiomatic measurement approach developed in the poverty and inequality literature can be usefully applied to the measurement of corruption. We develop a conceptual framework for organizing corruption data and discuss several objective, aggregate corruption measures consistent with axiomatic requirements. We then provide an empirical application of the methodology and estimate the respective corruption measures for a sample of over 25 countries during the year 2000. Our empirical analysis reveals significant discrepancies between the country rankings generated by these measures and those provided by the Corruption Perception Index (CPI) from Transparency International. To our knowledge, this paper represents a first analysis of corruption measurement using an axiomatic framework.

Keywords: corruption, illegal behaviour, corruption measurement, legal institutions

JEL classification: K42, O17, P37

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1. Introduction

Most cross-country or aggregate empirical studies of corruption rely on indices of corruption perceptions such as the annual Corruption Perception Index (CPI) from Transparency International. Perception-based indices, however, are inadequate for many research purposes: First, they may not capture quantifiable characteristics of corrupt behavior making it difficult to deduce the relation between perceptions and specific cardinal dimensions of corruption. Second, perceptions may deviate from actual corruption if they reflect factors such as racial or religious prejudice, preconceived notions, or past events.

In response to these limitations, alternative data collection mechanisms have emerged that record information about actual corrupt acts in addition to perceptions (See, for example, Seligson 2006, Reinikka and Svensson 2006, Olken 2007b, and Ferraz and Finan 2008). Unfortunately, the usefulness of such data is limited by the lack of a rigorous conceptual framework since it is not clear how to identify a corrupt act or how to generate an aggregate corruption measure. In this paper we provide such a framework.

Our approach adapts the axiomatic measure theory developed in the realms of poverty and inequality to organize corruption data and generate specific aggregate corruption measures. The axiomatic approach entails formal definition of potentially important properties of a measure (namely, the axioms) and then classification of measures according to such properties. Our objective is both to use axiomatic methodology to make more efficient utilization of existing data and to provide guidance for subsequent design of surveys and other data collection mechanisms.

As an illustration, we provide an empirical application of the methodology and estimate several aggregate corruption measures for a sample of over 25 countries during the year of 2000. Our empirical analysis reveals significant discrepancies between the country rankings generated by these measures and those provided by the existing perception-based indices.[1] These discrepancies have important policy implications, which we explore.

As noted by Bardhan (2006), when measuring corruption 'different people do it in different ways'. Some people focus on the number of corrupt transactions while others look at the amount of money that changes hands as part of those transactions. Still others focus on the percentage of government officials that are party to corrupt transactions. Olken (2007a), for example, used dollar amounts to measure corruption in Indonesian road projects. He obtained his measure by subtracting the total expenditures reported by public officials from the total expenses estimated by independent engineers. Wolfers (2006), in contrast, measured corruption in American collegiate basketball by counting the number of games for which some evidence of point-shaving could be found. Others like Svensson (2003) and Clarke and Xu (2004) use firm-level data to study the incidence (how often) and the level of bribes paid (how much) by private firms in connection with regulations, licenses, public utilities, etc. The non-uniformity of corruption measures is also evident in the theoretical literature. Çule and Fulton (2005), for example, measure corruption as the percentage of government officials that are willing to accept a bribe. While others like Cadot (1987), Shleifer and Vishny (1993), or Choi and Thum (2005), present theoretical models in which the extent of corruption is measured by the size of the bribe or unofficial payment exchanged.

1 Examples of other frequently cited perception indices include the ICRG index of corruption from Political Risk Services Inc and the IMD index of corruption from the Institute for Management Development. Both of these indices are highly correlated with the CPI.

Very few papers have dealt with construction and evaluation of aggregate corruption measures in a systematic way. Seligson (2006) and Reinikka and Svensson (2006) discuss the strengths and limitations of survey methodologies for the measurement of corruption in the forms of capture of public funds, amounts paid for bribes, and frequency or exposure to corruption, among others. Neither paper, however, addresses the implications of having multiple measures of corruption. Méndez and Sepúlveda (2009) use a theoretical model to illustrate the difficulties of using multiple corruption measures, but also do not provide viable solutions. The literature currently lacks a unifying framework by which different corruption measures can be evaluated and compared. Without such a framework it is difficult to settle questions about corruption, since the results obtained in any single study may depend entirely on the specific corruption measure chosen for the analysis.

The remainder of the paper is organized as follows: In Section 2 we introduce our general conceptual framework and the relevant terminology. In Sections 3 and 4, we propose specific aggregate corruption measures and discuss their axiomatic properties, respectively. Section 5 contains an empirical application of our new methodology using the World Bank's 'Business Environment and Enterprise Performance Survey'. We contrast our measures with the CPI and with each other to demonstrate the distinct dimensions of corruption they capture. Finally, Section 6 concludes and suggests extensions to the current work.

2. Terminology and Conceptual Framework

The axiomatic approach to poverty measurement was pioneered by Sen (1976, 1983) with a notable early application by Foster, Greer, and Thorbecke (1984). The methodology requires two distinct steps: *identification* and *aggregation*. In the poverty context identification determines who is poor in the population while aggregation maps the data of the poor into a measure of poverty. Analogously, corruption measurement requires explicit identification criteria and the aggregation of the data into an overall measure of corruption.

The identification and aggregation steps in the corruption context, however, are different from those in the context of poverty measurement. In the case of poverty there is a single person or household whose interaction with an impersonal market identifies them as poor. In contrast, corruption often involves a transaction between more than one party. The literature often focuses on bribe takers (rather than bribe payers) as exemplified by a public official who receives an under the counter payment in exchange for issuing a public permit. Our framework departs from this norm by taking the transaction itself as the object of analysis.

The potential gap between attempted and actual corruption also represents a departure from the measurement of poverty. That is, those who attempt to engage in corruption and do not succeed could be said to be corrupt without having actually consummated a corrupt act; but the same cannot be said of a poor individual.[2] In this paper we address actual corruption only. Thus, the case of a bribe offer that is that is not accepted will not be considered corruption. Though ideally such acts would be captured by an aggregate measure of corruption, data limitations preclude practical consideration of this form of corruption at this time.

2 There may well be a link here between corruptibility and the growing literature on vulnerability to poverty. See for example Dutta, Foster, and Mishra (2009) and the references therein.

We begin by introducing some terminology and notation. We classify individuals as either clients or officials. An *official* is defined as a public servant who performs specific functions such as issuing permits or penalties associated with government regulations, selling government goods or services, allocating government transfers and funds, and other similar tasks. We refer to all such functions simply as *services* and to the group of public officials associated with a single service as a *department*. In turn, a *client* is defined as a private agent who conducts business and may employ public services directly or indirectly. We use the letter i to index clients and the letter s to index the different services provided (or the departments). The total number of clients and departments are, respectively, I and S.

We are interested in recording the transactions between clients and government departments throughout a specific period of time (typically a year), where the size and purpose of these transactions vary with the type of service provided. Examples may include: the legal payment of a passport application fee, the bribe given in exchange for a driver's license, the illegal appropriation of public funds allocated to a specific department, etc. We choose to concentrate on transactions between clients and departments because data on corrupt payments at the departmental level are easier to obtain than data on corrupt transactions at the individual level. However, by treating each official as a single department, our methodology could be easily applied to individual level data, were it available.

Transactions are recorded in a $T{\times}I{\times}S$ dimensional *data matrix* D, which is essentially a workbook containing information from T many $I{\times}S$ dimensional spreadsheets or *transaction reports*, denoted by d_t. Entries in D are of two types: first, d_{tis} can be a number representing the monetary value of a transaction between a client i and an anonymous official from department s; second, d_{tis} can be an empty cell, indicating that no transaction between i and s was observed and recorded in the t^{th} report. Every transaction report d_t contains at least one transaction, but can also list several transactions between different client-department pairs. Multiple transactions between a specific client-department pair are recorded in different reports. T is the total number of transaction reports in D, and hence bounds the number of transactions between any specific client-department pair.

There are several ways in which independent observers obtain information regarding corrupt transactions. Authors like Seligson (2006), for example, have collected data on corruption by using victimization surveys. These surveys are designed to gather information on specific government departments or officials by means of denunciation, where the questions in the survey invite the respondents to denounce corrupt acts and portray themselves as victims of corruption instead of active partners in corrupt transactions. Reinikka and Svensson (2006), in turn, discuss the collection of data on capture of public funds by using Public Expenditure Tracking Surveys. They also collect data on other types of corrupt acts via service provider surveys, and enterprise surveys.

Another way to obtain information regarding corrupt transactions is through external audits that track public resources and estimate the amount lost to theft or graft. Ferraz and Finan (2008) and Olken (2007b), for example, have gathered data in this manner. Such types of corrupt acts do not involve a specific client directly, but can still be accounted for within our framework by adding a state auditor as an element in the client vector. A similar approach could be used to incorporate information about corrupt transactions uncovered through criminal investigations.

As data collection mechanisms improve, the quality and variety of the corruption data that makes up our matrix D should also improve and expand. Information regarding services rendered in corrupt transactions, for example, is rarely collected by victimization surveys. Thus, the case of a client who pays a bribe of \$10 to expedite a bureaucratic process and waits for 30 minutes cannot be differentiated from the case of a client who pays \$10 for the same purpose but waits only 20 minutes. If such data was available, however, it could be easily incorporated into our methodology either as an alternative service or in terms of dollars per unit of service rendered instead of total dollars exchanged in each transaction.

In Section 5, we present an empirical exercise that shows how our approach can be applied to existing data sets. The following hypothetical example will also help make our new methodology more concrete. Consider the following $2\times4\times4$ dimensional data matrix D made up of two reports d_1 and d_2 covering four clients and four departments.

Figure 1: The data matrix *D*

$$
\begin{array}{cc}
 & \text{Departments}_s \\
d_1 = & \begin{pmatrix} . & \$0 & \$7 & \$0 \\ \$0 & \$2 & \$2 & \$0 \\ \$1 & \$0 & \$0 & \$0 \\ \$0 & \$0 & \$0 & \$4 \end{pmatrix} \text{Clients}_i
\end{array}
\qquad
\begin{array}{cc}
 & \text{Departments}_s \\
d_2 = & \begin{pmatrix} \$0 & \$2 & \$2 & \$0 \\ \$1 & \$3 & \$2 & \$0 \\ \$0 & \$0 & . & \$0 \\ \$0 & \$0 & \$0 & \$2 \end{pmatrix} \text{Clients}_i
\end{array}
$$

In the example, entry $d_{113} = 7$ indicates that a transaction of 7 was observed between department 3 and client 1. Other entries such as d_{111} are missing, reflecting the fact that no transaction between department 1 and client 1 was included in report 1.[3] Also note that the transaction amount between a client and department might be zero. For example, a policeman on a corner might be expected to provide protection services to citizens without payment. Other government services have statutory prices greater than zero.

2.1 Identification

It is arguable that the identification step for corruption is more objective than for poverty. Poverty identification generally entails specification of a fundamentally arbitrary poverty line in income space, or dimension-specific cutoffs in capability space. Though there might be general consensus that people living on less than a dollar a day are poor, there is no compelling reason to consider those earning $1.01 to be non-poor.[4] In contrast, the *illegality* of certain transactions between an official and a client could, in principle, be objectively determined independent of the magnitude of the bribe.[5] For example, the acceptance of bribe by a government official in exchange for an illegal action would be *prima-fascia* corrupt.

However, in practice the identification of a corrupt transaction may not be so straightforward. In some cases, even the smallest payments can constitute a corrupt act. In other cases, however, the line may not be drawn at zero. *The Economist* (2006), for example, describes how in some settings an acceptance of a gift is considered acceptable as long as it is 'consumable in a single day'. Similarly, in high-income western countries, bringing a government clerk cookies on her birthday is perfectly acceptable, but may be indistinguishable from a small bribe. In fact, whether the payment received or the alteration granted is big enough to warrant identifying a transaction as corrupt is likely to depend on several factors including the legal statutory price of the service, the local culture and habits, the type of service that is provided,

3 It is natural for each transaction report d_t to contain exactly one transaction; the example has many transactions per report for illustration purposes.

4 Indeed, the dollar a day cutoff is actually $1.08 at 1993 purchasing-power parity (PPP). The inherent arbitrariness of poverty lines is addressed by Foster and Shorrocks (1988) and Ravallion (1994).

5 Poverty can also be 'objectively' defined by statute (e.g., the supplementary benefits line in the UK), while on the other hand it can be practically difficult to separate out bribes from customary gifts, one could argue against the distinction we are making.

and other potentially important elements such as the institutional framework and the costs of legal bureaucracy.

In what follows, we explicitly allow different tolerance levels to be applied to the transactions involving different departments by specifying a vector Z of tolerance level cutoffs, one for each department. Cutoff z_s is interpreted as the payment level beyond which a transaction for service s is considered corrupt, so that transaction d_{tis} from D is identified as corrupt if $d_{tis} > z_s$ and not if $d_{tis} \leq z_s$. One convenient by-product of using a cutoff to identify corrupt transactions is that only the total amount paid in the transaction is required for the measures to be constructed. Thus, whenever the information is collected via personal interviews, for example, the investigator does not need to ask how much was spent in the form of bribes or illegal payments, but only how much was spent in total for the specific service (a question which some individuals might be more willing to answer truthfully). Another convenient aspect is that it allows the researcher to include tolerance levels of zero ($z_s = 0$) to include extortionary corruption, or cases in which clients are required to pay for a service they are supposed to obtain for free.

2.2 Aggregation

The aggregation step takes into account all instances of corrupt transactions to obtain an overall level of corruption. The resulting *measure of corruption* C will depend on the data available in D and the cutoffs given in Z. In addition, the extent of corruption may depend on the resources of clients, as indicated by a resource vector Y with typical entry y_i. Consequently we view the corruption measure as a function $C(D; Z, Y)$ of the data matrix D, the cutoff vector Z, and the resource vector Y.

We will construct specific corruption measures by fixing a *corruption function* $f(d_{tis}; z_s, y_i)$, which indicates the corruption level of a single transaction d_{tis} given the departmental cutoff z_s and client resource level y_i. An associated *corruption matrix* D_f replaces each transaction d_{tis} with its associated corruption level $f(d_{tis}; z_s, y_i)$, while leaving the empty cells in D untouched. A corruption measure C_f can then be constructed by taking the mean value across all nonempty entries of the corruption matrix, or $C_f(D; Z, Y) = \mu(D_f)$. In other words, C_f is the sum of the corruption levels $f(d_{tis}; z_s, y_i)$ across all transactions, divided by the total number of transactions. The next section explores three possible forms that the corruption function may take and their associated corruption measures.

3. Aggregate Corruption Measures

There are numerous ways in which data can be aggregated and mapped to a single corruption measure C. We will focus here on a subset of measures that are reasonably compatible with the currently available cross-sectional data sets and consistent with approaches advanced in recent theoretical papers.

3.1 Frequency Measure of Corruption

The first measure we consider is based on the simplest of individual corruption functions that takes a value of 1 when a transaction is corrupt, and 0 when it is not. Define f_1 by $f_1(d_{tis}; z_s, y_i) = 1$ if $d_{tis} > z_s$ and $f_1(d_{tis}, z_s, y_i) = 0$ if $d_{tis} < z_s$, and denote the associated corruption matrix by D_1. The *frequency measure of corruption* $C_1(D; Z, Y) = \mu(D_1)$ measures corruption as the fraction of transactions that are corrupt. C_1 is clearly bounded between 0 and 1, with higher numbers indicative of greater corruption incidence; it is analogous to the simple head-count ratio from the poverty literature.

Refer back to the example *2×4×4* matrix *D*, and suppose the cutoff vector is *Z = [$0, $0, $2, $0]*. We apply the corruption function f_1 to the transactions in *D* (given *Z*) to obtain the corruption matrix D_1 below, which contains 1 for every transaction higher than its respective cutoff and 0 for every transaction that is not.

Figure 2: The Corruption Matrix D_1

$$\begin{array}{cc} \text{Departments}_s & \\ \begin{pmatrix} . & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} & \text{Clients}_i \end{array} \qquad \begin{array}{cc} \text{Departments}_s & \\ \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & . & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} & \text{Clients}_i \end{array}$$

By counting the number of corrupt transactions and the overall number of transactions, we find that the corruption frequency measure C_1 is 8/30 or 0.26.

3.2 Excess Value Measure of Corruption

One disadvantage of using frequency measures of corruption alone is that they do not account for the amount of resources captured by corruption, or the depth of corruption. For example, an economy in which one out of ten transactions is corrupt is characterized by a frequency measure $C_1 = 0.1$, regardless of whether the typical corrupt transaction involves a bribe of, say, $1,000,000 or $10.

In order to account for this added dimension, one can construct a corruption measure that uses the excess value of a transaction as its individual corruption function. In symbols, define $f_2(d_{tis}; z_s, y_t) = d_{tis} - z_s$ if $d_{tis} > z_s$, and 0 if $d_{tis} \leq z_s$,, and let D_2 be the associated corruption matrix. Then the *excess value measure of corruption* $C_2(D; Z, Y) = \mu(D_2)$ evaluates corruption in terms of the average amount by which payments to officials exceed their cutoffs. In other words, C_2 is the aggregate amount of money paid in bribes divided by the total number of transactions. This measure takes on nonnegative values and is analogous to the poverty gap measure of poverty.

In our example, after applying the cutoff vector *Z* = [*$0, $0, $2, $0*] and corruption function f_2, we obtain the corruption matrix D_2 whose values reflect the excess payments to government officials above the respective cutoffs.

Figure 3: The Corruption Matrix D_2

$$\begin{array}{cc} \text{Departments}_s & \\ \begin{pmatrix} . & 0 & 5 & 0 \\ 0 & 2 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 4 \end{pmatrix} & \text{Clients}_i \end{array} \qquad \begin{array}{cc} \text{Departments}_s & \\ \begin{pmatrix} 0 & 2 & 0 & 0 \\ 1 & 3 & 0 & 0 \\ 0 & 0 & . & 0 \\ 0 & 0 & 0 & 2 \end{pmatrix} & \text{Clients}_i \end{array}$$

Averaging over all the transactions yields the value $C_2 = 20/30 = 0.66$.

3.3 Relative Burden Measure of Corruption

A characteristic of C_2 is that it measures corrupt transactions in absolute terms and does not take into account the varying resource levels of clients or the aggregate size of the economy as a whole. One may argue that a given sized bribe represents a greater burden on a client who has more limited resources; similarly, an economy that loses 10 per cent GDP to corruption is arguably more corrupt than an economy that loses 2 per cent of GDP, even if the aggregate value of all bribes is the same for both. C_2 or C_1 would not be useful for making this distinction.

In order to account for the relative burden of corrupt transactions we use a corruption function f_3 that measures the excess payment relative to the client's resources: $f_3(d_{tis}; z_s, y_i) = (z_s - d_{tis})/y_i$ if $d_{tis} > z_s$, and 0 if $d_{tis} \leq z_s$.[6] Where D_3 is the associated corruption matrix, we define the *relative burden* measure of corruption C_3 by $C_3(D; Z, Y) = \mu(D_3)$, or the sum of the relative burdens divided by the total number of transactions. The steps involved in the calculation of this measure are analogous to our previous example, and so we omit a separate illustration. Note that the C_3 measure is bounded between 0 and 1.

3.4 Weighted Measures of Corruption

All of the measures presented so far implicitly regard each department as equally important for corruption measurement. Thus, whether corruption takes place in the presidential office or in the office of horse-racing regulations is of no consequence for the measures C_1 to C_3. In some instances, however, one may want these measures to weight certain departments more heavily than others by virtue of their function, visibility, or their institutional placement.

To achieve this one may use a weighting vector w that assigns weight w_s to department s according to its relative importance. Weights can be determined by subjective evaluations or via objective indicators of relative importance, such as: the percentage of bureaucrats that work in a particular department; the percentage of the fiscal budget allocated to a particular department; or the percentage of transactions that go through a particular department. Each of the measures developed in this section can be modified to include weights as follows: For k = 1, 2, 3, define $C_{kw}(D; Z, Y) = \mu_w(D_k)$, where μ_w is the 'weighted mean' which weights transactions involving department s by w_s.

4. Properties of Corruption Measures

We now analyze the properties of the corruption measures developed above. As in the literatures on poverty and inequality literature, an axiomatic framework provides a clear and transparent methodology for classifying corruption measures; it can aid the researcher or policy-maker in choosing a measure and interpreting empirical findings. We begin with a set of basic axioms that we would expect all corruption measures to satisfy. Then we consider additional axioms that help to distinguish measures from one another, and to define more clearly what each is measuring.

Consider a generic corruption measure $C(D; Z, Y)$, which employs a tolerance vector Z to convert the data in D and client resources Y into a corruption metric. The following four definitions are useful in stating the subsequent axioms:

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6 An alternative might be to divide transactions by resources and express cutoffs in percentage terms.

(1) D' is obtained from D by a *reordering of observations* if there exist two observations $u \neq v$ such that $d'_{uis} = d_{vis}$ and $d'_{vis} = d_{uis}$ for all i,s, while $d'_{tis} = d_{tis}$ for all t,i,s such that $t \neq u$ and $t \neq v$. In other words, all observations are the same except for two whose order has been switched.

(2) D' is obtained from D by a *replication of observations* if there exist an integer $m \geq 2$ such that $T' = mT$ and $D' = (D,\ldots, D)$ where D' is an $mTxIxS$ dimensional matrix. In other words, for every observation in D there are m copies of the same observation in D'.

(3) D' is obtained from D by an *increment* if $d'_{tis} > d_{tis}$ for a given index combination (i,s,t) while $d'_{ujr} = d_{ujr}$ for all $(u,j,r) \neq (t,i,s)$. This occurs when a single payment amount is increased, and all other entries are unchanged. The increment is said to be *within tolerance* if $z_i \geq d'_{tis}$; *frequency increasing* if $d'_{tis} > z_i \geq d_{tis}$; and *excess payment increasing* if $d_{tis} > z_i$. In the first, the payment level begins and ends within the tolerance cutoff, and neither transaction is considered to be a bribe; in the second, the payment begins within and ends above the tolerance cutoff, and so the increment transforms an allowable transaction into a bribe; in the third, the payment begins and ends above the tolerance cutoff, thus increasing the size of an existing bribe.

(4) We say that $(D'; Z', Y')$ is obtained from $(D; Z, Y)$ by a *proportionate change* if $(D'; Z', Y') = \alpha(D; Z, Y)$ for some $\alpha > 0$. A proportionate change scales up or down all observations, incomes and cutoffs by the same factor.

With these definitions in mind, we now state the following four basic axioms:

Symmetry: If D' is obtained from D by a *simple reordering of observations*, then $C(D', Z, Y) = C(D; Z, Y)$.

Replication Invariance: If D' is obtained from D by a *replication of observations*, then $C(D', Z, Y) = C(D, Z, Y)$.

Focus: If D' is obtained from D by a *within-tolerance increment*, then $C(D'; Z, Y) = C(D; Z, Y)$.

Frequency Monotonicity: If D' is obtained from D by a *frequency increasing increment*, then $C(D',Z, Y) > C(D; Z, Y)$.

Symmetry ensures that the observations are all that matter to a corruption measure, not the order in which they are recorded.[7] Replication invariance ensures that the measure does not depend on the absolute number of observations or transactions, but rather on their number relative to the total number. In this way, the measure does not treat countries with a lower number of transactions more favorably, but rather measures corrupt activity relative to the total number of government services provided. The focus axiom makes sure the measure is unresponsive to payment sizes for transactions that are not considered to involve corrupt acts. Finally, frequency monotonicity requires a measure to increase when the value a transaction rises above the tolerance threshold.

It is straightforward to verify that all of our measures C_1, C_2, and C_3 satisfy the four basic axioms. Note that frequency monotonicity would be violated by a simple department headcount ratio that measures

[7] Two other forms of symmetry might be justified: *symmetry in departments* which would leave the measured level of corruption unchanged if two departments exchange indices; *symmetry in clients* which would require an analogous form of equal treatment across clients. Both forms are satisfied by our measures. Of course, as noted above, there may be applications that would require corruption in different departments to be treated differently, in which case we could use the weighted indices that violate department symmetry. In other circumstances it may make sense to consider different weights on specific classes of clients as well, leading to a violation of client symmetry.

corruption as the percentage of departments that accepted at least one bribe.[8] The next three axioms help distinguish between the three measures:

Bribery Monotonicity (MN): If D' is obtained from D by an *excess payment increasing increment*, then $C(D'; Z, Y) > C(D; Z, Y)$.

Client Enrichment (CE): If D contains at least one transaction with positive excess value, and Y' is obtained from Y by a *proportionate increase*, then $C(D; Z, Y') < C(D; Z, Y)$.

Scale Invariance (SI): If $(D'; Z', Y')$ is obtained from (D, Z, Y) by a *proportionate change*, then $C(D'; Z', Y') = C(D, Z, Y)$.

Axiom MN ensures that the corruption measure is increasing in the sizes of the bribes paid. The frequency measure C_1 ignores the bribe size and violates this axiom; the other two measures take into account the sizes of excess payments and thus satisfy this property. CE implies that measured corruption should fall if clients become uniformly richer and the absolute sizes of the bribes remain the same. That is, the level of corruption is a function of the burden of the bribes relative to client resource levels. Scale invariance likewise ensures that if all monetary quantities are expressed in different units (say from dollars to hundreds of dollars), the measure of corruption is unchanged. Neither C_1 nor C_2 depends on the size of client incomes and each just violates the CE axiom. The definition of C_3 alone expresses excess payments as a percentage of a client's income and thus satisfies CE. The identification step is unaffected by a proportional change, and the bribe size relative to a client's resources will also be unchanged; hence C_1 and C_3 satisfy the SI axiom. In contrast, the bribe size is not independent of the proportional change and hence C_2 violates SI.

In certain applications it may be helpful to be able to decompose the measure of corruption level across population subgroups. For example, decomposition by firm size, department, or region may be of interest to the policymaker. The following axiom permits this form of analysis:

Decomposability (DC): Let D' and D be two data matrices and let $E = (D, D')$ be the matrix obtained by combining the two. Then where $n(D')$, $n(D)$, and $n(E)$ are the respective numbers of (non-missing) transactions they contain, we have

$$C(E; Z, Y) = [n(D')/n(E)]\ C(D'; Z, Y) + [n(D)/n(D)]\ C(D; Z, Y).$$

By DC, the overall corruption level is just the weighted sum of the subgroup corruption levels, where the weights are the shares of transactions in the respective subgroups. Since each of our measures is constructed using a mean, each satisfies DC and thus is amenable to subgroup analysis.[9] Table 1 summarizes the axioms satisfied by our measures.

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8 A similar issue is encountered in chronic poverty measurement and multidimensional poverty measurement. See Foster (2009) and Alkire and Foster (2007).

9 In addition, this implies that each measure is *subgroup consistent* in that lower regional corruption levels are reflected in a lower overall level of corruption. See Foster and Sen (1997) for a related discussion in the context of poverty and inequality measurement.

Table 1: Axiomatic satisfied by the measures

	4 basic axioms	***MN***	***CE***	***SI***	***DC***
C_1	Y	N	N	Y	Y
C_2	Y	Y	N	N	Y
C_3	Y	Y	Y	Y	Y

Note: 'Y' indicates the axiom is satisfied by the measure; 'N' indicates it is not.

5. Empirical Application

We utilize data from the Business Environment and Enterprise Performance Survey (BEEPS), developed jointly by the World Bank and the European Bank for Reconstruction and Development. This is a survey of over 4,000 firms in 27 transition countries conducted in 1999-2000 that examines a wide range of interactions between firms and the state. Based on face-to-face interviews with firm managers and owners, BEEPS is designed to generate comparative measurements in such areas as corruption, state capture, lobbying, and the quality of the business environment, which can then be related to specific firm characteristics and firm performance.[10]

The survey allows us to reconstruct important elements of the *D* matrices including information on frequency and the monetary value of corrupt acts. Question 28, for example, asks 'How often do firms like yours nowadays need to make extra, unofficial payments to public officials' for seven different government functions. These functions are: (i) Connect public services like electricity and telephone; (ii) Get licenses and permits; (iii) Deal with taxes; (iv) Gain government contracts; (v) Deal with customs procedures and importing; (vi) Dealing with courts; (vii) Influencing law decrees and new regulations. We use these seven functions as the seven departments of our *D* matrices.

The respondents to question 28 were asked to estimate the frequency of unofficial payments and choose one of the following answers: 'always', 'mostly', 'frequently', 'sometimes', 'seldom', and 'never'. For the purposes of our example, we have imposed numerical values to these answers in the following manner: 'always' = 100%, 'mostly' = 80%, 'frequently' = 60%, 'sometimes' = 40%, 'seldom'= 20% and 'never' = 0%.

Similarly, question 27 asked 'What percentages of revenues (on average) do firms like yours typically pay per annum in unofficial payments to public officials?' The possible answers to this question were: '0%', 'less than 1%', 'between 1% and 1.99%', 'between 2% and 9.99%', 'between 10% and 12%', 'between 13% and 25%', 'over 25%'. For the purposes of our example, these answers were given a numerical value equal to the median of the provided ranges, except for the 'over 25%' category, which was maxed at 26%.

10 More information on the survey, the BEEPS research project, and related papers, can be found at the website: http://www.worldbank.org/wbi/governance/pubs_statecapture.

Together with question 27, questions 29 and 51 give us more details regarding the magnitude of the unofficial payments. Question 51 asks the respondent to estimate the firm's annual sales, annual assets and annual debt to the nearest range, where the possible ranges started at 'below $250,000' and continued until '$500 million or more'. We again take the median of these ranges as the numerical value of the answer. In turn, question 29 asks the respondent to estimate the exact share of the total unofficial payments spent at each government department. Thus, by combining the information on questions 27, 29, and 51, we can estimate the total number of dollars spent at each department in the form of unofficial, corrupt payments.

We also use other information regarding firms' behavior and perceptions in our empirical analysis. Question 24, for example, asks firms to report the percentage of senior management's time that is spent in dealing with government officials about the application and interpretation of laws and regulations. Other questions ask the respondents to report on the likelihood of finding an honest official, the degree to which public policies are predictable, and the degree to which they consider corruption an obstacle for doing business.

Finally, for comparison purposes, we utilize the Corruption Perception Index (CPI) from Transparency International for the year 2000. In two instances, the CPI was not available for that year, so we utilize the index for the previous year instead. The original CPI ranges from 0 to 10, with a higher number indicating less corruption. In our analysis we have inverted the CPI so that a higher number indicates more corruption.

5.1 Empirical Measures and Comparative Results

The empirical computation of the proposed measures can now be described. To derive the measures, we need information on the number of all transactions that are due to a given client-department pair – information that is not available in the dataset – and we therefore make the strong assumption that this number is the same for all pairs. The dataset contains the frequency with which corrupt payments are made on average, and so by averaging these reported values over all respondents and all departments, we obtain the measure C_1. A similar process is followed for constructing C_3 and C_2. In the case of C_3, each surveyed firm has reported the total excess payments as a percentage of total revenues and the percent of total excess payments going to each department. From this we obtain the excess payment to department s as a share of the firm's revenue, which we interpret as $\Sigma_t(d_{tis} - z_s)/y_i$. We then use the mean value of these aggregate relative burdens for our final estimate of C_3.[11] The process for computing C_2 is identical to that for computing C_3, except that total payments $\Sigma_t(d_{tis} - z_s)$ are used.

Having computed the corruption measures, we can now compare the country rankings that result from using the different measures to the rankings established by the CPI. We rank countries from the most corrupt to the least corrupt. We focus on country rankings because the scales of the measures are not directly comparable though similar conclusions are obtained if the levels are used instead. Table 2 below presents a Spearman rank correlation matrix of the resulting country rankings.

[11] The original C_3 and C_2 measures described in the theoretical section take the mean over all transactions. Our empirically constructed values take a mean over $I \times S$ aggregates. This simplification entails no loss of generality since we assume each client-department pair has the same number of transactions. Our computed values C_3 and C_2 are a constant (the number of transactions per pair) times the original values and are hence preserve the rankings.

Table 2: Spearman correlations between corruption measures

	C_1	C_2	C_3	CPI
C_1	1			
C_2	-0.27	1		
C_3	0.52	-0.26	1	
CPI	0.63	-0.37	0.67	1

The ranking of the CPI is positively correlated with those of both C_1 and C_3; but is correlated negatively (weakly) with that of C_2. Together, these correlations suggest that aggregate perceptions might be more susceptible to the frequency and the relative costs of corruption than to the absolute amounts involved in corrupt transactions. Such a conclusion, however, seemingly contradicts the findings of Donchev and Ujhelyi (2008), who report that individual perceptions are more influenced by absolute rather than relative measures of individual corruption experiences. This apparent contradiction could be explained by noticing that the measure C_2 can be influenced by a small number of firms with very large transactions, and if the set of corrupt firms were small enough to escape general notice, there may be little impact if any on the perceived prevalence of corruption. Consequently, C_2 could well increase while perceived corruption remains unaltered.

Table 2 reveals a weak positive rank correlation between C_1 and C_3, and a weak negative rank correlation between C_1 and C_2. Thus, Table 2 suggests that the three measures provide significantly different perspectives on corruption. For more insight, the full rankings of all countries are provided separately in Table 3, where we divide the sample into four groups: Low CPI (between 0 and 5.9), Medium-Low CPI (between 5.9 and 6.7), Medium-High CPI (between 6.7 and 7.6), and High CPI (above 7.6).

Two aspects of Table 3 are particularly striking. First, our measures reveal different corruption patterns for different countries with a similar CPI. Take, for example, the cases of Romania and Armenia. They both have a Medium-High CPI, but while Romania is ranked high by C_1 and low by C_3, Armenia is ranked low by C_1 and high by the C_3. Thus, Table 3 suggests that although the CPI measure of *perceived* corruption would rank both countries similarly, the types of corrupt acts that affect these countries may well be dissimilar.

A detailed analysis of why corruption perceptions deviate from the experiences captured in our axiomatic-based measures is beyond the scope of the current work. Here our objective is simply to point that these measures deviate significantly from perception-based measures and from each other. That is to say, the CPI, C_1, C_2, and C_3, capture different dimensions of corruption.

A more important question is whether our measures are capable of providing new insights regarding corruption beyond those yielded by perception-based measures alone. In this respect, we provide some suggestive examples of how axiomatic-based measures might contribute to key issues in the literature.

Table 3: An empirical illustration of alternative rankings

Low

Country	C_1 Rank	C_2 Rank	C_3 Rank
Slovenia	3	24	9
Estonia	4	22	10
Hungary	2	18	7
Belarus	1	2	6
Poland	13	21	3
Lithuania	17	10	14

Medium-Low

Country	C_1 Rank	C_2 Rank	C_3 Rank
Latvia	8	6	2
Croatia	6	19	4
Bosnia	14	7	15
Slovakia	15	15	19
Czech R.	7	20	16
Turkey	21	26	8
Macedonia	23	4	17
Bulgaria	16	13	5

Medium-High

Country	C_1 Rank	C_2 Rank	C_3 Rank
Kazakhstan	10	25	11
Uzbekistan	20	17	25
Romania	24	8	12
Moldova	19	16	23
Armenia	9	12	21

High

Country	C_1 Rank	C_2 Rank	C_3 Rank
Russia	11	23	13
Albania	25	14	18
Ukraine	22	11	26
Georgia	18	9	24
Azerbaijan	26	5	20
Kyrgyzstan	12	3	22

For example, there has been debate as to whether corruption 'greases the wheels' of commerce by enabling businesses to circumvent bureaucratic delays, or whether it 'sands the wheels' by causing a deterioration of public institutions and worsening the delays. Some authors like Kauffman and Wei (1999) and Meon and Sekkat (2005) have found support for the latter hypothesis. Kauffman and Wei (1999) find a positive and significant relationship between firms' perceived level of corruption and the reported waste of time with bureaucracy. Unfortunately, since they used measures of perceived corruption, they cannot provide details about the specific factors that shape the managerial decision of time allocation.

We confirm the result of Kauffman and Wei (1999); that is, we find a positive correlation between the amount of perceived corruption and the time wasted by management officials in dealing with government officials. As shown in Table 4, the correlation is positive and equal to 0.36.

Table 4: Correlations between time wasted and corruption

	C_1	C_2	C_3	CPI
Time wasted	0.07	0.39	0.37	0.36

A more detailed picture emerges, however, when we take note of the correlation coefficients for our three measures. As shown in the correlation matrix, time wasted also shows a positive correlation with both C_2 and C_3: these coefficients are 0.37 and 0.39, respectively (slightly greater than that observed for the CPI). However, the correlation coefficient between time wasted and C_1 is only 0.07. It appears, then, that the prevalence of corruption has less influence on managerial time allocation decisions than do the measures accounting for the depth of corruption. In other words, frequent but petty processes, such as the payments of utility bills or the compliance with traffic regulations, may be less harmful than, say, contract rigging.

Another question frequently visited in the literature is whether corruption hinders investment and therefore growth. Authors like Mauro (1995), for example, have reported a negative relationship between aggregate investment levels and aggregate corruption perception indices. In our sample, firm managers were asked to estimate the percentage increase in investments over the previous three years. In Table 5 we show the respective correlations between their answers and our corruption measures.

Table 5: Correlation between investment and corruption

	C_1	C_2	C_3	CPI
Investment	-0.38	0.01	-0.63	-0.55

The results confirm a negative correlation between investment and corruption perception, but at the same time provide a more nuanced assessment of that relationship. The relative burden of corruption C_3 has a strong negative correlation with investment, and the magnitude is greater than the one inferred from the CPI. The frequency measure C_1 and the absolute costs of corruption measure C_2 have much smaller correlations with investment decisions, and the magnitudes are smaller than the one obtained with the CPI. The implication is that given two otherwise identical countries with the same CPI, we would expect the country with greater C_3 to experience greater deterioration in investment levels. The measures improve our understanding of the corruption-growth relation by identifying the aspects of corruption that hinder investment.

6. Conclusions

To our knowledge, this paper represents the first analysis of corruption using an axiomatic approach to measurement. We have identified meaningful differences among our three measures and between these measures and the CPI. Perhaps most importantly, we find that our measures generate additional insights and illuminate distinct dimensions of corruption that cannot be seen with the standard perception-based measures.

Though our analyses are preliminary, we believe they are quite promising. Our methods of organizing data, constructing corruption measures, and specifying axioms, are readily implemented given appropriate data. They suggest additional survey questions that can improve the accuracy of results and their comparability over space and time. However, to assess whether a given comparison in statistically significant, or to test associated hypotheses concerning corruption, an additional set of statistical tools will need to be developed. This will be investigated in future work.[12]

The current paper presents corruption measures that are defined for a given time period; we have not focused on the time trend of overall corruption or for specific client-department pairs. For example, with the BEEPS data we have information regarding the total number of bribes over the total time interval, but no indication of how they are distributed across time. In addition, the time interval of respective questions about corruption is often relatively short (frequently a year). With such data it is difficult to differentiate between a level of corruption that appears randomly throughout different departments, and is eradicated afterwards, and the type of corruption that is engrained in the institutions; i.e., *chronic* corruption. And yet the two forms of corruption may demand different policy responses. In subsequent work, we will extend our framework to include measures and axioms that distinguish chronic corruption from the transient variety.

[12] Note that since each of the measures we have developed is based on a mean, this task should be a relatively straightforward.

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