Abstract

This paper uses panel dat from 61 countries at different stages of development over a twenty-year period and a dynamic panel data estimator to investigate the effect of corruption on economic growth in a sample of countries. Using two measures of corruption, we find that corruption has a strong negative and statistically significant impact on economic growth. The negative growth impact of corruption we find is robust to various specification as well as the conditioning variables. We find that corruption decreases growth rate of income both directly and indirectly through decreased investment in physical capital. A one standard deviation increase in corruption directly decreases the growth of per capita income by .75 percentage points a relatively large effect. The total growth effect of a one standard deviation increase in corruption is to decrease the growth rate of per capita icome by 1.15 percentage points—a relatively large impact, given that the average growth rate of per capita income in the sample was 1.9%. We also find that corruption increases income inequality as measured by the gini coefficient. A one standard deviation increase in corruption is is correlated with a .11 point increase in the gini coefficient of income inequality. Our results are consistent with those of previous research. The results have important policy implications for economic growth, especially in low income countries with high rates of corruption.

KEY WORDS: CORRUPTION, GROWTH, INCOME INEQUALITY, GINI COEFFICIENT, PANEL DATA, DYNAMIC PANEL ESTIMATOR

JEL CLASSIFICATION: O55, C33

Corruption, Income Growth, and Inequality: A Dynamic Panel Approach

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1 Introduction

This paper uses panel data from a sample of both developed and developing countries and a dynamic panel estimator to investigate the effects of corruption on the growth rate of per capita income and the distribution of income in a sample of countries. We do so by estimating a growth equation using panel data and a dynamic panel estimator and an equation of gini coefficient of income distribution with corruption as an additional regressor in both equations. The objective of economic development, broadly defined, is to increase the living standards and the well-being of all citizens in a country. Improvements in the quality of life include increase in material well being, widening the distribution of goods and services, as well as expanding the range of choices available to all citizens in an economy. To the extent that corruption has a negative effect on the growth rate of per capita income and increases the income of the rich at the expense of the poor, it hampers economic development. To what extent does corruption affect economic growth and poverty reduction in Less Developed Countries (LDCs)? If corruption affects economic growth and income distribution, what is the mechanism through which it affects economic performance?

While economist recognize the role of corruption in economic performance, most efforts in the economics literature has focused on the causes of corruption and the effect it has on economic growth. A large number of researchers have used have used cross-national data to investigate the effects of corruption on economic performance. While cross-national data allows the researcher to investigate the effects of corruption on growth across countries, it does not allow the researcher to investigate the effects of *changes* in corruption over time on the growth rate of income in the same country. Researchers who have used panel data have employed either the Fixed Effects (FE) estimator or the Random Effects (RE) estimator to estimate the income growth equation. In the presence of dynamics and endogenous regressors, neither the FE nor the RE is appropriate (Baltagi: 1995). As argued by Caselli *et al* (1996) point out, growth equations, by their nature, contain dynamic effects and endogenous regressors making both RE and FE inappropriate estimators. We attempt to rectify this problem by using a dynamic panel estimator proposed by Arellano and Bond (1991) that produces consistent estimates in the presence of dynamics and endogenous regressors. We use data from 61 countries that include low income agrarian economies, high income industrialized countries, and transitional economies. We also use two measures of corruption in our analysis to ensure that our results are not driven by a particular measure of corruption we use to estimate the equation. As far as we know, this paper is the only one that uses two measures corruption, panel data, and a dynamic panel estimator to investigate the effects of corruption on growth as well as investigate the effects of corruption on income inequality in the same study.

Recently, a few studies have tried to link corruption to income distribution in a sample of countries.[1] However, none of these studies contain the growth effects and income distribution of corruption in one paper. Second, only a few of these studies use panel data to increase the precision of estimates. We neither limit ourselves to political corruption, ethical issues of corruption; nor do we concern ourselves with the causes of corruption. We only focus on the economic consequences of corruption.

We find that corruption has a negative and statistically significant effect on the growth rate of per capita income. A one standard deviation increase in corruption directly decreases the growth rate of per capita income by about .75 percentage points. The total growth effect of one standard deviation increase in corruption is 1.15 percentage point—a relatively large effect given that the average growth rate of per capita income growth in the sample is 1.9% per year. Corruption decreases the growth rate of income directly through reduced productivity of existing resources as well as decrease investment in physical capital. Secondly, we find that corruption increases income inequality, as measured by the gini coefficient. A one standard deviation increase in the corruption index increases the gini coefficient of income inequality by between 2.5 and 3.2 points. To the extent that rapid economic growth increases the incomes of the poor and hence reduces poverty, increases in corruption additionally hurts the poor rather than the rich and powerful. The implication of our results is that decreasing corruption increases the growth rate of income as well as improve the distribution of income. Our results are robust to various specifications of the growth equation and different measures of corruption.

The rest of the paper is organized as follows: Section 2 provides a working definition of corruption and briefly reviews the literature on the economic consequences of corruption. Section 3 presents a growth equation that relate corruption to the growth rate of per capita income and an income distribution equation that also depend on corruption, among other variables. The section also describe the estimation method for the growth equation. Section 4 describes the data while section 5 presents and discusses the statistical results. Section 6 concludes the paper.

2 Working Definition and Literature Review

Corruption means different things to different people. We take a purely economic approach to the definition of corruption rather than a legal approach since not all corrupt practices are illegal and not all illegal activities are corrupt practices. . We define corruption, in this paper, as the use of public office for private gain. We define public broadly to include private businesses, government, international organizations, and State-owned-enterprises (SOEs). Defined this way, corruption is seen as a special case of the principal agent problem. In this case, the general public is the principal, and the public official is the agent. Jain (2001) identifies three categories of corruption—grand, involving political elite, bureaucratic involving corrupt practices by appointed bureaucrats, and legislative corruption involving how legislative votes are influenced by the private interest of the legislator. The three types of corruption differ only in terms of the decisions that are influenced by corrupt practices. The ultimate result of corruption in each case is the same—the misallocation of resources. Our working definition of corruption is broad enough to include all these categories of corruption.

Even with this narrow definition of corruption, there may still be problems of interpretation and measurement of corruption. For example, when does a "gift" to a high ranking public official become a bribe? To what extent is money given to an African public official to influence policy (which will generally be considered bribery and therefore a corrupt practice) different from a contribution to a congressional campaign in the US (not considered bribery and therefore not a corrupt practice)? There is also the problem of common comparative measures. Suppose corruption takes the form of bribery, does the extent of corruption depend on the absolute size of the bribe taken/given? To what extent is decentralized and competitive corruption more deleterious to growth and development than centralized corruption? We do not attempt to answer these issues. Readers should, however, keep these issues of definition in mind when evaluating the results of this paper.

Although economists have known about the existence of corruption for a long time, it is only quite recently that the profession has come to study the relationship between corruption and economic performance. Economists generally see corruption as part of the problem of rent seeking (Acemoglou and Verdier: 2000, Barreto: 2000, Ehrlich and Lui: 1999, Gray and Kaufmann: 1998, Tanzi: 1997, Shleifer and Vishny: 1993, Mauro: 1995 among others).[2] In this approach, corruption slows the pace of economic growth because it distorts incentives and market signals leading to misallocation of resources. Second corruption and the opportunities for corrupt practices lead resources, especially human resources, to be channeled into rent seeking rather than productive activities. Third, corruption is seen as an inefficient tax on those who are forced to pay it hence it raises the cost of production. Fourth, because corrupt practices are conducted in secrecy and contracts emanating from them not legally enforceable, corruption increases transactions cost. Fifth, corruption may lead bureaucrats to channel government expenditures into unproductive sectors, such as defense, that offer opportunities for rent seeking (Gupta *et al*: 2000). Corruption also distorts the proper functioning of state institutions allowing a few interest groups to seize these institutions for their private interest (Helman, Jones, and Kaufmann: 2000). Finally, corruption increases not only the cost of production but also uncertainty, especially in the case of decentralized corruption hence decreasing investment in both physical and human capital (Wei: 2000, Alesina and Weder: 1999).

Several studies have empirically investigated the causes of corruption using data from a sample of countries. Among the factors found to increase corruption are low levels of law enforcement, lack of clarity of rules, of transparency and accountability in public actions, too many controls that give too much discretion to the public official, over-centralization and monopoly given to the public official, low relative wages of public officials, as well as the large size of the public sector (Tanzi: 1997, Van Rijckeghem and Weder: 2001, Goel and Nelson: 1988, Ades and Di Tella: 1999, Kaufmann and Siegelbaum: 1997, and Rose-Ackerman: 1997). Other researchers point to the weakness of political institutions as a cause of corruption (Rose-Ackerman: 1999). While these studies do not generally agree on all the factors that determine corruption all the time, they all agree that the larger the government sector, the lower the relative wage of the public sector, and the lower the quality of the bureaucracy, the more widespread corruption is likely to be. Although this paper does not deal with the causes of corruption, knowing the causes of corruption can provide guidance on reducing corruption.

Mauro (1995, 1997) uses data from a sample of developed and developing countries to investigate the effects of corruption on economic growth. Using a single equation model and employing both Ordinary Least Squares (OLS) and Instrumental Variables (IV) estimating techniques, he finds that corruption has a negative and statistically significant impact on economic growth. Most of the growth impact, he finds, comes through decreased investment in physical capita. Tanzi (1998) and Tanzi and Davoodi (1997) investigate the effects of corruption on economic growth and government expenditures. They find that corruption increases government expenditures but decreases expenditures on maintenance and this leads to reduced economic growth since the new capital cannot be put to use for lack of complementary inputs. They also find that corruption decreases private investment. Alesina and Weder (1999) investigate whether corrupt governments receive less foreign aid and conclude that corrupt governments do receive *more* foreign aid under some circumstances. Wei (2000) finds that corruption has a negative impact on the inflow of foreign direct investment, all things equal.

A few studies have investigated the effects of corruption on income distribution.[3] Li *et al* (2000) investigate the effects of corruption on income growth and the gini coefficient of income distribution using data from Asian, OECD, and Latin American countries. They find that corruption increases the gini coefficient in a quadratic way; the gini coefficient is higher for countries with intermediate level of corruption while it is low for countries with high or low levels of corruption. They also find that corruption affects the gini coefficient through government consumption. They, however, do not allow economic growth to influence the gini coefficient. Gupta *et al* (1998) finds that corruption increases income inequality in a sample of developing countries. They also find that increased corruption is associated with decreases in the share of government expenditures devoted to education and health care. To the extent that the poor in LDCs rely on government educational programs to escape poverty and on government health care programs for improved health more than the rich, decreases in these expenditures decreases the welfare of the poor. Hendriks *et al* (1998) and Johnston (1989) find that the distributional effects of corruption and tax evasion are regressive, hence increases income inequality.

Most of the studies mentioned above treat corruption and other determinants of growth and income distribution as exogenous. The literature on the determinants of corruption suggests that corruption cannot be treated as exogenous in a growth equation. Using OLS methods under these circumstances leads to biased and inconsistent estimates. The few studies that use IV estimates to account for the endogeneity of corruption in growth equations treat other regressors in the equation as exogenous. However, as argued by Caselli *et al* (1996), most regressors in growth equations cannot be treated as exogenous on account of dynamics of the growth process. In our study of the effects of corruption on income inequality, we treat income inequality, growth rate of per capita income, and corruption as jointly endogenous, hence we use an IV estimator to investigate the impact of corruption on income inequality.

3 Model and Estimation Method

In this section, we present outlines of income growth and income inequality equations that include corruption as an added variable that we estimate. In addition, we discuss the dynamic panel estimator that we use to estimate the income growth equation. The first subsection introduces the growth and inequality equations while the second subsection discusses the estimator.

3.1 Model

3.1.1 Income Growth Rate

Endogenous growth theory suggests that institutions are important determinants of the long term growth of an economy. We see corruption as an indicator of institutional failure and introduce this institutional failure variable into a standard Barro type growth equation, estimated by many researchers (Caselli *et al*: 1996, Gyimah-Brempong and Traynor: 1999, Levine and Renelt: 1992, Mankiw, Romer and Weil: 1992, Sachs and Warner: 1997, and others), in our study. Since this growth equation is well known, we do not spend time to develop it but mention the outlines of the equation we estimate. The development economics literature suggests that corruption has a deleterious effect on economic growth through two main channels. It decreases growth directly by decreasing the productivity of existing resources through lower productive effort or through a non optimal input mix. Indirectly, corruption decreases economic growth through a reduction in investment in both physical and human capital (Wei: 2000, Gupta: 2000, Mauro: 1997, Tanzi and Davoodi: 1997). Corruption has its own momentum; increase corruption decreases the marginal value of honesty, hence most human resources are channeled towards rent seeking activities.

In its simplest form, we postulate that the growth rate of per capita income depends on investment rate (k), initial level of income (y_0), growth rate of real export ($\dot{x}$), and the stock of human capital stock which we proxy by the educational attainment of the adult population (edu). In addition to these variables, we include corruption ($corrupt$) to measure the quality of institutions in an economy. We specify the growth equation in a linear form. The growth equation we estimate is given as:

$$\dot{y} = \alpha_0 + \alpha_1 k + \alpha_2 edu + \alpha_3 \dot{x} + \alpha_4 corrupt + \alpha_5 y_0 + +\epsilon \qquad (1)$$

where $\dot{y}$ is growth rate of real income, ϵ is a stochastic error term, α_is are coefficients to be estimated, and all other variables are as defined above in the text. We include the growth rate of exports as a regressor in the growth rate of income equation on the strength of the arguments made by Feder

(1983) and Balassa (1988). In accordance with the economic growth literature, we expect the coefficients of k, *educ* and $\dot{x}$ to be positive, while *corrupt* is expected to have a negative coefficient. We expect the coefficient of y_0 to be negative if the convergence hypothesis holds for the countries in our sample.

In the growth equation presented above, we argue that corruption affects the growth of income in two possible ways. Directly, corruption can reduce income growth rate through a reduction in the productivity of existing resources. Indirectly, corruption can reduce the growth rate of income through reduction in the quality and quantity of investment in physical and human capital (Wei: 2000, Mauro: 1995). Corruption can also affect economic growth negatively through a destruction of economic and social institutions. The total growth effect of corruption is therefore likely to be larger than the one estimated by the coefficient of *corrupt* in the growth equation. Though we do not model this indirect effect, we will refer to this possibility in our discussions.

3.1.2 Corruption and Income Inequality

Gupta *et al* (1998), Li *et al* (2000), Hendriks *et al* (1998), Jain (2000), and Johnston (1989) argue that corruption increases income inequality in a country through several channels. First, to the extent that corruption decreases economic growth, it increases income inequality and poverty since the poor are the most likely to suffer during periods of economic stagnation. Second, corruption leads to a bias of the tax system in favor of the rich and powerful, thus making the *effective* tax system in a country regressive (Hendriks *et al*: 1998). Regressivity of the tax system implies that the burden of the tax system falls disproportionately on the poor. Corruption leads to the concentration of assets among a few wealthy elite. Because earning power depends, to some extent, on resource endowment (including inherited wealth), the rich are able to use their wealth to further consolidate their economic and political power.

Education in LDCs is as a way out of poverty and the poor also benefit from government spending on social programs, such as health care. Corruption, it is argued, decreases the quantity of, as well as the effectiveness of, resources spent on social programs that benefits the poor. Even when the total quantity of resources spent on such social programs are not reduced, corruption changes the distribution of social spending in such a way as to benefit the rich at the expense of the poor (Gupta *et al*:2000, Tanzi and Davoodi: 1997). For example, health care expenditures may be tilted toward building the most "modern" hospital that caters only to the rich at the expense of preventive health care that benefits the poor. In the same way education spending could be skewed towards higher education that benefits the rich rather than towards primary and secondary education that benefit the poor. Another mechanism through which corruption can affect income distribution is the choice of development strategy. Fields (1980) argues that the choice of development strategy influences income inequality as labor intensive development strategy leads to equitable distribution of income while the opposite is true for a capital intensive development strategy. When corruption leads to subsidies on capital hence a capital intensive development strategy, income inequality increases.

In view of these considerations, we investigate the effects of corruption on income distribution by estimating a simple equation of the gini coefficient of income distribution (*gini*) using cross country data. We regress the gini coefficient of a country on the growth rate of per capita income, the level of per capita income (y), government consumption (*govcon*), education, and corruption. The gini equation we estimate is:

$$gini = \gamma_0 + \gamma_1 \dot{y} + \gamma_2 edu + \gamma_3 y + \gamma_4 corrupt + \gamma_5 govcon + \xi \tag{2}$$

where ξ is a stochastic error term, γ_is are coefficients to be estimated, and all other variables are as defined in the text above. Consistent with the arguments above, we expect corruption to be positively correlated with the *gini* coefficient.

3.2 Estimation Method

3.2.1 Growth Equation: The Dynamic Panel Estimator

The growth equation presented above is estimated with data panel data from 61 countries between 1980 and 1998. In panel data estimation, neither the Generalized Least Squares (GLS) estimator the Fixed Effect (FE) estimator will produce consistent estimates in the presence of dynamics and endogenous regressors (Baltagi: 1995). As argued by Caselli *et al*, growth equations, by their nature have unobserved endogenous regressors as well as unobserved country fixed effects which are correlated with the regressors hence the orthogonality condition is not likely to be met for a GLS or FE estimator to produce consistent estimates. An instrumental variables (IV) estimator that can correct for correlated fixed effects as well as account for endogeneity of regressors is therefore needed.

Arellano and Bond (1991) have proposed a dynamic panel General Method of Moments (GMM) estimator that optimally exploits the linear moment restrictions implied by the dynamic panel growth equation we estimate here. The dynamic GMM panel estimator is an IV estimator that uses all past values of endogenous regressors and the current values of all strictly exogenous regressors as instruments. We use the dynamic panel estimator partly because we do not have reasonable instruments for the endogenous regressors that can be excluded from the growth equation and partly because the dynamic panel estimator provides consistent estimates in the presence of endogenous regressors. Arellano and Bond provide a family of dynamic panel GMM estimators in the DPD program that allows for one to estimate IV coefficients from levels, first difference or orthogonal deviation of the variables.[4] In this study, we estimate the growth equation in levels, first difference, as well as in orthogonal deviation to ensure that our results are not dependent on the way we estimated the equation.

The dynamic panel estimator is given as:

$$\hat{\theta} = (\mathbf{\bar{X}'ZA_NZ'\bar{X}})^{-1}\mathbf{\bar{X}'A_NZ'\bar{y}} \tag{3}$$

where $\hat{\theta}$ is a vector of coefficient estimates on both exogenous and endogenous regressors, $\mathbf{\bar{X}}$ and $\mathbf{\bar{y}}$ are the vectors of first differenced regressors and dependent variables respectively, $\mathbf{Z}$ is a vector of instruments and $\mathbf{A_N}$ is a vector used to weight the instruments. The estimator uses all lagged values of endogenous and predetermined variables as well as current and lagged values of exogenous regressors as instruments in the differenced equation. For example, for the equation: $\Delta y_{i3} = \alpha\Delta y_{i2} + \beta\Delta x_{i3} + \Delta\zeta_{i3}$ we use y_{i1}, x_{i1} and x_{i2} as instruments. For the Δy_{i4} equation, $y_{i1}, y_{i2}, x_{i1}, x_{i2}$ and x_{i3} serve as valid instruments. Instruments for other cross sectional equations are constructed similarly. These instruments are correlated with the endogenous regressors but not correlated with the error terms, hence they are "good" instruments. The dynamic panel estimator is a GMM IV equivalent of an efficient Three Stage Least Squares (3SLS) estimator. The estimator requires the absence of serial correlation among the error terms.

Arellano and Bond proposed two estimators—one- and two-step estimators—with the two-step estimator being the optimal estimator. The one-step estimator uses the weighting matrix given by $A_N = (N^{-1}\sum_i Z_i' H Z_i)^{-1}$ where H is $T-2$ square matrix with 2s in the main diagonal, -1s in the first subdiagonal, and 0s everywhere else. The optimal two-step estimator uses an estimated variance-covariance matrix formed from the residuals of a preliminary consistent estimate of $\hat{\theta}$ to weight the instruments. The optimal choice of $\mathbf{A_N}$ is given as: $A_N = \hat{V_N} = N^{-1}\sum_i Z_i'\hat{\bar{v}}_i\hat{\bar{v}}_i Z_i$ where $\hat{v_i}$ is the residual obtained from a preliminary consistent estimate of θ.

We use the two step estimator to estimate the coefficients of the growth equation because it is more efficient than the one-step estimator. The one-step and two-step estimators will be asymptotically equivalent if and only if the error structure is spherical. However, the nature of the model with endogenous regressors and possible correlated fixed effects, suggests that the conditions for spherical error structure will not be met. Also, Arellano and Honore (1999) argue that in the absence of "good" instruments, the two-step estimator underestimates the standard errors of the coefficient estimates, hence providing inflated "t" statistics. The one-step estimator is not subject to such false sense of precision, hence may be more reliable than the two-step estimator. For these reasons, we also present estimates for the one-step estimator as a check on the validity of our use of the two-step estimates in our discussions.

In estimating the model, we lag all variables by one period to ensure that y_{t-1} can be treated as exogenous in period t. We make two identifying assumptions of no serial correlation among the error terms, and that the endogenous regressors are not considered predetermined for $v_{i,t}$ but are considered so for $v_{i,t+2}$. This allows us to use all values of x_t up to x_{t-1} as valid instruments for $\hat{x_t}$. The linear moment restriction implied by the model is $E[(\Delta\tilde{y}_{it} - \Delta\tilde{X}'_{i,t-1}\Theta)X_{i,t-j}] = 0$ for $j = 2, ..., t-1$, where $X' = (y_{t-1}, X)$ is the vector of lagged endogenous and strictly exogenous regressors. The consistency of the estimates hinges on the assumption of lack of autocorrelation of the error terms. Therefore, we test for the absence of serial correlation of the error terms. We also perform Sargan test of over-identifying restrictions which is a joint test of model specification and appropriateness of the instrument vector. If all regressors are strictly exogenous, both the dynamic panel estimator and the FE estimator are consistent but the latter estimator is efficient. On the other hand, if there are endogenous regressors, the FE estimator is inconsistent. We therefore use a Hausman test to test for the strict exogeneity of all regressors used to estimate the model.

3.2.2 The Gini Equation

The growth rate of income and *corrupt* are endogenous regressors in the *gini* equation. However, we have only a single cross-section data for the *gini* equation, hence we cannot use the dynamic panel estimator to estimate that equation. We therefore used the Two-Stage Least Squares (2SLS) estimator to estimate the *gini* equation.

4 Data

The dependent variables in our model are the growth rate of per capita real income ($\dot{y}$) and a measure of income inequality (*gini*). We measure $\dot{y}$ as the annual growth rate of real per capita income in a country in a year. There are several possible ways to measure income inequality, none of which is perfect. We measure income inequality by the gini coefficient of income distribution (*gini*) in a country in a year. We chose *gini* as our measure of income inequality because it is the inequality index that is most commonly available and also because it is easy to interpret.

The explanatory variables in our model are investment (k), the growth rate of real exports ($\dot{x}$), education (*edu*), corruption (*corrupt*), government consumption (*govcon*), and initial income (y_0). Following earlier researchers (Barro: 1991, Easterly and Levine: 1997, Levine and Renelt: 1992, Gyimah-Brempong and Traynor: 1999), we measure k as the gross domestic investment/GDP ratio in a country in a year. Measuring k this way allows us to control for the size of an economy, hence help to reduce heteroskedasticity. Initial income (y_0) is measured as the real per capita GDP at the beginning of a period. $\dot{x}$ is measured as the growth rate of real export earnings in a country in a year. We measure *edu* as the average years of education attained by the adult population (25 years and above) in a country in a year. We note that this measure of education does not account for the *quality* or the *productivity* of education; all what it does is to measure the average years of educational attainment. *govcon* is measured as the ratio of government consumption to GDP in a country in a period.

Corruption (*corrupt*) is hard to measure and quantify. For one thing, what is a normally accepted practice in one country or time period in the same country may be considered a corrupt practice in another country or time period. Second, because corruption often involves illegal activities, most corrupt practices are hidden, hence not easily quantifiable. Instead what the researcher is left with is the *perception* of corruption. There are very few reliable statistics on corruption, hence we use the perception of corruption indices published annually by Transparency International and University of Gottingen as our measure of corruption. The index is an average of different surveys of *perceptions* of corruption in a country in a year. The index is ranked from 0 to 10 with 10 being the least corrupt and 0 the most corrupt. While this data source is widely cited and used, it has its disadvantages. For one thing, it is based on a survey of *perceived* corruption. What may constitute corrupt practices to a Western visitor to an African or Asian country may be gift giving in the African or Asian context. Second, the index says nothing about the degree to which corruption affect resource allocation, hence efficiency. On the other hand, if a large number of surveys agree that corruption is high in a particular country, one has to put some credence in this index. Our results should therefore be interpreted with these data problems in mind.

In addition to TI's corruption perception index, we use two additional corruption perception indices calculated by Mauro (1995)—Business International's index of corruption (BI) and bureaucratic efficiency ($efficiency$)— from the data files of Business International to estimate the growth equation to test for robustness. The BI index is calculated from a survey of businesses of their perception of corruption in a country and ranges from 1 to 10 with 1 being the most corrupt while 10 is the least corrupt country. Mauro (1995) also calculated a broader index of corruption ($efficiency$), which averages the BI index of corruption, index of red tape, and an index of efficiency of the legal system. The data for BI and *efficiency* were obtained from Mauro (1995). Data for $\dot{y}$, y_0, k, $govcon$, and $\dot{x}$ were obtained from the World Bank's *World Development Indicators Dataset*, (Washington D.C.: World Bank, 2000). Data for *edu* was obtained from Barro and Lee (1997) and updated with data from the World Bank's *World Development Report, 1999/2000*. Data for *gini* were obtained from Deininger and Squire (1996) and supplemented with data from World Bank's *World Development Indicators, 2000*. All nominal variables were converted to real equivalents with 1987 as the base year.

The data are annual observations for a sample of 61 countries for the 1980-1998 period.[5] In our estimation, we take five year averages of the variables in order to reduce the noise in the annual data. Besides, reducing the noise in the annual data, the five year averages adopted here also decreases the impact of business cycle on the estimated relationship. This approach is similar to the approach adopted by earlier researchers (Barro and Lee: 1994, Mankiw, Romer, and Weil: 1991, among others). Taking five year averages gives us four observations four each country, giving us a total of 244 observations for our empirical analysis. For the income inequality equations, we had 164 observations because not all countries had income inequality data for all years and some countries did not have any observations at all for income distribution and were therefore excluded from the *gini* equation.[6] For the BI and $efficiency$ data set, we only had observation averaged over the 1980- 1983 period. We therefore merged that data set with observations for the first period (1980-1984) of our larger data set for that part of the analysis. Merging the two data sets gave us a sub-sample with 48 usable observations.[7]

Summary statistics of the data are presented in Table I. The summary statistics indicate that growth rate, investment, per capita income, as well as other variables vary greatly across countries in our sample. An interesting observation is the wide variation in average of the corruption index with *corrupt* ranging from a low of .25 for Nigeria in the last period in our sample to a high of 9.6 for Iceland indicating that our sample include countries that are perceived to be highly corrupt as well as those that are perceived to be highly corrupt. All three indices of corruption average about 5 with a standard deviation of about 2.5. The Pearson correlation coefficients between *corrupt* and

BI, *corrupt* and $efficiency$, and BI and $efficiency$ are .89, .87, and .93 respectively, indicating a high degree of correlation among the three measures of corruption. BI and $efficiency$, similarly, show wide variations across countries in our sample. We also note that our sample includes countries from all continents as well as all levels of income and social development.

5 Results

This section presents and discusses the coefficient estimates of the growth and income inequality equations. The first subsection presents and discusses the estimates for the income growth equation while the second subsection presents and discusses the estimates for the *gini* equation. In the first subsection, we follow the initial discussion of the coefficient estimates of the income growth equation with a discussion of some indirect channels through which corruption might affect economic growth. This is followed by a number of robustness test before we go on to the second subsection to discuss the estimates for the *gini* equation.

5.1 Income Growth Equation

5.1.1 Coefficient Estimates

Coefficient estimates of the per capita income growth equation using the two step estimator are presented in Table II. Column 2 presents the levels estimates, column 3 the first difference estimates, while column 4 presents the estimates based on orthogonal deviation. The table also presents test statistics for first order serial correlation, joint test of significance, Hausman exogeneity test, asymptotic 't' statistics calculated from heteroskedastic consistent standard errors of the estimates, and Sargan test of model specification and over-identifying restrictions. Test statistics presented in Table II indicate that the model fits the data relatively well. The test statistics indicate that there is no evidence of first order serial correlation and the Sargan test statistics of model specification and over-identifying restrictions indicates that the equation is correctly specified with instrument vector that is appropriate. The joint test of significance statistics rejects the null hypothesis that all slope coefficients are jointly equal to zero at any reasonable level of confidence. The Hausman test statistics lead to a rejection of the null hypothesis that all regressors in the growth equation are strictly exogenous. This indicates that the dynamic panel estimator is the appropriate estimator to be used to estimate the growth equation.

The coefficient estimates of k in the two-step estimator presented in Table II is positive and significantly different from zero at 5% significance level, indicating that all things equal, high investment/GDP ratios are correlated with faster growth rate. This result is similar to the results obtained by earlier researches (Barro: 1991, Levine and Renelt: 1991, Mankiw, Romer and Weil: 1992, and Caselli *et al*: 1996, among others). The coefficient of $\dot{x}$ is positive, relatively large, and significantly different from zero at $\alpha = .01$ or better in all the three specifications. A 1% increase in the growth rate of exports is associated with .23 percentage points increase in the growth rate of per capita income. This result is consistent with the result of research that finds a positive relationship between export growth and the growth of per capita income (Feder: 1983, Balassa: 1988). *edu* has a positive coefficient but it is statistically insignificant in all the three specifications. The insignificance of the *edu* coefficient may be due to the way we measured the variable—the number of years of education completed by the population that is 25 years and older without taking the quality and productivity of years of education attained. The coefficient of y_0 is negative and significantly different from zero at the 10% significance level, indicating the existence of conditional convergence in our sample countries. The coefficient of $Time$ is positive, relatively large, and significantly different from zero at $\alpha = .05$ of better. The positive and significant coefficient of $Time$ suggests that the growth rate of per capita income increased in the latter part of our sample period. Perhaps, this is due to rapid technical progress in the latter part of the sample period, a period that coincide with the "micro chip revolution".

The coefficient of *corrupt* in columns 2-4 in Table II is positive, relatively large and significantly different from zero at $\alpha = .05$ or better. A one unit increase in corruption decreases the growth rate of per capita income by about .3 percentage points a relatively large effect given that the average growth rate of per capita income in the sample is 1.9%.[8] A one standard deviation decrease in corruption increases the growth rate of per capita income by .74 percentage points. The effect of decreasing corruption from the level of Cameroon (75th percentile in our sample) to that of France (25th percentile in our sample) increases the growth rate of per capita income by about 1.4 percentage points. This growth effect is remarkably consistent across all three estimates.[9] Thus decreasing corruption will have enormous impact on the growth rate of incomes of most countries. For example, most African countries could see a 1 percentage point increase in the growth rate of per capita income by reducing corruption their levels of corruption to the sample mean 5. The finding that corruption has a negative and significant effect on the growth rate of per capita income is similar to the results obtained by earlier researchers (Mauro: 1995, 1997, Rose-Ackerman: 1999, Shleifer and Vishny: 1993, Wei: 2000, Tanzi and Davoodi: 1997, Barreto: 2000, among others). The implication of this result is that per capita income growth rate can be substantially increased by reducing corruption.

The results discussed above are based on the two-step estimator. However, when there are no "good" instruments, the two-step estimator under-estimates the standard errors of the coefficient estimates leading to a false sense of precision of estimates. The one-step estimator, however, does not have such a drawback and the asymptotic 't' statistics are not robust to heteroskedasticity. We estimate the growth equation with the one-step estimator and compare the estimates to the estimates obtained from the two-step estimator. We do this to show that our results do not depend on the two-step estimator we use to estimate the growth equation. The coefficient estimates of the one-step estimator are presented in Table III. Column 2 presents the levels estimates, column 3 the first difference estimates, while column 4 presents the orthogonal deviation estimates. As in Table II, Table III also presents statistics to test for first order serial correlation, joint test of significance, Hausman exogeneity test, and Sargan test of over-identifying restrictions.

Similar to the two-step estimator presented in Table II, the estimates in Table III indicate that the equation fits the data relatively well as indicated by the model's fit statistics. In particular, the joint test of significance rejects the null that all slope coefficients are jointly equal to zero, there is no evidence of fist-order serial correlation, and the Sargan test statistic indicates that the equation is well specified and the vector of instruments is not correlated with the error terms. The Hausman test statistic indicates that not all regressors are strictly exogenous, hence the dynamic panel estimator is the appropriate estimator. All the coefficient estimates have the expected signs and the one-step estimator produce estimates that are precisely estimated as their two-step counterparts presented in Table II above.

The coefficients of k, $\dot{x}$, and $Time$ in Table III are all positive and significantly different from zero at the 10% level or better in all three specifications. The coefficient estimates indicate that these variables are positively and significantly correlated with the growth rate of per capita income in our sample, all things equal. The coefficient of y_0 is negative and significant at $\alpha = .10$ in all three specifications, suggesting the presence of conditional convergence in the sample of countries. As in the two-step estimates, the coefficient of edu in Table III is positive but insignificant at any reasonable confidence level. We note that the signs, absolute magnitudes, and precision of the one-step estimates are remarkably similar to those of the two-step estimates.

The coefficient of *corrupt* in columns 2-4 of Table III is positive, relatively large, and significantly different from zero at $\alpha = .05$. This suggests that high levels of corruption are correlated with slow growth of per capita income, using the one-step estimator; a result that is the same as the one we obtained from the two-step estimator. Moreover, the absolute magnitude and the precision of the one- step estimates are the same as those of the two-step estimates presented in Table II. The one-step estimates therefore corroborates the results obtained from the two-step estimates. The fact that the one-step and two-step estimators produce the same estimates suggests that our results that corruption has a significantly negative effect on the growth of per capita income is not dependent on the two-step estimator we use to estimate the growth equation. The rest of our discussions will therefore be based on the two-step estimator.

5.1.2 Transmission Mechanism

The results above indicate that corruption has a negative and statistically significant impact on the growth rate of per capita income in our sample. It did not indicate the mechanisms through which corruption affects the growth rate of income. In this subsection, we speculate on the mechanisms through which corruption affects the growth rate of per capita income. There are several possible ways through which corruption can affect the growth rate of per capita income. One way in which corruption may affect income growth rate negatively is through the misallocation of existing resources and thus reduce the productivity of these resources. Another possible mechanism through which corruption affects economic growth is reduced resource mobilization. Several authors have argued that corruption reduces investment in physical and human capital (Wei: 2000, Gupta *et al*: 1998, among others). Other authors argue that corruption destroys or renders institutions (such as property rights laws, proper functioning of markets) ineffective in providing an environment in which to conduct business, hence leading to economic stagnation (Rose-Ackerman: 1999).

We are not able to investigate all these channels, given the data we have available. We, however, conduct a preliminary investigation into whether corruption affects the growth rate of per capita income indirectly through reduced investment in physical capital. We do so by estimating a very rudimentary accelerator model of investment with corruption as an added regressor to see the impact of corruption on investment rate. We regress investment rate (k) on the growth rate of per capita income ($\dot{y}$), real per capita income (y), corruption, government consumption ($govcon$), and $Time$. The investment equation we estimate is given as:

$$k = \gamma_0 + \gamma_1 \dot{y} + \gamma_2 corrupt + \gamma_3 govcon + \gamma_4 y + \gamma_5 Time + \mu \tag{4}$$

where μ is a stochastic error term and all other variables are as defined in the text. Coefficient estimates of this rudimentary investment equation based on the two-step estimator are presented in Table IV. Column 2 presents the levels equation, column 3, the first difference equation, while column 4 presents the estimates for the orthogonal deviation equation. The regression statistics indicate that the simple accelerator investment equation fits the data reasonably well.

The coefficients of $\dot{y}$ and y are positive, relatively large, and significantly different from zero at $\alpha = .05$ or better in all three specifications. This result confirms the accelerator hypothesis for this sample. Secondly, it also suggests that investment rate is positively correlated with the level of per capita income in this sample. The coefficient of *govcon* is negative and significantly different from zero at $\alpha = .05$ in all three specifications. This indicates that government consumption crowds out investment in physical capital. The coefficient of $Time$ is negative but statistically insignificant in all three specifications.

The coefficient of *corrupt* is positive, relatively large, and significantly different from zero at $\alpha = .05$ or better in all three specifications. The positive and significant coefficient of *corrupt* in the investment equations suggests that corruption has a statistically significant negative effect on investment rate in our sample. Good governance, as measured by honesty therefore increases the rate of capital formation a result that is consistent with Wei's (2000) findings. Given that the growth rate of per capita income is positively correlated with the investment rate, corruption decreases the growth rate of per capita income indirectly through reduced investment. Moreover, since the coefficients of *corrupt* and k in the growth equation are significant when we include both variables as regressors, the indirect growth effect that corruption has through reduced investment is independent of the direct negative impact that corruption has on the growth rate of per capita income. It is therefore important that researchers account for both direct and indirect effects of corruption on the growth rate of per capita income.

The total growth effect of corruption both direct and indirect through reduced investment—is given by $dg/dcorrupt = \partial g/\partial corrupt + \partial g/\partial k * \partial k/\partial corrupt = \frac{1}{1-\alpha_1\gamma_1}[\alpha_1\gamma_2 + \alpha_4]$.[10] Using the coefficient estimates to evaluate this expression, the total growth effect of one standard deviation increase in honesty (reduction in corruption) is to increase the growth rate of per capita income by 1.158 percentage points a year. This is a relatively large effect, given that the average growth rate of per capita income in our sample is 1.9% per year.

5.1.3 Robust Tests

It is possible that our results depend crucially on model specification, omitted variable bias, or on the sample used to estimate the growth equation. In this subsection, we investigate the robustness of our estimates of the effects of corruption on the growth rate of per capita income. Our objective here is to see whether our results are robust to various specifications and sample selection. We begin by adding additional explanatory variables one at a time to the basic growth equation to see if this affects the coefficient of *corrupt* in the growth equation. We then estimate the basic equation using sub-samples of the data to see if our results are driven by a subset of the sample used to estimate the equation.

5.1.3.1. Additional Explanatory Variables

Sachs and Warner (1997) have argued that geography has an effect on the growth rate of income as Tropical countries tend to grow slower than non tropical countries. We therefore tried distance from the equator (*equator*) as an additional variable in the growth equation. This variable is usually scaled to range between 0 and 1. We follow this convention. The data for *equator* was obtained from La Porta, R., F. Lopez-de-Silanas, A. Shleifer, and R. Vishny (1999), "The Quality of Governments", *Journal of Law, Economics, and Organization*, **15**, 222-279. Several authors have argued that increased government consumption decreases economic growth (Barro: 1991, Mankiw, Romer, and Weil: 1992, among others. The second additional variable we use therefore is government consumption/GDP ratio (*govcon*) in a country. Data fore *govcon* were calculated from the World Bank's *World Development Indicators, 2000*. Finally, several authors find that political instability has a negative effect on the growth rate of per capita income (Barro: 1991, Alesina and Perroti: 1988, Gyimah-Brempong and Traynor: 1999). We therefore use an index of political insatiability (PI) as an added regressor. We measure PI as in Gyimah-Brempong and Traynor (1999). Data for the calculation of PI were obtained from A. Banks (1995), *Cross-National Time-Series Data Archive*, Center for Social Analysis, State University of New York at Binghampton, Binghampton, New York.

Results of this exercise are presented in panel A of Table V. Columns 2, 3, and 4 of panel A present the coefficient estimate of *corrupt* when *equator*, *govcon*, and PI, respectively are included as additional regressors. Rows 1-3 in each panel presents the estimates for the levels, first difference, and the orthogonal deviation estimators respectively. The coefficient of *corrupt* presented in panel A of Table V is positive and significantly different from zero at $\alpha = .05$ regardless of the additional variable we add or the dynamic panel estimator used to estimate the growth equation. We note that adding government consumption decreases the absolute magnitude of the coefficient of *corrupt* but it remains statistically significant. The positive and significant coefficient of *corrupt* after we have included addition explanatory variables suggests that our basic results are not driven by omitted variable bias.

5.1.3.2. Subsamples

It is possible that our results depend crucially on the inclusion of some countries. For example, the evidence suggests that growth rate in Sub-Saharan Africa has been very low while they have high indices of corruption. On the other hand OECD countries are generally perceived to be less corrupt and have had respectable rates of per capita income growth over the sample period. To see whether our results are driven by the sample of countries used, we first estimate the growth equation for a sample that exclude African countries, and another sample that exclude OECD countries. The estimates for this sub-sample are presented in columns 2 and 3 of panel B in Table V. It is possible that corruption affects economic growth differently when it becomes endemic in a country than in countries where corruption is not entrenched. We therefore split the sample into high and low corruption countries and estimate the growth equation for these two sub-samples. We classify a country as a high corruption country if its corruption perception index is 5 or less and as low corruption country if its corruption perception index is greater than 5. The coefficient estimates for these sub- samples are presented in columns 4 and 5 of Table V.

Estimates of the coefficient of *corrupt* are presented in panel B of Table V. Columns 2 and 3 present the estimate for the samples that exclude African and OECD countries while columns 4 and 5 present the estimates for high and low corruption countries. In all four sub-samples, the coefficient of *corrupt* is positive and significantly different from zero at $\alpha = .10$ or better. We note that the coefficient of *corrupt* is larger, although in some cases less precisely estimated in the high corruption sample than in either the whole sample or the low corruption countries, suggesting that corruption is more deleterious to income growth in high corruption countries than in low corruption countries. The implication of the exercise above is that the relationship between corruption and growth we find in this study is robust to several specifications and sample selection.

5.1.3.3. Alternative Measures of Corruption

Our results are based on the use of corruption perception index published by Transparency International and the University of Gottingen. It is possible that our results are driven by this particular measure of corruption. To investigate this possibility, we use two additional measures of corruption to investigate the effects of corruption on the growth rate of per capita income. A measure of corruption that has been used in the literature is Business International's corruption index (BI) calculated and used by Mauro (1995) in his study. The BI index is calculated from a survey of business people of their perception of corruption in a country and ranges from 1 to 10 with 1 being the most corrupt while 10 is the least corrupt country. Mauro (1995) also calculated a broader index of corruption ($efficiency$), which averages the index of corruption, index of red tape, and an index of efficiency of the legal system. We used these two measures of corruption as explanatory variables to estimate the growth equation. The data for BI and *efficiency* are calculated for the 1980-1983 period. We are therefore not able to use a panel estimator to estimate the growth equation. Instead, we estimate the growth equation with a cross-national data that averages the variables over the 1980-1983 period. As indicated in section III above, there were a total of 48 countries with usable observations in the sample.

It is possible that both BI and $efficiency$—the two alternative measures of corruption we use in this section—are correlated with the error term, hence OLS estimates may not be appropriate. An IV estimator is therefore called for. We follow Mauro (1995) and use ethno-linguistic fractionalization index (ELF) as an instrument for both measures of corruption. ELF is defined as the probability that two randomly selected individuals in a country do not belong to the same ethno-linguistic group and ranges from 0 to 1 with 1 being the most ethnically fractured society and 0 being the score for the most ethnically homogenous country. The data for ELF were obtained from Mauro (1995). The results of the IV estimates using BI and $efficiency$ as our measures of corruption are presented in Table VI.[11] Columns 2 and 3 present the estimates when BI is used as the index of corruption while columns 4 and 5 present the estimates when *efficiency* is used as the index of corruption. The regression statistics indicate that equation fits the data relatively well. The R^2 for the first stage regressions are .59 and .63 for BI and *efficiency* respectively, indicating a high degree of correlation between ELF on the one hand and BI and *efficiency* on the other respectively. The high R^2 confirms that ELF is a "good" instrument for BI and $efficiency$.

The coefficient estimate of BI in column 2 is positive, relatively large and significantly different from zero at $\alpha = .05$, suggesting that corruption, when proxied by the BI index, has a significantly negative effect on the growth rate of per capita income. The estimates in column 3 adds additional regressors to the BI index of corruption. The coefficient of BI in column 3 is positive and significantly different from zero at $\alpha = .05$ as in column 2 where the growth rate of income is regressed on only BI. Moreover, the coefficient of the additional regressors are of the expected signs and are all significantly different from zero at $\alpha = .05$ or better. The coefficient of $efficiency$ in column 4 is positive, relatively large, and significantly different from zero at $\alpha = .10$, suggesting that a one unit increase in honesty (one unit decrease in corruption) increases the growth rate of per capita income by .35 percentage points. Adding more regressors to $efficiency$ in column 5 does not change the sign and absolute magnitude of the coefficient of $efficiency$ but there is an improvement in the precision of the estimate. Moreover, the coefficient estimates of the other variables are of the expected signs and, with the exception of *edu*, are precisely estimated. This suggests that negative growth effect of BI and $efficiency$ we find in this section does not depend on omitted variable bias.

The coefficients of BI and $efficiency$ are remarkably similar in sign, absolute magnitude, and precision to that of *corrupt* presented in tables II and III, suggesting that the negative impact corruption has on the growth rate of per capita income we find in this study does not depend on the measure of corruption we use. The conclusion we draw from these estimates is that corruption has a strong negative impact on the growth rate of per capita income and this effect is robust to several specification tests and different measures of corruption. Our results are similar to those of earlier research (Barreto: 2000, Barro and Lee: 1994, Ehrlich and Lui: 1999, Jain: 2000, 2001, Mauro: 1995, 1997, Rose-Ackerman, Tanzi and Davoodi: 1997, and Wei: 2000). What policy implications can be drawn from our results? Almost all countries aspire to faster economic growth rate. The need to grow faster in order to improve the living standards of a majority of citizens is greatest in low income countries. Often, these countries look to foreign direct investment (FDI) to generate the desired growth rate. Our results indicate that corruption directly decreases the growth rate of per capita income. In addition, other researchers (Wei: 2000) find that corruption decreases FDI. The implication is that high corruption countries can increase the growth rate of per capita income by taking steps to decrease corruption. The increased growth rate could come from both increased FDI, allocative efficiency, and increased productivity. More important, because reducing corruption may involve institutional reforms, the resulting growth is likely to be sustainable and long-lasting.

5.2 Corruption and Income Inequality

How does corruption affect income distribution in a country? We used data on gini coefficient of income inequality from a sub-sample of countries in our data to estimate the income inequality equation in (2).[12] In estimating the *gini* equation, we recognize that corruption and the growth rate of income are not likely to be exogenous. We therefore treat both as endogenous in the *gini* equation. We also do not have enough data to use the dynamic panel estimator so we estimate the *gini* equation by Two Stage Least Squares (2SLS). The results are presented in Table VII. Column 2 presents the coefficient for *corrupt* when we regress *gini* on a constant and *corrupt*, column 3 presents estimates when we add additional regressors, while column 4 presents coefficient estimates when we add additional regressors and three continental dummies. The coefficient of corrupt in column 2 is negative, relatively large and significantly different from zero at $\alpha = .01$, suggesting that high levels of corruption are associated with high income inequality in our sample. Moreover, corruption alone explains about 11% of the variation in the gini coefficient of income inequality in our sample. In column 3, we add the growth rate per capita income, education and government consumption as additional regressors to the *gini* equation. The coefficient of corrupt does not significantly change although the degree of precision of the estimate decreases (although it is still significantly different from zero at $\alpha = .01$). We also note that the coefficient of $\dot{y}$ and *edu* are negative while that of *govcon* is positive and all are significantly different from zero at $\alpha = .01$. This suggests that higher levels of education and faster income growth are negatively correlated with income inequality while high government consumption is correlated with income inequality.

Column 4 adds dummies for Africa, Asia, and Latin America to the variables in column 3. The excluded region is the industrialized regions of North America, Europe, Australia and New Zealand. The coefficients of all three regional dummies are positive, very large, and significantly different from zero at $\alpha = .01$. This suggests that income inequality is higher in Africa, Asia, and Latin America relative to the excluded regions, all things equal. More important, including these regional dummies do not change the signs or statistical significance of the coefficient of *corrupt* or the other regressors. While the absolute magnitude of the coefficient of *corrupt* decreases by about 25% when the regional dummies are included in the *gini* equation, its precision remains unchanged. The conclusion we draw from this is that corruption significantly increases income inequality in our sample. This positive relationship between income inequality is robust to various specifications. Our results that corruption is positively correlated with income inequality is similar to the results obtained by Gupta *et al* (1998), Gray and Kaufmann (1998), Hendriks *et al* (1998) and Li *et al* (2000).

The estimates from the *gini* equation indicate that corruption significantly increases income inequality in our sample. A one standard deviation increase in corruption directly increases the gini coefficient of income inequality by about 11.6 percentage points. In addition to the direct effect, corruption also increases income inequality through decreased economic growth. The direct effect we have estimated above is therefore likely to be a lower bound of the effect of corruption on income inequality. The policy implications flowing from this results is that the growth rate of per capita income across all countries can be greatly enhanced by reducing corruption. Decreasing corruption by 5 points (on a 10 point scale) will increase the growth rate of per capita income by about 1.4 percentage points. For most poor countries, this increase in growth rate is large enough to reverse decades of economic stagnation. Our results also imply that reducing corruption will also reduce income inequality, thus spreading the benefits of economic growth to a large segment of the population. Although we have indicated that decreasing corruption will increase the growth rate of income as well as improve income distribution, we do not have any policies to recommend to decrease corruption. The issues involved is beyond the scope of this paper. While there is no easy way to reduce corruption, any successful effort will involve both domestic institutional reforms and international cooperation (Klitgaard: 2000).

6 Conclusion

This paper uses a panel data from a sample of developed and developing countries and a dynamic panel estimator to investigate the effects of corruption on the growth of per capita income. Using Transparency International's corruption perception index as our measure of corruption, we find that corruption has a negative, relatively large, and statistically significant effect on the growth rate of per capita income. We find that corruption decreases the growth rate of income directly through misallocation of resources and indirectly through decreased investment in physical capital. Directly, a one standard deviation increase in corruption is associated with a .75 percentage point reduction in the growth rate of per capita income. The total effect of a one standard deviation increase in corruption is to decrease the growth rate of income by 1.15 percentage points. The result is robust to different specifications, samples, and alternative measures of corruption. We also find that corruption increases income inequality, hence reducing corruption will not only increase the growth rate of per capita income, it will enhance economic *development*. Our results are robust to different specifications and different measures of corruption. However, our results should be intepreted cautiously since the measure of corruption we use here is, at best, the *perception* of corruption. Preceptions may be differrent from reality.

7 Notes

1. See Gupta *et al* (1998), Li *et al* (2000), Johnston (1989), among others.

2. See Bardhan (1997), Gupta (2001), and Lambsdorff (2001) for excellent reviews of the theoretical and empirical literature.

3. In this paper, we use income distribution and income inequality interchangeably.

4. Orthogonal deviations expresses each observation as the deviation from the average of future observations in the sample for the same country, and weight these each deviation to standardize the variance. Formally, the orthogonal deviation of the variable x, (x^*_{it}) is given as:

$$x^*_{it} = (x_{it} - \frac{x_{i,t+1} + ... + x_{i,T}}{T-t})(\frac{T-t}{T-t+1})^{.5} \qquad for \quad t = 1, ..., T-1 \tag{5}$$

Arellano and Bond show that if the original errors are uncorrelated and homoskedastic, the transformed errors will also be uncorrelated and homoskedastic.

5. The countries in the sample are: Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Cameroon, Canada, Chile, China, Colombia, Cote d'Ivoire, Denmark, Equador, Egypt, El Salvador, Finland, France, Ghana, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kenya, Korea, Luxembourg, Malawi, Malaysia, Mauritius, Mexico, Morocco, Namibia, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Senegal, Spain, Sweden, Switzerland, Thailand, Tunisia, United Kingdom, United States, Uruguay, Venezuela, Zambia, and Zimbabwe. Countries contained in the sample was dictated by data availability, especially data on corruption.

6. We note that the reliability of the *gini* data varies across countries as Deininger and Squire cautions. Readers should therefore treat our results as indicative rather than definitive. For the *gini* equation, we had no data for Iceland, Jordan, and Namibia and were therefore excluded from the sample. Other countries did not have data for all four periods so we had a total of 164 observations.

7. Countries in this sample are: Argentina, Australia, Austria, Belgium, Brazil, Cameroon, Canada, Chile, China, Colombia, Cote d'Ivoire, Denmark, Equador, Egypt, Finland, France, Ghana, Greece, Hong Kong, Iceland, India, Ireland, Israel, Italy, Japan, Jordan, Kenya, Korea, Malaysia, Mauritius, Morocco, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States of America, Uruguay, Venezuela, and Zimbabwe.

8. Because the index is measured in such a way that higher scores imply low levels of corruption, the positive coefficient implies that corruption has a large, significantly negative effect on the growth rate of per capita income.

9. We note that low levels of *corrupt* imply high levels of corruption, hence the 75th percentile corruption corresponds to the 25th percentile of *corrupt* in the sample.

10. It must be noted that this is not the usual multiplier effect since corruption is not exogenous. The expression is the *total effect* of a change in corruption on the growth rate of per capita income regardless of the source the change in corruption.

11. In this section, we do not present the full set of estimates in order to conserve space. We also present only the estimates from the two-step estimator.

12. There are a total of 164 observations made of 52 countries observed over 2-4 periods each. We note that this is an unbalanced sample. Countries in this sample are: Argentina, Australia, Belgium, Bolivia, Brazil, Cameroon, Canada, Chile, China, Colombia, Cote d'Ivoire, Denmark, Equador, Egypt, Finland, France, Ghana, Greece, Hong Kong, Hungary, India, Indonesia, Israel, Italy, Japan, Kenya, Korea, Malawi, Malaysia, Mauritius, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Portugal, Senegal, Spain, Sweden, Switzerland, Thailand, Tunisia, United Kingdom, United States, Uruguay, Venezuela, Zambia, and Zimbabwe.

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Table I

SUMMARY STATISTICS OF SAMPLE DATA

Variable	Mean*	Standard Error	Minimum	Maximum
$\dot{y}$ (%)	1.9038	2.3715	-5.7033	9.0192
y (87 PPP$)	8257.85	6863.10	352.94	27459.30
$corrupt$	5.1567	2.5624	0.2800	9.5500
k (%)	22.1031	5.7757	9.2246	40.9958
$\dot{x}$	6.9335	4.7755	-13.8739	21.3539
edu	5.3492	1.6665	1.8200	12.0100
$gini$	.3832	.0937	.2097	.6200
BI	7.1328	2.6076	0.20	10.00
$efficiency$	6.9065	2.4203	0.2776	10.00
ELF	33.3114	29.2194	1.00	89.00
$N = 244$				

* these are unweighted averages.

Table II

TWO-STEP COEFFICIENT ESTIMATES OF GROWTH EQUATION

Variable	Coefficient	Estimates	
	Levels	First difference	Orthogonal dev.
k	0.0824	0.0819	0.0824
	(1.6853)*	(1.6469)	(1.6683)
$corrupt$	0.2961	0.2948	0.2961
	(2.0097)	(1.9824)	(2.0097)
edu	0.0314	0.0312	0.3134
	(0.4403)	(0.4354)	(0.4403)
$\dot{x}$	0.2294	0.2258	0.2269
	(4.6970)	(4.7077)	(4.6969)
y_0	-0.5618	-0.5569	-0.5617
	(1.6317)	(1.6007)	(1.6317)
$Time$	0.6009	0.5980	0.6009
	(2.0038)	(1.9893)	(2.0038)
N	244	244	244
First oder ser. corr.	0.08 [61]	0.084 [61]	0.0804 [61]
Joint test of Significance	40.3597 [6]	39.8807 [6]	48.3597 [6]
Joint-jg sig. of time dum.	9.0151 [1]	7.4142 [1]	9.9867 [2]
Sargan Test	5.0218 [8]	4.0283 [8]	5.0210 [8]
Hausman m	89.2761 [5]	69.7812 [5]	98.2198 [5]

* absolute value of asymptotic “t” statistics in parentheses.

Table III

ONE-STEP COEFFICIENT ESTIMATES OF GROWTH EQUATION

Variable	**Coefficient**		**Estimates**
	Levels	First difference	Orthogonal dev.
k	0.0914	0.0897	0.0914
	(2.1593)*	(2.5907)	(2.1591)
$corrupt$	0.2908	0.2793	0.2909
	(2.1197)	(2.6867)	(2.1904)
edu	0.4561	0.5253	0.4562
	(0.6335)	(1.1083)	(0.7074)
$\dot{x}$	0.2162	0.2105	0.2161
	(5.1978)	(5.3258)	(5.3370)
y_0	-0.5494	-0.5204	-0.5494
	(1.8459)	(2.2879)	(1.8437)
$Time$	0.2712	0.2683	0.2710
	(0.7652)	(0.6232)	(0.7651)
N	244	244	244
First oder ser. corr.	0.188 [61]	0.201 [61]	0.187 [61]
Joint test of Significance	56.3257 [6]	68.5411 [6]	56.2754 [6]
Joint-jg sig. of time dum.	0.5855 [2]	1.2047 [2]	1.0244 [2]
Sargan Test	5.6283 [8]	4.5223 [8]	6.2654 [8]
Hausman m	59.6170 [5]	48.8912 [5]	68.4498 [5]

* absolute value of asymptotic “t” statistics, non-robust to heteroskedasticity in parentheses.

Table IV

TWO-STEP COEFFICIENT ESTIMATES OF INVESTMENT EQUATION

Variable		**Coefficient**	**Estimates**
	Levels	First difference	Orthogonal dev.
corrupt	1.7252	1.9180	1.7252
	(2.6038)	(2.4058)	(2.6038)
$\dot{y}$	4.6741	4.6443	4.6741
	(3.2798)	(2.6195)	(3.2798)
y	0.9502	1.4443	1.9502
	(2.1189)	(1.9873)	(2.1189)
govcon	-0.1869	-0.2014	-0.1921
	(2.4831)	(2.6840)	(2.3896)
Time	-1.3416	-1.3913	-1.3417
	(1.4821)	(1.0026)	(1.4821)
N	244	244	244
First oder ser. corr.	0.683 [61]	0.410 [61]	1.013 [61]
Joint test of Significance	36.108 [5]	469.4366 [5]	68.1081 [5]
Joint-jg sig. of time dum.	2.1961 [1]	1.0707 [2]	2.2035 [2]
Sargan Test	7.0218 [7]	4.9938 [7]	5.0210 [7]
Hausman m	78.4121 [4]	89.2181 [4]	88.3382 [4]

* absolute value of asymptotic "t" statistics in parentheses.

Table V

ROBUST TESTS

Panel A: Additional Regressors

Estimator	equator	gov	PI
Level	0.2892	0.2768	0.2998
	(2.0981)*	(1.9987)	(2.0017)
First difference	0.2896	0.2618	0.2986
	(2.2187)	(2.109)	2.4281)
Orthogonal Deviation	0.2916	0.3001	0.2892
	(2.3142)	(1.9978)	2.3218)
N	210	210	210

Panel B: Different Samples

Estimator	Excl. Africa	Excl. OECD	High Corrupt.	Low Corrupt.
Level	0.2689	0.3129	0.3110	0.2489
	(2.3281)	(1.9982)	(2.2572)	(2.1892)
First Difference	0.2831	0.2989	0.2998	0.2109
	(2.4138)	(2.0012)	(1.8926)	(2.2293)
Orthogonal Deviation	0.2498	0.2189	0.3129	0.2349
	(2.3214)	(1.9421)	(2.2831)	2.4129)
N	188	160	124	120

* absolute value of asymptotic "t" statistics, non-robust to heteroskedasticity in parentheses.

Table VI

ESTIMATES OF GROWTH EQUATION: ALTERNATIVE CORRUPTION INDICES

Variable		**Coefficient**	**Estimates**	
k		0.1316		0.1199
		(2.342)*		(2.2281)
BI	0.2908	0.2909		
	(2.0521)	(2.1904)		
$efficiency$			0.3504	0.3497
			(1.786)	(2.3489)
edu		0.4561		0.4562
		(0.6335)		(0.7074)
$\dot{x}$		0.2850		0.2871
		(4.468)		(4.7337)
y_0		-0.6658		-0.6218
		(3.6529)		(3.3437)
N	48	48	48	48
$\bar{R}^2$	0.188	0.261	0.187	.3018
F	13.6170	24.8912	18.4498	24.8921

* absolute value of "t" statistics in parentheses.

Table VII

ESTIMATES OF GINI COEFFICIENT EQUATION

Variable	Coefficient	Estimate	
$\dot{y}$		-0.4720	-0.4138
		(20.031)	(9.1589)
corrupt	-1.2242	-1.2359	-0.9802
	(4.4917)*	(2.9723)	(2.8907)
edu		-1.8497	-0.8792
		(5.7283)	(2.221)
govcon		.4589	0.4361
		(3.2164)	(2.9913)
Africadum			16.3136
			(7.6728)
Latindum			14.3162
			(8.0291)
Asiadum			8.9273
			(6.9824)
N	164	164	164
F	20.17	26.201	30.118
$\bar{R}^2$	.1107	.4892	.5173