CORRUPTION, INEQUALITY, OR GROWTH: ILLUMINATIC TRINITY OR NATURE?

by

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ABSTRACT

JOE CALVIN FOWLER III. Corruption, inequality, or growth: illuminatic trinity or nature?. (Under the direction of DR. CRAIG A. DEPKEN II)

This paper explores popular economic, political, and social conceptions of the relationship between income inequality and corruption. Contemporary politics have become heavily divided on income inequality. Therefore, using current econometric methods such as panel Granger (non)-causality, dynamic panel models, and cross-lagged maximum likelihood estimation to understand better the underlying data generating process. The significance of this paper is threefold. First, multiple dynamic regressions are used to test the econometric assumptions identifying possible bidirectional causality. Second, the analysis finds that income inequality is not a statistically significant determinant of contemporaneous corruption. However, preceding values of the income share of the top 1% do correlate with future values of corruption in all dynamic models. Last, to test these assumptions against the new institutional hypothesis proposed by North (1990), a Panel Vector Autoregression tests whether specific political environments favor economic growth. The Panel Vector Autoregression results show that variations in per capita GDP can explain 8% of the variation, and 1% income share explains 13% of the variation in corruption perceptions. Further, robustness checks of the dynamic panel models include the use of two different periods. First, by using data from 2000 and 2002 through 2017 and because of the slow movement to change in corruption and inequality, I took the average over three-year periods from 2002 through 2017.

DEDICATION

I dedicate this to studying higher learned beings, the dimensional time-warping creatures from Xendog, and the Illuminati for giving me enough time to publish this before I perish. Further, I would like to dedicate this work to my beautiful wife, who had to sit through countless hours of listening to me whine on about econometrics and corruption. My daughter, whose laughter and love has always been the most significant piece of motivation in my life, pushes me to work harder. Lastly, I want to dedicate this to all my teachers from kindergarten up to dropping out of high school that consistently told me that I would never amount to anything. Thanks for the motivation and passion!

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PREFACE

The established narrative in society about corruption at the highest government and business levels has become subsumed by viral tweets and other social media posts. Society now lives in the wake of Attorney General Barr's Durham probe, which was a policy response to the public outcry of the alleged suicide of Jefferey Epstein. In this paper, I try to establish the effect between corruption and income inequality and the effects that these two measures have on economic growth. This paper seeks to address the literature on the relationship between income inequality and political corruption. While many variables can be used to map political corruption to a subset of $\mathbb{R}_{\ltimes}$, the GINI index is one of the most commonly utilized metrics to measure income inequality Dutt and Tsetlin (2016).

Despite Gini's wide use in the literature, there are documented shortcomings of this indicator.[1] Despite its wide use in the literature, the shortcomings of this indicator seem ubiquitous. 1 The GINI Index is sensitive to the underlying distribution. Thus, there is a possibility of reducing the Gini Index with an increased share of income at the top 1%. Improper parameters in the Gini index can cause distortions in tax structures that could further drive a wedge in income inequality by increasing the earnings captured by the top 1% Rodriguez (2004). As discussed in a theoretical paper by Gozgor and Ranjan (2017), policy responses to increases in income inequality increase redistributionary efforts are not uncommon. Acemoglu et al. (2015) suggest substantial heterogeneity among policy responses to increased income inequality in practice and relaxation of the median voter rule. As such, I employ different income inequality measures capable of including effects of political capture; the share of income by the top 1% and 10%.

[1] The Gini Index is an approximate measure of the distribution of income in an economy based on the Lorenz Curve.

Second, most literature focuses on assuming reverse causality through theory. Theories are treated as tautologies (Friedman, 1953), and this allows for the empirical testing of the phenomena through econometric practices. The assumption of the tautology without being tested becomes theory without measurement Zellner (2007) which does not allow for additional hypotheses to be formulated from facts deduced by new evidence (Friedman, 1953). The philosophy of econometrics assumes that the data generating process (DGP) underpins reality, and through careful thought and experimentation, we can uncover that underlying reality. This investigation builds on the two groups of relations outlined in Pasinetti (2019) of natural and institutional relationships and the definition of causality proposed by Simon (1952). The assumption of a bi-directional institutional relationship has led me to quantify and estimate the parameters of economic relationships. Moreover, this allows researchers contending alternative observationally equivalent causal representations to understand the process by which this causal relationship is structured.

The motivation for studying the dynamics between corruption, income inequality, and growth is straightforward. There is a great deal of literature on how these variables impact economic growth, with corruption being substantial and significant and income inequality being ambiguous. However, the proposition that income inequality causes or has reciprocity with corruption would imply an unambiguous response in the literature. Meaning, if income inequality causes corruption, and corruption reduces economic growth, then by simple deduction, income inequality reduces economic growth. However, the literature does not prove this to be true. Therefore, a Panel Vector autoregression is used to test the variance structure and impulse response from exogenous shocks to the variables. This decomposed structure of the variables will be used to interpret the impacts of inequality measures and corruption on economic growth.

This paper will be looking at the possible bi-directional or nonlinear causality that may exist for corruption and income inequality. This severely limiting factor can undermine a researcher's ability to determine causality as a function of the increased complexity. The principles of linear causality, in its modern form, were established in Hume (1739). The principle of temporal succession: X must come before Y, the correlation is not spurious, and there are no endogenous variables. Later, Hoover (1990), articulated causality in econometrics through operating in the domain of representing a natural experiment. Attempts to operate in the domain of a representative natural experiment showed that valid causal order could be established by allowing complications that show the effects from the marginal distribution to the conditional distribution, and vice versa. However, the problem becomes more complex with the introduction of nonlinear dynamics. Nonlinear causality lacks determinism, compounding feedback loops, and a lack of single path finality (Goldstein, 1996). This complication may reflect the lack of empirical evidence in a broad sampling of countries and the discrepancy between identifying causal patterns in The Organisation for Economic Co-operation and Development (OECD) (Paldam, 2020) that are more easily observed in weaker institutions because the causal factors are more likely sequential. The lack of sequential causality found in the relationship between income inequality and corruption motivates several dynamic tests to identify the temporal relationship. The measure for the top 1% share of income shows robust evidence in favor of predicting and/or causing corruption. There is evidence for unidirectional causality in the measure top 10% where the 10% indicates the level of corruption The last income inequality measure, the Gini index, in all empirical investigations done in this paper rejects both uni-directional and bi-directional causality. Further, I study the effects that corruption and income inequality have on economic growth using a Panel Vector Autoregression (PVAR) to estimate the impulse responses and forecast error variance decomposition's (FEVD) of these three endogenous variables based on the Cholesky decomposition to study the interactions between economic growth, corruption, and income inequality.

In this paper, for the sixteen-year sample, there is evidence of a lagged change in the top 1% share and correlation with future changes in the perception of corruption index. This lagged effect holds in both the lagged first difference (LFD) and Arellano-Bond General Method of Moments (AB) Estimator. Further, evidence of a similar structure to the top 1% of income share, where the top 10% of income share with a lagged correlation to corruption perception changes for the AB estimator. There is no evidence of any contemporaneous or lagged effect from any income inequality measure on corruption in the AB or LFD estimations in the three-year averaged short T panel.

The cross-lagged panel (CLPM) model has an additional constraint where panels ($t > 10$) and unbalanced panels can cause estimation problems due to the iterative algorithm; therefore, I only test the three-year average period. In line with the previous estimation, only lagged 1 and 10 % share of income were significant in the CLPM. The lagged effects of the 1 and 10 % share of income identify that the Gini index may not directly relate to corruption as a measure of inequality. The lack of significance from the Gini index implies that previous work may have misidentified bi-directional causality and relied on the correlation between the Gini index and the top share of income.

When studying economic growth and development, the importance of institutions and public perception are paramount. In Acemoglu et al. (2001), the author's give evidence against the geography hypothesis of economic growth. The authors further laid the groundwork and bolstered the new-institutional arguments presented by North (1991). Considerable research focuses on understanding the interaction between growth, institutions, income inequality, and corruption. The interaction between income inequality and corruption perceptions has led me to research the relationship between growth, income inequality, and corruption.

CHAPTER 1: CORRUPTION AND ECONOMIC GROWTH

1.1 Corruption: Grease the Wheel

The grease the wheel hypothesis proposes that corruption may be beneficial to an economy as a means of getting around red tape or an ineffective government. A recent case comes from Mexico during the initial Covid-19 outbreak; Mexican criminal groups built political capital by giving out food and other humanitarian aid measures Felbab-Brown (2020). The theoretical considerations of corruption greasing the wheel of government in efficiency can be traced back to Leff (1964), who argues that bribery and other forms of corruption are a hedge against bad public policies. An instance of corruption impeding inefficient regulations and limiting their adverse effects can be seen in the Jim Crow law era of the Southern United States. In the south, private owners of streetcar, bus, and railroad companies lobbied against the Jim Crow laws during their legislation, challenged the laws in the courts upon passing, and dragged their feet in enforcing those laws after the courts upheld them.

Further, one of the most important breakthroughs in public economics (Leys, 1965) shows that the depressed wages of public servants may negatively impact the incentive of government officials. Thus, Leys proposes that to draw the highest quality prospects for public service, the possibility of non-legal or nefarious perks may outweigh wages from private sector employment. Therefore, corruption has a net positive benefit to society as it increases human capital decision-making processes. Furthermore, there are strong arguments that corruption may improve the quality of investments, most notably inefficient government spending.

An example of corruption being more efficient in place of the alternative revolves around tax evasion. Suppose that the government spends taxes on fruitless and destructive investments. Thereby, citizens withholding public funds through tax evasion and assuming that bribes are given to efficient investment opportunities. Under those two conditions mentioned above, corruption is likely a net-positive outcome to government taxation.

Another case that is a hot-button topic, especially in defense spending, is the contract choice of competing firms. Most people loathe the bribery for government contracts, but is it more efficient despite the negative connotations? Lien (1986) showed that there is a Nash equilibrium that is symmetric in a competitive bribery game with incomplete information. The bribery game's symmetry replicates the non-corrupt competitive auction as ranking bribes is a proxy for ranking by efficiency.

Grease the wheel hypotheses are considered politically and philosophically aligned with laissez-faire policies and attitudes based on the presumption that markets tend to be more efficient than governments. Thus, by reducing government interference into the market, corruption can positively impact growth, social relations, and other issues associated with a defective institutional framework. It should be noted, corruption may not comprise the most economically beneficial outcomes because despite the benefits it may add. Corruption can negatively affect trust, impose additional costs, and heighten perverse incentive structures that lead to monopolies.

1.2 Corruption: Sanding the Wheel

The more academically rigorous and defended position is that corruption negatively impacts growth. Most people feel opposed to corruption in nearly all forms to the extent that it is a part of our collective moral foundations (Egorov et al., 2019). Sanding the wheel emphasizes that corrupting forces magnify market failures and interfere with government corrective actions leading to government failures.

For every argument proposed in greasing the wheel, there is a strong counterargument with as much, if not more, empirical evidence. The previous section provided an example Lien (1986), which showed a competitive auction where ranking bribes is a proxy for efficiency ranking. Rose-Ackerman (1997) provides a counterargument that ranking by bribes as a proxy for efficiency is an error because the signal may be that the one who bribes the most may also be most willing to compromise the quality of goods produced. The logic is that if a firm is willing to cheat, they are also more likely to compromise their quality in the search for increasing profits. Thus, under these conditions, corruption is a net loss for society as the most efficient agent of resources has not utilized those resources.

Another glaring problem is the efficient investment issue. The assumption that the private markets are more efficient than government-regulated markets and that the briber has a more efficient investment strategy implies that tax evasion is a net benefit. However, according to Piketty and Saez (2013), under the Rawlsian theory [1], the generalized social marginal welfare weights are concentrated solely on the most disadvantaged members of society. society is left more inefficient due to the increasing concern for horizontal equity concern[2] via tax evasion.

To conclude, both Greasing the Wheel and Sanding the Wheel have solid theoretical underpinnings, as well as a large body of empirical evidence in support. Thus, this paper aims to apply a new econometric technique to deal with the possible reciprocal causation of horizontal inequity and corruption.

[1] The difference principle states that social and economic equality are to be arranged so that they are to the most significant benefit of the most disadvantaged.

[2] The theory that people should be treated the same by imposing the same income tax level to people in the same income group.

CHAPTER 2: INCOME DISTRIBUTION DYNAMICS AND ECONOMIC GROWTH

Parallel to corruption and growth, there is a body of evidence in the literature regarding the relationship between inequality and growth. The growth literature has a conflicting body of evidence surrounding income inequality and growth. The literature's conflict is a primary motivator explored in this thesis, demonstrating and understanding the nonlinear causality between corruption and income inequality. The reasoning is that in the development literature, there appear several theories regarding these two phenomena that may be jointly impacting growth. More clarity on the relationship between economic inequality and economic growth or finding evidence for uni/bi-directional causality would greatly benefit other researchers.

2.1 Income Inequality: Grease the Wheel

Stiglitz (1969) finds a positive relationship between income inequality and growth under the Neo-Classical growth model's assumptions. The foundation for the positive relationship is that because the upper-income individuals' savings rate is generally higher than that of the lower-income individuals, there should be increased aggregate savings. With increased aggregate savings, there is the assumption of increased growth. Further, Goel and Saunoris (2020) find evidence that a greasing effect on growth is identified across alternative income inequality measures. Either effect for sanding or greasing is due to the internal countries prevalence of entrepreneurship. The authors also point to a threshold level of entrepreneurship where a state moves from sanding the wheel to greasing the wheel as an impact of income disparities on entrepreneurship.

Notable work on spillover effects related to income inequality, Sveikauskas (2007) finds in the literature review that research and development (R&D) investments typically do not accrue to the original investor. Instead, returns to spill over to other economic agents. The author further contrasts between public and private forms of R&D, such that private R&D returns will typically outweigh government and university R&D returns as many publicly financed returns are near zero. Sveikauskas (2007) supports Stiglitz (1969) with some empirical backing as the rate of returns for private enterprise, in general, provides larger social welfare benefits. The private forms of R&D have spillover effects from inequality that lead to all groups increasing per capita wealth and standard of living, further demonstrated in Hagopian and Ohanian (2012).

Later investigations into income inequality try to control for possible endogenous effects. Aiyar and Ebeke (2020) find that intergenerational mobility accounts for a large amount of the variance in economic growth instead of income inequality. The authors also empirically test the Great Gatsby Curve (GGC)[1]. When controlling for the GGC, the researchers found that inequality of opportunity is not reducible to an initial level of income inequality. Thus, income inequality is mediated by equality of opportunity, and policies should focus more on redressing this issue as it encapsulates the majority of the negative impact.

A significant influence behind this is the empirical investigation of the Inequality-Growth Kuznets curve (Kuznets, 1955). A later formulation of Kuznets waves proposed in Milanovic (2016) as a response to Piketty and Goldhammer (2014) attacking the Kuznets curve's historicity. The Kuznets Wave hypothesis argues that people should see an upswing in current income inequality trends as society transfers from homogeneous factory work to heterogeneous skill services based on human capital.

[1] Countries with more inequality at one point in time also experience less earnings mobility across the generations.

2.2 Income Inequality: Sand the Wheel

The bulk of the literature in political science and sociology point to the negative relationship between economic growth and income inequality; however, the economics literature is more agnostic on the relationship. A notable standout is Benhabib and Rustichini (1996), producing a game-theoretic model that shows that, under pronounced and persistent inequality, those disadvantaged groups would likely move the median voter to increase the redistribution of wealth by the government. Changes in the median voter rule and redistribution tastes would directly reduce growth by discouraging domestic investment, reduced political consensus, and increased political stability that may indirectly impact foreign investment.

Galor and Moav (2004), show that a primary reason for the hypothesized inverted-U relationship between inequality and growth rests on replacing physical capital accumulation with human capital accumulation. Thus, as replacement is in process, the benefits from physical capital on the growth process are being reversed. However, equality is more conducive for human capital accumulation, where inequality promotes physical capital accumulation through the savings channel. Therefore, income inequality is now a net negative interaction for growth as it reduces the main driver of the growth process, human capital.

CHAPTER 3: INEQUALITY, CORRUPTION, AND GROWTH: ESTABLISHING CAUSALITY

The ongoing debate on income inequality has opened numerous avenues to study the effects of income inequality on health outcomes, violent crime, and resource allocation. A significant aspect of income inequality is the nonlinear interaction between economic inequity and government corruption. There is evidence of income inequality increasing corruption through the material and normative mechanisms sung Sanjeev Khagram (2005). Corruption has been shown to cause increases in income inequality by reducing growth, negatively impacting progressive tax structures, altering social and public spending patterns, and reducing the formulation of human capital (Davoodi, and Alonso-Terme, 1998). Davoodi, and Alonso-Terme (1998) also find that a one standard deviation increase in corruption results in a reduction of income for the poor of 7.8% a year. A primary mechanism of corruption causing income inequality was explored in Esteban and Ray (2006), who creates a model of allocative efficiency used to judge the equilibrium output ratio to maximal output. She shows that despite reward signals from highly productive individuals, the lobbying equilibrium changes, which causes losses in productive sectors.

Other researchers have found a mutual influence between income inequality and corruption, as described by Arsyad, and Pradiptyo (2018). The researchers find a reciprocal relationship between corruption and income inequality that gives evidence to the corruption-income inequality trap pioneered by Uslaner (2008). The authors use ordinary least squares (OLS), the Tobit method for censored data, and two-stage least squares (2SLS) to deal with potential endogeneity problems associated with the reciprocal effects. Applying a dynamic panel estimator to a sample of African countries, Gyimah-Brempong (2002) find an increase in corruption is positively correlated with income inequality. Further, the combined effects of decreased income growth and increased inequality show that corruption tends to favor the rich while negatively impacting Africa's poor. The author also finds that increased corruption tends to decrease economic growth indirectly through decreased investment in physical capital.

Another component of corruption and income inequality is given in Thorbecke and Charumilind (2002). The author explores the four distinct transmission channels of income inequality and lower rates of growth through a review of the empirical evidence relating inequality to growth. Those are: i) encourages rent-seeking actions that reduce private property rights; ii) social tensions as described by discontent from relative economic deprivation; iii) distortions in the economy caused by a poor populace voting for more redistributive policies and higher taxation; and iv) more inequality means less share of the income to the middle class which has a negative effect on fertility, and this, in turn, has a significant and negative impact on growth. The authors find evidence in all categories that the direction of income inequality is a massive determinant in each socio-political class.

Another possible consequence of corruption is the impact on human capital. Thi Hoa (2020)finds that corruption has both positive and negative impacts on human capital accumulation, supporting both greasing and sanding the wheel hypotheses. The negative impact comes from reducing the positive effect of local government spending, while also increasing the advantages of local schools in competition to get central government funds. Thi Hoa (2020) finds that the full impact of corruption in human capital is a net loss, which negatively impacts growth. Furthermore, using an overlapping generations model Ahsan and Blackburn (2015) find that higher levels of corruption coincide with higher poverty levels. The authors studied the effects of corruption in determining income distribution, which bears on how corruption will exacerbate persistent inequality through compromising public service provision. Corruption compromises public service provision by reducing earnings and increasing the population of those who rely primarily on public services.

When examining the relationship between corruption and income inequality, it is necessary to see the push-back mechanisms ascribed to political capture by elites. Muller (1985) gives two hypotheses for political violence. First, the relative deprivation hypothesis states that there are feelings or measures of an individual's economic, political, or social deprivation that are more relative rather than absolute. Relative deprivation argues that there is a direct impact of one's feelings in socioeconomic standing and collective political violence through the discontent channel. Muller and Seligson (1987) reduce attention in the maldistribution hypothesis's literature with more focus on income distribution as a direct cause of political violence. One reason provided by Solt (2008) is that greater inequality tends to shape political inequalities through the depression of political pursuits and participation in all but the most influential groups. Thus, it stands to reason that as political participation is depressed, there will be a violent backlash such as that described above by Muller.

CHAPTER 4: DATA OVERVIEW

4.1 Dependent Variables

All data are panel ranging from 2000 and 2002 to 2018, and the respective descriptive statistics are (full-time-period A.1) & (three-year-average A.2) located in the appendix. In this analysis, I use multiple dependent variables in the PVAR estimation; the Gini index obtained from WorldBank (2020), the corruption perceptions index (PCI) from EuroStat (2020), and percent share of income by the top one and ten percent Alvaredo et al. (2020, 2013).The Gini index is a measurement of the dispersion of income across the income distribution. The PCI is an indicator based on a combination of surveys and assessments of corruption from thirteen different sources and scores and ranks countries based on how corrupt a country's public sector is perceived to be.

The Eurostat derives the PCI from Transparency International, a global non-profit, non-governmental organization committed to fighting corruption (Index, 2018). The income shares methodology is based upon the notion of Distributional National Accounts (DINA), describing the entire distribution of income and wealth, from bottom to top, using concepts consistent with national macroeconomic accounts.

One issue found in the dependent variable was the lack observations for the Gini index. As shown in A.1 with 668 less observations than 1% share of income & A.2 with 166 less observations in the 3-year-average sample. Further, the 3-year-average, did not have any significant impact on the between-country and within-country variations. The low within and larger between country variation, with the lack of observations compared to other inequality measures, might explain the lack of significance.

CHAPTER 5: METHODOLOGY

This study uses data derived from World Bank estimates of high and middle-high-income countries because low-income countries stereotypically have higher income inequality and corruption. This representative sample encapsulates the majority of the wealthy and close to wealthy countries in the world. In this analysis, two of the variables are transformed: First, PCI reversal leads to a more interpretive representation where the larger the number, the worse corruption is. Second, GDP per capita is transformed into natural logarithms, aiding in interpretation and achieving linearity. Third, further data manipulation is achieved by averaging across three-year periods to increase the within-country variation based on the slow movement of the PCI and income inequality indicators.

5.1 Granger (non)Causality

The panel Granger (non)causality test based on Dumitrescu and Hurlin (2012) is used to determine if there is some causal relationship from x to y. The motivation for testing the bi-directional causality comes from Law et al. (2013); Lee and Kim (2009) found bi-directional causality running from institutions and economic growth with heterogeneity in the results based on countries income placement. The presence and direction of the causality between the income inequality measures and corruption are examined using a panel bootstrap method Dumitrescu and Hurlin (2012, Sec. 6.2) which allows for heterogeneity and cross-sectional dependence. I test Transparency International Perceptions of Corruption Index (reversed) versus each income inequality measure to determine possible causal ordering (Policardo et al., 2019). The standardized test statistic based on Dumitrescu and Hurlin (2012) is the *Z Bar Tilde*, the rejection criteria is the 95% confidence level. One major flaw in using panel granger tests is the sensitivity of the test to misspecification of the regression lag length. EViews (2017) show that size distortion is most minor with p=1, no matter the actual data generating process. I consider that the test can be underpowered when regression lags of order p differ from the real temporal structure of the two variables. In response, the lag structure tested is based on three different information criteria: Akaike information criterion (AIC), Bayesian Information Criteria (BIC), and Hannan-Quinn information criterion (HQIC). In this estimation, this sensitivity is shown to be highly significant in the interpretation of results. Granger causality test's significance is to look at the underlying data generating process and determine if there is likely a third variable Z which affects both X and Y at different times in the system (Pesaran, 2015) & (Papagiannopoulou et al., 2017).

5.2 Dynamic Panel Models

Because of the study's design, there is endogeneity resulting from simultaneity (and/or feedback loops). I use a battery of estimations to test for causality ordering, and this is motivated by Leszczensky and Wolbring (2019) who show that you can identify and control reverse causality and temporal ordering under numerous conditions. The study favored the cross-lagged panel model (CLPM) with fixed effects stating, under Monte Carlo Simulations, the CLPM offered protection against bias from reverse causality under a wide range of conditions. Further, the CLPM helps circumvent misspecified temporal lags commonly used to critique dynamic panel models.

Implementation of a Lagged First Difference (LFD) is used to study the direction of causality (Allison, 2009). Estimates from the LFD model suffer from severe bias from the temporal structure of the lags Vaisey and Miles (2017).

Further, an Arellano-Bond (AB) GMM estimator is used because the estimation method is robust against Nickell bias (Anderson and Hsiao, 1981, 1982). AB-type panel estimators weaken the exogeneity assumption for some subset of regressors, which attempts to provide consistent estimates even under reverse causality conditions.

The last model used to test the assumption of reverse causality is the Cross-Lagged Panel Model, formulated by Moral-Benito (2013). Later research shows that the method can be obtained in a structural equation model (SEM) (Allison et al., 2017), and this motivated the development of the Stata command *XTDPDML* (Williams et al., 2016). This model tends to suffer less temporal bias than the other dynamic panel estimators.

5.2.1 Lagged First Difference Estimation

One of the first representations of the LFD model was Allison (2009), utilized for empirical purposes in England et al. (2007); Levanon et al. (2009) and Martin et al. (2012).

Consider the first difference $\Delta y_t = \Delta x_t$. The panel differencing approach follows the cross-sectional approach, unlike the time series operations, which require estimating additional parameters due to the cross-sectional and time-varying nature. Following equation (5.2.1), the panel regression equation can be written as

$$\Delta Y_{ij} = \Delta \mathbf{X}_i' \beta \Delta + \varepsilon_{ij} \tag{5.1}$$

where ΔY_{ij} $(= Y_{ij,t=1} - Y_{ij,t=0})$ is the reversed perception of corruption (revPCI) for individual i in the difference wave j, $\Delta \mathbf{X}_i$ $(= X_{ij,t=1} - X_{ij,t=0})$ is the vector of the income inequality (II) measurement.

Additional parameterization of the lagged difference dependent variable yields

$$\Delta Y_{ij} = \beta_0 + \beta_1 \Delta Y_{i,j-1}\beta + \Delta \mathbf{X}_i'\beta + \varepsilon_{ij} \tag{5.2}$$

However, due to the dependent variable's introduction to the equation's right-hand side, Nickell bias has been introduced. Under the condition that the lagged dependent variable is correlated with X's current values, the independent variables are also biased. To deal with this and to further capture temporal structure, a lagged and differenced independent variable is introduced; this leads to the final equation.

$$\Delta Y_{ij} = \beta_0 + \Delta Y_{i,j-1}\beta \ + \Delta \mathbf{X}_i'\beta + \Delta \mathbf{X}_{ij-1}\beta + \varepsilon_{ij} \tag{5.3}$$

$$\Delta revPCI_{ij} = \beta_0 + \Delta revPCI_{i,j-1}\beta + \Delta \mathbf{II}_i'\beta + \Delta \mathbf{II}_{ij-1}\beta + \varepsilon_{ij} \tag{5.4}$$

Due to the LFD eliminating the unit-specific error term, α_i through first difference transformation, this permits researchers to establish causal ordering as they can allow x_{it} correlate with future values ϵ_{it}.

5.2.2 Arellano-Bond Estimator

A dynamic linear panel data model can be represented as follows (in notation based on Arellano (1993)):

$$y_{it} = \alpha y_{i,t-1} + \beta' x_{it} + \eta_i + v_{it} \tag{5.5}$$

first-differencing eq. (5.5) yields

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \beta' \Delta x_{it} + \Delta v_{it} = \gamma' W_{it} + \Delta v_{it} \tag{5.6}$$

Here $y_{i,t}$ and $y_{i,t-1}$ denote the dependent variable and its lag, α is the lag parameter, and $x_{i,t}$ is a single covariate with corresponding slope coefficient β. The error term in (5.6) by construction, being autocorrelated and correlated with the lagged dependent variable. Therefore, an estimator that takes both issues into account is needed. Consistent with the cross-sectional framework, the endogeneity issue is solved by noting that all values of $y_{i,t-k}$, with $k > 1$ can be used as instruments for $\Delta y_{i,t-1}$: unobserved values of $y_{i,t-k}$. The missing values of the data are substituted with 0, thus

$$E(\Delta v_{it} \cdot y_{i,t-k}) = 0, \quad k > 1, \tag{5.7}$$

is an orthogonality condition. Autocorrelation is dealt with by noting that, if v_{it} 5.8is a white noise representation, separated into an unobserved individual-specific effect η_i and an idiosyncratic remainder component $\varepsilon_{i,t}$, then the covariance matrix of the vector whose typical element is Δv_{it} is proportional to a matrix H that has 2 on the main diagonal, -1 on the first subdiagonals and 0 elsewhere.

$$u_{i,t} = \eta_i + \varepsilon_{i,t}. \tag{5.8}$$

Yields

$$revPCI_{i,t} = \alpha \times revPCI_{i,t-1} + \beta II_{i,t} + \eta_i + \varepsilon_{i,t}, . \tag{5.9}$$

5.2.3 Cross-Lagged Panel Model

The cross-lagged panel model's first step is to convert the data from the typical stacked format of long-format vectors of length NT into T individual vectors of length N. This change affects the vectors of responses in y_{it}. Ignoring covariates and strictly focusing on the dependent variable $y_{it} = \alpha_i + \varepsilon_{it}$. Conversion to wide format gives T

individual equations,

$$y_t = \alpha + \varepsilon_t \tag{5.10}$$

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{Nt} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{Nt} \end{bmatrix} \tag{5.11}$$

for each $t = 1, 2, ..., T$. Under the assumption that the idiosyncratic errors are uncorrelated across units and across time, the covariance between any two of the new wide vectors $(y_{ti}, y_{si}) = (\alpha_i)$, $t \neq s$. Otherwise, when $t = s$, the covariance $(y_{ti}, y_{ti}) = (\alpha_i) + (\varepsilon_{ti})$. Model notation differs substantially, and Bollen (1989) gives an overview. However, Graff (1979) is my preferred notation due to the similarities to aforementioned AB model:

$$y^+ = {\Lambda_y}^+ \eta^+, \tag{5.12}$$

$$\eta^+ = B\eta^+ + \zeta^+, \tag{5.13}$$

where $\eta^+ = (y, x, \eta, \xi)^\intercal$, $\zeta^+ = (\varepsilon, \delta, \zeta, \xi)^\intercal$, and $y^+ = (y, x)^\intercal$, y is a vector of observed dependent variables, x is a vector of observed independent variables, η is a vector of the latent dependent variables, ξ is a vector of latent independent variables, ε and δ are vectors of the observed dependent and independent variables' errors, and ζ is a vector of the errors, or disturbances, of the latent variables.[1] Thus, η^+ is a vector that holds the observed and latent variables, both dependent/endogenous and independent/exogeneous [2], ζ^+ symbolizes the errors for the observed variables and the latent variables' disturbances. y^+ holds just the observed variables, both dependent

[1] + symbol is just meant to differentiate the vectors with them from those without them.

[2] The terms endogenous and dependent, and exogenous and independent are used interchangeably in the structural equation model framework.

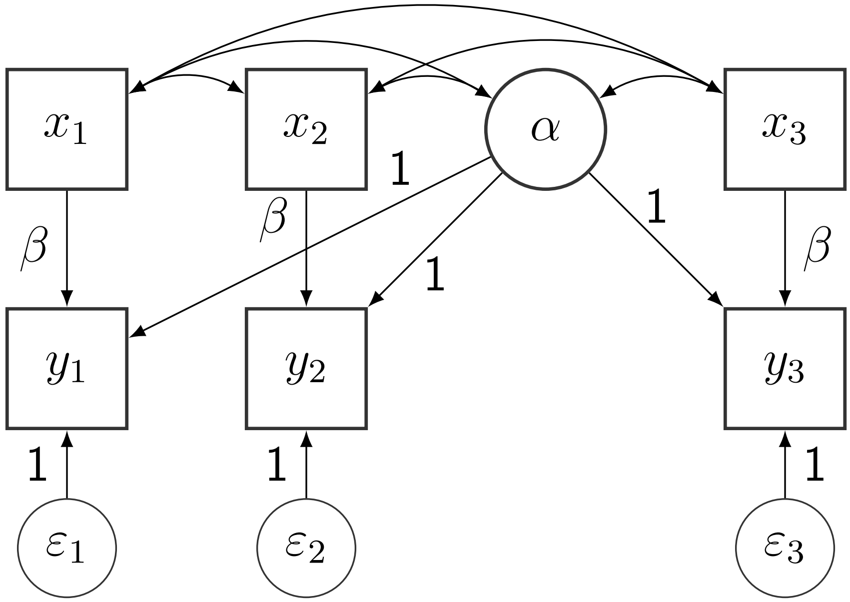

Figure 5.1: Typical Three-Wave FE-SEM Model with Contemporaneous Effects

and independent, and ${\Lambda_y}^+$ is a matrix of ones and zeros that selects the observed variables from η^+. Lastly, B is a matrix that holds the regression coefficients.

If we say that p and q stand for the number of observed dependent and independent variables, respectively, and m and n stand for the number of latent dependent and independent variables, respectively, then η^+ and ζ^+ are $p+q+m+n$, y^+ is $p+q$, ${\Lambda_y}^+$ is $(p+q)\times(p+q+m+n)$ and B is $(p+q+m+n)\times(p+q+m+n)$ (Bollen, 1989) & (Moral-Benito et al., 2019) .

5.3 Growth Equation

5.3.1 Panel Vector Auto Regression

The PVAR derives methodologically from the AB method used above. However, implementing cross-sectional demeaning before the first difference transformation due to the estimation's nature. The lagged dependent variable is on the right-hand side of the equation in this specification, using up to four lags of the dependent and independent variables to instrument. To test the lag order of the dependent variables, the command $PVARSOC$ reports the models' overall coefficient of determination, the Hansen J test, (Hansen, 1982), and moment model selection criteria (Andrews and Lu, 2001) which allows researchers to find the best fit.

This estimation identifies structural shocks, restricting the variance-covariance structure on the residuals such that σ_μ takes the form of a lower triangular matrix. First, we check the stability conditions as per Kilian (2005), which states that a panel VAR is invertible under the stability condition and has an infinite-order vector moving-average (VMA) representation, a necessary condition for interpretation. Cholesky decomposition is used to provide a known interpretation to an estimated impulse-response function and forecast-error variance decompositions. As per Sims (1980) the Cholesky ordering is based on two premises. First, the assumption that a country's economic performance precedes the distribution of its resources; therefore, I set the income inequality variable to have no contemporaneous influence on the log of GDP per capita. Second, because our measures of corruption are measured by perception, I assume corruption to be the most endogenous element of the model as it will manifest after measures of the economic performance and income distribution. The exogenous to endogenous diagram leads me to conclude that the three variables are contemporaneously impacted by growth (Amorim and Da Silva, 2016). Goes (2016) estimates that the corruption perception can be contemporaneously impacted income inequality, which coincides with the theoretical considerations built thus far. Therefore, I order the baseline model as:

$$Y_{it} = [log(GDP)_{it}, II_{it}, RevPCI_{it}]$$

. I used the Stata command $PVAR$ (Abrigo and Love, 2016) for this estimation because it is built from the AB estimation model previously used. The AB estimator lessens the exogeneity assumption in dealing with Nickell bias, and under correct temporal specification, protects against reverse causality. Based on these three tests, I specify one lag in each dependent variable.

CHAPTER 6: RESULTS

6.1 Expected results

My initial expectation is that there exists a heterogeneous impact of income inequality causing corruption. Looking at nonlinear causality and nonlinear dynamics, I find that the current literature review does not properly account for the economic structures (Constantine, 2017). I believe that corruption will cause increased income inequality given a lower level of governance or economic structure. My theoretical assumption is that governance is the necessary and sufficient condition to hold back income inequality as a causal mechanism of corruption Acemoglu and Robinson (2012). Given the New-Institutional framework, a robust governing body will reduce the adverse spillover effects caused by income inequality Acemoglu et al. (2001, 2015). Good governance reduces corruption, meaning that good governance in my model comes before corruption as we estimate mid to high-level-income countries. Much of the research done on the income inequality-corruption trap is based on low-income countries, and this sample selection bias may increase the endogeneity in the nonlinear causality.

The institutional decision-making process that may influence how income inequality and corruption work together are influenced by political decision-making processes. Assuming that inclusive institutions are good for economic growth and development, that does not mean those in power would benefit from this inclusive institution. It stands to reason that in an area with low governance, the elite who have captured political power would set up institutions that would benefit them and be extractive to the rest of the nation (Acemoglu et al., 2005).

Failure to address the possible selection bias leads to another problem not identified in the literature. Extractive forces from the elite typically have a life span predicated on conflict theory (Marx, 1973, 1976). Building on conflict theory. Deiwiks et al. (2012) show that individual wealth differences are not as valuable as regional-level inequality in determining civil war and secession. Meaning that the life span of an institution's extractive and rent-seeking forces can only last if the people under it will tolerate it Lipset and Bendix (1991). Thus, there is a lack of historical validity to the notion that corruption is caused by income inequality as it would be cyclical.

The last issue for finding a direct causal link is that the definition of corruption and how the institutions perceive corruption are complex with no known mediation. Johnston (1991) provides a brief overview of how the world's roaming cultural institutions may not lead to convergence. The institutional, cultural divergence contrasts with the institutional catch-up hypothesis, as the neoclassical growth model for growth convergence, with expectations to create convergence in these developing nations. Further, Klašnja et al. (2016) show that political and electoral institutions may induce a corruption trap through three mechanisms: One, politicians choosing to engage in more corrupt behavior. Two, voters being more tolerant or even approving of corrupt politicians (a matter of culture). Three, those predisposed to corruption being more apt to enter politics. Thus, the direct causal link proposed here shows that in democratic countries, corruption is deterministic and predicated on the institutional system, which may cause inequality but is unlikely to be motivated by inequality.

I assume that there is no linear causality from income inequality to corruption but that corruption can cause an increase in income inequality. My second assumption is that better governance or economic structure will mitigate this effect in a given country. Third, I hypothesize that income inequality does not affect growth in all cases. Some institutions could have income inequality negatively impact growth, but

I do not believe this to be the case as a general rule. Given the paradigm between cutthroat and cuddly capitalism, Acemoglu et al. (2012) create a model showing that the world equilibrium is asymmetric in economic growth. This asymmetry generates greater inequality and more innovation as the more unequal economies become the technology leaders. Thus, higher-income inequality could positively affect economic growth, leading to the affirmation of the income inequality greasing the wheel hypothesis.

In the growth model, I expect that all income inequality measures will have little to no effect. The reasoning behind this is that I find each measure of inequality to lack the requirements for reducing growth. Aiyar and Ebeke (2020) show that inequality alone is not a determinant of reduced growth but that inequality conditioned on intergenerational mobility interaction appears crucial to growth. My expectation for the corruption indicator will be a significant determinant of economic growth. The literature and theoretical model prove to be convincing that corruption would harm economic growth. Considering the data is sampled from World Bank estimates of middle-high to high-income countries, there is already an established relationship and that corruption will necessarily drive down growth.

The basic model representation for the dynamic panel to test the contemporaneous effect:

$$RevCPI_{it} = RevCPI_{it-1} + II_{it} + \epsilon_{it}$$

The model testing for a lagged effect:

$$RevCPI_{it} = RevCPI_{it-1} + II_{it} + II_{it-1} + \epsilon_{it}$$

The reversed order is tested for robustness.

6.2 Reverse Causality test: Granger

In this paper, I have attempted to find and order the case of bi-directional causality between income inequality and corruption by empirically testing through LFD, AB GMM, and CLP modeling. First, the initial expectations stated above were that there would not be bi-directional causality in all panels and that the causal ordering would heavily favor corruption versus income inequality. Second, that there would be a lack of contemporaneous effect between the two variables. For the first test, I use the Granger causality test with bootstrapped standard errors tested as:

H0: X does not Granger-cause Y.

H1: X does Granger-cause Y for at least one-panel state identifier.

Where three information criteria determine the lag order, (AIC),(BIC), and (HQIC), the test is only conducted on the sixteen-year sample, as the minimum required is $T > 5 + 3K$, where K is the lag order.

The granger causality test for the top 10% income share does not show an ongoing mutual granger causality relationship. Of the six tested procedures, all corruption granger does not cause 10% income share rejected the null hypothesis B.3, but top 10% income share failed to reject the null B.4. This implies granger causality in one direction. The failure of significance in 10% income share granger-causing corruption gives evidence against the bi-directional theory.

In the granger causality test, the top 1% income share finds that in the six tests performed, only the BIC finds mutual granger causality B.2 & B.1. The other criterion, AIC, and HQIC both fail to reject causality in either direction. The BIC is based on one lag against the other measures on three lags. The single lagged results are in line with later dynamic panel models that 1% income share capture has mutual reciprocity with corruption.

The Gini index, in all instances, failed to reject granger causality B.5 & B.6. The failure of Gini is likely due to instability, as there is fewer data in the sixteen-year panel. As addressed previously in the methodology section, an endogeneity problem affects each variable in different periods. This temporal phenomenon calls into question the granger causality results, even when specified by bootstrap to deal with cross-sectional dependency and state heterogeneity. In my view, this gives evidence to the initial hypothesis that there is no observable feedback effect and limits the reliability of assuming bi-directional causality between income inequality and corruption in all cases.

6.3 Reverse Causality test: Dynamic Panel Models

6.3.1 Lagged First-Difference

Full Time Specification   The LFD for the top 1% share of income shows no evidence of a contemporaneous effect C.1, but the lagged top 1% share of income is statistically significant at the 5% level. The negative coefficient gives evidence that a 1% increase in the top 1% share of income is correlated with an approximate 14.6 point reduction in corruption perceptions. This result was not expected as theory assumed that elite capture through income inequality by top 1% share of income would lead to an increase in corruption.

Full Time Specification   The top 10% share of income found in C.2 found no statistical significance in either the contemporaneous or lagged specification, which was expected based on the granger results.

Full Time Specification   The Gini index model C.3 found no correlating relationship with corruption perceptions in the contemporaneous or lagged specification. This was expected based on the granger results and the lack of observations in comparison to the 1% & 10% share of income measures.

3 yr Averaged Time The LFD for the top 1% share of income under the 3-year averaged time shows no evidence of a lagged or contemporaneous effect C.4.

3 yr Averaged Time The top 10% share of income found in C.5 found no statistical significance in either the contemporaneous or lagged specification.

3 yr Averaged Time The Gini index model C.6 found no correlating relationship with corruption perceptions in the contemporaneous or lagged specification.

6.3.2 AB GMM

Full Time Specification The AB for the top 1% share of income shows evidence of a contemporaneous effect with statistical significance at 10% C.1 with a positive coefficient conditioned on a lagged value. The contemporaneous coefficient in the lagged AB model shows that a 1% increase in top 1% income shares correlates with an approximately 27.93 point increase in corruption perceptions. The lagged top 1% share of income is statistically significant at the 1% level. The negative coefficient gives evidence that a 1% increase in the top 1% share of income is correlated with an approximate 43.5 point reduction in corruption perceptions. This result was not expected as theory assumed that elite capture through income inequality by top 1% share of income would lead to an increase in corruption. However, this gives some indication that of a policy response to an increased likelihood of elite capture, at least through the economic inequality channel.

Full-Time Specification The AB for the top 10% share of income shows no evidence of a contemporaneous effect C.2, but the lagged top 10% share of income is statistically significant at the 5% level. The negative coefficient gives evidence that a 1% increase in the top 10% share of income is correlated with an approximate 41.81 point reduction in corruption perceptions. This result was not expected as theory assumed that elite capture through income inequality by top 10% share of income would lead to an increase in corruption.

Full Time Specification The Gini index AB model C.3 found no correlating relationship with corruption perceptions in the contemporaneous or lagged specification.

3 yr Averaged Time The AB for the top 1% share of income under the 3-year averaged time shows no evidence of a lagged or contemporaneous effect C.4.

3 yr Averaged Time The top 10% share of income found in C.5 found no statistical significance in either the contemporaneous or lagged specification.

3 yr Averaged Time The Gini index model C.6 found no correlating relationship with corruption perceptions in the contemporaneous or lagged specification.

6.4 Reverse Causality test: Cross Lagged Panel Model

The CLPM shows similar results to the AB and LFD estimates where there is statistical significance in the lagged coefficient of 1 and 10% income shares C.7. The lagged 1% share of income was statistically at the 5% level and was a negative coefficient, differing from previous dynamic models. The negative coefficient showed that a 1% increase in 1% share of income there is a 35.61 point increase in corruption. The 3-year average specification likely captures the contemporaneous effect seen in the AB model and rising income inequality biased by business cycle changes relating to the 2008 recession Brzezinski (2018).

The lagged 10% share of income was statistically at the 10% level with a similar coefficient to the lagged 1% income share. The negative coefficient showed that a 1% increase in 10% share of income there is a 31.74 point increase in corruption. This most likely shows the high correlation between 1 and 10% income share.

6.5 Growth Model

6.5.1 PVAR Structural GMM Equation

In D.1 first equation of the transformed per capita GDP, I find that the log of GDP per capita strongly influences itself with the other two endogenous variables failing to predict future values. A 1% change in the log of GDP per capita leads to an increase in GDP per capita by 0.5%. In the second equation of income share for the top 1%, I also find prior values of 1% share strongly influence future values and comes with a negative sign. Given a previous 1% change in the top 1% share of income reduces the next years' share of income by 0.29%. The reduction in future values of the top 1% share of income may show that as the top 1% share of income increases, the following temporal structure shows government intervention through increased taxes or market corrections.

Further, I find that GDP per capita strongly predicts future income share values where a 1% increase in GDP per capita leads to a .009% increase in top income shares. The increasing top 1% share of income due to previous GDP per capita values may be a manifestation of increasing growth coinciding with increased inequality, as proposed by the wave-Kuznets hypothesis. The third equation reversed corruption perceptions shows no influence from past values but is strongly predicted by GDP per capita. GDP per capita's strong predictive power reflects the solid economic growth structure and development in more modernized economies. GDP per capita growth does not reflect that increased growth eliminates corruption, but given the positive trajectory of economic growth I, assume that the corruption perceptions are reduced. Furthermore, as shown in Cassin (2017); Campbell (2013), the CPI may be an inappropriate measurement of a country's corruption perceptions when dealing with risk. Given that the corruption perceptions may bias private firm investments away from the bad countries and steer towards the good countries, this biasing of private firm investments may have the knock-on effect of maintaining the hegemonic power structure (Bratsis, 2014). The reduced investments may further damage places that need these investments to boost their economies' growth and development. Based on the evidence in the PVAR, increasing economic growth would substantially reduce corruption.

6.5.2 Orthogonalized Impulse Response Function

The impulse response functions of decomposed PVAR D.1. First, the response of corruption to a one standard deviation (STD) shock in income share coincides with a one-year increase of corruption perception by three points followed by a sharp decline. A one STD shock to the log of GDP per capita is followed by a decline of one STD reduction in corruption perceptions; after five time periods, the system equilibrates. The response of income share to an STD shock to corruption shows a decrease of one period and an increase in the following period, which levels off in the third period. A one STD shock to the log of GDP per capita shows a one-period increase in income share. A one STD shock to corruption shows a one-period decline in GDP per capita and three-step recovery. The STD shock to income share on GDP shows a huge confidence band but decreases income share on average. The large confidence band may be a function of the differences in the institutional response to income share capture.

6.5.3 Forecast-Error Variance Decomposition

The only significant interpretation from the FEVD D.2 is in the corruption perceptions. The evidence suggests that the top 1%' income share explains roughly 13% of the variance in future corruption values and economic growth explains roughly 8% of the variance in corruption perceptions. This finding is in line with the previous literature but furthers the understanding that many of these variables may be institutionally or economically structurally dependent.

CHAPTER 7: DISCUSSION

As stated previously, I sought to investigate two pieces of the current growth puzzle. First, the bi-directional causality of income inequality and corruption. Second, building on this revelation, investigating the impact either variable has on economic growth.

In this thesis, I find that there is possible bi-directional causality from the income share of the top 1% and corruption perceptions, which opens the literature for further investigation by removing the clunky Gini index. Second, I have find strong evidence that a country's growth can be independent rather than conditioned on the distribution of resources and the corruption perceptions. This implies that exogenous shocks, institutions, institutional reform, and country-specific indicators, e.g., economic structure, matter more than international perceptions. The results from this paper give reason to further these specifications to the microeconomic level as the macroeconomic specification has several issues. Most notably, the large between countries and small within-country variations of the macroeconomic indicators. Despite my efforts to average the periods to allow for more significant movement in the variables, the offset was not statistically or economically beneficial, except in the CLPM.

In this task, I cannot say this was a successful endeavor as the data, and the underlying generating process seemed to lack consistency. First, there is serious doubt on the utility of the corruption perceptions index before the 2012 cross-country comparisons were implemented. The Gini index provided by the world bank was severely lacking in observations. The accounting method used to produce the top income shares has been marred in controversy.

However, I did find success in better understanding the relationship between income inequality and corruption. There is a legitimate concern for political capture by economic elites. However, this is mitigated in many ways by the West's institutions and other high to high-middle-income countries. The institutional effect leads to further investigation on the impact that income inequality may have on long-run institutions. Also, the results of the PVAR tend to favor the hypothesis that the production structure of an economy is the fundamental determinant of its economic performance and that economic development determines the direction and rate of institutional change (Reinert, 2019; Khan et al., 2000; Chang, 2002).

CHAPTER 8: CONCLUSIONS

To sum up my thesis, I attempted to understand better the underlying data generated structure of the bi-directional causality of income inequality and corruption perceptions. I tested the bi-directional causality through a battery of different estimators robust to reverse causality to estimate the data generating process and underlying temporal structure. Second, I study the impacts income inequality and corruption have on economic growth through a PVAR.

Summary of results can be found at D.3. In this analysis, four different dynamic panel models were used to test the validity of the bi-directional cause claim. The Granger (non)causality specification found evidence for bi-directional causality in the 1% income share under one lag and corruption perceptions. Further, support for uni-directional causality in the 10% income share and corruption perceptions was found. The LFD found a negative coefficient in the 1% share under the full-time sample and no other significant indicators in either time sample. The AB estimator found significance in both lagged 1 and 10% income share with a negative coefficient under full-time sample. Further, the contemporaneous 1% income share was significant at the 10% level with a positive coefficient indicating a correlation between income distribution and corruption perceptions. The AB did not find any significant relationships under the three-year average sample. The CLPM using the three-year averaged sample, found a positive coefficient in the lagged 1 and 10% income shares, indicating a correlation between previous income distribution and future corruption values.

The PVAR is broken down into three separate equations, decomposed impulse responses, and forecast error variance. The economic growth equation showed that previous values of GDP per capita predict future GDP per capita values. The 1% income equation shows that GDP per capita influences future values of the 1% income share in the positive, and that 1% share changes predict a decrease in 1% share. Last, a change in GDP per capita on average leads to a reduction in corruption perceptions. The orthogonalized impulse response shows that a shock from GDP per capita reduces both 1% and corruption perceptions and increases GDP per capita. A shock from 1% share reduces corruption perceptions, increases 1% share and GDP per capita. Last, A shock from corruption perceptions increases 1% share, corruption perceptions, and reduces GDP per capita. The FEVD for GDP per capita and 1% share show no measurable variation conditioned on the ordering. However, the decomposition corruption perceptions found that GDP per capita made up 8% of the variation, and 1% share made up 13% of the variation.

I find strong evidence to support the institutional hypothesis and the economic structures hypothesis, but the heterogeneous responses make identifying the underlying causal structure difficult. To deal with the variables' slow movement, I take the average over three years to maximize the possible changes in the variables. I also ensure my techniques are robust to reverse causality and robust to the orderings of exogeneity. The robustness checks reveal similar conclusions for ordering and different time structures.

Based on these conclusions, researchers should consider the impact of income inequality and intergenerational mobility on institutions and economic structures in the long run. This would better capture the impact of inequity on corruption and bolster the theoretical foundation of the corruption-income trap hypothesis since institutions and economic structures, in the long run, mitigate the impact of corruption and income inequality on economic growth. Further research should be conducted to understand better the actual data generating process for income inequality to parse out short-run fluctuations in the business cycle. Parsing out short-run fluctuations may involve Fourier transformations to smooth business cycle fluctuations and multivariate Bayesian Vector Autoregression. Last, I would recommend a dynamic common correlated effects estimation (Chudik and Pesaran, 2015) as it is robust to error cross-sectional dependence, possible unit roots in factors, and slope heterogeneity.

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APPENDIX A: SUMMARY RESULTS SECTION IN APPENDIX

Table A.1: Panel Descriptive Statistics: Full Time Length

		Mean	Std. Dev.	Min	Max	N/n/T-bar
PC GDP (log)	overall	9.354	1.069	6.434	11.685	1677
	between	.	1.000	7.638	11.42634	99
	within	.	.389	7.533	10.297	16.939
Reversed Corruption Index	overall	49.274	21.539	1.00	88	1549
	between	.	20.756	7.882	83.600	99
	within	.	5.221	-1.668	107.921	15.647
Gini Index	overall	36.74384	8.654	23.700	64.800	885
	between	.	8.821	24.886	62.400	82
	within	.	1.884	30.544	46.738	10.793
Share of income for top 1%	overall	.150	.056	.054	.325	1553
	between	.	.0536	.067	.287	94
	within	.	.015	.064	.240	16.521

Table A.2: Panel Descriptive Statistics: Three-Year-Avg.

		Mean	Std. Dev.	Min	Max	N/n/T-bar
3 yr avg PC GDP (log)	overall	9.367	1.0583	6.635	11.618	592
	between	.	.994	7.675	11.434	99
	within	.	.371	7.927	10.217	5.980
3 yr avg Reversed Corruption Index	overall	49.743	21.169	3	86.667	571
	between	.	20.604	8.083	83.083	99
	within	.	4.729	29.021	75.854	5.768
3 yr avg Gini Coef	overall	37.349	8.863	24.300	64.800	394
	between	.	8.808	24.860	62.400	82
	within	.	1.768	31.149	44.224	4.805
3 yr avg Share of income for top 1%	overall	.150	.055	.057	.304	560
	between	.	.053	.0674	.287	94
	within	.	.013	.104	.2335	5.958

APPENDIX B: GRANGER RESULTS RESULTS SECTION IN APPENDIX

Table B.1: Bootstrapped Panel Granger-cause from Corruption to 1% income share

H_0: Corruption does not Granger-cause 1% income share.

Test statistic	Critical Value	p-value
Z-bar tilde(AIC Lags-3) 2.052	3.3697	0.17
Z-bar tilde(BIC Lags-1) 4.830	4.701	0.035
Z-bar tilde(HQIC Lags-3) 2.052	3.056	0.18

Conclusion: Fail to reject H_0 at 5% significance level.

Table B.2: Bootstrapped Panel Granger-cause from 1% income share to Corruption

H_0: 1% income share does not Granger-cause Corruption.

Test statistic	Critical Value	p-value
Z-bar tilde(AIC Lags-3) 2.611	3.103	0.085
Z-bar tilde(BIC Lags-1) 5.643	4.443	0.010
Z-bar tilde(HQIC Lags-3) 2.611	3.103	0.085

Conclusion: Fail to reject H_0 at 5% significance level.

Table B.3: Bootstrapped Panel Granger-cause from Corruption to 10% income share

H_0: Corruption does not Granger-cause 10% income share.

Test statistic	Critical Value	p-value
Z-bar tilde(AIC Lags-3) 3.047	3.122	0.055
Z-bar tilde(BIC Lags-1) 6.002	4.453	0.005
Z-bar tilde(HQIC Lags-3) 3.047	2.825	0.035

Conclusion: Reject H_0 at 5% significance level.

Table B.4: Bootstrapped Panel Granger-cause from 10% income share to Corruption

H_0: 10% income share does not Granger-cause Corruption.

Test statistic	Critical Value	p-value
Z-bar tilde(AIC Lags-3) 2.816	2.953	0.075
Z-bar tilde(BIC Lags-1) 5.003	5.164	0.060
Z-bar tilde(HQIC Lags-3) 2.816	3.265	0.110

Conclusion: Fail to reject H_0 at 5% significance level.

Table B.5: Bootstrapped Panel Granger-cause from Corruption to Gini

H_0: Corruption does not Granger-cause Gini.

Test statistic	Critical Value	p-value
Z-bar tilde(AIC Lags-3) -0.413	2.157	0.670
Z-bar tilde(BIC Lags-1) 0.447	3.407	0.675
Z-bar tilde(HQIC Lags-3) -0.413	2.459	0.595

Conclusion: Fail to reject H_0 at 5% significance level.

Table B.6: Bootstrapped Panel Granger-cause from Gini to Corruption

H_0: Gini does not Granger-cause Corruption.

Test statistic	Critical Value	p-value
Z-bar tilde(AIC Lags-1) 0.869	3.342	0.410
Z-bar tilde(BIC Lags-1) 0.869	3.342	0.455
Z-bar tilde(HQIC Lags-3) 0.995	1.741	0.245

Conclusion: Fail to reject H_0 at 5% significance level.

APPENDIX C: DYNAMIC PANEL RESULTS SECTION IN APPENDIX

Table C.1: Dynamic Panel Models: Full Time 1% Share of Income

Reversed Corruption Index	FD Contemp.	FD Lagged	GMM DPD Contemp.	GMM DPD Lagged
D.Share of income for top 1%	17.021	12.342		
	(10.479)	(10.649)		
LD.Share of income for top 1%		-14.599**		
		(7.217)		
L.Share of income for top 1%				-43.514***
				(16.097)
Share of income for top 1%			0.283	27.932*
			(13.894)	(14.685)
L.Reversed Corruption Index			0.912***	0.906***
			(0.061)	(0.061)
Constant	-0.023	-0.054		
	(0.115)	(0.121)		
F-Test	2.638	2.547*		
R2	0.002	0.004		
Observations	1306.000	1237.000	1213.000	1210.000

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table C.2: Dynamic Panel Models: Full Time 10% Share of Income

Reversed Corruption Index	FD Contemp.	FD Lagged	GMM DPD Contemp.	GMM DPD Lagged
D.Share of income for top 10%	5.613	3.102		
	(7.903)	(8.065)		
LD.Share of income for top 10%		-6.973		
		(8.488)		
L.Share of income for top 10%				-41.807**
				(17.526)
Share of income for top 10%			1.336	31.880
			(22.825)	(20.429)
L.Reversed Corruption Index			0.939***	0.937***
			(0.061)	(0.060)
Constant	-0.022	-0.058		
	(0.115)	(0.120)		
F-Test	0.504	0.459		
R2	0.000	0.001		
Observations	1306.000	1237.000	1213.000	1210.000

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table C.3: Dynamic Panel Models: Full Time Gini Index

Reversed Corruption Index	FD Contemp.	FD Lagged	GMM DPD Contemp.	GMM DPD Lagged
D.gini	-0.004	0.012		
	(0.073)	(0.083)		
LD.gini		0.106		
		(0.095)		
L.gini				-0.056
				(0.160)
gini			0.048	0.082
			(0.138)	(0.183)
L.Reversed Corruption Index			0.797***	0.775***
			(0.044)	(0.047)
Constant	-0.158	-0.126		
	(0.126)	(0.137)		
F-Test	0.003	0.648		
R2	0.000	0.002		
Observations	687.000	624.000	668.000	622.000

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.4: Dynamic Panel Models: Three Year Avg.

Reversed Corruption Index	FD Contemp.	FD Lagged	GMM DPD Contemp.	GMM DPD Lagged
D.3 yr avg Share of income for top 1%	-16.394	-17.726		
	(13.776)	(14.872)		
LD.3 yr avg Share of income for top 1%		4.771		
		(17.792)		
L.3 yr avg Share of income for top 1%				-39.312
				(55.671)
3 yr avg Share of income for top 1%			-39.068	-10.845
			(55.631)	(69.111)
L.3 yr avg Reversed Corruption Index			0.984***	0.960***
			(0.137)	(0.143)
Constant	-0.314	-0.374		
	(0.226)	(0.255)		
F-Test	1.416	0.824		
R2	0.002	0.003		
Observations	449.000	364.000	356.000	355.000

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.5: Dynamic Panel Models: Three Year Avg.

Reversed Corruption Index	FD Contemp.	FD Lagged	GMM DPD Contemp.	GMM DPD Lagged
D.3 yr avg Share of income for top 10%	-8.650	-2.844		
	(12.736)	(14.390)		
LD.3 yr avg Share of income for top 10%		6.290		
		(14.938)		
L.3 yr avg Share of income for top 10%				-4.602
				(56.647)
3 yr avg Share of income for top 10%			-70.971	-74.367
			(59.845)	(77.171)
L.3 yr avg Reversed Corruption Index			1.098***	1.092***
			(0.150)	(0.154)
Constant	-0.318	-0.357		
	(0.226)	(0.253)		
F-Test	0.461	0.094		
R2	0.001	0.000		
Observations	449.000	364.000	356.000	355.000

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.6: Dynamic Panel Models: Three Year Avg.

Reversed Corruption Index	FD Contemp.	FD Lagged	GMM DPD Contemp.	GMM DPD Lagged
D.3 yr avg Gini Coef	0.209	0.213		
	(0.170)	(0.201)		
LD.3 yr avg Gini Coef		0.165		
		(0.178)		
L.3 yr avg Gini Coef				0.436
				(0.449)
3 yr avg Gini Coef			-0.401	-0.696
			(0.399)	(0.592)
L.3 yr avg Reversed Corruption Index			0.943***	0.888***
			(0.132)	(0.139)
Constant	-0.184	0.113		
	(0.299)	(0.366)		
F-Test	1.522	1.064		
R2	0.005	0.008		
Observations	295.000	223.000	244.000	222.000

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.7: Cross Lagged Panel Model: Three Year Avg.

Reversed Corruption Index	CLPM C. 1%	CLPM L. 1%	CLPM C. 10%	CLPM L. 10%	CLPM C. Gini	CLPM L. Gini
3 yr avg Reversed Corruption Index						
L.3 yr avg Reversed Corruption Index	1.113***	0.938***	1.111***	1.095***	1.107***	1.119***
	(13.84)	(51.44)	(11.45)	(11.92)	(12.49)	(13.95)
3 yr avg Share of income for top 1%	41.03	-32.59				
	(0.48)	(-1.35)				
L.3 yr avg Share of income for top 1%		35.61**				
		(1.97)				
3 yr avg Share of income for top 10%			-0.478	-30.75		
			(-0.01)	(-0.69)		
L.3 yr avg Share of income for top 10%				31.74*		
				(1.87)		
3 yr avg Gini Coef					0.286	-0.0209
					(0.22)	(-0.01)
3 yr avg Gini Coef						0.164
						(0.35)
Observations	99	99	99	99	99	99

t statistics in parentheses
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

APPENDIX D: PVAR AND SUMMARY RESULTS SECTION IN APPENDIX

Table D.1: Estimation results : Panel Vector AutoRegression

Equation 1 : PC GDP (log)		
L.PC GDP (log)	0.526***	(6.43)
L.Share of income for top 1%	-0.788	(-1.19)
L.Reversed Corruption Index	-0.00226	(-1.78)
Equation 2 : Share of income for top 1%		
L.PC GDP (log)	0.00922**	(3.01)
L.Share of income for top 1%	-0.297***	(-5.05)
L.Reversed Corruption Index	-0.000126	(-1.10)
Equation 3 : Reversed Corruption		
L.PC GDP (log)	-13.87**	(-2.86)
L.Share of income for top 1%	98.04	(1.04)
L.Reversed Corruption Index	0.0436	(0.36)
Observations	1020	
Hansen's J stat	82.328	0.000
Final GMM Criterion Q	.08071	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure D.1: Orthogonalized Impulse Response Functions

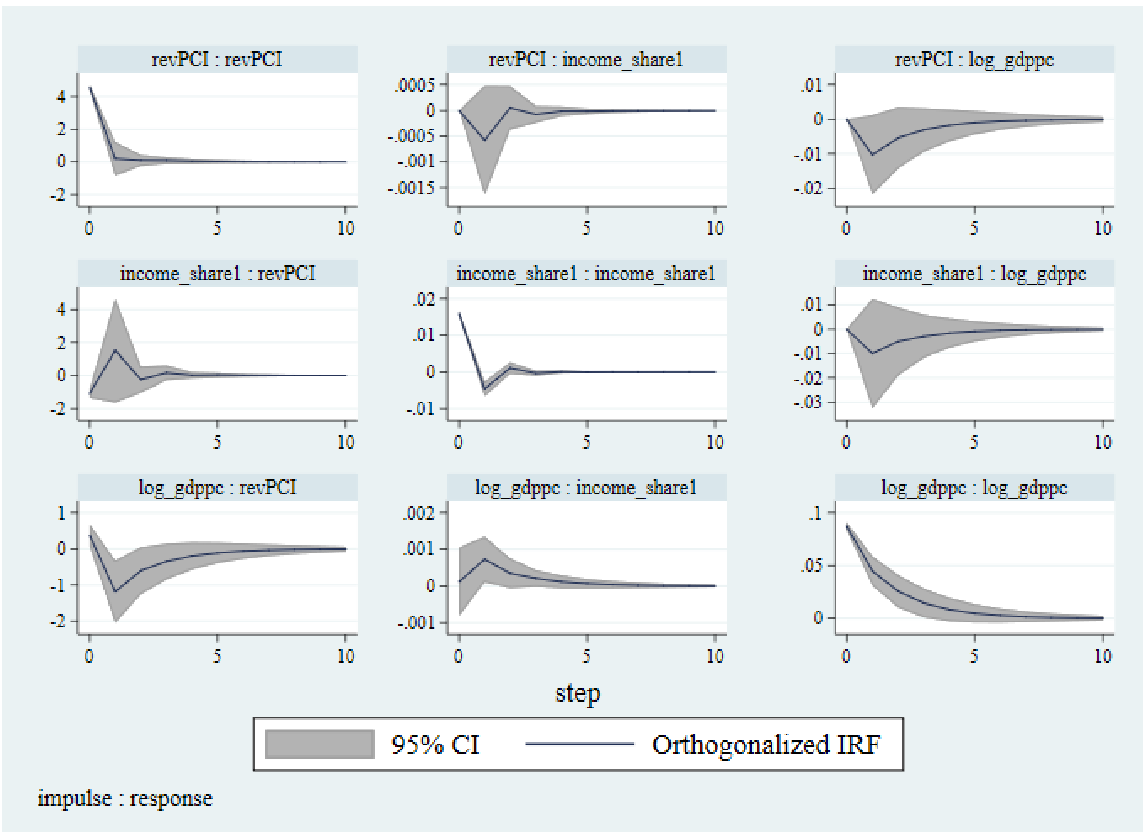

Table D.2: Forecast-Error Variance Decomposition

Response variable	Impulse	variable	
Forecast horizon	log_gdppc	income_share1	revPCI
PC GDP (log)			
0	0	0	0
1	1	0	0
2	0.9788803	0.0103181	0.0108016
3	0.9750753	0.0120772	0.0128475
4	0.9738946	0.0126408	0.0134646
5	0.9735296	0.0128125	0.0136579
6	0.9734117	0.0128684	0.01372
7	0.9733738	0.0128863	0.01374
8	0.9733614	0.0128921	0.0137464
9	0.9733576	0.0128939	0.0137485
10	0.9733562	0.0128945	0.0137492
Share of income for top 1%			
0	0	0	0
1	0.0000547	0.9999453	0
2	0.0019588	0.996823	0.0012182
3	0.0023936	0.9963843	0.0012221
4	0.0025528	0.996204	0.0012431
5	0.0026023	0.9961537	0.001244
6	0.0026186	0.9961364	0.001245
7	0.0026238	0.9961309	0.0012452
8	0.0026256	0.9961292	0.0012453
9	0.0026261	0.9961286	0.0012453
10	0.0026263	0.9961284	0.0012453
Reversed Corruption Index			
0	0	0	0
1	0.00619	0.0521088	0.9417011
2	0.059434	0.1327304	0.8078356
3	0.0723721	0.1328007	0.7948271
4	0.0765691	0.1330547	0.7903761
5	0.0779309	0.1328579	0.7892112
6	0.0783699	0.1328187	0.7888114
7	0.0785121	0.1328014	0.7886866
8	0.0785581	0.1327964	0.7886456
9	0.0785729	0.1327947	0.7886324
10	0.0785778	0.1327941	0.7886281

Table D.3: Summary of Results

Estimation	**Direction of Impact**	**Comments**
Gran: 1% to RevCPI	(+)	Bi-Directional
Gran: 10% to RevCPI	(+)	Uni-directional
Gran: Gini to RevCPI	**Not Significant**	
Gran: RevCPI to 1%	(+)	Bi-Directional
Gran: RevCPI to 10%	**Not Significant**	Uni-directional
Gran: RevCPI to Gini	**Not Significant**	
LFD: Full-Time 1%	(−)	Lag: Significant 5%
LFD: 3-Year 1%	**Not Significant**	
LFD: Full-Time 10%	**Not Significant**	
LFD: 3-Year 10%	**Not Significant**	
LFD: Full-Time Gini	**Not Significant**	
LFD: 3-Year Gini	**Not Significant**	
AB: Full-Time 1%	(−)/(+)	L: Sig. 1% C: Sig. 10%
AB: 3-Year 1%	**Not Significant**	
AB: Full-Time 10%	(−)	Lag: Significant at 5%
AB: 3-Year 10%	**Not Significant**	
AB: Full-Time Gini	**Not Significant**	
AB: 3-Year Gini	**Not Significant**	
CLPM: 1%	(+)	Lag: Significant at 5%
CLPM: 10%	(+)	Lag: Significant at 10%
CLPM: Gini	**Not Significant**	
PVAR: Log GDP pc	(+)	GDPpc
PVAR: 1%	(+) /(−)	GDPpc & 1%
PVAR: CPI	(−)	GDPpc
OIRF: Log GDP pc	(−)/(−)/(+)	CPI & 1% & GDPpc
OIRF: 1%	(−)/(+) /(+)	CPI & 1% & GDPpc
OIRF: CPI	(+) /(+) /(−)	CPI & 1% & GDPpc
FEVD: Log GDP pc	**Not Significant**	GDPpc & 1% & CPI
FEVD: 1%	**Not Significant**	GDPpc & 1% & CPI
FEVD: CPI	**≈ 8 % ≈ 13 % ≈ 79 %**	GDPpc & 1% & CPI

Gran indicates Granger (non)Causality test, LFD indicates Lagged First-Difference, AB indicates Arellano-Bond GMM, CLPM indicates Cross-Lagged Fixed Effects, PVAR indicates Panel Vector Autoregression, OIRF indicates Orthogonalized Impulse Response Function, and FEVD indicates Forecast-Error Variance Decomposition.
(+) indicates a positive coefficient in the LFD/AB/PVAR, in the Granger represents a statistically significant relationship, the OIRF represents a positive movement after shock.
(−) indicates a negative coefficient in the LFD/AB/PVAR, in the OIRF represents a negative movement after shock.