INCOME INEQUALITY, CORRUPTION AND MARKET POWER: AN ECONOMETRIC ANALYSIS

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Abstract

Income inequality refers to how unevenly income is distributed in society. Income inequality has been perceived to escalate generally due to excessive gains by the top income earners. Rising income inequality across OECD countries and in the United States has become a center stage in policy debates across the world. The main objective of this study is to empirically explore the econometric linkages between income inequality, corruption and market power. This study seeks to shed light on possible causal links by utilizing international data on OECD countries and micro data for the United States at the state level to account for problems associated with data issues at the international level, such as unobservable institutional factors. This thesis uses data for 26 OECD countries (1984 to 2014) and 50 states of United States (1977 to 2014).

Causality and copula analyses are undertaken to explore the empirical nexus of income inequality, corruption and market power. For causality testing, this study implements a procedure proposed by Dumitrescu and Hurlin (2012) for testing Granger causality in panel datasets. In a trivariate setting, this research extends Dumitrescu and Hurlin (2012) method and adapts Toda and Yamamoto (1995) approach in time series datasets.

Causality analysis is employed to understand the causation between these three main issues. However, this analysis does not allow information on the total correlation of variables of interest (Chong and Gradstein, 2007). Thus, the copula approach is applied to complement causality analysis. Copula approach is a well-known tool in financial risk management and insurance applications and has proven to be a superior tool for modeling dependency structures. To our knowledge, it has rarely been used in economy applications. In this study, this study employed bivariate copula and Vine copula.

The evidence presented here consistently shows that there is a strong linkage between income inequality, corruption and market power. However, the dependence between linkages is unique and varies between countries and states in the United States. The results demonstrate the strong dependence between these three factors. Most of the time, the linkage is slightly stronger for income inequality and corruption. These advances econometric method does provide a new insight in exploring the nexus of income inequality, corruption and market power. Further, Granger causality and dependence seems to be more pervasive in US states than OECD countries, possibly due to more accurate and consistent measurement of corruption and market power, and less unobservable heterogeneity in the former dataset.

Overall, this research reveals some important results regarding the linkages of three variable of interest. The study also demonstrates that combining copula approach and causality testing can provide a comprehensive way to understand the linkages. This approach can lead to incremental insights and conclusions. The insights offered here are expected to be valuable for public policy on market distortions, income distribution and economic growth.

Student Declaration

"I, Nadiah Ruza declare that the PhD thesis entitled "Income Inequality, Corruption and Market Power: An Econometric Analysis" is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

Signature Date 17 November 2018

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Chapter 1. Introduction

1.1. Background of the Study

Globally, income inequality has become a central issue in public debate and remains a defining challenge of the 21st century economy (Milanovic, 2013, 2016). Income inequality has been perceived to escalate generally due to excessive gains by the top income earners. Stiglitz and Bevan (1979) describe income inequality as an important feature to stimulate market economies. Thus, by reducing it this will have a significant impact on national income.

Corruption can be loosely described as public officer abuse for private benefit or gain. Corruption scandals occur around the globe, whether in developing countries or developed countries. Corruption is regarded as a norm in developing countries such as India, China and Nigeria (Dong, 2011). Corruption, especially in the public sector is perceived as the major problem in the development of an economic system (Kaufmann, 1997). There have been several studies (see Mauro, 1995) that identified the harmful impact of corruption-related factors on such variables as environmental quality, economic growth, social welfare and investment. Precise understanding of its causes and consequences are required to reduce corruption. Thorough investigations of corruption for both within and across countries are needed in order to develop effective anti-corruption policies. Nevertheless, the causes and consequences of corruption are still debated and less understood which makes it difficult for governments to develop effective policies to control corruption.

Next, market power has long preoccupied the economics discipline. Monopolistic markets have been considered to be one source of market power but in recent times, other forms have been examined (e.g., oligopolistic collusion, barriers to entry etc.). According to Stiglitz (1979), businesses strive to acquire some market power so they can exercise some control over market prices. The exploitation of market power can lead into income inequality in several ways. There is a large volume of published studies showing income inequality can also be viewed as a consequence of monopolies. The increase in market power has shown to have strong implications for income inequality. With higher pure profits, capitalist tend to receive a higher share of output and workers to receive a lower share. This mechanism will increase income inequality since the poorest individuals generally do not hold financial assets and individuals with higher incomes receive a larger percentage of their income as capital income. Income inequality and economic efficiency will increase if monopolies are curtailed.

Many studies have investigated the impact of income inequality on corruption and market power. A wide range of income inequality, corruption and market power measures as well as different ways of integration have been examined. In this overview, this study intends to emphasize that it is imperative to study income inequality, corruption and market power in an integrated framework.

This study provides new insights in exploring the nexus of income inequality, corruption and market power. The linkages of variables of interest are explored employing a cross-country strategy. This study provides micro level evidence for a specific country as well. Firstly, this thesis examines the theoretical background of income inequality, corruption and market power as suggested in literature in both cross-country and within-country contexts. Secondly, it comprehensively examines the empirically linkages of income inequality, corruption and market power across countries and across regions within the United States. This thesis starts the analysis by conducting bilateral relationship between two variables among the three variables to understand the issues in depth. Next, advanced approach of trivariate setting will be performed to provide complimentary insight of the three issues as a whole. In summary, this study is expected to make a substantial contribution to research on income inequality, corruption and market power, thus to add to effective public policy on these three issues.

1.2. Income Inequality

The section of this thesis will give a brief overview of the income inequality. The topic of income inequality across many countries has gained considerable attention in recent years. Income inequality shows a significant increase across the globe over the past two decades of deepening globalization. Most notable are Milanovic (2016) on *global inequality and globalization* and Piketty's (2014a) *Capital in the Twenty-First Century.*

In general, income inequality refers to how even or uneven income is distributed in society. In most advanced countries, the causes of rising income inequality are still being debated. Over the past decade most research in inequality has emphasized inequality in the context of workers' human capital, competitive markets, investors, and innovators. The changes in globalization, education and technology have promoted productivity growth by encouraging productive labour, innovation and wise investments.

Income inequality has become a central issue among economists and policy-makers. Some view inequality as important in market economies whereby its reduction can affect national income (Stiglitz and Bevan, 1979). Thorbecke and Charumilind (2002) argue that the richest individuals constitute only one-eighth of the world population but their income covers about half of the worldwide income. They also found that income inequality varies among different countries. Interestingly, some middle-income countries with relatively similar GNP per capita (Poland, Malaysia, Venezuela, Brazil, and South Africa), are characterized by very different degrees of inequality.

Next, another way to look at inequality between individuals is to look at inequality between all individuals in the world instead in the confines of a political community (nation state). This might not be relevant and important for an average individual as inequality within his nation state will gain in importance. However, once we compare ourselves with people from other parts of the world, we are indeed interested in global income distribution (Milanovic, 2013).

As compared to inequality within countries, inequality across the globe as a whole seems to have decreased and stabilized. In recent decades, fast growth in many emerging and poorer countries has lifted hundreds of millions of people out of poverty, curbing the trends observed in developed countries. Interestingly, the biggest income gains from 1988 to 2008 went to households between the 15th percentile and the 65th percentile of global income when measured at a global level (Milanovic, 2013).

A considerable amount of economic literature has been published to explain two particular issues: (i) why does inequality change over time and differ across countries; and (ii) why might the distribution of income be well-represented by a Pareto distribution (see Gabaix, 1999; Luttmer, 2007). There are several ways to measure and study income inequality. The most common measure of income inequality is the Gini coefficient. The Gini coefficient is a measure of statistical dispersion intended to represent the income distribution of a nation's population. Mathematically, this value is based on the Lorenz curve, which plots the proportion of the total income of the population that is cumulatively earned by the bottom percentage of the population. This number aimed to measure how far a country's wealth distribution deviates.

However, there are some issues when interpreting Gini coefficients. For instance, the same coefficient may result from many different distribution curves. To study income inequality, the ideal dataset should include demographic and geographical identifiers along with regular measurements of income for all individuals or households. Such information exists through income tax returns. However, many researchers are unable to access personal records; Piketty's (2014) main work on top income is stratified by percentiles. A study conducted by Roine et al. (2009) shows that for the rest of the population, periods of high economic growth disproportionately increase the rich people income share.

Finally, a third measure of income inequality is Theil's T statistic, proposed by econometrician Henri Theil as an alternative measure of population dispersity given the limitations of the Gini coefficient. This index measures an entropic "distance" the population is away from the "ideal" egalitarian state of everyone having the same income. The U.S. Bureau of Economic Analysis (BEA) uses tax records to produce income estimates for each county in the United States per annum. Given this annual data set, Theil's T can be calculated for between-country income inequality. This entropy attempts to compare the distribution of resources by intelligent market agents with a maximum entropy random distribution.

Income Inequality in OECD Countries

Richer OECD countries are considered similar in many respects. However, regarding income distribution, there are many prevailing differences. According to Molander (2016), the main justification for these distributional differences lies in economic policies. For example, tax and transfer systems can influence income distribution. Yet in most OECD countries, a clear trend toward increasing disparities in income can be seen in the past two decades alone, the difference has increased by 16 percent on average.

In most OECD countries, income equality at its highest level since 30 years (Cingano ,2014). The gap between the top percentile and the bottom percentile is at ratio 9.5:1 which could translate that the top 10 per cent of the population in the OECD countries earn 9.5 times the income of the poorest 10 per cent. This trend has been rising continuously from 1980s where this ratio stood at 7:1. The income Gini coefficient for OECD countries ranged between 0.24 and 0.49, with Slovenia being the lowest and Chile the highest. The rise in overall income inequality is not all about surging top income shares. Often, incomes at the bottom fall during downturns and grow much slower during prosperous years putting relative income poverty on the radar of policy concerns.

According to Alderson and Nielsen (2002), inequality variation in OECD countries is principally affected by the percentage of the labor force. This is followed by institutional factors such as union density. Longitudinal variation in inequality is also affected by aspects of globalization, such as direct investment outflow and southern import penetration and even by migration. To put it another way, globalization explains the longitudinal trend of increasing inequality that took place within many industrial countries better than it does cross-sectional inequality differences among countries.

Income Inequality in United States

Although income inequality is a global issue, it is particularly prominent in the United States. The rise of income inequality in the United States since the 1970s has been well documented. A wide range empirical and theoretical research has been conducted over the past twenty years in an attempt to understand the causes of this trend (Acemoglu, (2011, 2012); Song et al., 2015). In the same vein, data from several sources have identified that the United States experience was similar to other countries until the 1980s. However, the United States has continued to diverge further from other advanced economies. From 1990 to 2010, the top 1 percent's income share rising 0.2 percentage point a year on average in the United States. The gains of the top 1 percent in the USA have continued after 2010 but international data are scarce.

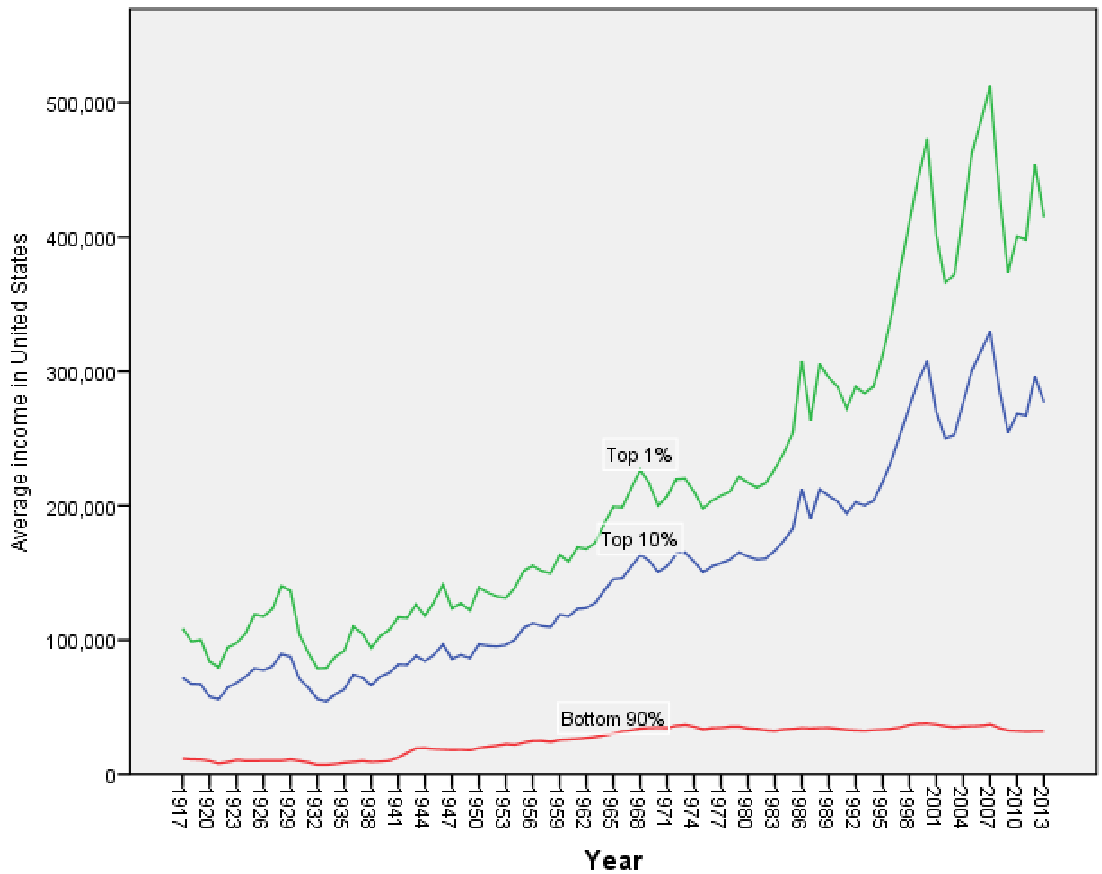

Figure 1.1 National Average Income in US[1]

It is worth noting and appreciating the macroeconomic consequences of the inequality that Piketty and his coauthors write about. Figure 1.1 applies the average income in the United States from 1917 to 2013 for the top 1 percent, top 10 percent and the bottom 90 percent of the country's population. Despite a small decrease in average income during the Great Depression in the 1930s and followed by World War II in the United States, it

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[1] *Note: This figure displays an estimate of average income in the United States for the top 1%, top 10% and the bottom 90%. Source of data are taken from Sommeiller et al. (2016) and can be found at http://go.epi.org/unequalstates2016data.*

is clear that a very large gap between the bottom income earners and top income earners can be seen across the period observed here. As the years pass, the gap between the top 1 percent, top 10 percent and bottom 90 percent widens. As mentioned by Jones (2015), much of the rise in income inequality during the last several decades is associated with labor income. Work by Galbraith and Hale (2014) in United States suggests that income inequality rises when poor counties become relatively poorer, middle income counties lose population share, and rich counties get relatively richer. Other explanations could relate to rent seeking in the next section.

1.3. Corruption

Corruption can potentially be present anywhere in the world. It can be broadly defined as the abuse of power by public officers for their own private benefit (Dong, 2011). Similarly, corruption also can be defined as private gain obtained from a public office or government office (Tanzi, 1998). This activity has always been viewed as negative and subjected to moral censure because it does not promote equal opportunity (Thompson, 1993) especially for the poor. Corruption takes place when an individual does not abide by the law and conspires with others for their private benefit.

Corruption is not only considered as a norm in developing countries, such as Nigeria, India and China, but has also been observed in developed countries. Developed countries also face the same problem such as in France, the United Kingdom and the United States. The scandals involving political machinations during the late 19^{th} and early 20^{th} centuries in large cities in the United States (Clifford, 1975) and in Britain where parliamentary seats were for sale before the Reform Act of 1832 in ‘rotten boroughs’ are among the famous historical examples of corruption (Pearce and Stearn, 2000).

There are many consequences from the pursuit of corruption. It may cause a decline in economic growth or a country’s competitiveness and may result in a decrease in government spending on health and education (Rose-Ackerman, 1999; Tanzi, 1998).

Corruption may also increase income inequality and distort a nation's market mechanism and resources allocation (Rose-Ackerman, 1999; Tanzi, 1998). To date, corruption in the public sector is typically seen as the major problem in economic development (Kaufmann, 1997). Previous studies have found strong evidence of a corruption effect on economic growth, social welfare, investment, education and even the quality of the environment (see Apergis et al., 2010; Chang et al., 2013; Dong, 2011; Gupta et al., 2002; Lambsdorff, 2002; Mauro, 1998; Tanzi, 1998).

Despite its negative impact on the economy, reducing corruption is not easy to achieve. It requires an in-depth understanding of what causes it in the first place, and its consequences. In-depth investigations and studies of corruption within and across countries are needed to ensure the effectiveness of anti-corruption policies development. However, to date, the causes and consequences of corruption remain only broadly discussed and poorly understood by research scholars (Dong, 2011).

Corruption is believed to damage economic development and hence social welfare. A considerable amount of literature stated that corruption improves efficiency and hence promotes economic growth (see Huntington, 2006). Nevertheless, most scholars argue that corruption may influence rent-seeking activities of skilled people Murphy et al. (1993), distort public investment decisions (Tanzi and Davoodi, 1998) and reduce the incentive of private investment (Bardhan and Mookherjee, 2006), thus, compromising economic growth. Furthermore, corruption has been found to have a significant impact on income distribution and increases income inequality (Gupta et al., 2002; Li et al., 2000).

Many studies have examined the negative impact of corruption on the environment. In developing countries, pollution is found to worsen with the presence of corruption (Welsch, 2004). Corruption also significantly reduces the stringency and integrity of environment policy (Pellegrini, 2011; Pellegrini and Gerlagh, 2006).

Up to now, the impact of corruption on economic growth is still debated. Previous literature reported that the act of corruption promotes economic growth. For instance, public officials can be influenced by using bribes to get things done (Huntington, 1968; Leff, 1964). As a result, the quality of civil services can be improved. Lui (1983) also found that bribes can accelerate the bureaucratic process efficiently. Nonetheless, Rose-Ackerman (1997) criticizes that in order to obtain high payments, public officials have the power to delay any transactions.

Other analyses emphasize that corruption decreases economic growth. In a corrupt society, most talented people are involved in rent-seeking activities (Murphy et al., 1993). As pointed out by Krueger (1974), these activities lower economic growth since it does not bring any benefit and positive returns to the wider society; it is only the rent seekers who benefit. In a corrupt environment, services are awarded to those offering the largest bribes, not to the most eligible or in need (Shleifer and Vishny, 1993).

Many scholars hold the view that corruption lowers economic growth. Work by Mauro (1995) found a negative association between corruption and productive investment and thus, reduced economic growth. Pellegrini and Gerlagh (2004) report that through corruption's impact on trade policy and investment, economic growth falls. Mo (2001) also provides evidence that corruption significantly hinders economic growth through channels of political instability, the share of private investment to only a few parties and the level of human capital that is utilized.

Also, corruption has been associated with economic growth in terms of the level or presence of institutional quality. Méon and Sekkat (2005) observed that particularly in countries with low quality governance, corruption has a significant impact on reducing economic growth. However, only a few studies provide evidence that in countries with weak institutions, corruption is beneficial and less harmful.

It is a widely held view that public expenditure stimulates economic growth. This expenditure includes education, science, infrastructure and many more aspects of society. In fact, health and other social services type of expenditure is known to improve public social wellbeing. Corruption may have a significant impact on public expenditure. Mauro (1998) stresses that corrupt public officials have the opportunity to increase expenditure that offers better opportunities for bribery and decreases expenditure with fewer opportunities. For example, one reason why corruption substantially leads to governments reducing education expenditure is that when compared to other spending, education provides less opportunity for bribery (Mauro, 1998). There is also evidence that corruption increases military spending by a government (Gupta et al., 2000). Tanzi and Davoodi (1998) on their work presented evidence that corruption increases large capital spending by government while reducing operation and maintenance spending.

1.4. Market power

In the literature, market power or market concentration tend to be used as an indicator of market performance (Sung, 2014). In order to assess the level of market competitiveness, market concentration indices such as the Concentration Ratio (CR) or the Herfindahl-Hirschman Index (HHI) are often considered. A market is regarded as moderately concentrated by the United States antitrust authorities if it has a HHI value between 1500 and 2500. It is highly concentrated if the value surpasses 2500 (U.S. Department of Justice and the Federal Trade Commission, 2010).

According to Stiglitz (1979), businesses strive to acquire some market power so they can exercise some control over market prices. The Competition Bureau Government of Canada (2012) has listed three market power abuses. First, anti-competitive behavior that attempts to block or eliminate potential competitors entering the market. Second, business practices seek to diminish competition by taking over a rival's suppliers, overstepping authority granted by intellectual property rights or by stopping consumers changing suppliers by using long-term contracts. Third, the capacity to set prices beyond competitive levels by means of a monopoly or collusion with other large firms.

A change in market power has a significant impact either on the severity of the consequent market disruption or the probability of a firm's distress (Cetorelli et al., 2007). Work done by Cetorelli et al. (2007) on the United States over the last decade shows that its financial market structure has no specific pattern of high and increasing level of market power. On this theme, the broad use of the term *stable market* is sometimes equated with a market that does not collapse while enduring shocks to demand or supply (Cetorelli et al., 2007). There are many factors that drive a market to experience shocks, for example: shifts in demographics, technological innovation, regulatory changes and knock-on effects from shocks to other economic sectors or markets. Cetorelli et al. (2007) found that the level of concentration of a market does not impact on the stability of the market.

Banks in concentrated markets are found to be motivated to reduce risk (Hellmann et al. 2000; Keeley, 1990). High concentration typically relates to low levels of competition and high levels of profitability. Thus, banks' franchise values will increase and reduce the equity holders' incentives to engage in excessive risk-taking behavior. Allen and Gale (2000) and Carlin et al. (2004) argue that a market that is concentrated and has only a few large players is usually stable as few firms cooperate optimally as oligopolists.

Previous studies by Hou and Robinson (2006) and Arrow (1962) in the United States found that dominant companies operating in concentrated industries have low innovation levels, are protected from competitive pressures and therefore experience lower stock returns and profitability. This contrasts with Gallagher et al. (2013) who found a significant relationship between market power in Australia with innovation expenditure. Market power is not necessarily bad. Work by Gallagher et al. (2013) in Australia found that significant risk-adjusted excess stock returns can be generated by big firms operating in concentrated industries, compared to firms operating in less concentrated industries. They also found that big firms invest at least three times more in innovation than small firms. Thus, a significant positive relationship can be seen between concentration and expenditure in innovation.

Technological progress can also account for increases in inequality (Autor, 2010). This study has shown that technology can most readily replace labor in tasks that are easily automated. In 1962, Arrow pointed to some ways where innovation is one of profitable investment in a perfect competitive market and big monopolists are inefficient in implementing innovation due to their size and technological inertia (capital investment in current technologies). Compared to smaller firms, these dominant companies will receive lower investment return from innovation. Thus, they are not motivated to invest in innovation and new innovation and industry technologies are driven by smaller competitors. Prior to Arrow's contention, Schumpeter's theory of monopoly profits and innovation stated that monopoly economic rents can be used by big firms in concentrated industries with market power to promote and fund innovation (Schumpeter, 1942).

1.5. Aim of the Thesis

Income inequality refers to how unevenly income is distributed in a society. Income not only can be defined as the wages and salaries received, but also dividends, rents, and state benefits, such as public pensions. In most advanced countries, the causes of rising income inequality are still being debated. While a variety of definitions of corruption has been suggested, this study will define corruption as the abuse of government office or public power for private gain and benefit. Based on this definition, it should not be concluded that within the private sector, corruption activity does not exist. It does exist and exert its influence in government regulated private activities or large business enterprises. Also, market power can be defined as a firm's ability to influence the whole market of a product. Market power could be related to the amount of influence that a firm has on the industry in which it operates.

Apart from technology-induced changes in skills and innovations, corruption and market power can also be a key driver of income inequality or vice versa. There is no doubt that the former and some activities attributed to the latter (e.g. IP rights and patents) have a positive impact on growth and productivity (e.g., wage and skill dispersion). However this study is more concerned about the linkages of income inequality, corruption and market power.

In recent years, there have been several investigations into the linkages between income inequality, corruption and market power. The causal relationship between these variables of interest and the direction of causality has been addressed by many researchers. Some argue that greater income inequality is caused by the increase of corruption and market power. There is imbalance effect on low income individuals who pay a larger proportion of their incomes in the form of bribes than high income individuals. This also applies in market power context. Some researchers find that corruption affects indirectly the redistributive role of government via taking government resources away from programs (i.e., health and education services) that benefit mostly low income individuals. Contrarily, greater income inequality may as well lead to the increase of corruption. Corruption tends to occur by high income individuals compared to low income individuals as the former have more resources to engage in bribery and opportunities. The number of low income individuals who are deprived of services provided by the government increases as income inequality increases. In turn, these individuals potentially become easy targets of bribery.

This study will employ datasets from OECD countries and states data from United States. Results obtained from this study may serve as a guideline for government policy-makers and business leaders from the countries involved. From a theoretical perspective, the results of this empirical study may point to future directions for research. In view of the importance of the research questions and the research gaps, the time-series horizon will cover the period from 1977 to 2014.

This thesis starts the analysis by conducting bilateral relationship between two variables among the three variables to understand the issues in depth. Next, advanced approach of trivariate setting will be performed to understand the income inequality, corruption and market power issues as a whole. Overall, the empirical study finds that there is a relationship between income inequality, corruption and market power. Between these three variables, most discernible is the strong relationship between income inequality and corruption, as compared to other pairs.

These findings make several noteworthy contributions to policy implications. The results have a significant implication on policy. Considering the bidirectional or one way directional from the causality between income inequality, corruption and market power, new policy could be introduced.

1.6. Research Objectives

This study will serve several objectives.

I. A better understanding of income inequality internationally (OECD countries) and across selected US states.

II. Investigate the causal links between corruption, market power and income inequality. Further, explore the potential nexus between corruption and market power, and their relative impact on income inequality.

III. Utilize econometric causality testing and copula techniques to estimate possible linkages.

Thus, this research seeks to address the following questions:

I. Does corruption or market power link systematically to income inequality?

II. What insights do causality and copula analyses provide for such potential linkages?

1.7. Research Significance

Contribution to Knowledge (Academic Contribution)

This study aims to contribute to the literature on income inequality and rent-seeking. The key hypothesis examined is that market power and/or corruption drive income disparities or vice-versa. A better understanding of these relations will help provide crucial information for future policies on income distribution and global development. Recent econometric techniques of the copula approach and causality tests will be employed to investigate these linkages.

This study empirically explores the linkages between income inequality, corruption and market power. The results from this research will enhance current knowledge in several ways as follows:

- The effect of corruption and market power on income inequality and vice versa.
- Structural changes in the causal linkages between income inequality, corruption and market power.
- The differences with respect to (1) and (2) between developed countries and across states in United States.

Contribution to Practice (Practical Contribution)

- This study empirically explores the linkages between income inequality, corruption and market power. The results from this research will enhance current knowledge on several issues:
- The effect of corruption and market power on income inequality and vice versa.
- Structural changes in causal linkages between income inequality, corruption and market power.
- The differences with respect to (1) and (2) between developed countries and across states in United States

1.8. Thesis Structure

This thesis mainly focuses on exploring the links between income inequality, corruption and market power in OECD countries, and provides a detailed analysis across states in the United States. This study is organized as follows.

The first part of the thesis is Chapter 1, where an introduction of the topic is presented. This is followed by Chapter 2 which consists of the literature review, then Chapter 3 describes the data used in this study as well as the theory and background of the econometric approach that have been employed. Chapter 4 presents the stylized facts on inequality, corruption and market power as they have evolved in OECD countries and the USA at the state level since the early 1980s. Chapters 5, 6 and 7 discuss the linkages of income inequality, corruption and market power in both cross-country and within one country, specifically the United States, employing both copula and casuality analysis. Specifically, Chapter 6 examines the links between all three variables of interest in cross-countries studies. Both chapters later compare these linkages between OECD countries. Chapter 7 examines the linkages between income inequality, corruption and market power specifically within the United States. Finally, Chapter 8 concludes the thesis with a summary of the main findings and brief remarks on study limitations and future research.

Chapter 2. Literature review

Chapter 1 provides a brief overview between income inequality, corruption and market power. In addition, it is important to ask how these variables related to each other. This raises questions about the linkages between income inequality, corruption and market power based on the previous literature which will be discussed in this chapter. The study offers some important insights between these three variables. Reflecting the actual literature, the review here discusses bivariate linkages between income inequality, corruption and market power. At the end, we identify some of the limitations in the literature that give impetus to this present study.

2.1. Income Inequality and Corruption Linkages

In recent years, the connection between income inequality and corruption has been examined in several empirical studies and has been an ongoing topic of debate. Huang (2013), Dincer and Gunalp (2012), Gupta et al. (2002), Gyimah-Brempong and Samaria (2006), Jain (2001) and Johnston (1989) suggest that corruption directly increases the level of income inequality. Comparably, Gupta et al. (2000) and Tanzi and Davoodi (1998) suggests that corruption only benefits high income people and changes the distribution spending to social welfare spending. However, Dobson and Ramlogan-Dobson (2010) in their studies on Latin America suggest that less corruption is associated with higher income inequality, a negative relationship. Similarly, income inequality does not generate the right incentives and directly have an impact towards corruption. It is showed that individuals have an incentive to divert their efforts towards securing favored protection and treatment which resulting corruption and resource misallocation (Dabla et. al.,2015).

In examining the causal links between income inequality and corruption, it is important to know the impact of income inequality on corruption and the reverse. Income inequality is considered fair when generated by productive activity and a greater contribution to society. However, income inequality that is generated by corruption activity is unfair. Stiglitz (2012) suggests that much high income may have been achieved by practising successful rent-seeking activities such as corruption. Corruption not only undermines competitiveness but may also lead to government spending cuts on programs that mostly benefit low-income groups (Chetwynd et al., 2003; Rose-Ackerman, 1999; Tanzi, 1998). Thus, this activity may also result in an increasing gulf between the rich and poor.

Income inequality may also influence corruption in several ways. When this activity diverts government spending that mostly benefits low-income groups away from them, it is likely to raise poverty by reducing the income potential of the poor (Chetwynd et al., 2003; Tanzi, 1998). This situation creates space for corruption both for the high-income and low-income individuals. Chetwynd et al. (2003) demonstrated that in certain countries low-income individuals spend a high proportion of their income on corruption activity such as bribes in order to survive, while high-income individuals take this opportunity to become richer. A study by Huang (2013) in Asian countries suggest that income inequality leads to an increase in corruption.

The level of inequality is higher among city populations of business employment. The size distribution of cities and firms are also stable when compared to the sharp rise in the United States' top income inequality (Jones, 2015). Work by Glaeser and Saks (2006) in the US found that as corruption increases, economic growth decreases. This is in line with the work by Fisman and Svensson (2007) in Ugandan firms where they found a negative association between bribery and firm growth. Cai et al. (2009) in their analysis on China discovered that corruption weakens firms' performance.

Finally, low wages of public officials is a major key driver of corrupt acts or behaviors (van Rijckeghem and Weder, 2001). Furthermore a significant causal relationship between the act of corruption and income level is evident (Treisman, 2007). Countries with educated and richer citizens are found to be less corrupt since the public is made aware of official malfeasance or incompetence. The effectiveness of the legal system for each country also affects the probability of being exposed. For example in Britain, the common law systems protect the property enforcement and rights more effectively than civil law systems (La Porta et al., 1999). Thus, common law countries have a higher probability of people being caught acting corruptly (La Porta et al., 1999; Treisman, 2000).

Another reason corruption occurring is related to economic and social heterogeneity factors. As income inequality increases, the poor are more easily blackmailed by the rich (Jong-sung and Khagram, 2005). Thus, for private gain, the rich can abuse their power and level of influence over others. As a result, the level of corruption increases, although Husted (1999) finds no significant causation between corruption and income inequality.

It is widely known that zero tolerance for corruption is prerequisite for economic growth. In contrast, to date, only a few empirical studies have studied links between corruption and income inequality. Using data from a mixed group of countries (i.e., low, middle, and high-income), Li et al. (2000) and Chong and Calderon (2000) find an inverse U-shaped relationship between corruption and income inequality. Both studies find a positive relationship in high-income countries and a negative relationship in low-income countries. On the other hand, Gupta et al. (2002), using a smaller sample of countries, finds a positive and linear relationship between income inequality and corruption.

Although these studies present persuasive evidence regarding the effects of corruption on income inequality, none of them addresses the issue of causality in the Granger-sense between corruption and income inequality. The underlying assumption in these studies is that the direction of causality is from corruption to income inequality. However, as alluded to earlier, it is very likely that the direction of causality is from income inequality to corruption. Uslaner (2006) argues that income inequality provides the basis for corruption, which in turn, leads to greater income inequality. According to Jong-sung & Khagram (2005), individuals who belong to high income groups have more opportunities and resources to engage in corruption.

People in low- and middle-income groups are unable to combat the spread of corruption, no matter how motivated they are, due to the lack of resources. As income inequality increases, a greater number of low-income individuals become susceptible to bribery in order to secure access to various government services. The issue of the link between income inequality and corruption has also been addressed by Chong and Gradstein (2007) and Apergis et al. (2010). They found bidirectional causality between income inequality and corruption. To this end, there is strong evidence for a relationship between inequality and corruption.

It is increasingly recognised that the fight against corruption is necessary for economic growth. However, there are only a few empirical studies that focus on causality between income inequality and corruption. According to Gupta et al. (2002), the benefits from corruption are likely to accrue within the high income groups than lower income groups. Corruption favours the ‘haves’ rather if the stakes are large than the ‘have nots’ particularly Johnston (1989). Corruption has shown to distort the redistributive role of government in that only the better connected individuals get the most profitable government projects according to Tanzi (1998). The government is seemed unable to make the economic system more equitable to all and improve the distribution of income.

Li et al. (2000) and Chong and Calderon (2000) showed an inverse U-shaped relationship between income inequality and corruption using data from a mixed group of countries (i.e., low, middle, and high-income). Both studies find a negative relationship in low-income countries and a positive linkage in high-income countries. Moreover, Gupta et al. (2002) find a positive and linear relationship between income inequality and corruption using a smaller sample of countries.

There has been studies present strong evidence regarding the effects of corruption on income inequality. However, there is no systematically addresses the issue of causality in the Granger-sense between income inequality or corruption under bivariate and trivariate setting. Most of the studies work based on the underlying assumption that the direction of causality is from corruption to income inequality. However, as referred before, it is very likely that the direction of causality is from income inequality to corruption. Uslaner (2006) explained that income inequality provides the basis for corruption, which in turn, leads to greater income inequality. The high-income groups have resources and opportunities to engage in corruption according to Jong-sung and Khagram (2005). In contrast, low- and middle-income groups are unable to engage with the corruption, no matter how motivated they are, due to the lack of resources. There a significant number of low-income individuals subject to bribery in order to secure access to various government services as income inequality increases.

Chong and Gradstein (2007) employ a panel dataset of more than 100 countries based between 1960 and 2000 to address the issue of causality between corruption and income inequality. Their empirical results support the presence of bidirectional causality between income inequality and corruption. While Apergis et al. (2010) empirically explore the causal relationship between income inequality and corruption using a panel dataset of all 50 United State states.

The debate on income equality and corruption has regained prominence. This study aims to fill the gap in existing literature using new data and empirical methodology.

2.2. Income Inequality and Market Power Linkages

The relative importance of income inequality and market power has been subject to considerable debate. The existing literature offers a set of results for the time-series and cross-national variations in income inequality. It is apparent from a different study that reports the levels of inequality could be a drive from market conditions such as economic growth, unemployment, female participation in the labour market, and openness to trade flows. However, there is no doubt about the significance of political and institutional factors which could relate to market power, the nature of wage bargaining, government partisanship, the power of unions or the generosity of the welfare state in determining the patterns and levels of income distribution (Kus, 2012).

Recently, it has been suggested the importance of market power to the income inequality. There is a need for a well-functioning economy. Otherwise, the firm with a strong market power tends to sell goods at higher prices in the absence of competitive pressure. The exploitation of market power by a certain company may impact on income inequality in several ways. This activity may affect competition in the marketplace (Pettinger, 2011). A company with market power would be able to control market price for its own benefit and create income re-distribution between shareholders of monopolies and customers. Monopolies or oligopolies may also employ fewer people than in more competitive markets and result in a higher rate of unemployment and inequality (Cotterill, 1986).

The changes in labour bargaining power could affect potentially the interaction of inequality. These findings further support the idea of bargaining power of the poorest workers have decreased. In contrast, the bargaining power CEOs and highest educated have increased. With the workers are taking a smaller portion of the profits and CEOs a larger portion, this would also make the income inequality more diverge.

Further, widening income inequality could has significant implications for economy stability and growth. It able to concentrate political and decision market power in the hands of few. This could raise crisis risk and lead to economic instability and suboptimal use of human resources (Dabla et al. 2015).

According to Khan and Vaheesan (2017), market power can be a powerful mechanism for transferring wealth from the middle and poor classes to the few belonging of rich. The monopoly pricing on goods and services able to turn the disposable income of many into recurring income , capital gains and executive compensation for the few. The aggregate wealth transfer effect from pervasive oligopoly and monopoly power is a serious problem.

The study between inequality and market power relationship has not been conducted extensively to this date. There is only few attempts to explore this linkage empirically (see (Kremp, 2012; Lin and Tomaskovic-Devey, 2013). This might be largely due to the scarcity of cross-national and time-series data on market power and inequality. This paper attempts to mitigate this and utilize new panel data sets.

In conclusion, most studies between this pair have been carried out in a small number of areas. This study systematically uses new data and advanced methodology to expand our understanding of the inequality-market power nexus. Consequently, introducing market power as a third causal factor may assist towards a more comprehensive understanding of the relationship between corruption and income inequality.

2.3. Corruption and Market Power Linkages

Corruption and market power are key drivers of income inequality, and they may also affect each another. One impact of market power on corruption is that it may diminish competition. Rather than competing, some big or powerful firms may find it much easier to maintain their power by engaging in corruption. Powerful firms can also afford to lobby politicians to introduce policies that benefit them (e.g., subsidies, tax credits, regulations that increase barriers to competition, etc.). Existing literature has yet to fully examine the linkages between income inequality, corruption and market power as a whole. The proposed study aims to fill the gap in the present literature. Work by Mauro (1998) has documented significantly distorted public investment and reduced public expenditure on education. He found that in order to collect bribes easily, corrupt politicians increase public expenditure.

A recent study by Khan and Vaheesan (2017) stated instead of regressive redistribution in the marketplace, market power gives firms huge political clout. In a system with few campaign finance constraints and circling door between industry and government, large business have huge power over politics. They can utilize their power to push regulators and legislators to lock their existing gains and lobby for policies which could be associate with a serious corruption.

There has been a wave of empirical studies on the causes and consequences of corruption since the beginning of the 21st century. Jain (2001) describes three key aspects for corruption taking place as follows: a) government officials have discretionary power; b) discretionary power by officials that is linked to economic rents; and c) low deterrence to corruption. There are various ways to reduce corruption which have been documented. Corruption may be curtailed by raising the possibility that corrupt acts are identified and punished, people are better educated, more media reporting on corruption, and high levels of economic development (Treisman, 2000). With these strategies in mind, the discretionary power of public officials is found to affect acts of corruption (Dong, 2011) and it arises when regulations are being enforced (Rose-Ackerman, 1999). The discretion to distribute resources is often assigned by public officials themselves when setting and executing regulations. More regulations lead to the increase of discretionary power. As a result, corruption increases.

By contrast, marketwise controlled economies also may decrease the level of corruption. Decentralization also has an impact on governmental discretionary power. However, to date, little evidence has been found for an association between corruption and decentralization. Decentralization is known to reduce bureaucratic profits from corruption by introducing competition between local institutions (Brennan & Buchanan, 1980; Weingast, 1995). Discretionary powers without economic rents are most unlikely to influence the act of corruption. Yet, acts of corruption are generated by economic rents that are related to discretionary powers (Dong, 2011). Work by Ades and Di Tella (1999) shows that countries tend to be more corrupt if they consist firms with high rents. Natural resource abundance also plays an important role in corruption (Leite & Weidmann, 1999). Natural resource abundance increases economic rents; yet, trade openness as a proxy for economic competition decreases the economic rents (see Ades & Di Tella, 1999; Fisman & Gatti, 2002a, 2002b).

Historical influences also have impacted on corruption activities in certain countries (Treisman, 2000). Freedom of the press is another critical factor for deterring corruption. Independent journalists are more likely to investigate, detect and report corruption and this discourages it when people are caught (Adsera et al., 2003; Brunetti & Weder, 2003). A considerable amount of literature found that the greater the press freedom, this leads to a decline in the level of corruption (Brunetti & Weder, 2003; Chowdury, 2004; Freille et al., 2007).

Gupta et al. (2002), among others, argue that the benefits from corruption are likely to accrue to individuals who are better connected with high income groups in society. Previous studies have reported corruption favours the wealthy group rather than poor particularly if the stakes are high (Johnston,1989). It has been suggested that corruption distorts the redistributive role of government in that only the individuals get the most profitable government projects (Tanzi,1998). It is therefore less likely that the government is able to improve the distribution of income and make the economic system more equitable.

In short, the empirical literature provides evidence regarding the volatility of the relationship between corruption and market power. This indicates a need to understand the various perception of this pair. This account seeks to understand this relationship.

2.4. Limitations of the Existing Literature

A review of the existing literature suggests that corruption and market power may cause income inequality or the reverse. Figure 2.1 depicts the conceptual framework for the proposed study.

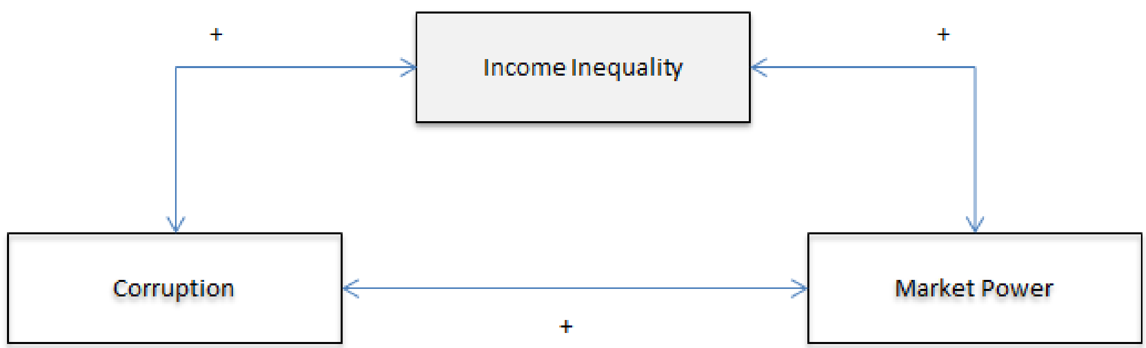

Figure 2.1 Conceptual Framework

Three empirical models were developed in this study to investigate: i) the nexus between income inequality and corruption; ii) the nexus between income inequality and market power; and iii) the nexus between income inequality, corruption and market power. In examining these relationships, previous econometric models in the literature are reviewed to determine the links between the dependent and independent variables.

A large and growing body of literature has investigated the linkages between income inequality and rent-seeking (see Apergis et al., 2010; Dincer and Gunalp, 2012; Gyimah-Brempong and Samaria, 2006; Krueger, 1974; Lambsdorff, 2002; Rose-Ackerman, 1999). However, there is no yet clear direction of causality between income inequality, corruption and market power. This study consequently aims to advance the literature by exploring the links between income inequality, corruption and market power by using modern econometrics for both developed and developing countries. This proposed study differs from these existing studies in several respects. There is not yet a clear direction of causality and there is little research that simultaneously explores these three main factors. Most of the research only explains the level of dependence between only two of these issues (see Atkinson et al., 2011; Chong and Gradstein, 2007; Galbraith and Hale, 2014; Glomm and Ravikumar, 2003; Huang, 2013; Rillaers, 2001; Sylwester, 2002). By exploring these three main issues, this study hopes to contribute to existing knowledge.

Next, the application of causality testing and copula analysis will be used in an attempt to understand the linkages between income inequality, corruption and market power. Corruption and market power do not always cause income inequality, but the reverse is possible. Causality analysis will be employed to understand the causation between these three main issues. However, this analysis does not allow information on the total correlation of variables of interest (Chong and Gradstein, 2007). Thus, the copula approach will be applied to overcome and complement causality analysis.

Finally, over the last four decades, major developments have taken place in the global economy, such as increased trade, financial liberalization, political and institutional interdependence between bodies in different countries. Thus, it is important to allow for structural changes in the linkages between corruption, market power and income inequality. Therefore, this study will draw on recent advances in econometrics to account for possible structural changes.

Chapter 3. Data & methodology

This chapter provides an overview of the data sources and empirical measures constructed here for the key variables of interest; that is, income inequality, corruption and market power. The choice of data is driven entirely by the ability to achieve a wide coverage of economic activity and to cover the longest possible period of time. The chapter also outlines the methodology adopted in this study with a description of the causality and copula techniques employed.

3.1. Data and variables

3.1.1 OECD Trend Data

This study uses annual data from 26 OECD countries covering the period from 1984 to 2014. The totals countries are then divided into two different categories which are low developed OECD countries and high developed OECD countries. The countries are classified on the basis of vulnerability to debt crisis among OECD countries, such as the PIIGS countries. The countries and categories are:

Table 3.1 OECD Countries

Low developed OECD countries	High developed OECD countries	
Chile	Australia	Republic of Korea
Greece	Austria	Luxembourg
Ireland	Belgium	Netherlands
Mexico	Canada	Norway
Portugal	Germany	New Zealand
Turkey	Denmark	Sweden
	Finland	United States
	France	Spain
	United Kingdom	Israel
	Japan	Italy

The comparison between groups based on growth rates will provide more insightful information. All of the variables are standardized prior to empirical analysis, except in the next chapter where variables remain untransformed for transparency and comparison with the literature. The data in Chapter 4 are also weighted by national population to minimize errors and accurately reflect the whole population.

Income inequality

Gini coefficient or also known as the Gini index, is the most frequently used measure in modern research. It was first introduced in the early 1900s by Corrado Gini, an Italian statistician and sociologist. The Gini index measures the expected difference between the actual distribution of wealth or income and a completely equal distribution. A Gini index is a score between 0 and 1. A 0 score expresses the income distribution to be completely equal and 1 score indicates all wealth or income is control by a single person. In OECD countries, the Gini index typically varies between 0.2 and 0.4.

This study uses the Gini coefficient as a proxy for income inequality and is extracted from Standardized World Income Inequality Database (SWIID) version 5.1 (Solt, 2016). The SWIID provides comparable Gini indices of net and gross income inequality for 174 countries from 1960 to the present day, along with estimates of uncertainty in these statistics. This database maximizes the comparability of income inequality statistics for the largest possible sample of countries and years and so is better suited than existing income inequality datasets for use by scholars engaged in broadly cross-national research. Further, another advantage of the SWIID data set is that it offer an explicit estimate of the measurement error related with the imputation required to generate comparable data (Berg et al., 2007).

There have been many income inequality cross-sectional datasets available over the past 50 years (Solt, 2009). Among the two leading datasets are the Luxembourg Income Study (LIS) and dataset developed by Deininger and Squire (1996). However, both datasets have certain limitations. The LIS dataset is regarded as the best dataset on income inequality for comparable cross-countries research. It provides reliable microdata of national household income surveys and uses a uniform set of assumptions and definitions to calculate income inequality statistics. The limitation of LIS data is that it covers the world's thirty leading countries with only five-year periods being observed. The dataset devised by Deininger and Squire (1996) offered many observations and combined many earlier datasets. The downside of this dataset is that it does not compare countries or across the period due to different income definitions and reference units.

In this study, Gini indices of net income is employed. This measurement is based on the estimation of Gini index of inequality in equalized (square root scale) household disposable (post-tax, post-transfer) income.

Corruption

This study applies the Bayesian Corruption Index (BCI) (Standaert, 2014) version BCI 2014 to represent the level of corruption. The two most influential corruption perception databases are the Worldwide Governance Indicators (WGI) published by the World Bank and the Corruption Perception Index (CPI) published by Transparency International.

BCI can be considered to be an improvement when compared to the standard corruption perception index, CPI. BCI extends the methodology of the WGI by applying Bayesian Gibbs sampler algorithm approach to fully utilize the time-structure present in corruption data and combining indicators of corruption. This approach significantly expands the period and coverage in predicting the level of corruption. Also, the BCI index overcomes selection bias issues suffered by CPI. In comparison with both CPI and WGI, BCI estimates are also more stable and have smaller confidence intervals by effectively removing random measurement errors. The BCI index values ranged between 0 and 100, where a higher index indicates a greater corruption level. Zero represents absolutely no corruption while 100 corresponds to the highest possible level of corruption.

Further, CPI will publish a ranking of countries based on their level of corruption. Though, these rankings have been criticized for being very sensitive to the smallest of differences in the actual scores of countries. The ranking of the countries in the BCI dataset only uses these significant differences to overcome this problem (Standaert,2015). An increase in the BCI index resultant to a rise in the level of corruption.

Market power

Market power measurement is a central issue for various policy decisions relating to taxation, redistribution or antitrust enforcement. While for antitrust policies, understanding of market power in a directly specified market may suffice, redistributive plans call for such knowledge for the entire economy. In a globalized and an integrated world, we need information on market power for the entire world for better understanding. In spite of its primary significance in understanding the health of an economic, little is known about the evolution of market power in virtually all economies, let alone at the global level.

Over the past 20 years, work done by Piketty and Saez (and their co-authors, Atkinson and Zucman) changed fundamentally the current understanding and knowledge about income inequality. Their main contribution is providing new insights about income inequality in addition to new data on wealth and capital. Piketty proposes a framework to describe and identify underlying forces that may have an impact on wealth and inequality which could be related to the market power. In Piketty's data, the labor share is simply one minus the capital share (Jones, 2015). However, the data on labor share is limited for the years and complicated for the countries level. This brings us to consider the number of union memberships to represent market power.

This study considers inverted union membership as a proxy of market power which adapts the theory developed through Piketty's (2014) model of inequality. Union membership has an inverse relationship with the market power (ie., lower membership means greater market power for employers). Data is taken from Trade Union Edition

2016. Based on the OECD Labour Force Statistics, trade union density could relate to the ratio of sssalary and wage earners that are trade union members, divided by the total number of salary and wage earners. The calculation of density is based on administrative data adjusted for non-active and self-employed members otherwise and survey data. Data are presented from 1980 annnd expressed in percentages.This data is covering the years between 1984 and 2014.

The data can be extracted from https://www.oecd-ilibrary.org/employment/data/trade-unions/trade-unions-trade-union-density-edition-2016_fbf99961-en

3.1.2. United States by States Data

The disadvantages experienced by cross-national studies, such as difference in measurement or unobservable institutional diversity, can be avoided if we use within-country objective data. This study uses annual data from 50 states in the United States covering the period from 1977 to 2014. The 50 states are then divided into three different regions based on percent change of economic growth from 1977 to 2014. The comparison between groups based on the growth will give better measurement and insightful information rather than group the states in US based on its regional. The regions and its states are:

Table 3.2 States in US

Less than 500 percent economic growth change from 1977 to 2014	Between 500 percent and 550 percent economic growth change from 1977 to 2014	More than 550 percent economic growth change from 1977 to 2014
Arkansas	Alabama	Alaska
Connecticut	Colorado	Arizona
Louisiana	Georgia	California
Maine	Iowa	Delaware
Massachusetts	Kansas	Florida
Minnesota	Kentucky	Hawaii
Nebraska	Maryland	Idaho
New Hampshire	Mississippi	Illinois
New Jersey	Montana	Indiana
New York	North Carolina	Michigan

North Dakota	Pennsylvania	Missouri
Oklahoma	South Carolina	Nevada
Rhode Island	Texas	New Mexico
South Dakota	Washington	Ohio
Tennessee		Oregon
Vermont		Utah
Virginia		West Virginia
Wyoming		Wisconsin

Using data from the United States on a state-by-state basis is quite advantageous for a variety of reasons. First, it minimizes the problems associated with data comparability often encountered in cross-country studies related to income inequality, corruption and market power. The data are more comparable than those across different countries. Second, it allows a consistent approach to measurement and very homogeneous institutions of interested variables to be used. All series are standardized prior to empirical estimation commences, except in the next chapter where variables remain untransformed for transparency and comparison with the literature. The data in Chapter 4 are also weighted by state population to minimize errors and accurately reflect the whole population.

Income inequality

This study uses the top 10% income shares as a proxy for income inequality as devised by Sommeiller et al. (2016). This database extends the work of Atkinson et al. (2011) from 1917 to 2013 for each of the 50 states plus the District of Columbia and 916 metropolitan areas and 3,064 counties. To remain consistent with the most current national data from Atkinson et al. (2011) all figures are in 2014 dollars. The data can be extracted from http://go.epi.org/unequalstates2016data.

Sommeiller et al. (2016) applied Pareto distribution to extract estimates of incomes at specific points in the distribution of income by knowing: firstly, the amount of income; and secondly, the number of taxpayers. The points in the distribution of income include the 90th, 95th, and 99th percentiles. With these threshold values, the average income of taxpayers with incomes that lie between these ranges, such as the average income of taxpayers with incomes greater than the 99th percentile is then calculated.

Corruption

Corruption is measured by the number of government officials convicted in a state of crimes related to corruption in a specific year. The data covers a wide range of crimes including wire fraud and election fraud. It is extracted from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section". This states conviction data has been used to measure corruption in several studies, for instance Dincer and Gunalp (2008) and Apergis et al. (2010). Following Apergis et al. (2010) to reduce heteroskedasticity, this study deflates the number of convictions by state population. The greater index corresponds to higher corruption level.

However, this study faces a problem concerning limitations for this data. This data captures both corruption and prosecution data. The main concern for this data is that prosecutions are caused by many factors. Corruption may not have led to prosecution; but not because it is not corruption. This data also is based on federal public corruption convictions and does not include the corruption cases tried by state and local prosecutors. Nevertheless, the number of convictions is a good measure of corruption in a state and at least provides the evidence for a culture of corruption in each state (Apergis et al., 2010). This measure of corruption is valid because results obtained by all of the empirical studies use the same measure are supported by theory. This corruption measure also is not related to prosecutorial resources in a state since the data are from convictions resulting from federal prosecutions.

Market power

A wide range of market power measures has been investigated by previous literature. This study considers Concentration Ratio (CR) as a parameter for measuring the degree of market concentration. Concentration ratios sum the market shares of the largest x firms in industry. The Concentration Ratio is:

$$CR_i = \frac{EMPi}{TOTEP} \tag{3.1}$$

Where i indicates each state, $EMPi$ indicates state employment, and $TOTEP$ indicates total employment in each state, respectively.

The Concentration Ratios in this study is defined as the percentage of employment by Parent Firms employing more than 5,000 people. The closer a market is to being a monopoly, the higher the market's concentration (and the lower its competition). It approaches zero when a market is occupied by a large number of firms of relatively equal size.

There are several ways to measure concentration and such example is the Herfindahl-Hirschman Index (HHI). HHI refers to the relative size distribution of the firms in a market. The value of HHI increases both as the disparity in size between those firms increases and as the number of firms in the market decreases.

The HHI index is:

$$H = \sum_{i=1}^{N} s_i^2 \tag{3.2}$$

where s_i is the market share of firm i in the market, and N is the number of firms. A small index indicates a competitive industry with no dominant players. If all firms have an equal share the reciprocal of the index shows the number of firms in the industry.

Next is the Lerner Index - a straightforward measurement of a firm’s profits:

$$L = \frac{p - c}{p} \tag{3.3}$$

where *L* is refer to index coefficient, *c* is the firm's marginal cost of producing the good and *p* is the price at which a firm sells a particular good. This calculation avoids the difficulties inherent in choosing the relevant group of firms and products that comprise a given market or industry. The Lerner Index has been criticized for its viability as a practical tool despite its theoretical attractiveness. This measurement often fails to reflect the competitive realities of a market.

Apart from various alternative ways to measure market power, Concentration Ratio fits most of the data of this study. Data are extracted from Business Dynamics Statistics (BDS) from the United States Census Bureau. This data is compiled from the Longitudinal Business Database covering the years between 1976 and 2014. The BDS includes firm startups, measures of establishment openings and closings, job destruction and creation by firm size, age, and industrial sector, and several other statistics on business dynamics. It provides annual statistics on gross job losses and gains by industrial sector and state.

Despite the large coverage of this data across states in the United States and years, this study faces certain data limitations. The firm size groups that are extracted from BDS are in terms of employment but by the Parent Firm at the national United States level. All firms employing the same number of workers in the state are treated differently when calculating on the basis of state employment. However, a firm that employs a few workers in a specific state may be part of a Large Firm (nationally) where the parent firm may employ numerous people. That particular firm will be included in the large "Firm Size" group (more than 1000) but it may employ not many workers. Thus, when Concentration Ratios are calculated, this firm will reduce the CR ratio and may mask the possibility that other firms in the same group may be very large. However, because of this or other firms such as this one, the CR will be smaller than what it should be.

Another limitation of this data that needs to be addressed is the CR series is based on employment which is problematic because employment can fall even if the market power stays the same or increases. In other words, workers are replaced by machines but the share of output can increase. Finally, the particular BDS definition of firm size based on national employment prevents the construction of a HHI while a Lerner Index is not feasible at all, given the unavailability of data on specific prices and firm costs.

3.1.3. Summary of Data

A dataset of 26 OECD countries namely Australia, Republic of Korea, Austria, Luxembourg, Belgium, Netherlands, Canada, Norway, Germany, New Zealand, Denmark, Sweden, Finland, United States, France, Spain, United Kingdom, Israel, Japan, Italy, Chile, Greece, Ireland, Mexico, Portugal and Turkey, has been used in this study to explore the linkage between income inequality, corruption and market power.

Annual data for 1984 to 2014 periods has been gathered from different sources. As shown in Table 3.3, the variable INEQ denotes income inequality, CORR indicates corruption, and MPOW indicates union membership as a proxy of marker power, respectively.

The variables are employed in natural logarithm forms. Thus, the natural logarithms of INEQ, CORR and UNION are used as proxies for income inequality, corruption and market power, respectively.

Table 3.3 Summary of OECD Countries Variables

Data	Source	Code
Income inequality	Standardized World Income Inequality Database (SWIID) version 5.1.	INEQ
Corruption	Bayesian Corruption Index (BCI) version BCI 2014	CORR
Union membership (proxy of market power)	OECD Trade Union Density version 2016	MPOW

A dataset of 50 states of United States namely Arkansas, Alabama, Alaska, Connecticut, Colorado, Arizona, Louisiana, Georgia, California, Maine, Iowa, Delaware, Massachusetts, Kansas, Florida, Minnesota, Kentucky, Hawaii, Nebraska, Maryland, Idaho, New Hampshire, Mississippi, Illinois, New Jersey, Montana, Indiana, New York, North Carolina, Michigan, North Dakota, Pennsylvania, Missouri, Oklahoma, South Carolina, Nevada, Rhode Island, Texas, New Mexico, South Dakota, Washington, Ohio, Tennessee, Oregon, Vermont, Utah, Virginia, West Virginia, Wyoming and Wisconsin, has been used in this study to explore the linkage between income inequality, corruption and market power within states of United States.

Annual data for 1977 to 2014 periods has been gathered from different sources of dataset. As shown in Table 3.4, the variable INEQ denotes income inequality, CORR indicates corruption and MPOW as a proxy of market power using concentration ratio data, respectively.

The variables are employed in natural logarithm forms. Thus, the natural logarithms of INEQ, CORR and MPOW are used as proxies for income inequality, corruption and market power, respectively.

Table 3.4 Summary of United States Variables

Data	Source	Code
Income inequality	Sommeiller et al. (2016)	INEQ
Corruption	Report to Congress on the Activities and Operations of the Public Integrity Section	CORR
Concentration ratio	Business Dynamics Statistics (BDS) from the United States Census Bureau	MPOW

3.2. Econometric Approach Methodology

This study has adopted two complementary approaches to testing for the existence of a bivariate or a trivariate relationship between income inequality, corruption and market power. First is the Granger causality approach uses state-of-the-art time-series techniques to test whether, on average, a variable has a causal effect on another variable over time. Second is the copula approach that tests for various forms of dependence that could provide insights on nonlinear relationships, such as tail dependence. This thesis starts the analysis by conducting bilateral relationship between two variables among the three variables to understand the issues in depth. Next, advanced approach of trivariate setting will be performed to understand the income inequality, corruption and market power issues as a whole.

Causality Testing

Granger causality tests are used to examine the direction of causality between two economic series has been one of the main subjects of a plethora of econometrics studies over the past three decades. Conventional F-test is normally used as test of causality to determine joint significance of regression-derived parameters. However, previous studies have revealed that if the variables are non-stationary and no standard distribution shown for the test statistic, the conventional F-test is not valid (Gujarati, 1995).

A simple definition of Granger Causality, in the case of two time-series variables, X and Y can be best described as:

"X is said to Granger-cause Y if Y can be better predicted using the histories of both X and Y than it can by using the history of Y alone."

Below we outline two Granger causality procedures we employ. These involve panel data as the time length of the three series is not long enough to allow for purely time-series tests on causality.

3.2.1. Dumistrescu-Hurlin

This study employs the heterogeneous panel causality test of Dumitrescu and Hurlin (2012). This method is designed for bivariate models of stationary, non-cointegrated variables and based on the stationary fixed-effects panel model.

In a bivariate setting with both variables Y_i and X_{1i} being stationary, a general *K*-th order panel VAR equation can be written as:

$$y_{i,t} \qquad = \alpha_i + \sum_{p=1}^{K} \beta_{i,p}\, y_{i,t-p} + \sum_{p=1}^{K} \gamma_{i,p}\, x_{1i,t-p} + \varepsilon_{i,t} \tag{3.4}$$

In this study, the Homogenous Non-Causality hypothesis of Dumitrescu and Hurlin (2012) is tested with the null and alternative hypotheses as follows:

H_0: $\gamma_i = 0 \quad \forall i = 1, \dots, N$

H_1: $\gamma_i = 0 \quad \forall i = 1, \dots, N_1;\ \gamma_i \neq 0 \quad \forall i = N_1 + 1, \dots, N$

Under H_0 it is assumed that there is no causality relationship for all *N*; while under H_1 there are *N*- N_1 causality relationships, where $N_1<N$. The null hypothesis can be written as $R\theta_i = 0$, where $R = [0{:}\, I_K]$ is a contrast matrix, constructed by a horizontally concatenated $(K, K+1)$ null matrix 0 and a (K, K) identity matrix I_K, and $\theta_i = (\alpha_i\ \beta_i'\ \gamma_i'\ )'$.

The authors explain that their test statistic is based on the individual Wald statistics of Granger non-causality averaged across the cross-section units. Dumitrescu and Hurlin (2012) assert their test has many advantages and they can be summarized as follows: (1) it is very simple to implement; (2) Monte Carlo simulations show that their panel statistics lead to substantial increase in the power of the Granger non-causality tests even for samples with very small T and N dimensions; (3) their test statistics do not require any particular panel estimation; and (4) the test can be easily implemented in unbalanced panels and/or panels with different lag order K for each individual.

3.2.2. Toda-Yamamoto Granger Causality

Next, we apply the more robust TY procedure developed by Toda and Yamamoto (1995) to test for Granger causality. According to Toda and Yamamoto (1995), Dolado and Lütkepohl (1996) and Giles and Mirza (1999), the proposed method is simple and gives an asymptotic chi-square (χ^2) null distribution for the Wald Granger non-Causality test statistic in a VAR model, irrespective of the cointegration or system's integration properties. In same vein, Zapata and Rambaldi (1997) explained that the advantage of using the TY procedure is that in order to test Granger causality in the VAR framework, it is not necessary to pre-test the variables for the integration and cointegration properties. This is provided the maximal order of integration of the process does not exceed the true lag length of the VAR model.

According to Toda and Yamamoto (1995), the TY procedure does not substitute the cointegration properties and conventional unit roots pretesting in time series analysis. Both are considered as complementing each other. The TY procedure basically involves the estimation of an augmented VAR $(k + d_{max})$ model, where k is the optimal lag length in the original VAR system and d_{max} is the maximal order of integration of the variables in the VAR system. The Granger non-causality test utilizes a modified Wald (*MWald*) test for zero restrictions on the parameters of the original VAR (k) model. The remaining d_{max} autoregressive parameters are regarded as zeros and ignored in the VAR (k) model. This test has an asymptotic χ^2 distribution when the augmented VAR $(k + d_{max})$ is estimated. Rambaldi and Doran (1996) have shown that the *MWald* tests for testing Granger non-causality experience an improvement in efficiency when Seemingly Unrelated Regression (SUR) models are used. Moreover, the *MWald* test statistic is also easily computed in the SUR system.

The basic steps for the TY procedure are:

- Determine the order of integration for each time series by testing stationary and non-stationary tests.

- m lags are the maximum order of integration for each group of time-series.
- VAR models are set up in the levels of the data.
- Information criteria are established to determine the appropriate maximum lag length for each variable in the VAR.
- VAR are well specified by ensuring no serial correlation in the residuals exists.
- Employ Johansen's Cointegration test to test cointegration in time-series.[2]
- m additional lags of each variable are added in the preferred VAR model.
- Testing Granger non-causality and do the Wald test to test the hypothesis. Coefficients for the extra m lags are not included when executing the Wald test.
- Under the null hypothesis, the Wald test statistics will be asymptotically chi-square distributed with p degree of freedom.
- Rejection of the null hypothesis supports the presence of Granger causality.

This study investigates the direction of causality between the three variables, based on the more robust Toda-Yamamoto (1995) Granger non-causality test which allows the Granger test to operate in an integrated system.

A general dynamic interaction between income inequality (*INEQ*), corruption (CORR) and market power (*MPOW*) for each individual country $i\ (i = 1, \cdots, N)$ at time $t\ (t = 1, \cdots, T)$ can be modelled using three K-th order trivariate panel vector autoregressive (VAR) equations as follows:

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[2] *Cointegration tests are essential if two or more time-series have the same order of integration in Step 1. Results from this step only provide a possible cross-check for the validity of results.*

$$INEQ_{i,t} = \alpha_{1i} + \sum_{p=1}^{K} \beta_{1i,p} INEQ_{i,t-p} + \sum_{p=1}^{K} \gamma_{1i,p} CORR_{i,t-p} + \sum_{p=1}^{K} \delta_{1i,p} MPOW_{i,t-p} + \varepsilon_{1i,t} \tag{3.5}$$

$$CORR_{i,t} = \alpha_{2i} + \sum_{p=1}^{K} \beta_{2i,p} INEQ_{i,t-p} + \sum_{p=1}^{K} \gamma_{2i,p} CORR_{i,t-p} + \sum_{p=1}^{K} \delta_{2i,p} MPOW_{i,t-p} + \varepsilon_{2i,t} \tag{3.6}$$

$$MPOW_{i,t} = \alpha_{3i} + \sum_{p=1}^{K} \beta_{3i,p} INEQ_{i,t-p} + \sum_{p=1}^{K} \gamma_{3i,p} CORR_{i,t-p} + \sum_{p=1}^{K} \delta_{3i,p} MPOW_{i,t-p} + \varepsilon_{3i,t} \tag{3.7}$$

Where $\varepsilon_{1i,t}, \varepsilon_{2i,t}$ and $\varepsilon_{3i,t}$ denote individual white-noise errors and are assumed to be independently and normally distributed with $E(\varepsilon_{li,t}) = 0$ and $E(\varepsilon_{li,t}^2) = \sigma_{li}^2, \forall l = 1,2,3$. The errors are also independently distributed across countries where $(\varepsilon_{l,t}\varepsilon_{lj,s}) = 0, \forall i \neq j, \forall t, s$. It is assumed that the models are heterogeneous panel data in which (1) $\alpha_{1i,}\alpha_{2i}$ and α_{3i} are fixed across time, (2) the lag order *K*, where $K > 0$, is constant across equations, and (3) $\beta_{li,p}$ and $\gamma_{li,p}$, $\forall l = 1,2,3$ may vary either in an equation or across equations. This study is interested at testing Granger causality between two variables of interest while controlling for the other variable. More details could be found in Andriansyah and Messinis (2018).

3.3. Copula Approach

The second methodological approach in this study deals with dependence between variables that the copula approach facilitates. Copula was first introduced by Sklar (1959) and is a function that links univariate distribution functions to establish a multivariate distribution function. The copula approach is easy to implement and sufficiently flexible to fit into a variety of distributional shapes (Smith, 2003).

This method has a number of advantages. Copulas are used as tools for capturing and modeling the dependence of two or more variables. Normally, Pearson's linear correlation coefficient is used to measure the dependence between two variables. However, a linear correlation is only useful for normal distributions. Therefore, it is more reasonable to use copula-based measured of dependence (Chinnakum et al., 2013).

As showed by McNeil et al. (2005), Jondeau and Rockinger (2006) and Junker et al. (2006),the widely used measure of dependence, known as the Pearson correlation coefficient, may not able to describe the type of dependence between data and consequently could lead to underestimating the joint risk of extreme events. In order to overcome this problem, the copula methodology may represent a very promising solution for characterizing multivariate distributions.

For this study, we will use bivariate copula to understand the link between two variables and vines copula for trivarite linkages.

3.3.1. Bivariate Copula

Copulas in statistics is described by the following Sklar's Theorem. Let X and Y be random variables with a joint distribution function H and marginal distribution functions F(x) and G(y), respectively. Then there exists a copula C such that:

$$H(x, y) = C(F(x), G(y)) \tag{3.8}$$

for all real numbers x, y

Archimedean and elliptical family of copulas

Five different types of copula functions under the Archimedean and elliptical family of copulas with symmetric and asymmetric tail behavior have been considered to explore the dependence between income inequality, corruption and market power under bivariate setting. In practice, Archimedean copulas allow a wide range of possible dependence behaviour and are very easy to construct. First, elliptical Gaussian and Student-t copulas are considered. There are defined, respectively, as:

$$C^{Gaussain}(u_t, v_t; \rho) = \Phi(\Phi^{-1}(u_t), \Phi^{-1}(v_t)) \tag{3.9}$$

$$C^{Student-t}(u_t, v_t; \rho, v) = \mathrm{T}_v(t_v^{-1}(u_t), t_v^{-1}(v_t)) \tag{3.10}$$

where Φ is the standard bivariate normal distribution with correlation $\rho(-1 < \rho < 1)$; $\Phi^{-1}(u_t)$ and $\Phi^{-1}(u_t)$ are standard normal quantile functions; T is the bivariate Student-t DF with degree-of-freedom parameter *v* and correlation $\rho(-1 < \rho < 1)$; and $t_v^{-1}(u_t)$ and $t_v^{-1}(v_t)$ are the quantile functions of the univariate Student-t distributions. Both copulas display symmetric dependence and capture no tail dependence.

Second, Frank copula - a copula with symmetric tail dependence is considered. They are defined, respectively, as:

$$C^{Frank}(u_t, v_t; \lambda) = \frac{-1}{\lambda} log\left(\frac{(1-e^{-\lambda}) - (1-e^{-\lambda u_t})(1-e^{-\lambda v_t})}{(1-e^{-\lambda})}\right) \tag{3.11}$$

where $\pi \in [0, \infty)\backslash\{1\}$ and $\lambda \in (-\infty, \infty)\backslash\{0\}$. This copula display tail dependence.

Next, copula functions with asymmetric tail dependence structures are considered, namely, Gumbel and Clayton copulas. They are specified, respectively, as:

$$C^{Gumbel}(u_t, v_t; \delta) = exp\left(-\left((-logu_t)^{\delta} + (-logv_t)^{\delta}\right)^{1/\delta}\right) \tag{3.12}$$

$$C^{Clayton}(u_t, v_t; \delta) = \max\{\left(u^{-\delta} + v^{-\delta} - 1\right)^{-1/\delta} \tag{3.13}$$

where $\delta \in (1, \infty)$. The upper and lower tail dependence structures of the Gumbel copula are $\lambda_{upper} = 2 - 2^{1/\delta}$ and $\lambda_{lower} = 0$, respectively, while the opposite holds for the Clayton copula. The upper and lower tail dependence structures of the Clayton copula are $\lambda_{upper} = 0$ and $\lambda_{lower} = 2^{-1/\delta}$.

Table 3.5 Bivariate Elliptical Copula Denotation and Properties

#	Elliptical Distribution	Parameter range	Kendall's τ	Tail dependence
1	Gaussian	$p \in (-1,1)$	$\frac{2}{\pi}\arcsin(p)$	0
2	Student-*t*	$p \in (-1,1) v > 2$	$\frac{2}{\pi}\arcsin(p)$	$2t_{v+1}(-\sqrt{v+1}\sqrt{\frac{1-p}{1+p}}$

Table 3.6 Bivariate Archimedian Copula Denotation and Properties

#	Name	Generator function	Parameter range	Kendall's τ	Tail dependence (lower, upper)
3	Clayton	$\frac{1}{\theta}\left(l^{-\theta}-1\right)$	$\theta > 0$	$\frac{\theta}{\theta+2}$	$\left(2^{-\frac{1}{\theta}},0\right)$
4	Gumbel	$(-\log l)^{\theta}$	$\theta \geq 1$	$1-\frac{1}{\theta}$	$\left(0,2-2^{\frac{1}{\theta}}\right)$
5	Frank	$-log\left[\frac{e^{-\theta t}-1}{e^{-\theta}-1}\right]$	$\theta \in \mathbb{R}\backslash\{0\}$	$1-\frac{4}{\theta}+4\frac{D_1(\theta)}{\theta}$	$(0,0)$

Estimation method of copula

There are two approaches for measuring copula parameters. Unlike most copula approaches with the parametric specification for the margins and the Inference for Margins (IFM) estimation proposed by Joe and Xu (1996), this study employs the Canonical Maximum Likelihood (CML) approach devised by Romano (2004). This is done to avoid model misspecification in the margins and emphasize the dependence structures (i.e. the copula with parameter δ)

Model selection criteria

There are many goodness-of-fit tests which can be used to identify a suitable model (Fermanian, 2005). In this study, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used which are derived from information theory. They are widely used to identify the best type of copula. Both AIC and BIC penalize the negative maximum log-likelihood of the estimated model based on the number of parameters in the model.

Measurement of AIC is based on the trade-off between information lost and complexities when a given model is used to represent the process that generates data. AIC can be written as:

$$AIC = -2log(likelihood) + 2k \tag{3.14}$$

where *k* is the number of parameters used in the model. AIC works based on the relative distance between the fitted likelihood function of the model and the unknown true likelihood function of the data. As a result, lower AIC denotes that the model is the best fit.

Bayesian Information Criterion (BIC) can be defined as:

$$BIC = -2log(likelihood) + k\log(n) \tag{3.15}$$

where *k* is the number of parameters used in the model and *n* is the number of data. BIC works similarly as AIC but it penalizes model complexity more heavily. The best model fit is the one with the relatively smallest BIC.

This study also applies Hannan–Quinn information criterion (HQC) to find the best model fit of the copula. It is an alternative criterion for model selection to AIC and BIC. It is given as:

$$HQC = -2L_{max} + 2kln(\ln(n)) \tag{3.16}$$

where $L_{max}$is the log-likelihood, k is the number of parameters, and n is the number of observations.

3.3.2. Vines copulas

While there is a large literature exploring dependence using bivariate copulas, the choice is much more restricted in the multivariate case. The two most popular choices allowing multivariate dependence to be modeled with a non-restricted correlation matrix are the normal and Student-t copulas. However, these models are restrictive in the tail and they do not allow asymmetric dependence. To overcome this problem, Bedford and Cooke (2001) and Bedford and Cooke (2002) introduced vines copula. These models are flexible graphical models enabling extensions to higher dimensions using a cascade of bivariate copulas. The great advantage of vine copula is that we can select bivariate copulas from a wide range of existing copula families (Aloui and Ben Aissa ,2016).

Pair-copula construction

This study employs two special cases of regular vines, i.e. C-vines and D-vines copulas to understand the behavior of dependence in three variables of interest. Vines are flexible graphical models that can depict pair-copula constructions (PCCs) in three dimensions, given that this study involves three main variables: income inequality, corruption and market power. It was first introduced by Joe and Xu (1996) and later extended by Bedford and Cooke (2001, 2002).

Vine copulas modeling scheme applies a cascade of pair-copulas or bivariate copulas to extend copulas to higher dimensions. It is based on $d(d-1)/2$ bivariate copula densities from a decomposition of a multivariate probability density and makes a dependence structure possible.

Consider three random variables $X = (X_1, X_2, X_3)$ with marginal distribution functions F_1, F_2 and F_3 and corresponding densities. By recursive conditioning, we have:

$$f(x_1, x_2, x_3) = f_1(x_1) f(x_2|x_1) f(x_3|x_1, x_2) \tag{3.17}$$

According to the Sklar theorem, the joint density can be decomposed further into univariate marginal densities and a copula density. It follows for the conditional density of x_2 given x_1 that:

$$f(x_2|x_1) = \frac{f(x_1, x_2)}{f_1(x_1)} = \frac{c_{1,2}\big(F_1(x_1), F_2(x_2)\big)f_1(x_1)f_2(x_2)}{f_1(x_1)} \\ = c_{1,2}\big(F_1(x_1), F_2(x_2)\big)f_2(x_2) \tag{3.18}$$

For three random variables X_1, X_2 and X_3,there are:

$$f(x_3|x_1, x_2) = \frac{f(x_2, x_3|x_1)}{f(x_2|x_1)} = \frac{c_{2,3|1}\big(F(x_2|x_1), F(x_3|x_1)\big)f(x_2|x_1)f(x_3|x_1)}{f(x_2|x_1)} \\ = c_{2,3|1}\big(F(x_2|x_1), F(x_3|x_1)\big)c_{1,3}\big(F_1(x_1), F_3(x_3)\big)f_3(x_3) \tag{3.19}$$

Thus, the three-dimensional joint density can be represented in terms of bivariate conditional copulas and marginal densities.

$$f(x_1, x_2, x_3) \\ = c_{2,3|1}\big(F(x_2|x_1)F(x_3|x_1)\big)c_{1,2}\big(F_1(x_1), F_2(x_2)\big)c_{1,3}\big(F_1(x_1), F_3(x_3)\big)f_1(x_1)f_2(x_2)f_3(x_3) \tag{3.20}$$

In the first C-vine tree, bivariate copulas for each pair are used to model the dependence with respect to the first root node. In other words, all nodes of the tree are connected to one unique node of the tree in a canonical vine structure. Conditioned on this variable, the second root node is modelled using pairwise dependencies with respect to the second variable. Above all, in each tree, a root node is chosen and all pairwise dependencies with respect to this node are modelled conditioned on all previous root nodes. The idea is that one variable plays a vital role in the dependency structure. The reasoning behind this is that one variable plays an essential role in the dependency structure, thus all other variables are connected to it.

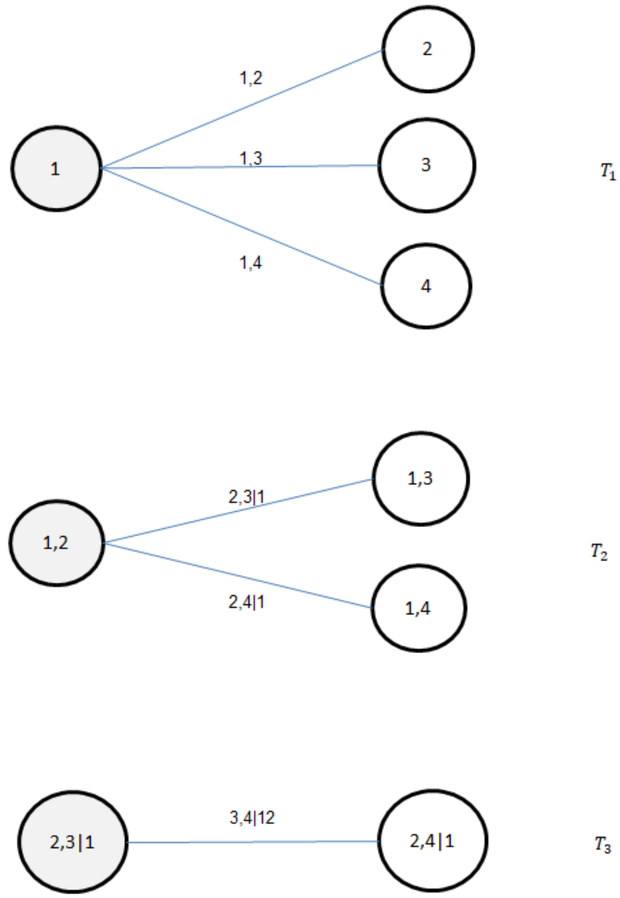

Figure 3.1 Examples of Four Dimensional C-vine Trees

Comparably, specific orders of the variables are chosen to construct D-vines. For the the first tree, pair-copulas are used to model the dependence of the first and second variable, of the second and third, and so on. Next, the conditional dependence of the first and third given the second variable (the pair (1, 3|2)), the second and fourth given the third (the pair (2, 4|3)), and so on, is modelled in the second tree (Brechmann and Schepsmeierz, 2013).

D-vines are uniquely characterized through their first tree which has a path structure. Therefore, the order of variables in the first tree defines the complete D-vine tree sequence.

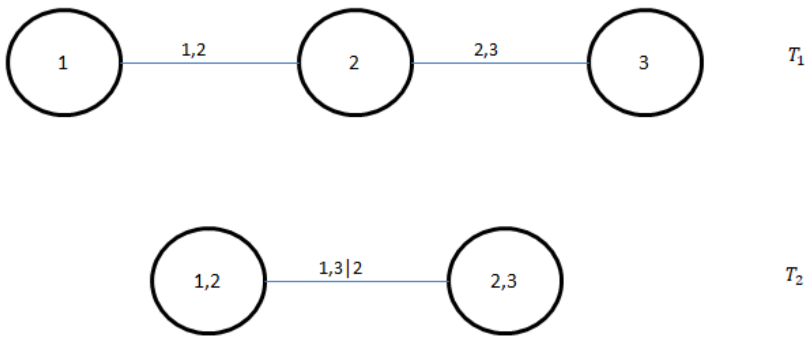

Figure 3.2 Examples of Three Dimensional D-vine Trees

Sequential estimation method

This study estimates the parameters sequentially using the maximum likelihood estimation method (Aloui et al., 2013). The log-likelihood function for the C-vine and D-vine copulas is:

$$l_{CV}(\theta_{CV}|u) = \sum_{k=1}^{N}\sum_{i=1}^{d-1}\sum_{j=1}^{d-i} log\left[c_{i,i+j|1:(i-1)}\left(F_{i|1:(i-1)}, F_{i+j|1:(i-1)}|\theta_{i,i+j|1:(i-1)}\right)\right] \tag{3.21}$$

$$l_{DV}(\theta_{DV}|u) = \sum_{k=1}^{N}\sum_{i=1}^{d-1}\sum_{j=1}^{d-i} log\left[c_{j,j+i|(j+1):(j+i-1)}\left(F_{j|(j+1):(j+i-1)}, F_{j+i|(j+1):(j+i-1)}|\theta_{j,j+i|(j+1):(j+i-1)}\right.\right. \tag{3.22}$$

Where θ_{CV} denotes the parameter set for the C-vine copula, while θ_{DV} denotes the parameter set for the D-vine copula, $F_{j|i_1:i_m} \coloneqq F\left(u_{kj}|u_{k,i_1,\cdots,u_{k,i_m}}\right)$. Note that the marginal distributions are uniform.

3.4. Conclusion

To this end, the study employed a panel Granger causality test that was developed by Dumitrescu and Hurlin (2012) and Toda-Yamamoto to understand the links between inequality, corruption and market power. Information about causality can be captured via this technique. For more insightful information about the density of relationships, this study uses the copula approach bivariate and vines to describe how strong the connection actually is. Information about relative strength can be measured.

Chapter 4. Inequality, market power & corruption: Facts and trends

Before employing these theories to examine the linkages between income inequality, corruption and market power, it is necessary to understand the facts and trends between these variables. This section documents the evolution of and major trends in inequality and rent seeking in both OECD countries and states within the USA. Note that all series are weighted averages using country or state population shares as weights.

4.1. World Trend Data

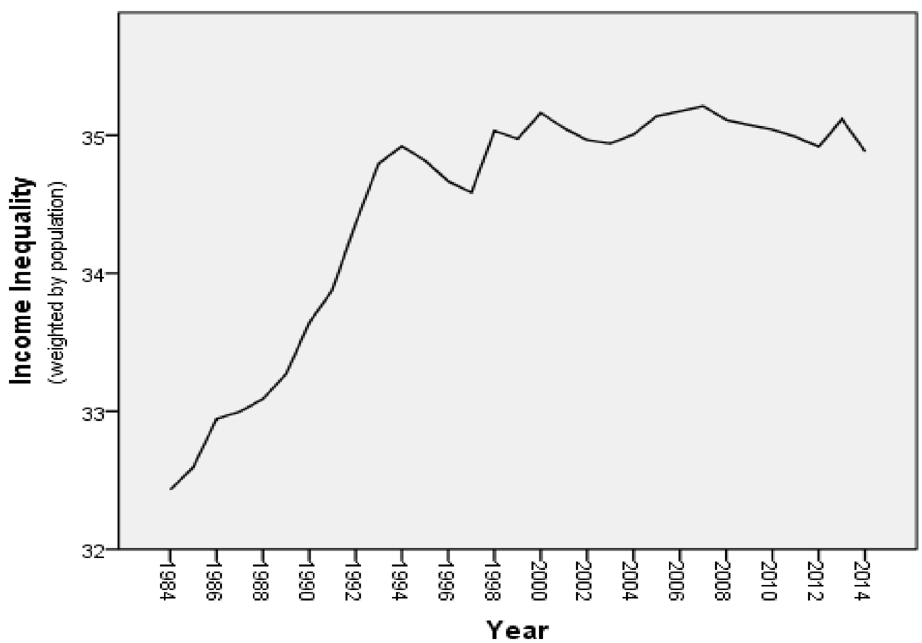

Figure 4.1 Income Inequality in OECD Countries

Figure 4.1 shows the income inequality series weighted by national population for OECD countries as a proxy for developed countries from 1984 to 2014. In general, it seems that income inequality increased over the period observed. The rise was brief and significant. The Gini index climbed from 31.93 in 1984 to 34.32 in 1995, which is an increase of 7.47 percent. However, income inequality decreases lightly after 1995 and later fluctuates until the end of the period observed. Based on this figure, income inequality is projected to range between 34 and 36 for the next few years. A possible explanation of the recent flattening of the series may be the awareness that has been created regarding of income inequality around the world.

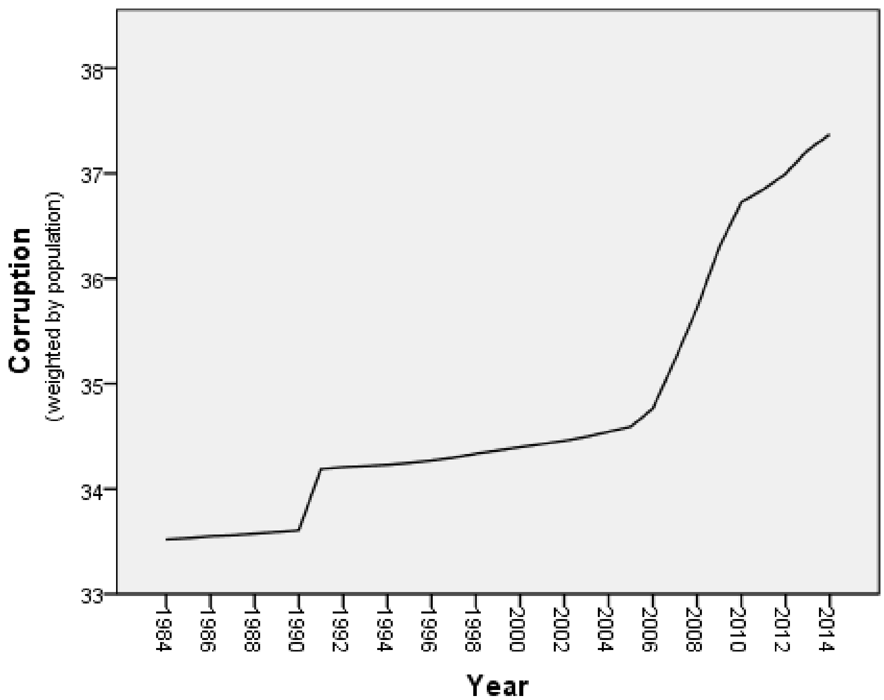

Figure 4.2 Corruption in OECD Countries

Figure 4.2 shows evolution of corruption weighted by national population for OECD countries as a proxy for developed countries for the years 1984 to 2014. In general, the changes in the increase of corruption are observed for the period. The level of corruption climbed from 33.52 in 1984 to 37.37 in 2014, an increase of 11.48 percent. From the late 1980s onward the level of corruption rose steadily until the early 1990s. It increases substantially until the end of the period observed. Figure 4.2 also reveals a sharp increase after 2006.

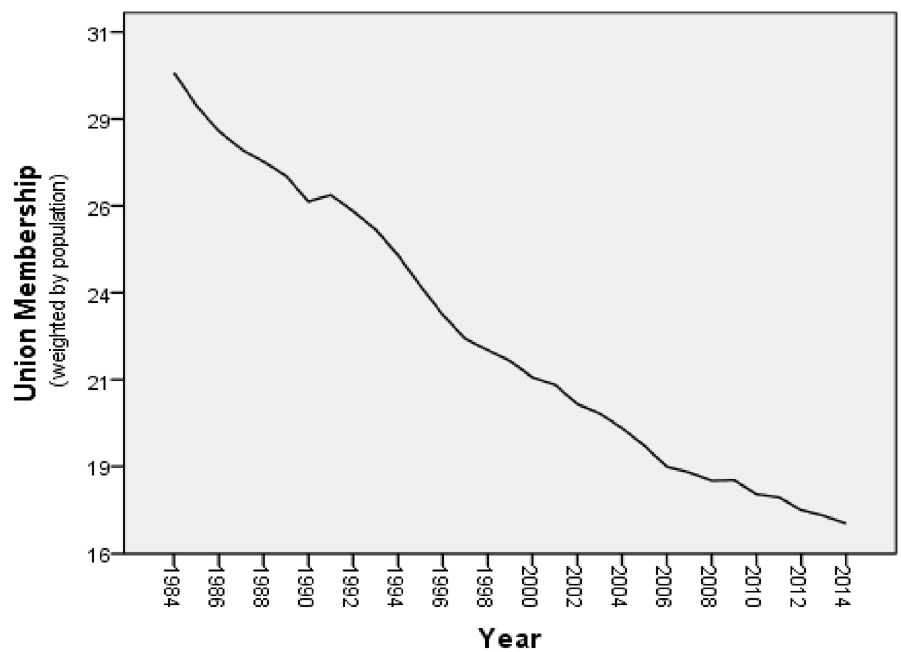

Figure 4.3 Union Membership in OECD Countries

Figure 4.3 shows union membership weighted by national population for OECD countries as a proxy market power in OECD countries from 1984 to 2014. In general, union membership shows a decline across the period observed compared to other variables of interest. The level of union membership reduced from 29.83 points in 1984 to 16.86 points in 2014. Again, union membership is expected to inversely relate to market power (ie., lower membership means greater market power for employers). This indicates that market power has increased between 1984 and 2014.

Table 4.1 Summary Statistics: OECD Countries

Statistics	$INEQ_{i,t}$	$CORR_{i,t}$	$MPOW_{i,t}$
No. observations	806	806	806
Mean	31.24	30.41	34.39
Std. deviation	6.8636	10.2538	19.7380
Minimum	16.67	14.52	5.68
Maximum	51.42	56.79	83.86
Pearson correlation			
Income inequality	1.000		
Corruption	0.618**	1.000	
Market Power	-0.580**	-0.506**	1.000
Normality testing			
Skewness	1.003	0.606	0.800
Kurtosis	0.986	-0.428	-0.291
Jaque-Bera	166.42**	55.48**	88.70**

*Notes: ** indicates correlation is significant at the 5% level. Data for summary statistics are not weighted by population and based on individual data. Jaque-Bera test ** significant at the 5% level.*

Table 4.1 shows reports summary statistics for individual countries of OECD countries as a proxy of developed countries. The Pearson product-moment correlation coefficients indicate a significantly positive association between income inequality and corruption, indicating that income inequality increases corruption or vice versa, respectively. The results also show there is a statistically significant, negative association between income inequality and union membership. Thus, as market power increases income inequality increases and vice versa. There is also a negative and significant association between corruption and union membership suggesting a positive relationship between corruption and market power. It can thus be claimed that corruption and market power go the same direction. This pattern suggests that market power may lead to higher corruption.

Given the positive values for skewness, Table 4.1 indicates that income inequality, corruption and market power are skewed to the right. Negative kurtosis indicates that the distribution has a flatter peak and lighter tails than the normal distribution. The results in Table 4.1 show that corruption and market power exhibit light tails and income inequality exhibits a heavy tails. It is clear from the Jarque-Bera results that all three variables are not normal distributed. Thus, the normality assumption is not valid for all variables.

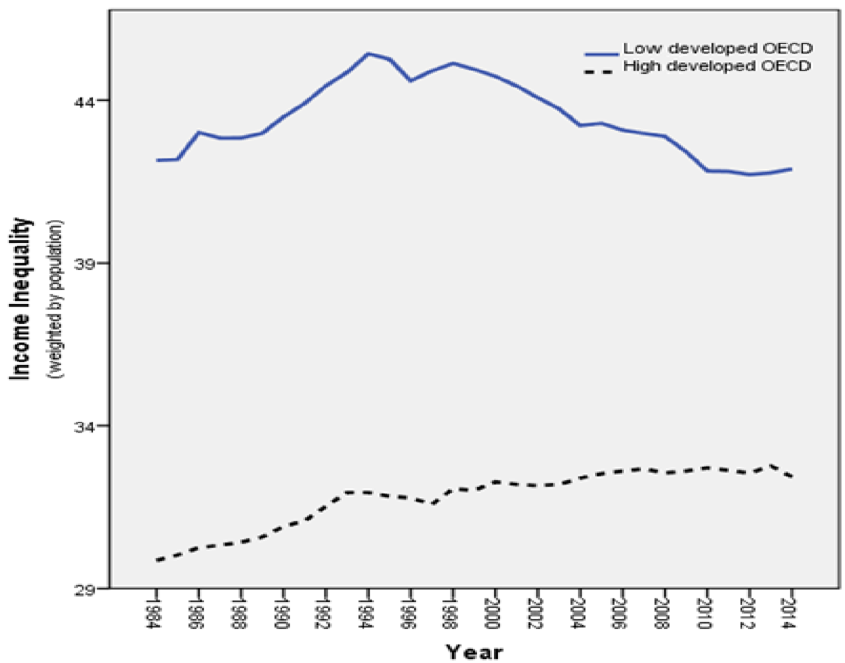

Figure 4.4 Income Inequality and Development in OECD Countries

Figure 4.4 depicts income inequality between low-developed and high-developed OECD countries across the period observed. The grouping is on the basis of vulnerability to debt crisis among OECD countries, such as the PIIGS countries. Income inequality grew for high-developed OECD countries over the period from 1984 to 2014, with the range between 29.86 to 32.42 points, which represents an increase of 8.57 percent. Starting from 1984, income inequality in high-developed OECD countries reveals a significant increase until 1993. From then on it continues to increase until the end of the period observed. High-developed OECD countries exhibit rate a much lower level of income inequality than low-developed OECD countries.

In contrast, the trend of income inequality in low-developed OECD countries shows strong compositional movement, with the range between 42.15 to 41.89 points across the period examined. The time-series pattern shows a steady rise and then a fall before and since 1998 respectively. In particular, low-developed OECD countries contributed most to the level of global income inequality across the period. The level of income inequality in low-developed OECD countries rose starting from 1984 until 1994. Since 1998, it decreases substantially until the end of the period observed.

Table 4.2 Summary of Income Inequality in OECD Countries

Developed countries	Change of income inequality (%)	Mean	Standard Deviation	Maximum	Minimum
Low-developed OECD countries	-1.17	39.32	7.3483	51.42	26.39
High-developed OECD countries	9.04	28.81	4.4253	39.62	16.67
Overall	**5.97**	**31.24**	**6.8636**	**51.42**	**16.67**

Notes: Data for summary statistics are not weighted by population and based on individual data.

Table 4.2 reports summary of income inequality in OECD countries. High-developed OECD countries experienced larger jumps in income inequality from 1984 to 2014 with 9.04 percent compared to low-developed OECD countries with -1.17 percent. The mean for low-developed OECD countries is 39.32 compared to high-developed OECD countries with 28.81. The standard deviation for low-developed OEC countries is almost twice than high-developed OECD countries. This could indicate that income inequality in low-developed OECD countries has been more volatile and/or more diverse than in high-developed OECD countries. Overall, income inequality has increased 5.97 percent over the period.

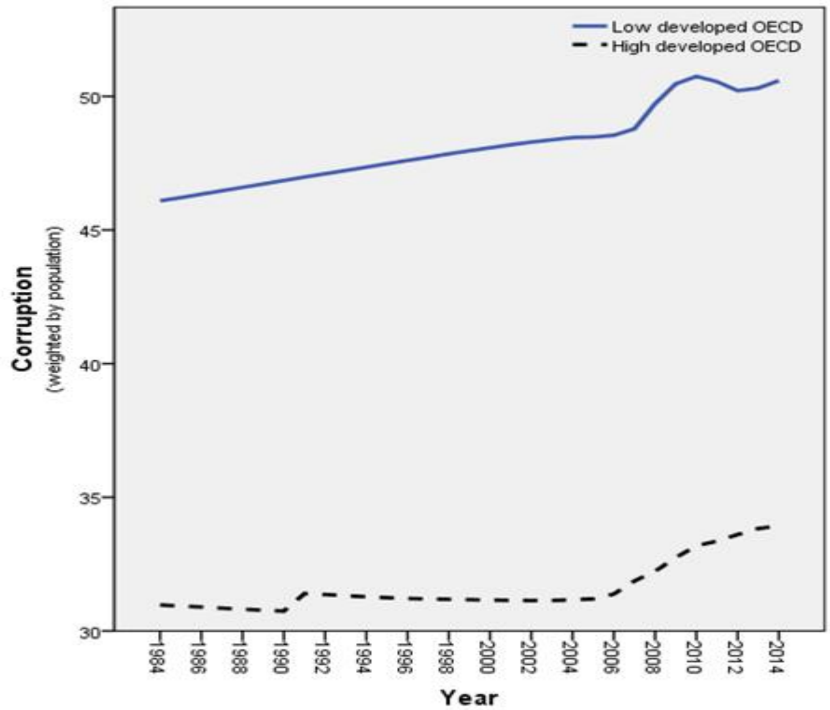

Figure 4.5 Corruption and Development in OECD Countries

Figure 4.5 compares corruption between low-developed and high-developed OECD countries across the period observed. There is a relatively large variation in the level of corruption in high developed countries when compared to those in the low developed group. Low-developed OECD countries show the highest level of corruption when compared to high-developed OECD countries. The level of corruption in low-developed OECD countries rises from 1984 to 2007 with an increase of 9.75 percent. The level of corruption rose sharply from 2007 to 2010 and since then, it increases gradually until the end of the period observed. For high-developed OECD countries, the level of corruption also presents a gradual increase across the period observed. Starting from 2006, the trend confirms a significant increase until 2014. The evidence suggests that low-developed countries have greater corruption than high-developed countries.

Table 4.3 Summary of Corruption: OECD Countries between Development

Developed countries	Change of corruption (%)	Mean	Standard Deviation	Maximum	Minimum
Low-developed OECD countries	7.22	40.80	9.3696	56.79	25.44
High-developed OECD countries	6.65	27.29	8.2660	54.47	14.52
Overall	**6.82**	**30.41**	**10.2538**	**56.79**	**14.52**

Notes: Data for summary statistics are not weighted by population and based on individual data.

Table 4.3 presents summary of corruption between OECD countries. Based on the averages across 31 years of the period, low-developed OECD countries are the most corrupt countries with an average of 40.80, compared to high-developed OECD countries with an average of 27.29. By comparing the change in corruption percentage from 1984 to 2014, low-developed OECD countries show a higher percentage with 7.22 percent. Meanwhile high-developed OECD countries show an increase of corruption by 6.65 percent. The maximum value of corruption recorded for low-developed countries is 56.79. While the maximum value of corruption recorded for high-developed countries is 54.47. These results would seem to suggest that low-developed countries experienced greater corruption and growth than high-developed countries.

A possible explanation for these results may relate to the idea that more developed markets restrain corruption and enhance democracies. Treisman (2000) argues that corruption significantly declines after 40 years of democracy experience. Montinola and Jackman (2002) also point to nonlinear linkages between democracy and corruption. There is no doubt democratization may increase corruption, however once past a threshold, democracy inhibits corruption.

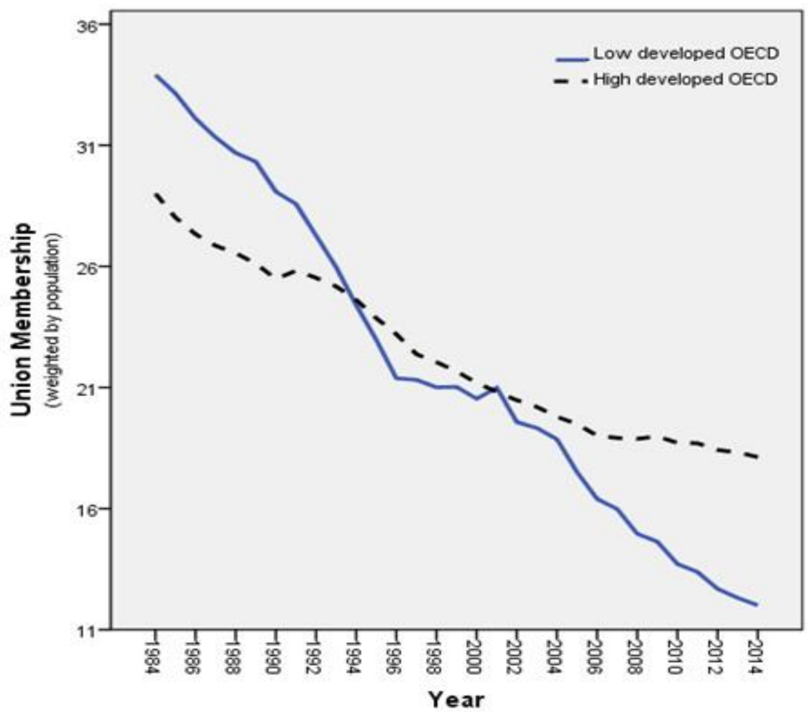

Figure 4.6 Union Membership and Development in OECD Countries

In general, union membership for low-developed countries exhibits a downward movement, with the range between 33.91 to 12 points from 1984 to 2014. The series of union membership for high-developed countries also decreases across the period examined. Union membership has inverse relationship with the market power (i.e., lower membership means greater market power for employers). This pattern suggests that market power has increased between 1984 and 2014. Union membership for low-developed countries was higher than for high-developed countries before 1995. However, this trend has changed after 1995, where the series of union membership in high-developed countries became higher than in low-developed countries.

Table 4.4 Summary of Union Membership: OECD Countries between Development

Developed countries	Change of union membership (%)	Mean	Standard Deviation	Maximum	Minimum
Low-developed OECD countries	-55.24	25.81	11.0903	57.01	5.68
High-developed OECD countries	-31.74	36.96	21.0033	83.86	7.55
Overall	**-36.49**	**34.39**	**19.7380**	**83.86**	**5.68**

Notes: Data for summary statistics are not weighted by population and based on individual data.

Table 4.4 reports summary of union membership. Looking at the change in union membership percentage, low-developed countries portray much steeper declines in union membership from 1984 to 2014 of 55.24 percent than those in high developed countries. The mean for low-developed countries is 25.81 while the mean for high-developed countries is 36.96, shows 11.16 differences. As a whole, developed countries experienced a decrease of 31.74 percent across the period observed. Altogether, these results suggest that as union membership declined, market power by business and capital income earners has increased, especially in low-developed countries.

4.2. United States by States Data

First, the evolution of income inequality, corruption and market power are documented for the United States since 1977.

Figure 4.7 Income Inequality in US

Figure 4.7 shows the changes in income inequality weighted by state population in the United States for the period 1977 to 2014. The top 10 percent of households' income share are used as a proxy of income inequality. This share of income captured by the top 10 percent climbed from 33.3 percent in 1977 to 49.3 percent in 2014, which is an increase of 47.90 percent. In general, the changes in income inequality in the United States slightly increased over the period observed, but the path was not smooth. The share of income earned by the top 10 percent decreased in the early 2000s recession but it was brief and sharp. The global financial crisis that erupted in 2007 reduced again the top 10 percent income share to 45.54 in 2009. On this theme, the income share of the top 10 percent reached a peak of 50.16 in 2012. The 2012 peak was in part the result of high-income earners shifting their income from 2013 to 2012 to reduce their tax liabilities in anticipation of higher top marginal tax rates that took effect in 2013 (Sommeiller et al., 2016). This kind of tax planning helped reduce the top 10 percent's take of all income in 2013.

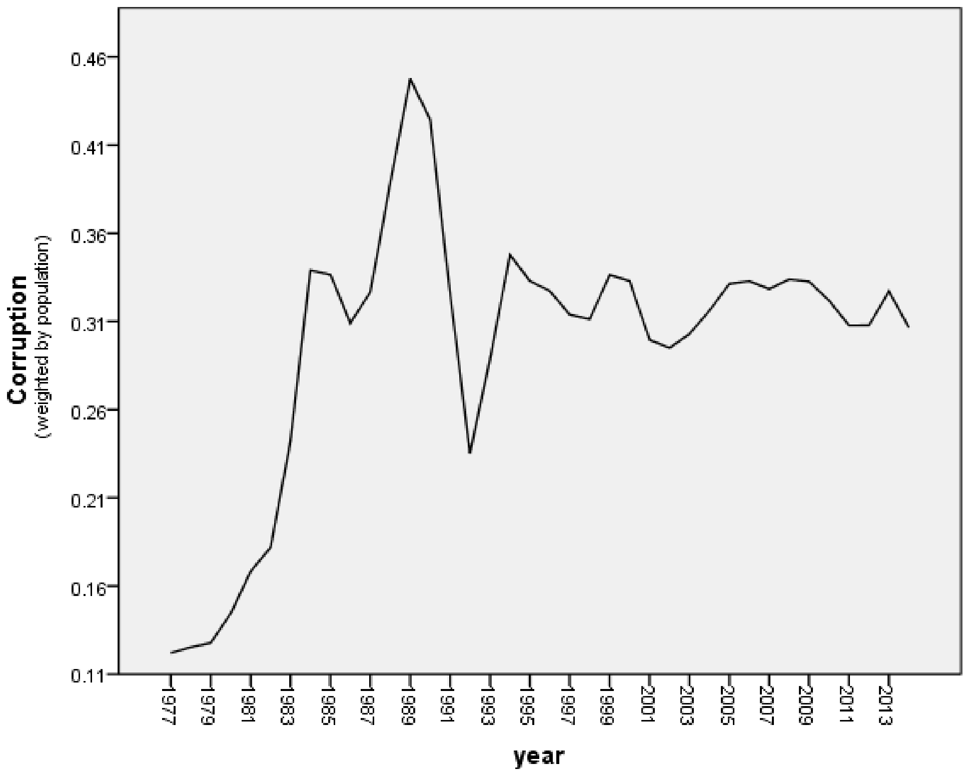

Figure 4.8 Corruption in US

Figure 4.8 shows the index of corruption weighted by state population in the United States from 1977 to 2014. In general, the changes in corruption in the United States slightly increased over the period observed, but the path was not smooth. In 1989, the level of corruption reached its highest peak with 0.46. From the early 1980s the level of corruption rose substantially but in 1989 the level of corruption decreased sharply. Since then, the level of corruption started to increase slightly until the end of the period examined. We can see the values of corruption range between 0.28 and 0.35 after 1995.

Figure 4.9 Concentration Ratio in US

Figure 4.9 examines trends in the market power series for United States (weighted by state population) for 37 years over the period from 1977 to 2014. In general, market power shows a steady rise across the period observed especially starting in the mid-1990s. The increase is becoming more pronounced as time goes on, especially after the 1995. This is consistent with the findings by Autor et al., (2017), Cetorelli et al., (2007) and De Loecker and Eeckhout (2017) where they found market power to rise steadily across the period observed especially since the early 1990s. In the early period observed, the level of market power decreased until 1978, before it started to increase until 1982. Since then, it decreases until the year 1995. After 1995, the level of market power began to increase sharply until the year 2000. Since then, it decreased due to early 2000s recession before began to increase again in 2005. However, the decrease is brief and shallow. At the end of the period in 2014 market power reached record levels at 33.45 points.

Table 4.5 Summary Statistics: US by States

Statistics	$INEQ_{i,t}$	$CORR_{i,t}$	$MPOW_{i,t}$
No. observations	1900	1900	1900
Mean	39.94	0.30	28.73
Std. deviation	5.7944	0.2534	5.6836
Minimum	21.81	0.0023	12.13
Maximum	62.17	2.0181	48.97
Pearson correlation			
Income inequality	1.000		
Corruption	0.121**	1.000	
Market Power	0.351**	-0.100**	1.000
Normality testing			
Skewness	0.621	2.002	-0.539
Kurtosis	0.740	6.320	0.101
Jaque-Bera	164.66**	4410.00**	92.64**

*Notes: ** indicates correlation is significant at the 5% level. Data for summary statistics are not weighted by population and based on individual data. Jaque-Bera test ** significant at the 5% level.*

Table 4.5 reports descriptive statistics using all pooled observations for 50 states of the United States, as well as diagnostic tests such as skewness, kurtosis and the Jarque-Bera test. It also shows the Pearson correlation coefficients that indicate a significantly positive association between income inequality with corruption and market power, indicating that income inequality increases corruption or market power increases, respectively. The results also show there is a statistically significant, negative association between corruption and market power. Thus, as corruption increases income inequality decreases or vice versa. It is apparent from this table, income inequality and market power depicts significant strongest correlation among all pairs.

Corruption has the highest skewness and kurtosis among the three variables. Skewness is a measure of the asymmetry of the probability distribution from its mean and could be positive or negative values. Here, it indicates that income inequality and corruption are skewed to the right while the market power series is skewed to the left. Table 4.5 also shows that income inequality, corruption and market power exhibit heavy tails. It is clear from the Jarque-Bera results that all three variables are not normal distributed. Thus, the normality assumption is not valid for all variables. Consequently, the copula approach seems to be appropriate.

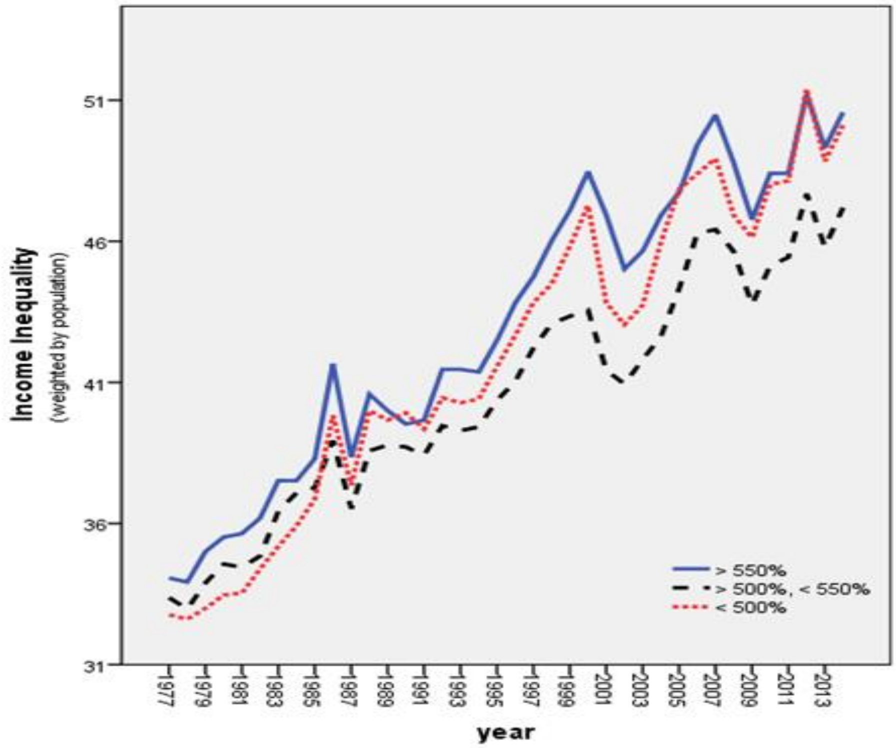

Figure 4.10 Income Inequality by Growth in US

Figure 4.10 shows the evolution of income inequality (weighted by state population) for groups of regions in the United States from 1977 to 2014. The top 10 percent of households' income share are used as a proxy of income inequality. This study group states on the basis of average growth rates over the whole period. This choice provides a perspective on US states that resembles the distinction between low-developed and high-developed OECD countries. The top 10 percent's share of income grew in every group of states during this period of time. The pattern for the three group are closely related until of the end of the period. States with more than 550 percent economic growth contributed most to the national level of income inequality with the highest increase, compared to other two groups. While as expected, states with less than 500 percent growth contributed least to the national level of income inequality. This indicates the trend for income inequality is widening for states that have greater economic growth. This may be consistent with the OECD evidence if the US states with the highest growth were mainly the ones less-developed in the initial period of the sample, if there was *conditional* convergence (i.e., the catch-up effect in growth theory).

Table 4.6 Summary of Income Inequality US by States

Percent of economic change	Change of income share (%)	Mean	Standard Deviation	Maximum	Minimum
Less than 500%	44.45	39.68	6.1613	60.86	21.81
Between 500% - 550%	38.28	39.64	4.5378	52.08	30.28
More than 550%	40.04	40.44	6.2440	60.86	27.75
Overall	**41.08**	**39.94**	**5.7944**	**62.17**	**21.81**

Notes: Data for summary statistics are not weighted by population and based on individual data.

Table 4.6 presents summary of income inequality for US based on growth. States with less than 500 percent economic growth have the biggest jumps in the top 10 percent share from 1977 to 2014 with 44.45 percent. This was followed by those states with more than 550 percent economic growth with 40.04 percent. Based on these results, states with more than 550 percent economic growth have had the highest income inequality among the group. Overall by 2014 in the US, the top 10 percent took home 41.08 percentage points higher than the income share in 1977.

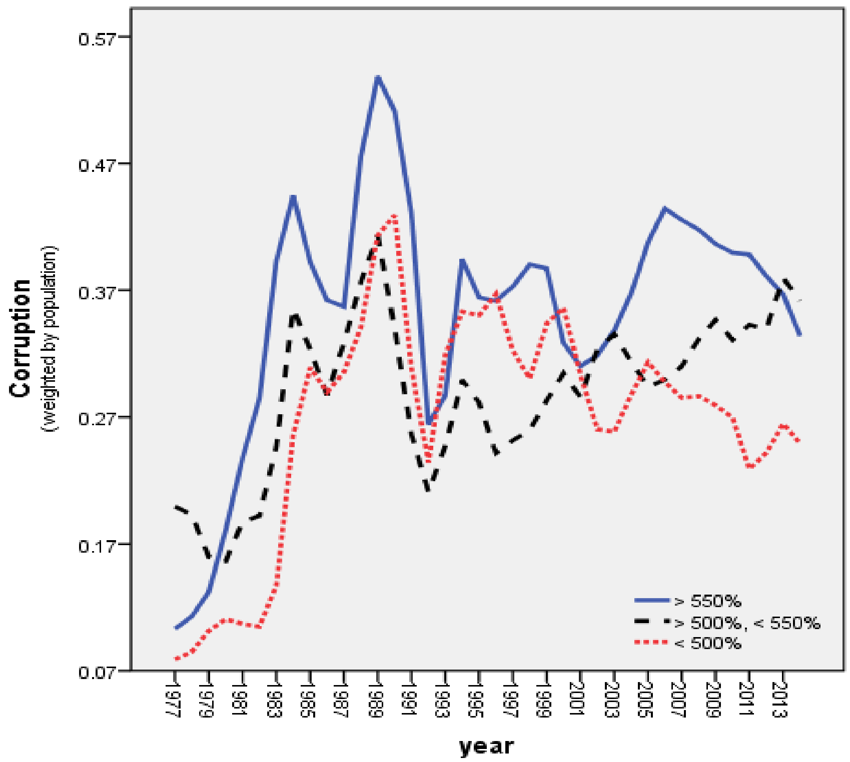

Figure 4.11 Corruption by Growth in US by States

Figure 4.11 illustrates the changes in corruption between regions in the United States weighted by state population over the period from 1977 to 2014. There is a relatively large variation in the number of convictions across the United States at the regional level. In general, the movement of corruption among all states is closely related. In the late 1980s, the level of corruption in all states rose substantially, but later decreased and fluctuated until the end of the period observed. However, only states with between 500 percent and 550 percent of economic growth indicated an increase in the level of corruption starting from the early 1990s.

Table 4.7 Summary of Corruption by Growth: US by States

Percent of economic change	Change of corruption (%)	Mean	Standard Deviation	Maximum	Minimum
Less than 500%	69.92	0.27	0.2283	1.7823	0.0031
Between 500% - 550%	122.33	0.31	0.2356	1.4728	0.0023
More than 550%	443.15	0.33	0.2855	2.0181	0.0024
Overall	**151.72**	**0.31**	**0.2534**	**2.0181**	**0.0023**

Notes: Data for summary statistics are not weighted by population and based on individual data.

Table 4.7 summarizes the average corruption levels in the United States from 1977 to 2014. Based on the averages across the 38 years, states with more than 550 percent economic change were the most corrupt regions with an average of 0.33; while the states with less than 500 percent of growth were the least corrupt regions with an average of 0.27. By comparing the change in corruption percentage from 1977 to 2014, those states with more than 550 percent economic change also showed the highest percentage (443.15 percent). Meanwhile the states with the least economic growth have had the lowest percentage change in corruption, 69.92 percent. These results seem counter-intuitive but they are consistent with the view that states with (high) low growth tend to be those (less) more developed and are thus (more) less vulnerable to corruption if there is catching up (i.e., conditional convergence) by less developed areas that tend, as in the OECD data, to be more prone to corruption.

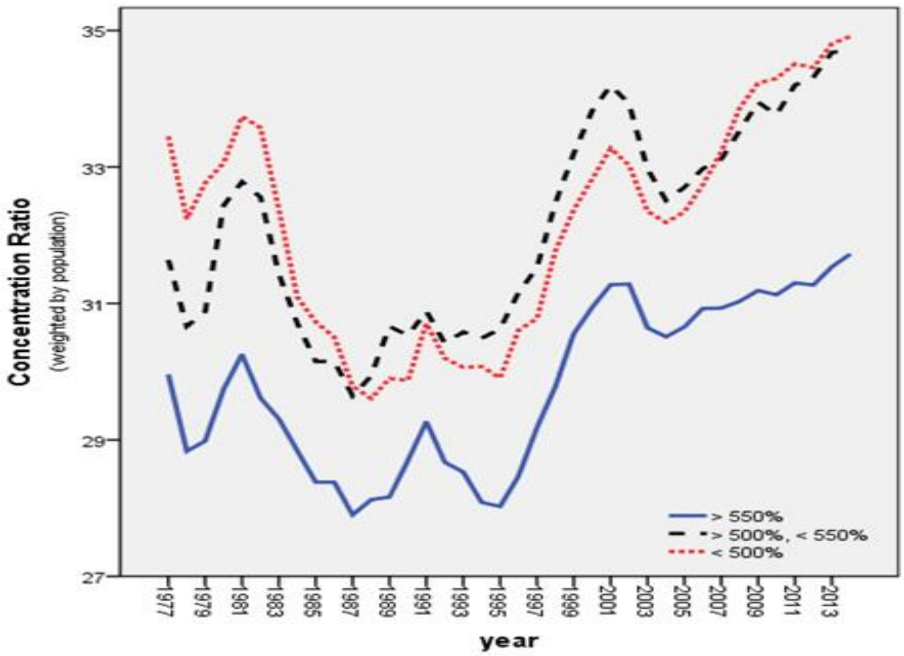

Figure 4.12 Concentration Ratio by Growth in US by States

Figure 4.12 shows the concentration ratio weighted by state population in the United States from 1977 to 2014. 50 states are divided into three different categories based on the percent of change in economic growth across time. In general, all states show a decrease of concentration ratio from 1977 to 1987. However, there is a significant increase in concentration ratio after 2008 before a slight decreasing between 2001 and 2005. Before 1987 and after 2006, states with less than 500 percent of growth has the greatest market power. While the states with more than 550 percent of growth have the lowest market power. In contrast, states with the weakest or moderate growth have much higher market power throughout the period. Thus, it seems intuitive that states where business are most productive and innovative (i.e., highest growth rates) are the least concentrated. Of course, it could also mean that locations with the least market concentration or power are more conductive to innovation and growth.

Table 4.8 Market Concentration by Growth: US by States

Percentage of economic change	Change of Market Concentration (%)	Mean	Standard Deviation	Maximum	Minimum
Less than 500%	6.96	30.05	5.5017	48.97	15.58
Between 500% - 550%	8.19	29.96	4.9137	40.29	13.85
More than 550%	8.16	26.44	5.7092	38.97	12.13
Overall	**7.71**	**28.73**	**5.6836**	**48.97**	**12.13**

Notes: Data for summary statistics are not weighted by population and based on individual data.

Table 4.8 is a summary of the average concentration ratio in the United States from 1977 to 2014. Based on the group averages across the 38 years for this period, the states with less than 500 percent economic change have overall the highest concentration ratio with an average of 30.05; while the states more than 550 percent have the lowest concentration ratio with an average of 26.44, respectively. Looking at changes in the concentration ratio in terms of percentage, states with between 500 and 550 percent economic change have the highest change in concentration ratio from 1977 to 2014. They are marked by an increase of 8.19 percent, while states with more than 550 percent economic change show the smallest change with an increase of 6.96 percent.

Chapter 5. Granger causality and Copula: OECD evidence

This chapter undertakes econometric and statistical analysis, as outlined in Chapter 3. It was mentioned in the previous chapter that the aim of this research project has been to explore the linkages between income inequality, corruption and market power. Here, we seek to examine the linkages between these variables in OECD countries. In order to have a comprehensive view of these linkages, four different techniques are employed: Dumistrescu-Hurlin causality, Toda-Yamamoto Granger non-causality, bivariate copula and vines copula. This thesis starts the analysis by conducting bilateral relationship between two variables among the three variables to understand the issues in depth. Next, advanced approach of trivariate setting will be performed to understand the income inequality, corruption and market power issues as a whole.

5.1. Dumistrescu-Hurlin Causality

5.1.1. Panel Unit Root Tests

This section applies panel unit root tests introduced by Im et. al. (2003) to determine the order of integration for the series; that is, the minimum times the series have to be differenced in order to become stationary. The panel unit root tests were run to assess unit roots in the series. A unit root could be associated with a stochastic trend in a time series. If a time series has a unit root, it shows the unpredictable pattern. Unit root tests are tests are used to test for the stationary in a time series. A time series is not stationarity if a change in time does cause a change in the shape of the distribution.

A large and growing body of literature has shown economic variables tend to be non-stationary over time. However, the series can become stationary by differencing the variables. In panel data setting, a series is considered stationary if the null hypothesis of assuming that all series in the panel are nonstationary processes is rejected. We also employ the cross-sectionally augmented Dickey-Fuller (CADF) test to check robustness of the results

Pesaran (2007) suggests CADF test for testing unit roots in a dynamic panel that allows of cross-sectional dependency as well as serially correlated errors. The standard Dickey-Fuller regressions are augmented with cross-sectional averages of lagged levels and first differences of the individual series in this test. Both of the above tests could yield different results depending on the number of lags included in the ADF regressions.

The results of the unit root tests with a trend for the variables in their levels and first differences are reported in Table 5.1. Note, as explained in chapter 3 above, market power in this chapter is proxied by union membership.

Table 5.1 Panel Unit Root Test

	IPS Test [W-t-bar]		CADF Test [Z-t-bar]	
Variable	Lag (1)	Lag (2)	Lag (1)	Lag (2)
Levels				
INEQ	-1.0618	-1.3505*	-2.555	-2.599*
CORR	-0.1683	5.7482	-3.140	-1.759
MPOW	0.6154	0.2493	-2.019	-1.776
First difference				
INEQ	-5.4405**	-7.2126**	-2.888**	-2.914**
CORR	-7.3937**	-2.4675**	-4.122**	-2.903**
MPOW	-6.8382**	-4.3308**	-3.395**	-2.726**

*Notes: ** and * indicate significance at 5% and 10% level respectively. The null hypothesis is panel containing unit roots. Tests include a trend.*

The results of the unit root tests are shown in Table 5.1. The null hypothesis for this test indicates all panels contain a unit root. The results in general reveal that all variables contain a unit root. IPS test strongly suggests the existence of unit roots for all variables except for INEQ for the two lags. However, the level of significance is at 10 percent level. For the first difference, we reject the null hypothesis at 5 percent level of significance and conclude that there are no unit roots in the panels. Next, the CADF test results indicate that all variables contain a unit root. Similar to the IPS test, CADF test shows the existence of unit roots for all variables except for INEQ for the two lags. CADF test using first difference indicates all variables are stationary when both lags are used.

From the table above, it is evident that all of the variables are stationary in first-difference for OECD countries. On the other hand, level results are mixed for the two lags. Overall, based on Table 5.1, this study considers that all variables are non-stationary. Further, results of the panel unit root tests in first difference show that the series are I(1) processes. As a result, Dumistrescu-Hurlin Causality and Toda-Yamamoto Granger non-Causality estimation below uses first differences of all observed variables.

Based on the unit root tests obtained in Table 5.1, there is a need to examine the cointegration relationship between the processes for OECD countries. Although cointegration tests are needed for verification, they do not affect the Toda-Yamamoto test.

5.1.2. Cointegration Test

Cointegration can be referred as the equilibrium or long term relationship between the two series. Cointegration tests do not affect the Toda Yamamoto test but there are needed for verification. Tests of cointegration analyze non stationary time series with the aim to identify the processes that have means and variances that vary over time. However, Bhaskara Rao (2007) draws that if the test fails to find any relationship between the series, it only suggests that one does not exist and it is not proof that one does not exist.

To date various methods have been developed to measure cointegration between time series. Westerlund (2007) introduced four cointegration tests that are based on structural rather than residual dynamics for panel data. These cointegration tests do not impose any common-factor restriction. The tests assume null hypothesis of no cointegration by assuming whether the error-correction term in a conditional panel error-correction model is equal to zero. As Persyn, D., and Westerlund (2008) state, two tests are aimed to test the alternative hypothesis that the panel is cointegrated as a whole, while the other two are designed to test the alternative that at least one unit is cointegrated. All series need to integrate of order one before Westerlund cointegration test is employed.

Table 5.2 Panel Cointegration Test for OECD Countries

Dependent variable	Independent variable				
	Statistic	Value	Z-value	P-value	Robust P-value
INEQ			CORR MPOW		
	G_t	-3.378	-5.154	0.000	0.350
	G_a	-7.555	4.227	1.000	0.970
	P_t	-20.751	-10.073	0.000	0.010
	P_a	-14.935	-3.355	0.000	0.040
CORR			INEQ MPOW		
	G_t	-2.482	0.280	0.610	1.000
	G_a	-9.742	2.706	0.997	1.000
	P_t	-9.276	2.648	0.996	1.000
	P_a	-6.607	2.928	0.998	1.000
MPOW			INEQ CORR		
	G_t	-2.707	-1.082	0.140	0.480
	G_a	-6.715	4.811	1.000	0.970
	P_t	-11.852	-0.207	0.418	0.760
	P_a	-10.306	0.137	0.554	0.500

G-statistics are for group mean tests assuming heterogeneity while p-statistics are for the panel test assuming homogeneity. The number of lags and leads in the error-correction tests are chosen by the Akaike criterion. Tests include a trend.

From the results, the null hypothesis of no cointegration at 5 percent and 10 percent level of statistical significant cannot be rejected for INEQ except for the P_t and P_a. For corruption, CORR, and market power, MPOW, all four tests lead to a clear non-rejection of the null, even at 1 percent level, which as strong evidence not in favour of cointegration. It is apparent from this table that there is no cointegration relationship for

CORR and MPOW. Overall, only when income inequality, INEQ, is the dependent variable, the results show two rejections for *P*, at the 5 percent level. As this rejection is only marginal (two from four tests) and the homogenous alternative hypothesis deliberated for this particular test may be overly limiting, these results are interpret as evidence in favour of no cointegration between INEQ, CORR and MPOW.

5.1.3. Causality Testing Results

Granger causality testing is used to understanding causality between two variables in a time series. The approach is based on a theory of probability to account of causality where data sets are employed to find patterns of correlation. The results for Granger causality test based on Dumitrescu and Hurlin (2012) and also the signs of the second lag parameter estimate for the independent variable of interest are summarized in Table 5.3.

The maximum lag length to be used in a standard VAR model varies, depending on the criteria used. The three criteria used in this study are: Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC) and the Hannan and Quinn information criterion (HQIC). Based on these three criteria, it is concluded that the maximum lag order for most of the OECD countries is two (*K=2*).

Table 5.3 Causality Testing

Causality	$\overline{W}$ statistic	$\bar{Z}$ statistic	$\tilde{Z}$ statistic
INEQ $\Rightarrow$ CORR	1.8147	-0.4725	-0.7951
CORR $\Rightarrow$ INEQ	1.6590	-0.8693	-1.1244
INEQ $\Rightarrow$ MPOW	2.6986	1.7812*	1.0751
MPOW $\Rightarrow$ INEQ	3.4860	3.7886**	3.7061**
CORR $\Rightarrow$ MPOW	1.9080	-0.2345	-0.5976
MPOW $\Rightarrow$ CORR	1.7295	-0.6897	-0.9754

*Notes: INEQ is income inequality, CORR is corruption, and MPOW is union membership. Lag order=2; '**' and '*' indicate significance level of 99 and 90 percent. $\Rightarrow$ stands for "Granger causes".*

The findings in Table 5.3 indicate the causality testing that shows the causal relationship between variables of interest. To put it another way, the results show which variable causes which variable. Yet, the test does not determine the strength and the sign of relationship (whether a positive or negative relationship).

Based on the Table 5.3, important issues emerge from these findings. Dumitrescu-Hurlin panel causality test showed a bi-directional relation of causality between income inequality and union membership (market power proxy). Panel causality tests reveal that the null hypotheses that income inequality does not cause union membership can be rejected at the 10 percent level. Next, the null hypotheses that union membership does not cause income inequality can be rejected at the 1 percent level. These findings suggest there is no evidence causality relationship for all variables except from market power (union membership) to income inequality and from income inequality to market power (union membership). Overall, the results in Table 5.3 indicate that market power has impact on income inequality and vice versa. More details about the sign relationship can be found on copula result.

5.1.4. Panel Vector Autoregression (VAR) Model

Given the failure to reject the null of panel cointegration, we next estimate a panel vector autoregression (VAR) model. It is used to capture the linear interdependencies in a multiple regression framework. By allowing more than one evolving variable, VAR models generalize the univariate autoregressive model. The assumptions about the intercept, slope coefficients and error term have to be considered when estimating panel data regression models. According to Green (2003), the estimation procedure is either random effects model or the fixed effect model. In this study, panel data Vector Autoregression (VAR) lag 2 are estimate in the causality analysis.

The fixed effects model (FEM) assumes that for all cross section units, the slope coefficients are constant, and the intercept does not vary over time but varies over individual cross-section units.

On the other hand, the random effects model (REM) assumes that for all cross-section units, the slope coefficients are constant. However, REM also assumes that the intercept is a random variables, that is, $\alpha_i = \alpha + \varepsilon_i$, where α is the intercept of all cross-section units mean value, and ε_i is a random error term which reflects the individual differences in the intercept value of each cross-section unit, and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$.

The Hausman test have been apply to choose between fixed effects model (FEM) and random effects model (REM) estimations before implementing the Wald test of coefficients to determine the Granger causality directions. It basically tests whether the unique errors (u_i) are correlated with the regressors, the null hypothesis is they are not. The null hypothesis in the Hausman test is that the correlated REM is appropriate. Fixed effects models (FEM) estimation can be apply if the null hypothesis is rejected. The Hausman test results from this study indicate that it is better to use the FEM to estimate all the equations. Table 5.4 presents estimates of a panel VAR model with fixed effects for OECD countries with four variables: INEQ, CORR, MPOW and GDP where the last controls for other omitted variables.

Table 5.4 Panel VAR Estimation: OECD Countries

Dep. Var.	Independent Var.								Wald
	$INEQ_{t-1}$	$CORR_{t-1}$	$MPOW_{t-1}$	GDP_{t-2}	$INEQ_{t-2}$	$CORR_{t-2}$	$MPOW_{t-2}$	GDP_{t-2}	F-stat
$INEQ_t$	0.558 (23.135)**	0.001 (0.848)	-0.099 (-4.112)**	0.049 (1.280)	0.109 (4.553)**	-0.003 (-1.867)*	0.060 (2.620)**	0.015 (0.409)	29.527**
$CORR_t$	-0.406 (-1.092)	0.755 (33.018)**	-0.615 (-1.657)*	-0.755 (-1.257)	-0.247 (-0.670)	-0.203 (-9.082)**	0.363 (1.023)	1.073 (1.892)**	7.574**
$MPOW_t$	0.006 (0.319)	-0.001 (-0.317)	0.827 (40.543)**	0.184 (5.578)**	0.0112 (0.579)	-0.002 (-1.540)	0.052 (2.688)**	-0.166 (-5.319)**	15.305**

*Notes: (1) Hausman test has been used in the selection of the fixed effects or random effects model. (2) Based on Hausman test results, all models fit the fixed effects model. (3) Reported numbers show the coefficients of regressing the row variables on lags of the column variables. (3) Heterokedasticity adjusted t-statistics are in parentheses. (4) * and ** denote the rejection of null hypothesis at the 10% and 5% level of significance, respectively.*

Table 5.4 also reports the Wald test of coefficients for Granger causality directions. For OECD countries, this study observes that the relation of INEQ to CORR and MPOW is negative in the estimated coefficients. In other words, market power and corruption significantly causes income inequality. As the activity of corruption and market power decreases, the level of income inequality increases. The coefficient of MPOW two periods lagged $(t-2)$ is also statistically significant in INEQ equation showing that the increase of market power activity leads to higher level of income inequality.

From the results, it is observe that the relation of CORR to MPOW is negative in the estimated coefficients, showing that as the activity of corruption increases, the level of market power decreases. The coefficient of GDP two periods lagged $(t-2)$ is also statistically significant in CORR equation showing that the higher economic activity leads to the increase of corruption.

The results also indicate that there is a significantly positive relation of GDP to MPOW. However, the coefficient of GDP two periods lagged $(t-2)$ shows a significantly negative relation to MPOW. In general, it can be conclude that the increase of economic activity may reduce or/and may increases the level of market power.

Based on the panel VAR-Granger causality Wald test, it is clear that INEQ, MPOW and GDP jointly have significant impact on CORR. The results also show that INEQ, CORR and GDP jointly cause MPOW. In addition, CORR, MPOW and GDP also jointly cause INEQ.

5.2. Toda-Yamamoto Granger Non-Causality Test

Granger causality test has its advantages and drawbacks. According to Toda and Phillips (1993), Granger causality tests might suffer from irritation parameter dependency asymptotically and the possibility of incorrect inference in some cases.

Thus, these tests can lead to unreliable results. In the Dumitrescu-Hurlin and Westerlund approaches to cointegration, a critical assumption is that the three series are I(1) and thus their first difference is stationary. Another approach was proposed by Toda and Yamamoto (1995) to overcome the complexity of pre-testing. This approach ensures that asymptotic distribution theory is valid for VAR systems, regardless of the order of integration. It is claimed that the T-Y test allows causality tests at the levels and between series that can be of different integration order and even I(1).

5.2.1. TY Granger Panel Data Results

Next, we employ the Toda-Yamamoto approach in panel data so we can compare the results with those of bivariate analysis using the Dumistrescu-Hurlin test in 5.1.3 section. Table 5.4 presents the results for the OECD panel. The number of additional lags is set to one (*m=1*) and the order panel VAR is set to two (*K=2*) based on the results from the individual time series above. Panel (a) represents the specification without conditioning on GDP whereas panel (b) reflects the specification with conditioning on GDP.

Table 5.5 Trivariate Toda-Yamamoto Panel Granger Non-Causality Tests

		Asymptotic Wald Statistics	Bootstrap critical values 1%	5%	10%
Panel *K=2, m=1*					
(a) Without controlling for GDP					
$Inequality_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	3.8811	8.8247	8.7830	8.7597
	$\tilde{Z}_{N}^{Hnc}$	1.2343	3.4077	3.3894	3.3791
$Inequality_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	9.9989	17.4651	15.1121	14.0734
	$\tilde{Z}_{N}^{Hnc}$	3.9240	7.2063	6.1719	5.7152
$Corruption_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	9.3304	142.0669	140.0614	139.1504
	$\tilde{Z}_{N}^{Hnc}$	3.6300	61.9857	61.1040	60.7035
$Corruption_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	4.4177	138.5703	134.9917	133.5121

	$\tilde{Z}_{N}^{Hnc}$	1.4702	60.4458	58.8752	58.2247
$Market\ Power_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	29.1970	8.3657	8.0968	7.9555
	$\tilde{Z}_{N}^{Hnc}$	12.3641	3.2059	3.0877	3.0256
$Market\ Power_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	5.2294**	2.1008	2.0617	2.0423
	$\tilde{Z}_{N}^{Hnc}$	1.8271**	0.4516	0.4345	0.4259
(b) With controlling for GDP					
$Inequality_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	1.9782	10.2963	10.2556	10.2327
	$\tilde{Z}_{N}^{Hnc}$	0.3947	4.0547	4.0368	4.0267
$Inequality_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	9.1212	17.2686	15.7486	14.9978
	$\tilde{Z}_{N}^{Hnc}$	3.5380	7.1199	6.4517	6.1216
$Corruption_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	1.9225	133.7690	132.7782	132.2673
	$\tilde{Z}_{N}^{Hnc}$	0.3732	58.3367	57.9020	57.6774
$Corruption_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	5.8605	150.8266	148.7352	147.8049
	$\tilde{Z}_{N}^{Hnc}$	2.1045	65.8368	64.9173	64.5083
$Market\ Power_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	12.8179***	0.4810	0.3188	0.2286
	$\tilde{Z}_{N}^{Hnc}$	5.1632***	-0.2505	-0.3318	-0.3714
$Market\ Power_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	2.4113***	-0.2023	-0.2333	-0.2515
	$\tilde{Z}_{N}^{Hnc}$	0.5882***	-0.5609	-0.5745	-0.5825

Notes: $\Rightarrow$ indicates the first variable Granger causes the second variable while holding the third variable constant. T-Y tests are performed on standardised data. The number of iterations for bootstrapped critical values is 10 000 times. *** denotes significance at 1% level ** denotes significance at 5% level, * denotes significance at 10% level, respectively. Market Power here is proxied by UNION, incident of union membership. $Z_{N,T}^{HNC}$ *is Zbar statistic and* $\tilde{Z}_{N}^{Hnc}$*is Zbar tild statistic (standardized for fixed T value).*

The results at Table 5.5 indicate the first variable Granger causes the second variable while holding the third variable constant. The null hypothesis assumes that there is no Granger causality from the first variable to the second variable. Different to Dumitrescu and Hurlin results, Table 5.5 provides no evidence of linkages between income inequality, corruption and market power under the panel data setting. However, the test results show market power Granger causes corruption, respectively. When we control for GDP, the null hypothesis that union membership does not cause income inequality can be rejected at the 1 percent level. The results demonstrate that market power also

Granger causes income inequality and similar with Dumistrescu-Hurlin causality test result.

5.3. Bivariate Copula

Interest in copula arises from several reasons. First, researches in econometrics or finance often possess more information about marginal distributions of related variables than their joint distribution. The copula approach is a useful method especially when the variables are not normally distributed for introducing joint distributions given the marginal distributions. Second, in a bivariate case, copula can be used to define nonparametric measures of dependence for pairs of random variables and developing additional concepts and measurement that go beyond linear association and correlation.

This section uses the bivariate copula analysis to OECD countries. This offers insightful information about how strong the relationship on pairs of variables. A strong dependence could translate how likely the variables related to each other. Archimedean and Elliptical families of copulas which are Gaussian, Clayton, Frank, Gumbel and Student t copulas. They serve to capture possible dependence between two different variables. This study uses AIC and BIC[3] as a goodness-of-fit test to select the best families of copulas**.** The lower the values of AIC and BIC, the better the data will fit to the model.

Another useful information from copula is tail dependence. This information indicating dependence in extreme values. Moreover, tail dependence is one of the characteristics that separate between the different families of copulas since there are families that cannot allow tail dependence (e.g., the Gaussian or normal copula).

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[3] *This study also applies the Hannan–Quinn information criterion (HQC) to find the best model fit of the copula. However, it provided results that were similar to the AIC and BIC.*

Table 5.6 Estimates of the Archimedean and Elliptical Families of Copulas

		Normal	Clayton	Frank	Gumbel	Student t
INEQ vs CORR	Parameter	0.621	1.044	5.411	1.720	(0.647,8.475)
	AIC	-392.892	-307.488	-457.775	-367.368	-409.673
	BIC	-392.886	-307.483	-457.769	-367.363	-409.661
INEQ vs MPOW	Parameter	-0.592	0.000	0.002	1.100	(-0.600,13.574)
	AIC	-348.195	0.071	0.328	131.762	-352.668
	BIC	-348.189	0.077	0.333	131.768	-352.656
CORR vs MPOW	Parameter	-0.515	0.002	0.002	1.100	(-0.519,99.995)
	AIC	-248.823	1.485	0.323	121.128	-247.276
	BIC	-248.818	1.491	0.329	121.134	-247.264

Notes: INEQ is income inequality, CORR is corruption, and MPOW is union membership. Student t copula shows two parameters as this type of copula captured two-tailed of dependence. '' signs show the best model of copula based on lowest AIC and BIC value.*

Table 5.6 reveals the results of estimation of five types of copulas for OECD countries. Normal, Clayton, Frank and Gumbel have one parameter while Student t copula has two parameters as this type of copula captures two-tailed of dependence. These values help to reveal the dependence relationships. It is clear that most of the time, Gaussian and Student t copula is the best model to capture the dependence between the pairs. We can also see a strong positive dependence existing between the INEQ-CORR pair. In contrast, there is a strong negative correlation regarding INEQ-MPOW and CORR-MPOW. However, MPOW is represented by the percentage of union membership, UNION. Note, the negative parameter coefficients in Table 5.6 between union membership and INEQ or CORR would indicate a positive link with market power. Thus, the negative correlation between INEQ-MPOW and CORR-MPOW imply a positive relationship between market power, and income inequality and corruption respectively.

For the INEQ-CORR link,there is a strong positive correlation based on the copula used. This indicates that inequality will increase if corruption increases, or vice versa. This also translated into how related these variables are to each other. The dependence for this pair also is the strongest when comparing all examples of dependence. This is based on the Gaussian, Frank and Student t values (0.621, 5.411 and 0.647, respectively). This shows that inequality has a strong relationship with corruption compared to all the others. Based on the value of AIC and BIC, Frank copula is the best model that fits the data. However, these values are not far from the Gaussian and Student t copula.

For the INEQ-MPOW and CORR-MPOW links, we observe strong negative correlations based on the Gaussian (see "Normal") and Student t copula with -0.592 and -0.599, respectively. These values could be considered higher and show the strong dependence existing between the pairs. The negative relationship could be translated as follows; when inequality or corruption increases, there is a high probability for union membership to decrease. This demonstrates a strong positive relationship between market power with income inequality and also corruption.

This result also demonstrates Frank, Gumbel and Clayton copulas are not suitable to examine INEQ-MPOW and CORR-MPOW pairs. The results of AIC and BIC from Frank, Gumbel and Clayton copulas are too far from Normal and Student t copula. Another useful information from copula is tail dependence. Details on tail dependence will be discussed in Section 5.4.

Overall, the results show strong and positive relationship between income inequality, corruption and market power. These seem consistent with most of the literature discussed in Chapter 2. Thus, the evidence here contributes to existing knowledge of the linkages between income inequality, corruption and market power with copula shedding additional insights on these linkages.

5.4. Vines Copula

This section extends the copula analysis to vines copula to further investigate empirically the relationship between income inequality, corruption and market power for OECD countries for the period 1977 - 2014. Standard multivariate copulas can become inflexible in high dimensional dependence modeling. At the same time, they do not allow for different dependency structures between pairs of variables. Combined with bivariate copula, regular vines have proven to be a flexible tool in high dimensions. For this chapter, Vines copula is used for our trivariate setting.

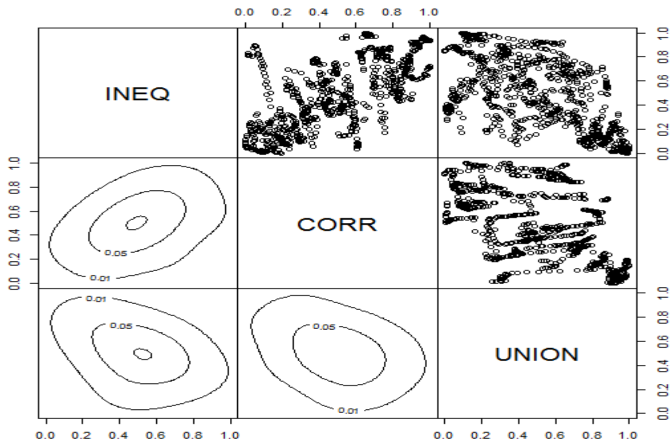

Figure 5.1 Copula with Scatter and Contour Plots

Figure 5.1 shows a pairs plot with scatter plots above and contour plots with standard normal margins below the diagonal. A contour plot is an illustration that can be used to understand the relationship between three variables. This graph shows the 3-dimensional relationship in two dimensions, with x and y factors plotted on the x and y scales and response values represented by contours. There is evidently a strong dependence between the INEQ-CORR pair, based on the diagonal density for all pairs of variables. The dependence in the CORR- MPOW pair (i.e., MPOW≡UNION) appears weaker than that in the INEQ-MPOW and INEQ-CORR pairs. There is evidence of tail behavior for the INEQ- MPOW pair because the scatter plot shows data tending to focus on the upper and lower diagonal. Copula that capture tail characteristics and dependence are more appropriate techniques to shed light on tail behavior for these pairs.

Table 5.7 Kendall Tau Correlation Results

	INEQ	CORR	MPOW
INEQ	1.000	0.478	-0.414
CORR	0.478	1.000	-0.355
MPOW	-0.414	-0.355	1.000

Notes: INEQ is income inequality, CORR is corruption, and MPOW is union membership.

In Table 5.7, estimated Kendall's tau are equal to 0.478, -0.414 and -0.355 for INEQ-CORR, INEQ-MPOW and CORR-MPOW, respectively. These values are then used to identify the variable sequence where the most important variable will be placed first in the sequence.

Maximum spanning trees with absolute values of pairwise Kendall's taus as weight are applied to select the vine structure as suggested by Dibmann et al. (2013). The tree selection algorithm suggests INEQ as the first root node in C-vine (C-vine tree with strongest dependencies in terms of absolute empirical values of pairwise Kendall's). This demonstrated how INEQ is a most important variable between these three variables. The next node order of the first tree determines the CORR and MPOW. The sequence for the first tree is INEQ, CORR and MPOW.

Next, adequate pair-copula families associated with the C-vine structure are identified. This study selects a copula family from the Gumbel, Frank, Student-t, Gaussian and Clayton variants. The selection of bivariate copula models is based on AIC and BIC information criteria corrected for the numbers of parameters (Brechmann, 2010). The choices of copula models in the first tree have a great impact on the global fit of the R-vine model. Thus, two goodness-of-fit tests are employed using a scoring approach introduced by Vuong (1989) and Clarke (2007). Both the Vuong and Clarke tests are model selection tests using the Kullback-Leibler information criterion.

The results suggest that for the first tree, Frank and Student t copulas are the best for

INEQ-CORR and INEQ-MPOW pairs, respectively. Next, corresponding copula parameters are estimated using the sequential method. Possible independent conditional variable pairs are identified by applying Kendall's tau preliminary bivariate independence test (Genest and Favre, 2007). The parameters obtained from the sequential method are used as starting values to establish corresponding MLE estimates. Thus, the estimation results can be improved. For the second level, Gaussian copula is the best fit compared to all the others. Results of the parameters estimation are documented in Table 5.8.

Table 5.8 C-Vine Copula Estimation Results

	Copula	Parameter (SE)		Kendall's	Tail Dependence
INEQ-CORR	Frank	5.411	-	0.482	-
		(0.267)	-		
INEQ-MPOW	Student-t	-0.600	13.691	-0.410	(U=0.000,L=0.000)
		(0.021)	-		
CORR- MPOW | INEQ	Gaussian	-0.275	-	-0.177	-
		(0.031)	-		

Notes: INEQ is income inequality, CORR is corruption, and MPOW is union membership. The table summarizes the C-vine copula estimation results for the overall sample. The values in parentheses represent the standard error of the parameters. There is only one parameter for Frank and Gaussian copula and two parameters for Student t copula.

Results in Table 5.8 show that all estimated parameters are significant at the 5% level. The strongest dependence is between INEQ-CORR as shown by Kendall's tau value with 0.482. Interestingly, there is a negative dependence between INEQ- MPOW as shown by Kendall's tau value with -0.410. The dependence between CORR- MPOW with the existing INEQ is also a negative value (Kendall's τ=-0.177). Similarly, the D-vine copula model is fitted and reported in Table 5.9. The results suggest for the first tree, Frank and Gaussian copula are the best copula for INEQ-CORR and CORR-MPOW pairs, respectively.

Table 5.9 D-vine Copula Estimation Results

	Copula	Parameter (SE)	Kendall's	Tail Dependence
INEQ-CORR	Frank	5.411 (0.267)	0.482	-
CORR-MPOW	Gaussian	-0.520 (0.023)	-0.348	-
INEQ-MPOW | CORR	Gaussian	-0.375 (0.028)	-0.246	-

Notes: INEQ is income inequality, CORR is corruption, and MPOW here is union membership. The table summarizes the C-vine copula estimation results for the overall sample. The values in parentheses represent the standard error of the parameters. There is only one parameter for Frank and Gaussian copula.

Results in Table 5.9 indicate that all estimated parameters are significant at the 5% level. The strongest dependence is INEQ-CORR as shown by Kendall's tau value (Kendall's τ=0.482). The INEQ-CORR pair shows positive dependence based on Kendall's tau value. Apparently, there is a statistically significant negative dependence between CORR and MPOW (Kendall's τ=-0.348). At the second level, the Gaussian copula seems to fit well with the pair given. The dependence between INEQ-MPOW|CORR (i.e., dependence between INEQ-MPOW conditional on CORR), also seems to be significantly negative (Kendall's τ=-0.246). The above suggest a strong relationship between income inequality, corruption and market power. To avoid confusion, recall that MPOW in this chapter is proxied by UNION and it is reasonable to expect an inverse relation between UNION and MPOW. Hence, we interpret the negative parameter signs in Tables 5.8-5.9 to indicate positive correlations and dependence between CORR or INEQ with MPOW.

To compare the two-fitted vines copula models, this study estimates the loglikelihood, AIC, BIC and p-values for the Vuong test as summarized in Table 5.10.

Table 5.10 The C-Vine and D-Vine copulas compared

	C Vine	D Vine
LogLik	436.832	413.924
AIC	-865.663	-807.772
BIC	-846.895	-821.849
Vuong Test	0.000	

Notes: The table reports the loglikelihood value, the AIC, the BIC and p-values of the Vuong test concerning the C-vine and D-vine copula models

In order to compare the two fitted vines copula models, we calculate the loglikelihood AIC, BIC and p-values for the Vuong test. The Vuong test compares two non-nested models with the aim being to measure the distance between two statistical models. According to the loglikelihood, Akaike and Bayesian Information criterion, the C-vine copula model produces a better fit, with little difference between the two specified vine structures.

Results in Table 5.10 shows that the C-vine copula model produces a better fit than D-vine copula with little difference between two specified vine structures for trivariate setting. Under the null hypothesis which contends that the C- and D-vine copula models are statistically equivalent, the Vuong test confirms the C-vine copula model is better than the D-vine model. It can be concluded that the C-vine copula model is more suitable for describing multivariate dependence between all variables of interest and can provide additional insights due to their specific structures.

Overall, we illustrate the use of the C- and D-vine copula models in quantifying the dependence between INEQ, CORR and MPOW. Our results demonstrate the relevance of the vine copula model for trivariate setting. The present study confirms previous findings and contributes additional evidence that suggests the linkages between these three factors.

5.5. Conclusion

This chapter has employed causality and copula analysis to examine the nature of the relationship between the three main variables of interest. It utilized data for developed OECD countries for the 1984 to 2014 period. The findings here add to our understanding of linkages between income equality, corruption and market power in OECD countries.

Results emanating from non-linear Granger causality tests in OECD countries reveal there is not much evidence of linkages between income inequality, corruption and market power for the time series data. This finding contrasts with literature expectations. Next, this chapter extended the stationary bivariate non-causality test for heterogeneous panels of Dumitrescu and Hurlin (2012) to a trivariate setting with possible non-stationary variables using the Toda-Yamamoto approach. Using the TY method, we can ascertain that the results are quite similar to those obtained in Dumistrescu-Hurlin causality tests for panel data. There is little evidence of Granger causality between the three variables. There are several possible explanations for this result. Difference in datasets or the exisiting of omitted variables might be the factors.

Next, this chapter applied the copula approach to explore the density of the links between income inequality, corruption and market power. Specifically, this study uses both bivariate and trivariate copula. Bivariate copula serves to find the dependence between pairs of variables. The results obtained show there is a positive correlation between income equality and corruption. There is an inverse relationship between income inequality or corruption with union membership. Also, union membership inversely relates to market power (i.e., lower membership means greater market power for employers). This indicates that market power has positive connection with income inequality and market power. These results of bivariate copula study confirm a positive correlation between variables which are income equality and market power; corruption and market power.

Next, this trivariate employed the CD Vine copula approach to capture the dependence between all three variables of interest. The strongest dependence is between income equality and corruption. Next, there is a positive dependence between income equality and market power. The dependence between corruption and market power with existing income equality is also positive. The results suggest income inequality as the first root node of C-vine and D-vine for OECD countries. The results also show that income inequality is more strongly linked to corruption than market power in OECD countries.

Finally, this study's results are consistent with most literature that suggests corruption and market power do have an impact on income inequality. However, the result is different between countries involved. To this end, this study does not suggest that corruption and market power are solely responsible to the increase in income inequality. Nonetheless they have likely played an important part in OECD countries.

Chapter 6. Granger causality and Copula: Evidence from USA states

Towards refutable scientific hypotheses, economic models on income distribution often rely on the assumption that institutional factors (e.g., the rule of law or official statistics) change very slowly or apply equally to all agents or units of study. This seems reasonable in the context of a single country. However, in international studies this assumption is more problematic when national institutions differ greatly and are often unobservable. Thus, model uncertainty increases substantially when dealing with cross-country panel data. Hence, this chapter confines our investigation of causal linkages between income inequality, corruption and market power at the micro level. That is, analysis is restricted to a single country, that of the United States, looking at the evolution of the three variables of interest over time. The chapter re-employs the same empirical techniques examining the same relationships as in the previous chapter but here the level of data aggregation is at the US state level rather than at the country level. Hence, this study utilise yearly data from 1977 to 2014 for 50 states. Also, recall from chapter 3 that the empirical measures of corruption and market power differ to those available for OECD countries. Here, we use per capita convictions of government officials and market concentration respectively while for OECD we used the Bayesian Corruption Index and union membership respectively.

6.1. Dumistrescu-Hurlin Causality

6.1.1. Panel Unit Root Test

This section applies panel unit root tests introduced by Im et. al. (2003) and Pesaran (2007) to determine the order of integration for the series. This process is to identify whether the series enter the model in a non-explosive form or not. The results of the unit root tests for the variables in their levels and first differences are reported in Table

6.1. Note, that in contrast to the previous chapter, we employ a different and more direct index of market power. Instead of the incidence of union membership, here we employ a market concentration index that measures the share of state employment captured by the largest companies (i.e., those with at least 5,000 employees nationally in the USA).[4]

Table 6.1 Panel Unit Root Test

	IPS Test [W-t-bar]		CADF Test [Z-t-bar]	
Variable	Lag (1)	Lag (2)	Lag (1)	Lag (2)
Levels				
INEQ	0.2264	1.0220	-8.595	-4.410
CORR	-13.7418	-9.0159	-12.818	-5.784
MPOW	0.2975	-0.8582	-4.196	-3.226
First difference				
INEQ	-28.2826**	-23.8499**	-25.334**	-18.147**
CORR	-34.9244**	-20.7822**	-28.110**	-16.060**
MPOW	-20.2906**	-26.0324**	-20.838**	-14.170**

*Notes: ** and * indicate significance at 5% and 10% level respectively. The null hypothesis is panel containing unit roots. CORR is per capita prosecutions of public officials and MPOW is market concentration by largest firms in terms of employment at the state level. Tests include a trend.*

The null hypothesis for both tests is that the series is a unit root. It is apparent from Table 6.1 the results reveal that all three variables do contain a unit root. At levels, the test fails to reject the null hypothesis at 5 percent level of significance and we thus conclude that there are unit roots in the panels. IPS test show the unit roots exist for all variables for both one and two lags. Similar to IPS test, CADF test indicates the existence of unit root for all variables in levels. Table 6.1 also reports unit root tests for first differences that confirm the variables are I(1) series.

[4] *See chapter 3 for more details.*

6.1.2. Cointegration test

Based on the unit root tests reported in Table 6.1, there is a need to examine the cointegration relationship between the processes for US states. Cointegration test is used to identify long-run and stable relationships between sets of variables. Cointegration tests are needed for verification but they do not affect Toda-Yamamoto test.

The panel cointegration test of Westernlund (2007) is employed for the panel data. This test applies the residual-based stationary bootstrap test to account for cross-section dependence issue. Each test is able to capture individual trend terms and specific intercept, as well as individual specific slope parameters, individual specific short-run dynamics, including serially correlated error terms and non-strictly exogenous regressors. The variables are pre-conditioned before the panel cointegration test of Westerlund is performed. The outcome of the Westerlund panel cointegration test is summarized in Table 6.2.

Table 6.2 Panel Cointegration Test for US States

Dependent variable	Independent variable				
	Statistic	Value	Z-value	P-value	Robust P-value
INEQ			CORR MPOW		
	G_t	-3.432	-7.598	0.000	0.020
	G_a	-18.379	-4.578	0.000	0.020
	P_t	-20.615	-4.921	0.000	0.100
	P_a	-15.728	-5.482	0.000	0.060
CORR			INEQ MPOW		
	G_t	-3.084	-4.673	0.000	0.340
	G_a	-13.379	0.244	0.597	0.010
	P_t	-24.225	-8.923	0.000	0.370
	P_a	-18.073	-7.935	0.000	0.010
MPOW			INEQ CORR		
	G_t	-2.376	1.279	0.900	0.900
	G_a	-8.795	4.666	1.000	0.990
	P_t	-11.280	5.427	1.000	0.970
	P_a	-7.247	3.390	1.000	0.960

G-statistics are for group mean tests assuming heterogeneity while p-statistics are for the panel test assuming homogeneity. The number of lags and leads in the error-correction tests are chosen by the

Akaike criterion. Tests include a trend.

Table 6.2 provides the results of cointegration tests for US States. In the first panel, the null hypothesis of no cointegration is rejected at 5% level of statistical significance for two out of four tests. Thus, it can be conclude that there is no clear evidence of cointegration in the panels when income inequality is set as the dependent variable. When CORR is the dependent, two out of four robust tests show the null hypothesis of no cointegration is rejected at 5% level. While the result for G_t, and P_t indicates there is no evidence to reject the null hypothesis. Next, all four tests lead to a clear non-rejection of the null at 5% level for MPOW which show an evidence in favour of no cointegration. These results are interpreted as evidence of no cointegration between INEQ, CORR and MPOW.

6.1.3. Causality Testing Results

This section employed the panel causality test introduced by Dumitrescu and Hurlin (2012). This non-causality test is used to suit heterogeneous panel data models with fixed coefficients. There is no causality relationship for any of the units of the panel under the null hypothesis.

The results are presented in Table 6.3 for each possible direction of causality (i.e., which variable ‘causes’ which variable). Note, however, that these causality tests here do not shed light on the sign of the causal relationship (i.e., whether negative or positive relationship) if there exists one. This qualitative information becomes clearer with copula analysis in section 6.3.

The maximum lag length to be used in a standard VAR model varies, depending on the criteria used. The three criteria used in this study are Akaike’s information criterion (AIC), Schwarz’s Bayesian information criterion (SBIC) and the Hannan and Quinn information criterion (HQIC). Based on these three criteria, it is concluded that the maximum lag is two ($K=2$).

Table 6.3 Dumistrescu-Hurlin Causality Results

Causality	$\bar{W}$ statistic	$\bar{Z}$ statistic	$\tilde{Z}$ statistic
INEQ $\Rightarrow$ CORR	1.6314	3.1572**	2.5696*
CORR $\Rightarrow$ INEQ	1.1674	0.8369	0.4807
INEQ $\Rightarrow$ MPOW	5.1000	20.4999**	18.1833**
MPOW $\Rightarrow$ INEQ	1.4059	2.0294**	1.5542
CORR $\Rightarrow$ MPOW	2.8262	9.1310**	7.9478**
MPOW $\Rightarrow$ CORR	1.2576	1.2880	0.8868

*Notes: INEQ is income inequality, CORR is corruption, and MPOW is market power. Lag order=2; '**' indicate significance level of 95 percent and '*' indicate significance level of 90 percent*

In Table 6.3, bidirectional Granger-causality seems present in all pairs except from corruption to income inequality and market power to corruption. Chong and Gradstein (2007) demonstrate the presence of bidirectional Granger-causality between corruption and income inequality for cross-country findings using a panel data set of all 50 U.S. states over the period in their study. Contrary to expectations, this research does not find a significant directional causality from corruption to income equality. This inconsistency may be due to differences in methodology and in datasets. In this study we employed Bayesian Corruption Index (BCI) as a proxy for the level of corruption. The two most influential corruption perception databases are the Worldwide Governance Indicators (WGI) published by the World Bank and the Corruption Perception Index (CPI) published by Transparency International. However, BCI can be considered an improvement and more advanced than the existing corruption perception databases.

Again, bidirectional Granger-causality could be found on income inequality and market power; corruption and market power. Overall, the findings in this study are consistent with existing literature except for the absence of causality from income equality to corruption.

6.1.4. Panel Vector Autoregression (VAR) Model

Next, we again estimate a panel VAR model. Table 6.4 reports the results of the model with four variables (INEQ, CORR, MPOW, GDP) for USA states.

Table 6.4 Panel VAR Estimation: USA States

Dep.	Independent Variables								Wald
Var.	INEQ $_{t-1}$	CORR $_{t-1}$	MPOW $_{t-1}$	GDP $_{t-2}$	INEQ $_{t-2}$	CORR $_{t-2}$	MPOW $_{t-2}$	GDP $_{t-2}$	F-stat
INEQ $_t$	1.163	0.019	0.010	-0.006	-0.319	-0.043	-0.005	0.007	0.647
	(31.867)**	(0.389)	(0.404)	(-0.670)	(-9.036)**	(-0.809)	(-0.210)	(0.941)	
CORR $_t$	0.016	1.379	-0.013	0.012	-0.001	-0.414	0.014	-0.007	3.566**
	(0.639)	(39.721)**	(-0.748)	(2.044)**	(-0.014)	(-11.161)**	(0.847)	(-1.323)	
MPOW $_t$	0.022	-0.064	1.359	0.019	-0.002	0.062	-0.385 (-	-0.027	2.389**
	(0.420)	(-0.8965)	(38.879)**	(1.605)	(-0.039)	(0.818)	10.973)	(-2.405)**	

*Notes: (1) Hausman test has been used in the selection of the fixed effects or random effects model. (2) Based on Hausman test results, all models fit the fixed effects model. (3) Reported numbers show the coefficients of regressing the row variables on lags of the column variables. (3) Heterokedasticity adjusted t-statistics are in parentheses. (4) * and ** denote the rejection of null hypothesis at the 10% and 5% level of significance, respectively.*

Table 6.4 presents the estimated panel data VAR by FEM and the Wald test of coefficients for Granger causality directions. For US by states, it is observed that the relation of CORR to GDP is positive in the estimated coefficients. This causality relation indicates that GDP causes corruption, showing that the increase of economic activity leads to the increase of corruption.

The coefficient of GDP two periods lagged $(t-2)$ is statistically significant in MPOW equation showing that higher market power leads to the decrease of economic activity. In general, this study found the evidence that GDP have reinforcing effects on corruption and market power.

Based on the panel VAR-Granger causality Wald test, it is clear that INEQ, MPOW and GDP jointly have significant impact on CORR. The results also show that INEQ, CORR and GDP jointly cause MPOW. However, CORR, MPOW and GDP do not jointly cause INEQ.

6.2. Toda-Yamamoto Granger non-causality test

6.2.1. TY Granger Panel Data Results

Further, the Toda-Yamamoto Granger non-causality test approach has also been employed to explore causality between income inequality, corruption and market power in panel data. This approach enables additional insights on these variables in a trivariate setting. Table 6.5 presents results for panel data of US States. The number of additional lags is set to one (*m=1*) and the order panel VAR is set to two (*K=2*) according to results from individual time series. Panel (a) represents the specification without conditioning on GDP whereas panel (b) reflects the specification with conditioning on GDP.

Table 6.5 Trivariate Toda-Yamamoto Panel Granger Non-Causality Tests

		Asymptotic Wald Statistics	Bootstrap critical values 1%	5%	10%
K=2, m=1					
(a) *Without controlling for GDP*					
$Inequality_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	2.9710	5.2749	4.2489	3.7223
	$\tilde{Z}_{N}^{Hnc}$	2.4568	4.6120	3.6522	3.1596
$Inequality_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	1.0576	3.3967	3.1993	3.0916
	$\tilde{Z}_{N}^{Hnc}$	0.6668	2.8550	2.6703	2.5695
$Corruption_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	3.4083***	-0.6247	-0.6834	-0.7149
	$\tilde{Z}_{N}^{Hnc}$	2.8658***	-0.9070	-0.9619	-0.9913
$Corruption_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	0.7146***	-1.0733	-1.1339	-1.1593
	$\tilde{Z}_{N}^{Hnc}$	0.3459***	-1.3266	-1.3833	-1.4071

$Market\ Power_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	2.4841***	0.9557	0.7927	0.7156
	$\tilde{Z}_{N}^{Hnc}$	2.0013***	0.5715	0.4189	0.3469
$Market\ Power_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	4.1563***	2.8164	1.9477	1.5048
	$\tilde{Z}_{N}^{Hnc}$	3.5656***	2.3121	1.4994	1.0851
(b) With controlling for GDP					
$Inequality_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	3.5567***	2.1053	1.5097	1.2177
	$\tilde{Z}_{N}^{Hnc}$	3.0047***	1.6469	1.0897	0.8166
$Inequality_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	1.5389	1.8521	1.7029	1.6335
	$\tilde{Z}_{N}^{Hnc}$	1.1171	1.4100	1.2705	1.2055
$Corruption_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	4.4655***	-1.0356	-1.0834	-1.1058
	$\tilde{Z}_{N}^{Hnc}$	3.8548***	-1.2913	-1.3361	-1.3570
$Corruption_{i,t} \Rightarrow Market\ Power_{i,t}$	$Z_{N,T}^{HNC}$	0.5139***	-0.9565	-1.0036	-1.0283
	$\tilde{Z}_{N}^{Hnc}$	0.1582***	-1.2174	-1.2614	-1.2845
$Market\ Power_{i,t} \Rightarrow Inequality_{i,t}$	$Z_{N,T}^{HNC}$	2.8727***	-0.8266	-0.9005	-0.9499
	$\tilde{Z}_{N}^{Hnc}$	2.3648***	-1.0959	-1.1650	-1.2112
$Market\ Power_{i,t} \Rightarrow Corruption_{i,t}$	$Z_{N,T}^{HNC}$	4.4937***	4.1141	3.0771	2.5869
	$\tilde{Z}_{N}^{Hnc}$	3.8812***	3.5261	2.5560	1.4190

*Notes: $\Rightarrow$ indicates the first variable Granger causes the second variable while holding the third variable constant. T-Y tests are performed on standardised data. The number of iterations for bootstrapped critical values is 10 000 times. *** denotes significance at 1% level ** denotes significance at 5% level, * denotes significance at 10% level, respectively. $Z_{N,T}^{HNC}$ is Zbar statistic and $\tilde{Z}_{N}^{Hnc}$ is Zbar tild statistic (standardized for fixed T value).*

Table 6.5 provides the estimation results on the linkages between the three variables in our panel data. T-Y tests reveal that the null hypotheses of corruption does not cause income inequality, holding market power constant, can be rejected at the 1 percent level, implying that the variations in corruption in the OECD countries significantly lead to changes in income inequality. Table 6.5 also demonstrates that changes in market power significantly result in variations in income inequality. There is a mutual relation of T-Y causality between corruption and market power. By comparing these results with bivariate Dumistrescu-Hurlin causality, 6.1.3 section, the trivariate approach here leads to starkly different findings.

When we control for GDP, there is a bi-directional of T-Y causality between corruption and market power and also between income inequality and corruption. Table 6.4 also reveals that the null hypotheses of income inequality does not cause market power while accounting for GDP cannot be rejected at the 1 percent level, implying that income inequality in the OECD countries does not affect market power.

In general, corruption Granger cause income inequality and market power under T-Y causality. At the same time, market power Granger cause income equality and corruption. However, there is no evidence that income equality Granger cause corruption or market power. When we control for GDP, all the pairs demonstrate Granger cause results except that income inequality does not Granger cause market power for US States. The present study confirms previous findings and contributes additional evidence the linkages between income inequality, corruption and market power.

6.3. Bivariate copula

Alike in the previous chapter, this chapter also employs bivariate copula for United States at the state level. The results provide insighs about the strength of pair-wise relationships. A strong dependence would indicate that the variables are highly related to each other.

Archimedean and Elliptical family of copulas which are Gaussian, Clayton, Frank, Gumbel and Student t copulas are used to capture possible dependency between two different variables. This study uses AIC and BIC[5] as a goodness-of-fit test to select the

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[5] *This study also applies Hannan–Quinn information criterion (HQC) to find the best model fit of copula. However, it gave similar results to AIC and BIC.*

best family of copulas; i.e., the one with the minimum AIC or BIC value. Table 6.10 shows the results of estimation of five types of copulas across 50 states in the United States.

The results make it clear that Clayton copula best capture the dependency of INEQ-CORR. This type of copula has left tail dependence. These results indicate that there is a high probability for corruption to decrease when income inequality decreases. However, this pair moves independently during other times and there is no significant relationship when corruption or income inequality increases. Note, AIC and BIC suggest that Normal and Student t copula are not too far from Clayton copula. These show Normal and Student t copula are also suitable to describe the dependecy of INEQ-CORR.

Table 6.6 Estimates of the Archimedean and Elliptical Families of Copulas

		Normal	Clayton	Frank	Gumbel	Student t
INEQ-CORR	Parameter	0.253	0.455	1.668	1.132	(0.269,11.211)
	AIC	-125.276	-222.631	-138.772	-50.787	-142.300
	BIC	-125.273	-222.628	-138.769	-50.784	-142.294
INEQ-MPOW	Parameter	0.345	0.000	0.002	1.100	(0.348,25.978)
	AIC	-240.418	0.131	0.489	191.991	-243.4713
	BIC	-240.415	0.134	0.492	191.993	-243.4655
CORR-MPOW	Parameter	0.198	0.000	0.0033	1.100	(0.200,85.214)
	AIC	-75.706	0.058	0.397	139.702	-75.935
	BIC	-75.703	0.061	0.400	139.705	-75.929

Notes: INEQ as income inequality, CORR as corruption, MPOW as market power. Student t copula shows two parameters as this type of copula captured two tail of dependence. '' signs show the best model of copula based on lowest AIC and BIC value.*

For INEQ-MPOW and CORR-MPOW, we observe a strong positive correlation based on the Student t copula (optimal copula types respectively) with 0.348 and 0.200. These values seem lower than the equivalent results in Chapter 5. In Chapter 5, the values for INEQ-MPOW and CORR-MPOW is more than 0.5, indicates a really strong connection between variables. However, the values in Chapter 6 could be considered high and show a strong connection between the pairs as they are more than 0.2. Based on the previous literature, any values larger than absolute value of 0.2 in copula could indicate a strong relationship. We observe the positive parameter signs for INEQ-MPOW and CORR-MPOW. These reveal that variations in income inequality could significantly lead to changes in market power. The same is observed for the relationship between corruption and market power. Increases in corruption correlate with increases in market power.

The results suggest that Student t copula is the best model to capture dependency in the INEQ-MPOW and CORR-MPOW pairs. This type of copula has upper and lower tail dependence. The results in Table 6.6 also imply that Frank, Gumbel and Clayton copula are not appropriate for the INEQ-MPOW and CORR-MPOW linkages.

Altogether, the evidence here points to a strong positive correlation for the INEQ-CORR pair. This is consistent with the findings of Kar and Saha (2012) where corruption increases income inequality. A positive relationship is also seen in INEQ-MPOW and CORR-MPOW. In the end, these empirical results are quite similar to those ovserved in OECD countries, Chapter 5.

6.4. Vines copula

Vines copula are also employed here to shed light on variable dependence at the state level within the United States. These copula allow for trivariate dependence.

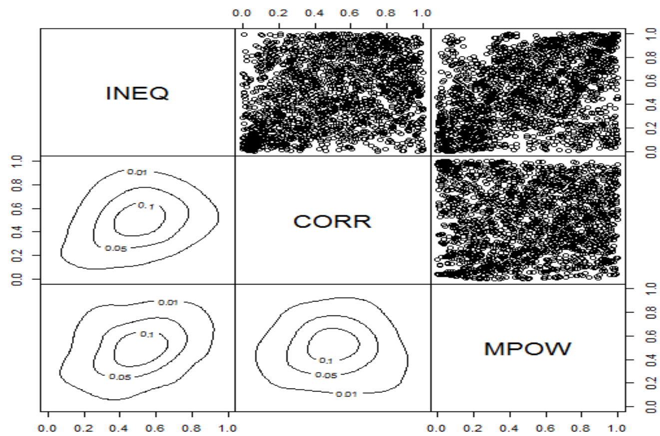

Figure 6.1 Copula with Scatter and Contour Plots

From the contour plots in Figure 6.1, the INEQ-MPOW pair shows the highest diagonal density, followed by the INEQ-CORR pair. This demonstrates strong dependency among the pairs. Low diagonal density in CORR-MPOW pair illustrates low dependence compared to other two pairs. There is tail dependence shown in scatter plot of INEQ-CORR and INEQ-MPOW pairs. The data seems to be concentrated at the diagonal. Figure 6.1 illustrates, especially the contour plots, a clear positive correlation in INEQ-MPOW and INEQ-CORR (i.e., contours are spread from top-right to bottom-left). The dependence between CORR-MPOW pair appears weaker than INEQ-MPOW and INEQ-CORR pairs.

Further, there is evidence of tail behaviour on INEQ-CORR pair as the scatter plot show data tends to focus on upper and lower diagonal. There is also evidence of upper and lower diagonal on INEQ-MPOW pair. This might make copula based on symmetric tail dependence is a good fit for the data; i.e., MPOW correlates with INEQ in both low and high levels. The dependency among all pairs can be best described in estimated parameter of copula in Table 6.8 and Table 6.9.

Table 6.7 Kendall Tau Correlation Results

	INEQ	CORR	MPOW
INEQ	1.000	0.178	0.227
CORR	0.178	1.000	0.128
MPOW	0.227	0.128	1.000

The estimated Kendall's tau is equals to 0.178, 0.227 and 0.128 for the INEQ-CORR, INEQ-MPOW and CORR-MPOW pairs respectively. These values will be used to identify the sequence of variables where the important variables will appear in the first sequence. Table 6.6 provides that income inequality and market power has the strongest relationship with value of 0.227. The direction is positive. This is followed by income inequality and corruption with 0.178.

Maximum spanning trees with absolute values of pairwise Kendall's taus as weights are applied to select the vine structure, as suggested by Dibmann et.al (2013). The tree selection algorithm suggests INEQ is the first root node in C-vine (C-vine tree with strongest dependencies in terms of absolute empirical values of pairwise Kendall's). The node order of the first tree is determined as INEQ, MPOW and CORR. This is based on the estimated Kendall's tau values. Important variable will be the first sequence. Interestingly, we find MPOW to be a more important variable than CORR.

Next, adequate pair-copula families associated with the C-vine structure are identified. We seek to select the optimal copula among five copula families: Gumbel, Frank, Student-t, Gaussian and Clayton.

Table 6.8 C-vine Copula Estimation Results

	Copula	Parameter (SE)		Kendall's	Tail Dependence
INEQ-MPOW	Student-t	0.349	26.005	0.226	(U=0.000, L=0.000)
		(0.020)	(15.848)		
INEQ-CORR	Student-t	0.269	11.211	0.173	(U=0.021, L=0.021)
		(0.022)	(3.070)		
MPOW-CORR | INEQ	Gaussian	0.119	-	0.076	-
		(0.023)	-		

Notes: The table summarized the C-vine copula estimation results over the overall sample. Student t *copula shows two parameters as this type of copula captures two-tail dependence. The values in parenthesis (below the parameter) represent the standard error of the parameters.*

The results suggest for the first tree, Student t copula is the best copula for INEQ-MPOW and INEQ-CORR pairs, respectively. Next, the corresponding copula parameters are estimated using the sequential method. Possible independent conditional variable pairs are identified by applying Kendall's tau preliminary bivariate independence test (Genest and Favre, 2007). Thus, the estimation results can be improved. From Table 6.8, is it valid to say that INEQ-MPOW is found to be the most important bivariate link. This is followed by INEQ-CORR. These results could interpret that linkage between income inequality and market power is the most important linkage for the US states. This is followed by a linkage between income inequality and corruption.

Results of the parameters estimation can be shown in Table 6.8. These show that all estimated parameters are significant at 1% significant level. The strongest dependence is between INEQ-MPOW as shown by Kendall's tau value (Kendall's τ=0.226). The dependence between INEQ-MPOW is positive means that changes in income inequality significantly lead to changes in market power. This is followed by INEQ-CORR. The dependence between INEQ-CORR is positive as shown by Kendall's tau value (Kendall's τ=0.173). INEQ-MPOW has values almost double than INEQ-CORR. This show income inequality has more relation with corruption than market power.

As for MPOW-CORR|INEQ (i.e., dependence between MPOW-CORR conditional on INEQ), the value Kendall's tau value is 0.076 and the value for INEQ-MPOW.is 0.226. The value Kendall's tau for MPOW-CORR | INEQ is about one third of the value Kendall's tau for INEQ-MPOW. Thus, we can conclude that the connection of INEQ-MPOW is three times stronger than that of MPOW-CORR | INEQ.

The dependence between INEQ-MOPW and INEQ-CORR | INEQ shows upper and lower tail dependence (λ_U=λ_L=0.000; λ_U=λ_L=0.021). The values for upper and lower tail for INEQ-MOPW pair is too small, approximately zero. However, we could see upper and lower tail behavior for INEQ-CORR. When income inequality increases, there is a high probability for market power to increase; or vice versa. These indicate that both high and low values of these variables are correlated to each other.

Similarly, D-vine copula models are fitted and reported in Table 6.9. The results also suggest for the first tree, Student t and Gaussian copula are the best copula for INEQ-MPOW and MPOW-CORR pairs, respectively. While for INEQ-CORR with the existing Market Power is best fit with the Frank copula.

Table 6.9 D-vine Copula Estimation Results

	Copula	Parameter (SE)		Kendall's	Tail Dependence
INEQ-MPOW	Student-t	0.348	26.005	0.226	(U=0.000, L=0.000)
		(0.020)	(15.848)		
MPOW-CORR	Gaussian	0.199	-	0.1275	-
		(0.021)	-		
INEQ-CORR | MPOW	Frank	1.425	-	0.1553	-
		(0.143)	-		

Notes: The table summarized the C-vine copula estimation results over the overall sample. Student t copula shows two parameters as this type of copula captures two-tail dependence. The values in parenthesis represent the standard error of the parameters.

Results in Table 6.9 shows that all estimated parameters are significant at 1% significant level. The strongest dependence is between INEQ-MPOW as shown by Kendall's tau value (Kendall's τ=0.226). The dependence between INEQ-MPOW shows both upper and lower tail dependence (λ_U=λ_L=0.000). When income inequality increases, there is a high probability for market power to increase; or vice versa. However, this pair moves independently during other time. This follows from INEQ-CORR | MPOW with the Kendall's τ coefficient equal to 0.153. This value means that the correlation between income inequality and corruption, conditional on market power is 0.153.

To compare the two-fitted vine-copula models, this study estimates the loglikelihood, AIC, BIC and p-values for Vuong test in Table 6.10.

Table 6.10 Comparison of the C-vine and D-vine

	C Vine	D Vine
Log Likelihood	206.316	209.682
AIC	-402.632	-411.363
BIC	-374.884	-389.165
Vuong Test	0.427	

Notes: The table reports the loglikelihood value, the AIC, the BIC and p-value of the Vuong test for the C-vine and D-vine copula models

The loglikelihood, AIC, BIC and p-values for Vuong test are calculated in Table 6.10 to compare C and D model. Again, the Vuong test compares two models against each other based on their null hypothesis for a statistically significant decision among the C and D models. According to the Akaike and Bayesian Information criteria, the D-vine copula model produces better fit, with little difference between the two specified vine structures. Results in Table 6.10 shows that the D-vine copula model produces better fit with little difference between two specified vine structures.

Under the null hypothesis that the C-vine and D-vine copula models are statistically equivalent, the Vuong test failed to choose between the two models. It can be concluded that both vines is suitable to describe multivariate dependence between all variables of interest and can provide additional insights due to their specific structures. Based on these results, it seems that the linkages between income inequality, corruption and market power can be well explained by C-vine or D-vine copula.

6.5. Conclusion

This chapter empirically explores the linkages between income inequality, corruption and market power for 50 states of United States from 1977 to 2013. This research combines methods from econometrics (causality test) and advance statistical (copula) models to study the linkages between the above three variables. On the basis of Dumistrescu-Hurlin causality tests, we find the presence of bidirectional Granger-causality between income inequality and market power; as well as between corruption and market power. One-way causality is observed between corruption to income inequality.

Interestingly, causal linkages seem to exist between income equality, corruption and market power in the trivariate TY framework for panel data. Here, Granger causation between the variables seems pervasive.

The chapter also applied copula analysis to explore the density of the links between income inequality, corruption and market power. It examined bivariate copula seeking to examine the existence of dependence between pairs of variables. The results obtained point to a positive correlation between all pairs. These indicate that any variations in one variable could lead the changes in other variable. For the trivariate copula, the results apparently demonstrate that income inequality is the most important variable between these three variables. This conclusion is based on the selection of income inequality as first root node in vines copula analysis. Interestingly, this is followed by market power as the next most important variable after income equality.

The analysis in this chapter has revealed that a strong relationship between income inequality, corruption and market power. The evidence here is supportive of the idea that linkages exist between income inequality, corruption and market power.

Chapter 7. Summary and conclusion

This final chapter summarises the main findings and offers suggestions for future research. First, we outline the main findings on the empirical linkages between income inequality, corruption and market power in OECD countries and US states. Second, we draw on some limitations of the study to envisage future extensions to this study that may provide more robust evidence on the trivariate relation examined in this study.

7.1. Main Findings

This study has examined the causal relationship between income inequality, corruption and market power by controlling with economic growth in the United States across 50 states for micro level (1977 to 2014) and OECD countries (1984 to 2014). The results are significant in four respects. This study employs a variety of quantitative methods to examine the linkages between income inequality, corruption and market power. Two main quantitative methods were employed: Granger causality tests and copula analysis. These provide complementary insights into the relationship between the three variables.

First, the study applied multivariate Granger causality tests to investigate the existence and direction of causal relationships among income inequality, corruption and market power, with and without conditioning on GDP. The results from Granger causality tests show that there is evidence of strong causal linkages between income inequality with corruption and market power; respectively in the United States across 50 states. In contrast there is no evidence causality relationship for all variables except from market power to income inequality for OECD countries. The test only showed a bi-directional relation of causality between income inequality and union membership (market power proxy). This could be due to unobserved heterogeneity that is less of an issue in microdata in a single country.

Second, the study also used panel data to examine a trivariate Granger causality between the three key variables of interest within the Toda-Yamamoto framework of analysis. The empirical findings in this study provide a new understanding of income inequality, corruption and market power under a trivariate setting. Many causal relationships have been observed in OECD countries, especially causality from income equality to corruption and from market power to income equality. The evidence also points to a two-way causality (bi-directional) between income inequality and market power. That is, this suggests that higher income equality leads to greater corruption and more market power as well as market power driving income inequality. These seem intuitive and consistent with claims by Nobel Prize Laureate Joseph Stiglitz that inequality feeds market power and rent-seeking which then can worsen inequality (Stiglitz, 2015).

Third, our results confirm the value of copula methods as complementary and insightful measures on the existence and direction of linkages; i.e. positive or negative relationship. The evidence for OECD countries and US States indicates the existence of a strong positive association between income equality and corruption. This is consistent with previous literature that shows corruption increases as income inequality increases. The evidence also to an positive relationship between income equality and market power, as well as between corruption and market power. This study has produced results which corroborate the findings of a great deal of previous work in this field.

Four, according to the trivariate copula analysis, income inequality is found to be the most important variable of the three variables for United States. Interestingly, this is followed by market power as the next most important variable next to income equality. The similar result is found for OECD countries. In contrast, corruption is second important variable for OECD study. These results confirm the relationship between income inequality and corruption for OECD countries and the relationship between income inequality and market power for United States are the most important bivariate linkage compared to all.

Altogether, the evidence suggests that corruption and market power have a positive and statistically significant impact on income inequality. This finding alludes to significant policy implications. Most of the results show that there is positive link between these three variables. Understanding the causal relationship between income inequality, corruption and market power may help us better decision to shape suitable policy.

The analysis undertaken in this study reveals mixed results. There is no clear relationship could be seen as different approach applied. However taken together, the results tend to show a strong and positive relationship between income inequality, corruption and market power. The results of this research supports the idea that there are existing of linkages between these three variables; income inequality, corruption and market power. Based on copula, the direction shows a positive correlation.

The empirical evidence presented in this thesis leaves little doubt that the rising incidence of rent-seeking associated with market power is contributing to increased inequality. Thus, public policy towards lower income inequality should aim to foster more competitive markets and change the balance of power in industrial relations towards collective bargaining and adjustable minimum wages that level the playing field for workers in negotiations with employers. Such policies may even strengthen a variety of incentives that can boost productivity; such as work effort, the accumulation of human capital and increased entrepreneurship.

Monopoly rents are often generated by firms with extensive market power. Although there exist trade practices and anti-trust regulations that prohibit certain barriers to trade and competition, there is still room for improvement at the level of antitrust enforcement, intellectual property regimes and rationalizing licensing requirements, all of which can have an impact on effective competition and reduce excessive rents.

Finally, policy makers are also subject to influence that powerful business interests can have on industry and taxation policy as a byproduct of market power or corruption. Thus, the need for policies that undermine the ability of vested interest and big corporations to extract rents via regulatory lobbying and political donations.

7.2. Limitations and Future Research Directions

This thesis has examined the complex nexus between income inequality, corruption and market power by using a variety of empirical methods and datasets. As an empirical study, it is subject to some limitations that is worth acknowledging that may assist future research.

One limitation relates to the datasets employed here where we utilised data for 26 OECD countries (1984 to 2014) and 50 states in the USA (1977 to 2014). It was noted earlier that these time-series lengths are prohibitive when it comes to exclusive time-series analysis of single countries. Also, the OECD dataset was overwhelmingly composed of advanced economies and thus the conclusions reached here do not necessarily apply to emerging economies (e.g., Brazil, Russia, China) or to much less developed countries in Africa and Asia. Future research could gain insights on these omitted countries by country-specific survey data that could facilitate analysis at the micro-level.

Further, it will of interest to compare advanced OECD countries with several emerging countries (Brazil, Russia, India and China (BRIC)). BRIC countries are considered important developing countries since they are among the fastest growing economies and largest emerging markets economies with the biggest source of labor (Economywatch, 2010; Georgieva, 2006). Georgieva (2006) argues that BRIC countries are the main driving force for global GDP growth and are likely to maintain their comparative advantages in the long term. It is thus important to explore such a comparison in the future as more time-series data becomes available.

An important puzzle emerging from this study is the discrepancy in the results obtained for OECD countries and the US States. These seem different with respect to causality and its direction. Recall, in OECD data, the Dumistrescu-Hurlin approach to panel Granger causality found weak evidence of causality, mainly from market power to income inequality. In contrast, the US States data there is more pervasive evidence of causality. A robust explanation for this result is beyond the present study but it is plausible that one could relate to some major differences in the operational definitions of market power and corruption.

This study utilized union membership data as a proxy for market power for OECD countries. Yet, it is not quite clear how good of a proxy this is. This is a likely source of discrepancy in the results between OECD and US States where in the later a more direct measure of market power was used. Until very recently, international time-series measures of market power have been lacking. Only most recently research attention has intensified efforts towards more robust and comparable indicators. Future studies deserve better empirical data on market power and the very recent global estimates of market power by De Loecker and Eeckhout (2018) may prove useful datasets.

Due to data limitations again, the study also used two very different empirical measures of corruption: the Bayesian Corruption Index for OECD countries and criminal convictions of public officers in USA States. Although both seem to proxy corruption, they are quite distinct. As new data emerge, further research could be undertaken to understand the relationship between income inequality, corruption and market power in order to examine how robust our findings are. This study can be employed for different countries or regional levels (BRIC countries or developing countries in Asia) to examine the linkage between income inequality, corruption and market power.

Finally, future research on this topic ought to utilize more sophisticated time-series methods that exploit recent advances in econometrics. Even visual inspection of the series examined suggests that the series might have been subject to structural changes at different times in different countries or US states. Unit root tests, cointegration tests and even Granger causality tests have been developed to account for breaks in the series in time-series or panel data series. Such tests would be most valuable in future research seeking to revisit the trivariate linkages examined here.

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