THE EFFECT OF INFORMATION AND COMMUNICATIONS TECHNOLOGY (ICT) DIFFUSION ON CORRUPTION AND TRANSPARENCY (A GLOBAL STUDY)

A Dissertation

by

LEEBRIAN ERNEST GASKINS

Submitted to Texas A&M International University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

May 2013

Major Subject: International Business Administration

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ABSTRACT

The Effect of Information and Communications Technology (ICT) Diffusion on Corruption and Transparency (A Global Study) (May 2013)

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Is the diffusion of information and communication technologies (ICTs) the "magic bullet" for effectively reducing corruption? Can government transparency be increased by ICT diffusion? Does ICT diffusion increase governmental transparency, thereby reducing corruption? A few previous studies have measured the relationship between ICTs, transparency, and corruption. Generally, such studies focus on the role of electronic governance (e-governance) in facilitating state-citizen interactions and how e-governance acts as a corruption deterrent. This study digresses from past literature by directly exploring the effects of the ICT environment, using the Networked Readiness Index (NRI), and diffusion of two specific ICTs (e.g. the number of Internet users per 100 people and mobile cellular phone users per 100 people) on corruption and transparency through structural equation modeling.

This study also examines how macroeconomic and national sociocultural variables mediate and moderate the relationships of ICTs on transparency and corruption. The results show that for each increase unit in NRI, transparency increased by 9.423% and corruption decreased by 14.017%. Furthermore, increasing access to the Internet by 27 people per 100 persons increased transparency by 17.581% and reduced corruption by 15.239%. Additionally, each unit increase in per capita GDP results in an increase in transparency by 7.068% and a decrease in corruption by 10.507%. Conversely, increases in FDI and mobile cellular diffusion demonstrated marginal results on increasing transparency and reducing corruption. Implications of these findings as well as avenues for further research are discussed.

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CHAPTER I

INTRODUCTION

1.1 Overview

Corruption, along with possible remedies and measures for fighting corruption, has been studied academically in a multitude of ways over the past sixty years (Akçay, 2006; Arvas & Ata, 2011; Donchev & Ujhelyi, 2009; Leff, 1964; Macrae, 1982; Mauro, 1995; McMullan, 1961; Myrdal, 1970a; Nye, 1967; Rose-Ackerman, 1978, 1999, 2008; Svensson, 2005). The wide-ranging definition used by the World Bank, Transparency International, and most scholars is that corruption is the abuse of public power for private benefit or profit (Amundsen, 1999; Andvig, Fjeldstad, Amundsen, Sissener, & Søreide, 2000; Gray & Kaufmann, 1998; Rose-Ackerman, 1996). Corruption, as similarly addressed in this paper, is the use of public office or power for personal gain. In its many forms, corruption leads to the misallocation of public resources, thereby creating bias against efficient projects and practices (Macrae, 1982).

Corrupt practices not only make public power and governance less efficient, such as the management of public resources, but they also adversely affect countries' competitiveness and human development (Akçay, 2006). Studies have shown that the effect of corruption on human development is more evident in some countries than others (Waheeduzzaman, 2005). In some countries, for instance, high levels of corruption reduce the productivity of public sector investments (Tanzi, 1995). International investment such as Foreign Direct Investment (FDI) into countries perceived as "corrupt" is substantially less than in countries without this perception (Habib & Zurawicki, 2002). Countries with higher levels of corruption suffer from less than optimal economic development (Cuervo-Cazurra, 2008; Habib & Zurawicki, 2002; Wei, 2000). Corruption has a profound mitigating effect on economic development variables

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such as Gross Domestic Product (GDP) per capita. Mauro (1995) found that the reduction of corruption is associated with a significant increase in GDP per capita. This finding is quite important as GDP per capita is one of the most widely used macroeconomic indicators of a country's standard of living (Ringen, 1991). Similarly, as corruption increases, personal income decreases (Alam, 1995; Husted, 1999).

The literature cited above demonstrates that corruption has a diminishing effect on macroeconomic variables. Corruption's effect on macroeconomic variables such as FDI and GDP per capita is particularly important since macroeconomic and technology development variables are interrelated. For example, there is evidence that FDI impacts information and communication technologies (ICTs) proliferation and development (Baliamoune-Lutz, 2003; Gholami, Lee, & Heshmati, 2006; Suh & Khan, 2003). Specifically, Lee, Gholami, and Tong (2005) demonstrated a dual causal relationship between investments in ICT and inflows of FDI. In the study by Lee et al. (2005), the dual causality relationship suggested that increased FDI inflows positively affected ICT investment and proliferation, and ICT investment and proliferation attracted more FDI inflows. There is reason to believe that any variable affecting FDI inflow would, in turn, affect ICT development. For example, FDI is substantially less in countries perceived as "more corrupt" (Campos, Lien, & Pradhan, 1999; Habib & Zurawicki, 2002). Therefore, countries perceived as corrupt would have substantially less FDI inflows. These reduced FDI inflows also would negatively affect ICT investment and proliferation.

A greater percentage of the world's population now has availability and access to ICTs such as Internet and mobile cellular technologies (Haddon, 2004). This increased availability of ICTs has inspired researchers to look into ways such technologies can improve economic and human development (Gascó-Hernández, Equiza-López, & Acevedo-Ruiz, 2007; Rahman, 2007).

Access to mobile communications and the Internet has enabled citizens to participate more directly in the political and social institutions and environment of their countries. Citizens are interacting more directly with their governments, elected officials, and other citizens through such means as e-governance (M. Backus, 2001), online political activism (Hill & Hughes, 1998), Internet political mobilization (Krueger, 2006), and online information gathering about political issues (Krueger, 2002).

Since corruption negatively affects economic and human development, ICTs have fostered academic interest as a tool in reducing corruption and increasing democracy (Soper, 2007). The Internet's potential for reducing corruption is "promising and obviously vast" (Vinod, 1999, p. 10). Past studies have examined the effects of e-governance on corruption (Hoque, 2005; Pathak & Prasad, 2005; Pathak, Singh, Belwal, Naz, & Smith, 2008; Pathak, Singh, Belwal, & Smith, 2007) and the effects of e-governance and social media on transparency (Bertot, Jaeger, & Grimes, 2010). These studies suggest that increased access to information through ICTs has a positive effect on transparency and reduces corruption.

While governments and scholars are researching ways to fight corruption, ordinary individuals armed with access to cellular phones, personal computers, and the Internet have begun a wave of participatory journalism targeted at corruption in society (Katz & Lai, 2009). For example, in Goa, India, an anonymous citizen uploaded to the Internet an eight-minute video of a drug dealer talking about his connections to high-ranking anti-narcotic police (MSNIndia, 2010). In Kenya, citizens have caught and filmed traffic cops collecting bribes from motorists (NTV, 2010). In the case of India and Kenya, citizens are acting as anti-corruption agents by bringing corrupt practices and officials into public awareness. Such cases illustrate that citizens have taken on the role of government in fighting corruption. Likewise, Hay and Shleifer (1998) found that in the absence of strong governmental anti-corruption efforts, private enforcement by citizens becomes a surrogate for public justice.

Vinod (1999) stated that increasing education and expanding economic freedoms are among the top actions in reducing corruption. ICT promotes greater governmental transparency by removing information barriers and asymmetry (Sturges, 2004). Mobile technologies and Internet access enables citizens to become more informed with relevant information about their government and society. The access and expansion of relevant information concerning governmental issues promotes greater transparency (García-Murillo, 2010). Also, the diffusion of ICTs has been shown to foster civil and political freedoms (Baliamoune-Lutz, 2003).

The diffusion of ICT affords citizens increased networking capacity and political awareness while reducing information transaction costs (Pirannejad, 2011). Usage of ICTs to organize, communicate, and raise awareness have been seen in such movements as the Arab world's "Arab Spring" and Mexico's narcobloggers (Hofheinz, 2005; Shirk, 2010). In countries such as India, Kenya, and Mexico, citizens are using ICTs to expose and fight governmental corruption and civilian crime (M. Backus, 2001). Indeed, Soper (2007) demonstrated that a negative relationship exists between investment in ICT and political corruption levels in emerging economies.

1.2 Research Question

Some previous studies have examined the relationship between ICTs and corruption. Such studies have focused on the role of e-governance facilitating state-citizen interactions, thereby increasing governmental accountability and transparency (Andersen et al., 2010; M. Backus, 2001; Bertot et al., 2010; Pathak et al., 2008; Shim & Eom, 2009) and how ICTs can improve economic and human development by reducing information asymmetry (Forestier, Grace, & Kenny, 2002; Gascó-Hernández et al., 2007; Opoku-Mensah, 2000; Rahman, 2007).

No research has yet examined if the relationship between the ICT environment, diffusion of specific ICTs, and the two macroeconomic variables of FDI and Gross Domestic Product (GDP) per capita has any potential effects on increasing transparency and reducing corruption. Therefore, this study attempts to fill a gap in the literature by directly examining the effects of the relationship of the ICT environment, diffusion of specific ICTs, FDI and GDP per capita on corruption and transparency through structural equation modeling.

1.3 Significance and Purpose of Study

Research on how ICT diffusion and environment can be used to increase governmental transparency and reduce corruption is important for several reasons. First, as suggested by Soper (2007), research into using ICTs to increase transparency and reduce corruption provides the "best scientific advice possible to world leaders who are seeking to lift their citizens…"(p. 8). ICTs have the ability to support the free exchange of information, thereby informing citizens about their government and society. ICTs promote greater transparency by removing information barriers and asymmetry (Sturges, 2004) and fostering civil and political freedoms (Baliamoune-Lutz, 2003). Indeed, there is a trend in many developed countries towards publishing information on the Internet concerning governmental issues (García-Murillo, 2010).

Secondly, the ability of ICTs to reduce corruption can expand economic freedom. As Vinod (1999) stated, increasing economic freedom and education is among the top actions in reducing corruption. There is less than optimal economic development in countries with higher levels of corruption (Cuervo-Cazurra, 2008; Habib & Zurawicki, 2002; Wei, 2000). Also, corruption reduces economic freedoms by placing a burden on the economy. Every dollar worth of corruption in developing countries, when viewed as a form of illegal taxation, equates to $1.67 worth of economic burden (Vinod, 1999). The economic burden of corruption in developing countries compounds over time and is more distortionary than actual taxes (Vinod, 1999). Therefore, a reduction of corruption would have a significant impact in the reduction of economic disparity.

The purpose of this study is to do as Pirannejad (2011) suggests: future research on how specific ICTs affect political development, especially in the context of how people monitor and hold their government accountable. First, this study attempts to fill a gap in the existing research advocated by Pirannejad (2011) by investigating the effects of the ICT environment and the diffusion of two specific ICTs on corruption and transparency. Secondly, this study sets forth a robust path model of the ICT environment, the diffusion of two specific ICTs, and two macroeconomic variables to examine the relationship among ICTs and macroeconomic variables in providing greater government transparency and reducing corruption. As of yet, no other research has examined such a relationship using a robust path modeling. Therefore, this study attempts to provide a significant contribution to the existing body of research by investigating the effect of the ICT environment and the diffusion of two specific ICTs on corruption and transparency in the context of two macroeconomic variables.

CHAPTER II

REVIEW OF THE LITERATURE

2.1 Corruption

Corruption has been a topic for writers and scholars since antiquity. The writer of the Arthashastra, an ancient Indian text written around 4 BCE, talks about the eventuality of corruption and the need to minimize it (Kautalya & Rangarajan, 1992). The academic study of corruption has been explored in several different ways over the past sixty years in international business, economics, and political science literature (Akçay, 2006; Arvas & Ata, 2011; Donchev & Ujhelyi, 2009; Leff, 1964; Macrae, 1982; Mauro, 1995; McMullan, 1961; Myrdal, 1970a; Nye, 1967; Rose-Ackerman, 1978, 1999, 2008). Such explorations on the topic of corruption have included: what corruption is, what the different types of corruption are, how corruption affect governments and their citizenry, and possible anti-corruption remedies and measures.

According to Myrdal (1970a), sparse serious academic attention was given to the topic of corruption prior to his seminal works as the topic was considered “taboo” (p. 227). Myrdal (1970a) suggested that empirical research should be done to “establish the general nature and extent of corruption… and any trends that are discernible” (p. 231). Earlier examination into systemic corruption focused on the moral, cultural, and historical causes and effects of corruption, while later studies began to examine institutional and political aspects of corruption (Galtung & Pope, 1999).

Several researchers have previously undertaken the task of defining corruption such as Myrdal (1970a), Heidenheimer (1970), Rose-Ackerman (1978), Macrae (1982), Colander (1984), and Ades and Di Tella (1999). Most authors admit that defining and conceptualizing corruption is difficult, thereby hindering research in the area (Farrales, 2005; Peters & Welch, 1978). There are a wide range of activities described in the research literature that can be classified as corrupt practices, from advantageous influence over and lobbying on government and political agents, to outright illegal activities such as bribery, extortion, and fraud. Furthermore, operationalizing corruption has proven difficult since corrupt behavior does not lend itself to direct, unbiased, and measurable observation (Andvig et al., 2000). Rose-Ackerman (1978) stated that corruption must be examined using political science and modern economics. This approach combines the economist's models of self-interested behavior with the political scientist's understanding of bureaucratic incentive structures.

Rose-Ackerman (1978) examined corruption through extending the principal-agent model found in the economics and political science research literature. The principal-agent model arises from the division of labor and exchange (Smith, 1776). The principal is someone who wishes for some action to be done but cannot or does not perform the action. The principal enlists the services of the agent to perform the desired action on the principal's behalf (Laffont, 2003). In political science, the principal consists of voters who enlist elected officials as agents to govern on the electorate's behalf. In the Rose-Ackerman (1978) principal-agent model, corruption is primarily bribery of an agent who is an elected or appointed official. The principal of this agent is the electorate or some supervisor who specifies desired outcomes. As monitoring of the agent is costly, in terms of time and resources, the agent has some freedom to place his own interest above that of the principal. A third person who can benefit from the agent's action or inaction offers the agent an incentive (e.g. a bribe) to influence his actions. The benefits of these incentives are not usually passed on to the principal. These incentives do not necessarily subvert the principal's objectives, and in some cases, the principal may be more satisfied with the agent's performance.

Another relevant model of corruption is that of Macrae (1982) in which corruption is defined as an "arrangement" (p. 678) involving "a private exchange between two parties (the 'demander' and the 'supplier'), which (1) has an influence on the allocation of resources either immediately or in the future, and (2) involves the use or abuse of public or collective responsibility for private ends" (p. 678). Thus, corruption is the use of public office or power for personal gain. In contrast to the Rose-Ackerman (1978) model, which examines corruption through the principal-agent problem, Macrae (1982)'s model of corruption explores a supply and demand relationship for the reallocation of public resources for private gain. Hence, corruption allows the misallocation of public resources, thereby creating bias against technological advances and efficient projects and practices (Mauro, 1995).

Corruption, according to Myrdal (1970a), has one defining aspect being the "difference in mores as to where, when, and how to make personal gain" (p. 233). Myrdal (1970a) further states that corruption introduces "irrationality" (p. 233) in government planning and fulfillment. Such irrationality influences development in such a way as to deviate from the intended plan and fulfillment for personal gain. Corruption, thereby, hampers the decision-making and execution processes at all levels of government (Myrdal, 1970a). Nye (1967) defined corruption as "behavior [that] deviates from the formal duties of a public role of private-regarding … pecuniary or status gains; or violates rules against the exercise of certain types of private-regarding influence" (p. 416). Nye (1967)'s definition speaks of formal rules and duties and is expansive, including such practices as nepotism, misappropriation, conflicts of interest, and bribery.

A widely utilized definition of corruption put forth by Heidenheimer, Johnston, and Le Vine (1989) and Rose-Ackerman (1978) is that corruption is a transactional relationship between public and private sector agents by which collective goods or services are converted (illegitimately) into private gains. Scholars in the study of corruption focus on one of two types of corruption: bureaucratic or political (Farrales, 2005). Furthermore, Huntington (1968a) posed that political corruption can exist in two forms. Some scholars propose that any valid assessment of corruption must include political dimensions (Hope & Chikulo, 2000; Johnston, 1997). Political corruption is generally viewed as the practice of using wealth, power, or status to influence the political system in order to gain political advantage. Conversely, another form of political corruption is when politicians use political influence and advantage to gain private wealth, power, or status. Political corruption usually takes place with highly placed or elected officials and is furthered by policy or legislation formation tailored to benefit the corrupt officials (Moody-Stuart, 1997). Bureaucratic corruption is the corrupt behavior in the administration of public policy. It seeks to influence governmental processes, such as obtaining permits or avoiding tariffs, or paying government enforcement officials.

Corruption can also be defined in economic and social terms. Economic corruption involves the exchange of tangible goods in a market-like situation such as bribes or rent-seeking (Andvig et al., 2000). Rent-seeking is often classified as a type of economic corruption. This type of corruption involves misuse of public power to derive excess earnings by the elimination of competition (Ades & Di Tella, 1999). Rent-seeking is not necessarily banned by legislation or shunned by society's moral obligation. However, it reduces public wealth in favor of private gain and generally proves economically wasteful and inefficient (Coolidge & Rose-Ackerman, 2000). Social corruption is understood best as an integrated part of clientelism, nepotism, class or group favoritism. In such social corruption, there is an exchange of material benefit based on some criteria having a large social or cultural implication (Briquet & Sawicki, 1998).

Amundsen (1999) put forth five main manifestations of corruption: bribery, embezzlement, fraud, extortion, and favoritism. The first and most quintessential manifestation of corruption is bribery. Bribery is a payment, usually to a government official, to receive some governmental benefit. Bribery has many effective forms such as kickbacks and pay-offs. The second manifestation of corruption is embezzlement. While embezzlement is not strict corruption, its practice deprives the government of funds. It is similar to bribery except that it typically does not involve the private sector. The third manifestation of corruption is fraud. This type of corruption involves the manipulation or distortion of information or fact by public officials. Fraud, similar to the Rose-Ackerman (1978) principal-agent model, involves an agent (e.g. public official) who carries out the directives of his principals (e.g. supervisors). The agent manipulates the flow of information for some illegal gain that may or may not benefit the principal (Eskeland, Thiele, & World Bank, 1999). The fourth type of corruption manifestation is extortion. Similar to bribery, this method extracts benefits by way of coercion, violence, or threat of force. Bribery and extortion are equivalent to extra taxes levied by – but not collected for – the government (Wei, 1997). The fifth manifestation of corruption is favoritism. This mechanism of corruption allows the differential access to governmental power or state resources regardless of merit. This method of corrupt behavior can be examined as enfranchising (e.g. preferential treatment, cronyism, and nepotism) or disenfranchising (e.g. discrimination) based on some criteria having a large social or cultural implication (Briquet & Sawicki, 1998).

The wide-ranging definition used by the World Bank, Transparency International and most scholars is that corruption is the abuse of public power for private benefit or profit

(Amundsen, 1999; Andvig et al., 2000; Gray & Kaufmann, 1998; Rose-Ackerman, 1996). Most literature examines governmental corruption, which is the relationship between the public and private entities engaged in corrupt behaviors. However, there exists corruption among private businesses and non-governmental organizations (Andvig et al., 2000). This private sector corruption exists with or without the involvement of a government official or political advantage.

Corruption is difficult to measure directly. Peters and Welch (1978) and Farrales (2005) noted that defining and conceptualizing corruption is difficult, thus hindering research in the area. There are a multitude of activities that can be classified as corrupt practices which makes operationalizing of corruption difficult. Corrupt practices would have to be measured by an unbiased observer familiar with rules and policies in a given context. Most corrupt behavior does not lend itself to such direct, unbiased, and measurable observation (Andvig et al., 2000).

One observable measure of corruption is court cases. Such judiciary data on corruption is collected on an international basis by the United Nations' Crime Prevention and Criminal Justice Division (United Nations, 1999). In such court cases, legal officials determine whether transactions or exchanges were actually corrupt. While court cases can provide an observable measure, Andvig et al. (2000) pointed out several issues with using such observations. First, using such court cases as an indication or prevalence of corruption relies on the honesty of the local judiciaries. Intraregional and international differences obviously exist in the honesty of judiciaries which make such observations problematic in a cross-country analysis. Secondly, local policing, judicial and political priorities usually determine which cases are prosecuted. Goel and Nelson (1998) suggest that court cases on corruption represent more of the judicial efficiency rather than corruption prevalence in a country. Police and other investigatory agencies reporting on corruption provide an additional observable measure of corruption. The quality of information from such agencies, however, is quite inconsistent and biased (Andvig, 1995; Duyne, 1996).

News reports and other investigative journalistic methods are another way to measure and fight corruption (Reinikka & Svensson, 2005). However, using such news reports and investigative journalism as an observable measure of corruption is problematic. News and media reports of corruption can show bias in a similar fashion to court cases and policing reports. Media and news reports tend to give priority to high-profile or sensational cases. This selective priority creates a bias that may not examine or expose the more pervasive everyday corrupt activities. Furthermore, reported stories often are a factor of press freedom which are not uniform among countries (Nixon, 1960). Therefore, the effectiveness of a free press on reducing corruption largely relies on the measure of press freedom (Brunetti & Weder, 2003). Also, public exposure of corruption and crime can be dangerous for the reporting journalists (Archibold, 2012). Corrupt and criminal officials typically do not care for such negative exposure due to repercussions from law enforcement or other criminal elements. Sources of corruption are strongly influenced by such biases as media attention, public opinion, and press freedom, making it difficult to use such stories in a cross-country comparison.

Though corruption is difficult to define, conceptualize, and operationalize (Farrales, 2005; Peters & Welch, 1978), there have been attempts to develop an empirical measure of corruption. These attempts to develop an empirical measure of corruption as based on the *perception* of corruption rather than the actual instances or experiences of corruption. There is some academic debate on whether a perception-based measure can adequately compare to an experience-based measure (Donchev & Ujhelyi, 2009; Kaufmann, Kraay, & Mastruzzi, 2007, 2010). However, the indices listed below became the de facto empirical measures of corruption used in academic research (Lambsdorff, 1999a; Lancaster & Montinola, 1997).

Business International Corporation (BI) created one of the first corruption perception measurements. BI was a business advisory firm founded in 1953 which assisted American companies in foreign business operations. BI surveyed its network of international businesspeople, journalists, and country specialists, determining whether or not and to what extent businesses were engaged in corruption transactions. BI also gathered survey data on such factors as political risk, commercial hazard, and level of corruption in various countries. This perceived level of corruption was measured on a scale from 0 to 10. BI undertook efforts to make ranks consistent among respondents. Using the BI data for fifty-two countries, Mauro (1995) conducted the first quantitative study of corruption using an econometric model. Mauro (1995)'s study examined the effect of corruption on the economic growth rate. As a result, Mauro (1995) found that corruption lowered investment, which in turn lowered economic growth.

The International Country Risk Guide (ICRG) contains another well-known corruption perception measurement. The ICRG has been published since 1980, making it the longest country risk analysis dataset. The ICRG measures several country factors, but the one most related to corruption is the ICRG bureaucratic quality scale. The scale measures expert opinions, from 1 to 6, and shows how efficiently and predictable bureaucrats operate (S. Johnson, Kaufmann, & Zoido-Lobatón, 1998). The ICRG is published by the Political Risk Services Group and provides a monthly political, economic, and financial risk ranking for 140 countries. The Political Risk Services Group, founded in 1979, is one of the earliest commercial providers of political and country risk data to companies doing international business. The ICRG also contains the rule-of-law scale, from 0 to 6, measuring the strength and application of law and order in the country.

Arguably the most well-known and widely-used index of corruption is the Corruption Perception Index (CPI) by Transparency International (TI) which is an international non-governmental organization founded in 1993 that monitors and reports on political and corporate corruption in international development (Andvig et al., 2000; Brown, 2006; De Maria, 2008; Lambsdorff, 1999b; Svensson, 2005). The CPI measures the perceived degree of corruption that exists among public officials and politicians (Lambsdorff, 1999a). The CPI is the most widely disseminated and popular index among policymakers. It is a composite index including survey data from country experts, businesspeople, global analysts, and experts who are residents of the evaluated countries (Svensson, 2005). The CPI focuses on perceptions of public sector corruption. This index ranks countries on a scale from 10 (representing a very clean/very little corruption government) to 0 (representing a highly corrupt government). TI uses 17 different surveys and polls from 10 independent organizations: Freedom House (FH); Gallup International (GI); The Economist Intelligence Unit (EIU); Institute of Management Development (IMD); International Working Group (developing the Crime Victim Survey); Political and Economic Risk Consultancy (PERC); Political Risk Service (PRS); The Wall Street Journal - Central European Economic Review (CEER); World Bank and University of Basel (WB/UB); and World Economic Forum (WEF). The CPI is widely-used as there is a high degree of correlation between the 17 polls and surveys used (Lambsdorff, 1999a). The use of several different survey instruments and the high inter-correlation between instruments results provide a major strength to the CPI. The surveys cover a wide range of corrupt behaviors and practices, and they do not distinguish between bureaucratic and political corruption (Lambsdorff, 1999a).

The CPI is an index ranking and should be understood as such. Lambsdorff (1999b) points out several caveats to understanding the CPI. First, countries for which at least three surveys were available are represented in the index. Several countries are not included for lack of available data. Secondly, the index is a perception of corruption and not based on a standardized estimation of the level of corruption. For example, the 2010 CPI ranked Mexico as 3.1 and United Arab Emirates was ranked 6.3. This does not imply that the United Arab Emirates is half as corrupt as Mexico. The index is best used in observing trends over time and comparing relative positions of countries to one another (Galtung, 1998).

While corruption is considered difficult to measure, corruption indexes are highly correlated with one another. For example, the CPI and BI indexes for 1996 and 1998 were highly correlated at 0.967 and 0.966 (Andvig et al., 2000; Treisman, 2000). The BI and CPI indexes show a similar high correlation to the ICRG (Andvig et al., 2000). While there are differences among the surveys and their methodologies, the high correlation implies that levels of perceived corruption are consistent among countries (Lambsdorff, 1999a).

Some scholars suggest that corruption has been the norm throughout human history (Klitgaard, 1988; Neild, 2002). Huntington (1968a) stated that lack of political or economic opportunities creates an environment by which people use wealth to buy power or pursue wealth by use of political power. One hypothesized cause of bureaucratic corruption is that government officials and civil servants maximize expected income (Becker & Stigler, 1974). Corrupt behavior is generally punished by job loss which provides a disincentive to engage in such behavior. However, bureaucratic corruption is more prevalent when the bribe levels are relatively high, the probability of detection is low, and/or the punishment for corrupt behavior is slight (Becker & Stigler, 1974).

Another hypothesis, the fair wage-effort, expounds that government officials and civil servants may forego corrupt behavior if their official government wages are high enough (Akerlof & Yellen, 1990). Tanzi (1995) found that low wages invite corruption and lead to societal acceptance of the practice. According to Becker (1968)'s seminar work, "Crime and Punishment: An Economic Approach," individuals, including government officials, make rational decisions between criminal and legal actions based on the probability of detection and severity of the punishment. Based on Becker (1968)'s considerations, the lack of appropriate wages, stronger investigatory agents, and harsher punishments, foster an environment for corruption.

Political science scholars view corruption as being caused by deficits in the democratic systems such as power-sharing, accountability and transparency, governmental checks and balances (Doig & Theobald, 1999). Corruption, in the view of political scientists, is seen as a lack of functioning democratic state, ethical leadership and good governance (Hope & Chikulo, 2000). Friedrich (1989) stated that corruption is inversely proportional to the amount of democracy. There exists a correlation between non-democratic rule and corruption (Amundsen, 1999). It is important to note that in non-democratic regimes, corruption's impact is somewhat mitigated by the level of functionality and control of the government (Girling, 2002). In regimes where the government exercises tighter control over the political environment and economy, the level of corruption is also controlled. This control makes the corruption more predictable and less economically and developmentally destructive (Campos et al., 1999).

Political scientists have examined internal and external political factors that cause and promote corruption. The internal view put forth by Myrdal (1970b) is that modernization promoted industrialization and economic and development growth. Corruption was the result of a failed or incomplete modernization process which left the countries in a mixed state between traditionalism and modernism. Corruption, in this view, would decrease as markets and government became more modern and efficient. The external political factor view puts forth that corruption is a product of external states and multinational corporations exploiting the underdeveloped countries, thereby creating and fostering corruption (Blomström & Hettne, 1984).

Another political science area of corruption research has developed called the “neo-patrimonial” approach. Scholars such as Hope and Chikulo (2000) and Coolidge and Rose-Ackerman (2000) state that in African and several small countries, the core characteristic of governance is founded on personal relationships. These relationships form the foundation of the political system, and there exists a weak distinction between public and private interests and affairs (Bratton & Van de Walle, 1997; Briquet & Sawicki, 1998). Such government constructs are characterized by high-ranking government officials engaging in rent-seeking behaviors that produce excessive intervention into the economy. This intervention, thus, creates and prorogates monopolies, inefficiencies, contradictory government regulations that obstruct overall economic growth (Coolidge & Rose-Ackerman, 2000).

Most of the world’s current bureaucratic structures existing today are a result of Western European influences. The notions of the legal authority model of governance and public office are very much European constructs (Weber, 1958). In legal authority governance, there is a tremendous non-ambiguous distinction between public office and private interest. This distinction is important in the modern study of corruption since the popular definition of corruption is based on using public office for private gain. The modern European form of bureaucratic governance developed over a long process in such countries as England and Spain as a result of long political struggles that eventually became codified and embedded in European cultural and political thought (Scott, 1969). The European model of governance was further developed by the late nineteenth century movement for government accountability (Scott, 1969).

In some cases, the copying or patterning of European government and bureaucratic structure to other countries occurred in a "schizophrenic" fashion (de Sardan, 1999, p. 47). Many countries, either by choice or by force, adopted European bureaucratic processes such as governance through legal authority and accountability through public oversight. However, in several of those countries, such methods of governance and accountability were not the norm. For example, in Africa and South Asia, such European bureaucratic structures based on legal authority were adopted out of the legacy of colonialism in spite of conflicting cultural or political norms (de Sardan, 1999). The adoption of such European bureaucratic structures in these countries were fraught with problematic issues such as viewing the colonial government as illegitimate, mistrusting and becoming increasingly frustrated with government officials, and disenfranchising the governed (R. Cohen, 1980).

The effects of corruption are widely debated in international business literature. Some authors suggest that corruption provides some economic benefit (Huntington, 1968b; Leff, 1964). Some authors have identified corruption as one of the major reasons for the decline and fall of the Roman Empire (MacMullen, 1988; Murphy, 2007; Stinger, 1985). Corruption produces a heavy burden on the poorest in a society who are less able to navigate the system of corruption for equal gains and distorts the state's ability to operate efficiently and effectively (Doig & Theobald, 1999). This excess burden and lack of efficiency and effectiveness manifests itself as the inability to redistribute resources, implement public policy, and collect taxes.

Corruption negatively impacts foreign and domestic investments, thus hampering economic growth and development (Ades & Di Tella, 1996; Macrae, 1982; Mauro, 1995; Robertson & Watson, 2004). Vinod (1999) pointed out that every $1 of corruption, when viewed as illegal taxation, created a $1.67 burden on the economy. Conversely, some forms of corruption have been found to be beneficial. Bribes, for example, can expedite bureaucratic processes, improve economic efficiency, and incentivize government employees to work harder. Bardhan (1997) stated that corruption might increase bureaucratic efficiency by speeding up the process of decision making in the presence of rigid regulation. By bribing government officials, firms can avoid such “inconveniences” as import tariffs or license requirements and provide “motivation” to hardworking government officials. In this case, corruption can be viewed as a tax on business operations. However, the research shows that the disadvantage of this type of corruption greatly outweighs its potential benefit. Shleifer and Vishny (1993) demonstrate that bribes have a higher cost than taxes due to their inherent uncertainty and secrecy. Firms utilizing this form of corruption typically spend more time negotiating with bureaucrats, thereby increasing the cost of capital (Kaufmann & Wei, 1999). Corruption, in the form of bribery, creates an economic societal gap between those who are financially able to pay for access to government resources and those who are not.

Corrupt practices not only make public power less efficient but also adversely affect countries’ competitiveness and human development (Akçay, 2006). The effect of corruption on human development has shown to be more evident in some countries than others (Waheeduzzaman, 2005). For example, many sub-Saharan peasant farmers engaged in subsistence crop production as a means of avoiding corruption which ultimately led to a reduced living standard (Bates, 1981). Other studies have demonstrated that corruption has a mitigating effect on economic development. International investment in the form of foreign direct investment (FDI) into countries perceived as “more corrupt” is substantially less than countries without this perception (Habib & Zurawicki, 2002). Thus, countries with higher levels of corruption suffer from less than optimal economic development. The detrimental effect of unpredictable corruption has been found to be economically significant (Wei, 2000). A higher level of corruption coupled with higher level of uncertainty caused by the corruption reduces FDI inflows (Campos et al., 1999).

Given the effects of corruption, significant time and energy has been placed into reducing or eliminating it. The Chinese Qin dynasty penal code had specific provisions and punishments for corruption (Lambsdorff, 1999a). The Council of Areopagus had, among its other duties, a requirement to report corrupt behavior (Wilson, 1989). Acemoglu and Verdier (2001), Akerlof and Yellen (1990) and Tanzi (1995) suggest that public wage changes should be prominently discussed as part of anti-corruption policy. Corruption thrives on information asymmetry. One method of reducing corruption has been to reduce the information asymmetry by means of newspaper articles informing the public. There is evidence that such methods have a positive impact on the reduction of corruption (Chowdhury, 2004; Reinikka & Svensson, 2005). For example, a Ugandan newspaper campaign provided parents with public funding information on local schools (Reinikka & Svensson, 2005). By providing parents with such vital information regarding the handling of public funds, there was a significant reduction in the misallocation of such funds and an increase in student enrollment and learning.

Political scientists see corruption as a lack of democracy (Doig & Theobald, 1999; Friedrich, 1989; Hope & Chikulo, 2000). Following this logic, increasing democracy would reduce corruption. Two mechanisms to increase democracy have been suggested: 1) strengthen democratic institutions such as legislative and judicial bodies to provide more oversight and control, and 2) strengthen the civil and public sectors such as the media. Increasing democracy does have a correlation for reducing levels of corruption, but such correlation has proven to be weak (Amundsen, 1999; Paldam, 2004). In some countries, the democratization process, moving from a controlled authoritarian regime to a loosely controlled quasi-democratic government, has led to increased corruption (Harriss-White & White, 1996). Treisman (2000) found that the degree of democracy was not correlated to the perception of corruption. Rauch and Peter (2000) found that democratization through improving public institutions and bureaucratic processes, especially predictability, reduces corruption.

A view put forth by Myrdal (1970b) suggested that modernization promoted industrialization which leads to economic development and growth. The view also holds that economic development and modernization would permeate through government and society, thus eliminating corruption. This view of modernization is similar to those held by other scholars that modern technologies are liberating and democratizing (Khan, 1998; Leon, 1984).

2.2 Information and Communication Technologies and Corruption

An important tool in modern communication and information sharing is Information and Communication Technology (ICT). ICTs consist of two parts: devices and systems, which are used to access, store, communicate, manipulate and share information (Melody, Mansell, & Richards, 1986). ICT devices are instruments such as cellular phones, televisions, and computers that are used by an individual to communicate over a network or system. ICT systems are interconnected devices and associated infrastructure such as networks used to facilitate communication and information sharing.

Technological innovations such as mass production and miniaturization have lowered the cost of ownership of several ICT devices such as computers and mobile cellular phones. Furthermore, technological advances such as proliferation of telecommunication satellites and broadband data communications have increased the global reach of ICT networks while reducing the cost of access. These reductions in cost have made ownership of ICT devices and availability of ICT systems available to a greater percentage of the world's population. ICT diffusion increases knowledge diffusion by facilitating and improving efficiency of communication (Jovanovic & Rob, 1989).

However, the reduced cost and increased availability of ICTs, such as mobile cellular phones and Internet access, have not led to uniform adaption throughout the world. This lack of uniform adoption is known as the digital divide (Norris, 2001). The digital divide is a term given to the inequality between groups in their knowledge of, access to, and use of ICTs (Chinn & Fairlie, 2007). There has been much scholarly debate on the exact nature and causes of the digital divide (Chinn & Fairlie, 2007; Crenshaw & Robison, 2006; Guillén & Suárez, 2005; Norris, 2001; Sharma, Ng, Dharmawirya, & Lee, 2008; Warf, 2001; Warschauer, 2002). Some authors have put forth such factors as income inequality, regulatory environment, foreign and domestic investment, cultural differences and quality of the technology as reasons for the digital divide (Dasgupta, Lall, & Wheeler, 2001; Erumban & de Jong, 2006; Jakopin & Klein, 2011; Wallsten, 2005). For example, Gholami et al. (2006) demonstrated that increases in FDI leads to growth in ICT investment and capacity by offering host countries more access to technology (OECD, 1991) and domestic investment (Agrawal, 2003). Jakopin and Klein (2011) showed that regulatory quality and market environment significantly affect Internet diffusion.

Much research and debate exists on the nature, extent, and reasons for the digital divide. However, there is more consensus among scholars on the effects of ICTs on improving transparency and governance. (Avgerou, 1998; Krueger, 2002; Opoku-Mensah, 2000; Soper, 2007). ICTs have proven to be tools in democratization (Opoku-Mensah, 2000; Soper, 2007), factors in economic growth (Avgerou, 1998), methods to help the poor (Forestier et al., 2002), and devices that facilitate and improve political involvement (Krueger, 2002, 2006; Norris, 2001). Geiger and Mia (2009) showed that mobile phone diffusion has a significant positive effect on economic growth and poverty reduction.

One important use of ICTs, and the main focus of this study, is the reduction of corruption. ICTs show great promise in increasing transparency and reducing corruption by improving governance. Vinod (1999) stated that the Internet's potential is "promising and obviously vast" (p. 10) for reducing corruption. Research has shown that there is a negative relationship between ICT investment and the level of political corruption in emerging economies. Soper (2007) showed that a negative relationship exists between the level of ICT diffusion and corruption. Additionally, Vinod (1999) stated that the top five actions in reducing corruption, in order of importance, are as follows: 1) reducing bureaucratic overhead (e.g. red tape), 2) increasing judiciary efficiency, 3) increasing GNP per capita, 4), increasing education and economic freedoms, and 5) reducing inequalities in income. ICTs such as Internet access and mobile cellular phones have the potential to do several of these actions, including informing citizens of relevant information regarding government and society. The trend in several developed countries includes having more transparency by publishing information on the Internet concerning governmental issues (García-Murillo, 2010). Baliamoune-Lutz (2003) showed that ICT diffusion fosters civil and political freedoms. Furthermore, Sturges (2004) showed that access to ICT promotes greater governmental transparency by removing information barriers and asymmetry.

Increased access to the Internet and mobile communications has enabled citizens to participate more directly in the political and social matters of their countries. This increased participation in government, in the form of e-governance, has reduced bureaucratic overhead while increasing governmental efficiency and transparency (Andersen et al., 2010; M. Backus, 2001; Bertot et al., 2010). In several countries, Internet access has become a surrogate for judiciary efficiency. In countries such as India, Kenya, and Mexico, citizens are using ICTs to draw attention to governmental corruption and civilian crime that would otherwise go unreported or unprosecuted (M. Backus, 2001).

Citizens engaging in societal participation have used ICTs to organize, communicate, and raise awareness in such ways as the Arab Spring Revolution in the Arab world and news webloggers who expose Mexico’s narcotic traffickers atrocities. Pirannejad (2011) found that diffusion of ICT increases citizens’ networking capacity and political awareness while reducing their transaction costs. Soper (2007) showed that a negative relationship exists between ICT investment and the level of political corruption in emerging economies. Hay and Shleifer (1998) noted that private enforcement of public laws is a market response to poor governmental control. Some examples of this participation are e-governance and news blogging (Katz & Lai, 2009).

2.3 Research Hypotheses

Based on the above presented literature review, several research hypotheses were addressed in this study. Stated below are those research hypotheses and supporting literature. Following the presentation of the research hypotheses and supporting literature, a theoretical model is presented. This theoretical model shows the specific predicted relationships between the independent, mediating, and dependent variables. The expected direction of each hypothesized relationship is shown as either positive (+) or negative (-).

As stated in the above literature, there is a digital divide that exists between groups in their knowledge of, access to, and use of ICTs (Chinn & Fairlie, 2007). Foreign and domestic investment and income inequality have been contributing factors for the digital divide (Dasgupta et al., 2001; Erumban & de Jong, 2006). As shown in previous research, macroeconomic variables such FDI and GDP per capita have an impact on ICT investment and capacity (Gholami et al., 2006; Kshetri & Cheung, 2002; OECD, 1991; Suh & Khan, 2003). For example, FDI presents host countries with access to newer technology (OECD, 1991). The increase in FDI inflows also increases domestic investment in ICT (Agrawal, 2003). Furthermore, Gholami et al. (2006) demonstrated that ICT investment and capacity increases with the inflow of FDI. Similarly, Kshetri and Cheung (2002) showed that rapid mobile cellular phone diffusion in China was due to large FDI inflow and rapid economic growth.

As stated earlier, Vinod (1999) suggested that two of the top five actions in reducing corruption were increasing GNP per capita and increasing education and economic freedoms. While GNP and GDP are closely related, there are some important differences. GNP measures all output generated by a country based on ownership of the means of production. In comparison, GDP measures all output generated by a country based on geographic location of the means of production. There are some scholars who suggest that the GNP, instead of GDP, is the most accurate measure of economy well-being and market activity (Brezina, 2012; Stiglitz, 2009). However, the Bureau of Economic Analysis (1991) has stated that “virtually all other countries have already adopted GDP as their primary measure of production” (p. 8). According to Ringen

(1991), GDP per capita is the most widely used macroeconomic indicator of a country's standard of living. Dewan, Ganley, and Kraemer (2005) found that GDP per capita had a positive effect on ICT diffusion.

A measure of the ICT environment among countries is the Networked Readiness Index (NRI) published in the Global Information Technology Report by the World Economic Forum together with INSEAD (French name "INStitut Européen d'ADministration des Affaires", or European Institute of Business Administration). The NRI measures the degree to which a country is positioned to utilize its ICT infrastructure for international competitiveness (Dutta, Lanvin, & Paua, 2003). The NRI is made of two parts: an index score and a rank. The index score is the numerical combination of the various ICT-related component and subcomponent indexes. There are three major component indexes in the NRI: environment, readiness, and usage (Dutta et al., 2003). The environment component examines the market, political, regulatory, and infrastructure environment that facilitate ICT development. The readiness component index reflects the preparedness of individuals, governments, and businesses to employ ICT resources to their fullest potential. Lastly, the usage component index indicates the level of usage among individuals, governments, and businesses. The NRI rank score is the particular country's numerical rank based on its index score.

The NRI provides an index for measuring the ICT environment and the level of ICT diffusion. GDP per capita and FDI should have a positive effect on NRI based on the research by Dewan et al. (2005) and Gholami et al. (2006). This leads to the following hypotheses:

Hypothesis 1a: FDI has a positive effect on networked readiness.

Hypothesis 1b: GDP per capita has a positive effect on networked readiness.

As previously stated, the NRI measures the degree by which a country is ready to use its ICT infrastructure. A component of the NRI is the usage of ICTs such as computers, telephone, and Internet usage. This usage component of the NRI also includes the diffusion of Internet access and mobile cellular phone usage among the country's population.

Access to the Internet and mobile cellular phone usage are important ways for citizens to more readily participate in their country's political and social matters. For example, e-governance has reduced bureaucratic overhead while increasing governmental efficiency and transparency (Andersen et al., 2010; M. Backus, 2001; Bertot et al., 2010). Furthermore, Geiger and Mia (2009) showed that mobile phone diffusion has a significant positive effect on economic growth and poverty reduction.

The difference between Internet access and mobile cellular phone as separate ICT modalities is slowly disappearing. Baliamoune-Lutz (2003) stated that differences between communication technology (e.g. mobile phones) and information technology (e.g. the Internet) have become blurred. While the Internet is an indicator of information technology, consumers can access data and information via mobile phones (H.-W. Kim, Chan, & Gupta, 2007). For example, in Japan, approximately 40% of the population accesses the Internet via mobile phones (Kenichi, 2004).

Based on the above literature, the state of ICT infrastructure, as measured through the NRI, should have a positive effect on the diffusion of Internet access and mobile cellular phones. Jakopin and Klein (2011) found that regulatory quality and market environment, two components of the NRI, significantly benefit Internet diffusion. Also, based on the finding of

Kenichi (2004), mobile cellular phone diffusion should lead to an increase diffusion of Internet access. This leads to the following hypotheses:

Hypothesis 2a: Networked readiness has a positive effect on Internet diffusion.

Hypothesis 2b: Networked readiness has a positive effect on mobile phone diffusion.

Hypothesis 2c: Mobile phone diffusion has a positive effect on Internet diffusion.

ICT has been shown to promote greater governmental transparency by removing information barriers and asymmetry (Sturges, 2004). Diffusion of ICTs raises citizens' participation in governance by increasing networking capacity and political awareness while reducing their transaction costs (Pirannejad, 2011). ICTs such as Internet access enables citizens to stay informed with relevant information about their government and society. E-governance and social media, which rely heavily on the Internet, also promote openness and transparency in government (Bertot et al., 2010). Additionally, García-Murillo (2010) found that access and diffusion of relevant information concerning governmental issues promotes greater transparency.

S. M. Johnson (1998) and Cuillier and Piotrowski (2009) demonstrated that the Internet expands public access to government information. Jakopin and Klein (2011) found that Internet diffusion significantly predicts governmental transparency, as measured by the Voice and Accountability indicator of the World Bank's Worldwide Governance Indicators. Based on the above cited research, Internet diffusion and mobile cellular diffusion should positively affect the level of transparency. These premises lead to the following hypotheses:

Hypothesis 3a: Internet diffusion has a positive effect on transparency.

Hypothesis 3b: Mobile phone diffusion has a positive effect on transparency.

Some authors have put forth the positive effects of ICTs on improving transparency and governance (Avgerou, 1998; Krueger, 2002; Opoku-Mensah, 2000; Soper, 2007). ICTs have been shown to be a tool in democratization (Opoku-Mensah, 2000; Soper, 2007) and a device that facilities and improves political involvement (Krueger, 2002, 2006; Norris, 2001).

ICTs improve governance by increasing transparency and reducing corruption. There exists a negative relationship between ICT investment and the level of political corruption in emerging economies (Soper, 2007). Baliamoune-Lutz (2003) showed that ICT diffusion fosters civil and political freedoms. Access to ICTs promotes greater governmental transparency by removing information barriers and asymmetry (Sturges, 2004). In addition, increased government participation by citizens in such forms of e-governance has been shown to increase transparency while reducing bureaucratic overhead (Andersen et al., 2010; M. Backus, 2001; Bertot et al., 2010).

Increased transparency through initiatives such as e-governance has been shown to be an effective anti-corruption tool (Bertot et al., 2010). A lack of transparency can exacerbate corruption-related problems (Kolstad & Wiig, 2009). Similarly, Brunetti and Weder (2003) found a strong association between transparency through greater press freedom and less corruption.

The main focus of this study is to explore the relationships between ICT diffusion and corruption. Given the above stated research and the goals of this study, the relationship between the diffusion of specific ICTs and reduction of corruption will be examined. This leads to the following hypotheses:

Hypothesis 4a: Internet diffusion has a negative effect on corruption.

Hypothesis 4b: Transparency has a negative effect on corruption.

Hypothesis 4c: Mobile phone diffusion has a negative effect on corruption.

The diffusion of ICTs, levels of transparency, and levels of corruption is not uniform throughout the world. One common thread set forth in prior research attempting to explain the non-uniform diffusion of technology and differences in transparency and corruption among countries are national culture differences and technology quality (Erumban & de Jong, 2006; Husted, 1999; Kenichi, 2004; Luo, 2008; Moghadam & Assar, 2008; Paldam, 2004).

In order to account for the effects of national culture differences, various studies examining ICT effects use the Hofstede Cultural Dimension framework (Erumban & de Jong, 2006; Moghadam & Assar, 2008; Straub, Keil, & Brenner, 1997; Stulz & Williamson, 2003). The Hofstede Cultural Dimension indices are the result of work by Geert Hofstede involving cultural dimensions of a society and how these dimensions affect behavior (Hofstede, Hofstede, & Minkov, 2010). Hofstede’s analysis of national cultures identified four anthropological systematic differences: power distance (PDI), individualism (IDV), uncertainty avoidance (UAI) and masculinity (MAS) (Hofstede, 1984). In 1991, Hofstede added the additional cultural dimension of long term orientation (LTO) (Hofstede, 1997).

The Hofstede Cultural Dimension framework has been used extensively in prior research. Erumban and de Jong (2006) found that power distance and uncertainty avoidance, two dimensions of the Hofstede Cultural Dimension framework, directly influence ICT adoption. Similarly, Straub et al. (1997) suggest that power distance and uncertainty avoidance may account for differences in e-mail usage. Furthermore, de Mooij and Hofstede (2002) state that culture replaces such things as personal income and national wealth in consumer consumption patterns and that Hofstede's uncertainty avoidance was related to such things as embracement of the Internet and the ownership of computers and mobile cellular phones. Given the potential influences of national cultural differences, dimensions of the Hofstede Cultural Dimensions framework were used as national culture control variables.

2.4 Theoretical Model

The literature cited in the above review suggests there are complex relationships that exist between key macroeconomic variables, ICT indices, corruption, and transparency. A deeper understanding and explanation of these relationships provide the foundation for this study. A brief description of the key and control variables is presented below. These key and control variables are discussed in further detail in section 3.3 Variable Description.

This study used seven key variables and five control variables in the theoretical model. The independent macroeconomic key variables in the theoretical model are Foreign Direct Investment (FDI) and Gross Domestic Product per capita (GDP per capita). The independent macroeconomic key variable of FDI is the net inflow of investment (measured in current U.S. dollars) into a domestic economy by foreign investors. The independent macroeconomic key variable of GDP per capita measures the gross domestic product divided by the midyear population.

The intervening key ICT variables in the theoretical model are Networked Readiness Index (NRI), Internet diffusion, and Mobile diffusion. The intervening key ICT variable of NRI measures the degree to which a country is positioned to use its ICT infrastructure for international competitiveness. The intervening key ICT variable of Internet diffusion measures the distribution of Internet access within a country. The intervening key ICT variable of Mobile diffusion measures the dispersion of mobile cellular phone access within a country. The intervening and dependent governance key variable of Transparency measures the degree to which governmental officials and processes are visible and accountable to those who are governed. This study's main dependent governance key variable of Corruption measures the degree of corrupt practices in a country's public sector.

This study also utilized five control variables. Four of these control variables were used as national culture control variables to examine potential cultural factors influencing the main dependent variable. These national culture control variables included the Hofstede Cultural Dimension indices of Power Distance, Individualism vs. Collectivism, Long- vs. Short-Term Orientation, and Uncertainty Avoidance. The national cultural control variable of power distance (H-PDI) measures the extent to which less powerful members of society accept and/or expect unequal distribution of power. The national cultural control variable for individualism versus collectivism (H-IDV) measures the extent to which individuals are incorporated into groups. The national cultural control variable for long- versus short-term orientation (H-LTO) measures the future orientation of a society. The national cultural control variable for uncertainty avoidance (H-UAI) measures the degree of tolerance for uncertainty and ambiguity. The year was also used as a control variable. The control variable of year was included as a twelfth variable in order to control for potential multiple year effects. The control variable of year is not considered to be a key variable, but it is shown in the theoretical model.

Figure 2.1 presents the hypothesized relationships between the key and control variables in a theoretical model based on supporting literature cited. As shown in Figure 2.1, the theoretical model illustrates these relationships along with their predicted effects. Figure 2.1 also shows the control variables used in the study. The theoretical model shows the expected direction of each hypothesized relationship and the expected effect of each relationship between dependent, mediating and independent variables as either positive (+) or negative (-).

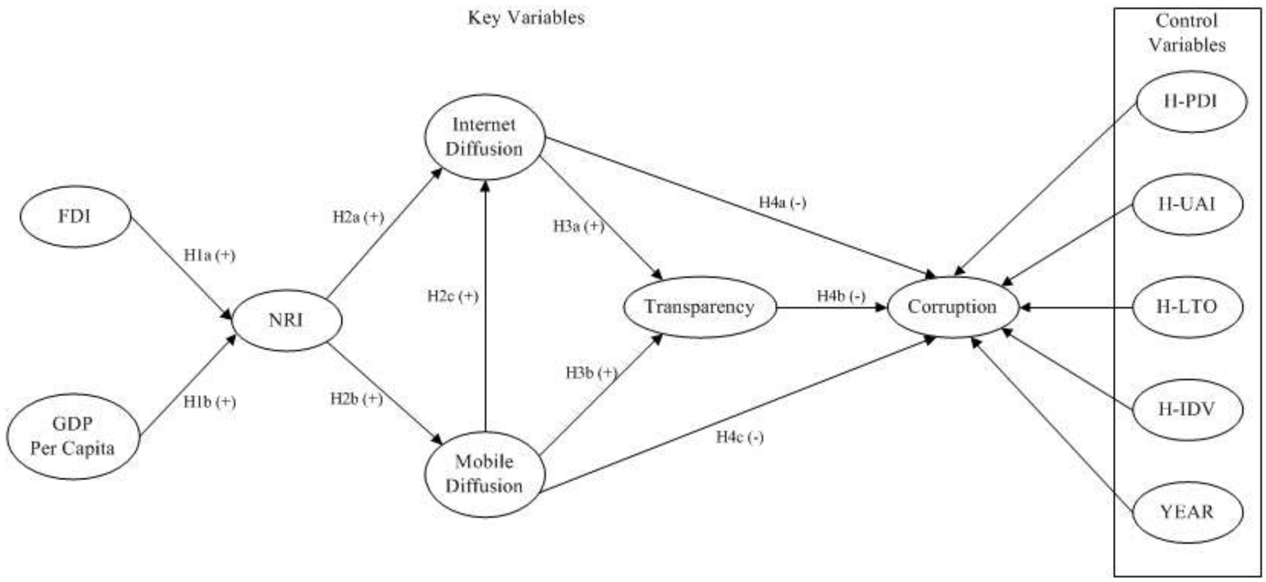

Figure 2-1. Theoretical model with hypotheses and predicted effects.

The theoretical model used in this study will be analyzed using path analysis. This theoretical model hypothesizes complex and intervening relationships. By using path analysis, indirect and total effects of variables within the model can be examined. Additionally, the model contains two or more variables pointing at one variable. Such multivariate adjustments may affect how the hypotheses are interpreted.

CHAPTER III

METHODOLOGY

The research design and methodology are explained in this section. In the first part of this section, an overview of the sample countries used in the study is provided. In the second part of this section, the variables used in the study are presented along with a focus on data collection and data sources. In the third part of this section, a detailed description of each variable is provided. In the fourth part of this section, the methods used to prepare the data for analysis such as completeness and multicollinearity tests are described. Finally, in the fifth and final part of this section, the method of data analysis is described.

3.1 Sample Design

As of 2012, there were 193 existing sovereign states and countries (United Nations, 2012). This study examined 121 countries of those 193 countries. Table 3-1 provides a list of the countries selected for analysis in this study. Countries were selected for inclusion in the study based on data availability of the key variables. The countries used in this study are representative of a diverse range of economic and political structures. The key and control variables used in this study are enumerated and described in section 3.3: Variable Description. This study used multi-year data for these key and control variables collected over a period from 2006 to 2010.

The study excludes 72 sovereign states and countries. These sovereign states and countries were excluded due to lack of data availability of the key variables (Messner, 1992). Key variable data was collected from several multinational datasets from various sources such as the World Bank World Development Indicators, World Economic Forum Global Information

Technology Report, World Bank Worldwide Governance Indicators, and Transparency International.

Table 3-1. List of countries used in this study.

Albania	Denmark	Lesotho	Romania
Algeria	Dominican Republic	Lithuania	Russia
Angola	Ecuador	Luxembourg	Singapore
Argentina	Egypt	Macedonia	Slovakia
Armenia	El Salvador	Madagascar	Slovenia
Australia	Estonia	Malawi	South Africa
Austria	Ethiopia	Malaysia	South Korea
Azerbaijan	Finland	Mali	Spain
Bahrain	France	Malta	Sri Lanka
Bangladesh	Georgia	Mauritania	Suriname
Barbados	Germany	Mauritius	Sweden
Belgium	Greece	Mexico	Switzerland
Benin	Guatemala	Moldova	Taiwan
Bolivia	Guyana	Mongolia	Tanzania
Bosnia-Herzegovina	Honduras	Morocco	Thailand
Botswana	Hong Kong	Mozambique	Trinidad and Tobago
Brazil	Hungary	Namibia	Tunisia
Bulgaria	Iceland	Nepal	Turkey
Burkina Faso	India	Netherlands	Uganda
Burundi	Indonesia	New Zealand	Ukraine
Cambodia	Ireland	Nicaragua	United Arab Emirates
Cameroon	Israel	Nigeria	United Kingdom
Canada	Italy	Norway	USA
Chad	Jamaica	Pakistan	Uruguay
Chile	Japan	Panama	Venezuela
China	Jordan	Paraguay	Vietnam
Colombia	Kazakhstan	Peru	Zambia
Costa Rica	Kenya	Philippines	Zimbabwe
Croatia	Kuwait	Poland	
Cyprus	Kyrgyzstan	Portugal	
Czech Republic	Latvia	Qatar	

3.2 Data Collection

Data for the key and control variables was collected by country and year using several online databases for the 121 countries used in this study. Table 3-2 summarizes the key and control variables and their related data sources. Data for the macroeconomic variables of FDI and GDP per capita used in this study were collected from the World Bank World Development Indicators. Data for the ICT variables of Internet diffusion and Mobile diffusion used in this study were collected from the World Bank World Development Indicators. Data for the ICT variable of NRI used in this study was collected from the World Economic Forum Global Information Technology Report.

Table 3-2. Data sources for variables.

Variable	Measure	Source
Transparency	Voice and Accountability Indicator	World Bank Worldwide Governance Indicators
Corruption	Corruption Perceptions Index	Transparency International
Internet diffusion	Internet users (per 100 people)	The World Bank World Development Indicators
Mobile diffusion	Mobile cellular subscriptions per 100 people	The World Bank World Development Indicators
FDI	Foreign direct investment, net inflows (balance of payments, current US$)	The World Bank World Development Indicators
NRI	Networked Readiness Index	World Economic Forum Global Information Technology Report
GDP per capita	Gross Domestic Product per capita (current US$)	The World Bank World Development Indicators
H-PDI	Power Distance Index	Hofstede Dimension Data Matrix
H-UAI	Uncertainty Avoidance Index	Hofstede Dimension Data Matrix
H-LTO	Long-Term Orientation Index	Hofstede Dimension Data Matrix
H-IDV	Individuality Index	Hofstede Dimension Data Matrix

Data for the variable of Transparency used in this study was collected from the World Bank Worldwide Governance Indicators. Data for the variable of Corruption used in this study was collected from Transparency International's Corruption Perceptions Index. Data for the national culture control variables of Power Distance Index, Uncertainty Avoidance Index, Long-Term Orientation Index, and Individuality Index used in this study was collected from the Hofstede Cultural Dimension scores gathered through the Geert Hofstede Dimension Data Matrix as presented in *Cultures and Organizations 3rd* edition (Hofstede et al., 2010). The total dataset consisted of 605 rows. Table 3-3 presents the key and control variables with the number of data items collected for each year.

Table 3-3. Number of data items collected for each variable by year.

Variable	2006	2007	2008	2009	2010	Total
Transparency	121	121	121	121	121	605
Corruption	120	120	121	121	120	602
Internet diffusion	119	119	119	119	120	596
Mobile diffusion	119	119	119	118	120	595
FDI	120	120	120	120	120	600
NRI	121	118	120	119	116	594
GDP per capita	120	120	120	120	120	600
H-PDI	75	75	75	75	75	375
H-UAI	75	75	75	75	75	375
H-LTO	86	86	86	86	86	430
H-IDV	75	75	75	75	75	375

3.3 Variable Description

This study explored the hypothesized relationships between macroeconomic, ICT, governance and sociocultural variables using the key and control variables as listed in Table 3-3. These relationships are put forth in the theoretical structural model as presented in Figure 2.1.

The independent and mediating variables in the theoretical model are Foreign Direct Investment, Gross Domestic Product per capita, Networked Readiness Index, Internet diffusion, Mobile diffusion, and Transparency. The intervening or mediating variables in the theoretical model are Networked Readiness Index, Internet diffusion, Mobile diffusion, and Transparency. Finally, the main dependent variable in the theoretical model is Corruption. The national culture control variables used in this study were Hofstede's Cultural Dimension indices of Power Distance, Individuality, Long-Term Orientation, and Uncertainty Avoidance. A further enumeration and detailed description of the key and control variables are presented below. Representations in the data analysis and structural models of these key and control variables are presented in parentheses.

The macroeconomic variable of Foreign Direct Investment (FDI) is the net inflow of investment, measured in current U.S. dollars, into a domestic economy by foreign investors. These investment inflows are shown in the balance of payments as financial transfers, including the sum of equity capital, reinvestment of earnings, short-term and long-term capital. Data for the variable of FDI was captured through *foreign direct investment, net inflows (BoP, current U.S. $)* indicator from the World Bank World Development Indicators which is reported in current U.S. dollars. The *foreign direct investment, net inflows (BoP, current U.S.$)* indicator as contained in the World Bank World Development Indicators data were supplied by the International Monetary Fund's Balance of Payments database and supplemented by data from the United Nations Conference on Trade and Development and other official national sources.

The FDI data values are quite large and varied -- ranging from hundreds of thousands to hundreds of billions of U.S. dollars. The large and varied values of the FDI data tend to increase variance. One method used in stabilizing variance is logarithmic data transformation (Bland, 2002). Logarithmic data transformation is the process of converting a data value into its logarithmic value using some base such as the natural base (e). Logarithmic transformations of data can transform non-linear relationships into linear ones and normalize positively skewed distributions (Sokal & Rohlf, 1969). Such logarithmic transformation allows easier handling and interpretation of data values with a high degree of variance (Zar, 1999). A general logarithmic transformation could not be performed because a few of the FDI data values were negative. Therefore, the logarithmic transformation was performed on the absolute value of the FDI data values. Depending on the sign of the original FDI data value, a logarithmic transformed value was multiplied by a constant of +1 or -1 to represent its original sign. For example, negative FDI data values, which represent divestiture or disinvestment, were represented by multiplying the logarithmic transformation value by negative 1.

The macroeconomic variable of Gross Domestic Product per capita (GDP per capita) measures the gross domestic product divided by the midyear population. Data for the variable of GDP per capita data was captured through the *gross domestic product per capita (current U.S. $)* indicator from the World Bank World Development Indicators and was measured in current U.S. dollars. The *gross domestic product per capita (current U.S.$)* indicator data as contained in the World Bank's World Development Indicators was supplied by the World Bank national accounts data and Organisation for Economic Co-operation and Development (OECD) National Accounts data files.

GDP per capita is the most widely used macroeconomic indicator of a country's standard of living (Ringen, 1991). There are some scholars who suggest that the GNP, instead of GDP, is a more accurate measure of economy well-being and market activity (Brezina, 2012; Stiglitz, 2009). However, Bureau of Economic Analysis (1991) has stated that "virtually all other countries have already adopted GDP as their primary measure of production" (p. 8). Studies researching the relationships between macroeconomic and ICT variables generally use GDP or GDP per capita to measure economic activity and growth (Addison & Heshmati, 2004; Dewan et al., 2005; Kiiski & Pohjola, 2002).

The ICT variable of Networked Readiness Index (NRI) measures the degree to which a country is positioned to use its ICT infrastructure for international competitiveness. Data for the variable of NRI was captured through the *Networked Readiness Index* index score as published in the Global Information Technology Report by the World Economic Forum together with INSEAD (French name "INStitut Européen d'ADministration des Affaires", or European Institute of Business Administration). The *Networked Readiness Index* as published in the Global Information Technology Report is comprised of two parts: an index score and a rank. In this study, only the index score was used as the measure of analysis. The index score is a composite of three component indexes: environment, readiness, and usage. The environment component index and its subcomponents examine the market, political, regulatory, and infrastructure conditions that facilitate or hamper ICT growth. The readiness component index and its subcomponents examine the readiness and preparedness of individuals, governments, and businesses to utilize ICT resources. The usage component index and its subcomponents examine the levels of usage among individuals, governments, and businesses. The composite index, ranging from 1.0 (worst) to 7.0 (best), provides a method for a) calculating the relative and overall development and use of ICT in countries and b) understanding the strengths and weaknesses of a country's ICT readiness to compete in a global environment. The rank is the particular country's numerical rank based on the index score.

This study utilized two variables to measure ICT diffusion. These two ICT variables include Internet diffusion and Mobile diffusion. The ICT variable for diffusion of Internet (Internet diffusion) measures the distribution of Internet access within a country. Data for the variable of Internet diffusion data was captured through the *Internet users (per 100 people)* indicator from the World Bank World Development Indicators. The *Internet users (per 100 people)* indicator measures the number of persons per 100 people of a country's population who have access to the Internet. Data for the *Internet users (per 100 people)* indicator as contained in The World Bank World Development Indicators were supplied by the International Telecommunication Union's World Telecommunication/ICT Development Report and World Bank estimates. The International Telecommunications Union (ITU) is a special agency of the United Nations responsible for global information and communication technologies coordination.

The ICT variable of mobile cellular diffusion (Mobile diffusion) measures the dispersion of mobile cellular phone access within a country. Data for the variable of Mobile diffusion was captured through the *Mobile cellular subscriptions (per 100 people)* indicator of the World Bank World Development indicators. This indicator measures the number of persons per 100 people of a country's population who have subscriptions to public mobile telephone services using cellular technology. These service subscriptions provide access to the public switched telephone network. Prepaid and post-paid subscriptions were included in the indicator.

Data for the *Mobile cellular subscriptions (per 100 people)* indicator as contained in the World Bank World Development Indicators were supplied by the International Telecommunication Union's World Telecommunication/ICT Development Report and database, and World Bank estimates.

The governance variable of Transparency (Transparency) measures the degree to which governmental officials and processes are visible and accountable to those who are governed. Data for the variable of Transparency was captured through the *Voice and Accountability (VA)* indicator of the World Bank's Worldwide Governance Indicators. The *Voice and Accountability (VA)* indicator forms one of six World Bank governance indicators. The Worldwide Governance Indicators are a set of six indicators for 215 world economies. These six indicators are: Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption.

The *Voice and Accountability (VA)* indicator measures the extent to which a country's citizens are able to participate in their governance by examining several aspects of a country's political processes, including civil liberties, political rights, and a free media (Kaufmann, Kraay, & Mastruzzi, 2009). As presented in Table 3-4, the *Voice and Accountability (VA)* indicator is a composite of twenty representative and non-representative data source types such as government and public sector (GOV), non-governmental organizations (NGO), commercial business information providers (CBIP), and surveys of households and firms (SURVEY). The *Voice and Accountability (VA)* indicator, ranging from around -2.5 to 2.5, measures countries' accountability and citizen participation in relation to the global average (equaling zero).

This composite indicator served as a measure for transparency in this study since public voice and methods of accountability in a society create a perception of more transparency (Andrea & Antonio, 2007). The variable of Transparency served as a dependent and intervening variable in this study.

Table 3-4. Voice and Accountability (VA) indicator data types and sources.

Source	Type*
African Electoral Index (IRP)	NGO
Afro-barometer (AFR)	GOV
Bertelsmann Transformation Index (BTI)	NGO
Cingranelli Richards Human Rights Database and Political Terror Scale (HUM)	GOV
Economist Intelligence Unit Risk-wire & Democracy Index (EIU)	CBIP
Freedom House (FRH)	NGO
Freedom House Countries at the Crossroads (CCR)	NGO
Gallup World Poll (GWP)	SURVEY
Global Insight Business Conditions and Risk Indicators (WMO)	CBIP
Global Integrity Index (GII)	NGO
IFAD Rural Sector Performance Assessments (IFD)	GOV
Institute for Management and Development World Competitiveness Yearbook	SURVEY
Institutional Profiles Database (IPD)	GOV
International Budget Project Open Budget Index	NGO
Latino-barometro	SURVEY
International Research and Exchanges Board Media Sustainability Index	NGO
Political Risk Services International Country Risk Guide (PRS)	CBIP
Reporters Without Borders Press Freedom Index (RSF)	NGO
Vanderbilt University Americas Barometer	SURVEY
World Economic Forum Global Competitiveness Report (GCS)	SURVEY

Note: “type” refers to the nature of the data source. Data sources for Voice and Accountability are from government and public sector (GOV), non-governmental organizations (NGO), commercial business information providers (CBIP), and surveys of households and firms (SURVEY).

The governance variable for Corruption (Corruption), the main dependent variable in this study, measures the degree of corrupt practices in a country’s public sector. The data for the variable of Corruption was captured through the *Corruption Perceptions Index (CPI)* from Transparency International. This index measures the degree of corruption that exists among public officials and politicians (Lambsdorff, 1999a). The CPI is the most disseminated among policymakers and is a composite index that includes survey data from country experts, businesspeople, global analysts, and experts who are residents of the evaluated countries

(Svensson, 2005). The CPI focuses on perceptions of public sector corruption – the use of public office for private gain.

The CPI index ranks countries on a scale from 10 (representing a very clean/minutely corrupt government) to 0 (representing a highly corrupt government). On the CPI scale, countries with lesser perceptions of corruption score higher. Thus, the CPI scale lends itself to be interpreted as 'the absence of corruption' perception index. To make the CPI values reflect the presence of corruption, a data transformation was performed on the CPI data. The original CPI values were multiplied by the constant of negative 1 to inverse the scaling while preserving the rank of the values. This data transformation resulted in highly corrupt countries having a higher value than those with lower levels of perceived corruption.

Given the potential important influences of sociocultural values on corruption and ICT diffusion, this study included four Hofstede's Cultural Dimension indices as national culture control variables. Husted (1999) found that corruption was significantly correlated to the Hofstede cultural dimensions of power distance, masculinity, and uncertainty avoidance. According to Myrdal (1970a), corruption is defined, in part, by sociocultural mores and values. Furthermore, many scholars suggest that corruption can be defined in sociocultural terms (Friedrich, 1989; Johnston, 1997; Rose-Ackerman, 1978, 1996). Also, several authors such as N. Rosenberg (1972), Erumban and de Jong (2006), Moghadam and Assar (2008), Jakopin and Klein (2011), suggest that sociocultural values influence individuals in a society in a way that facilitates or impedes technology adaptation and diffusion. For example, Erumban and de Jong (2006) found that countries with high power distance and uncertainty avoidance have lower ICT adoption rates.

This study used the Hofstede's Cultural Dimension indices of Power Distance (H-PDI), Individuality (H-IDV), Long-Term Orientation (H-LTO), and Uncertainty Avoidance (H-UAI) as national culture control variables to address potential influences of sociocultural factors. Data for the national culture variables were imputed from the Hofstede Cultural Dimension scores for each country used in the study. The Hofstede Cultural Dimension scores were gathered from the Geert Hofstede Dimension Data Matrix as presented in *Cultures and Organizations 3rd* edition (Hofstede et al., 2010). The Hofstede Cultural Dimension indices are the resulting work of Geert Hofstede research into cultural dimensions of a society and how these dimensions of culture affect behavior. In 1967, Hofstede began a large scale survey study on differences in cultural values of employees in different subsidiaries of IBM Europe. Hofstede compared answers of tens of thousands of employees in over 40 countries. The analysis of the surveys identified four anthropological systematic differences in national cultures: power distance, individualism, uncertainty avoidance, and masculinity (Hofstede, 1984). In 1991, Hofstede added the additional cultural dimension of long term orientation (Hofstede, 1997).

The Hofstede Cultural Dimension indices contained power distance, individualism, uncertainty avoidance, masculinity and long term orientation scores for 110 countries and regions. However, there were some countries that had missing scores within Hofstede-defined regions. These missing scores were replaced with regional data scores. For example, Egypt did not have scores for the four Hofstede cultural dimension indices. However, Egypt is classified within a region of Arab countries which had regional Hofstede Cultural Dimension scores. Therefore, Egypt's missing country scores were replaced by the Arab regional scores. This method of imputation of missing data using regional scores was the first method used to achieve completeness of the Hofstede Cultural Dimension data. After this missing data method was applied, the cultural dimension data was examined for completeness and further missing data treatments were employed. These further missing data treatments are outlined and detailed in section 3.4 Data Preparation. A description of each Hofstede Cultural Dimension index used in this study follows. The year for the country observations was also used as a control variable.

The national cultural control variable for power distance (H-PDI) measures the extent to which less powerful members of society accept and/or expect unequal distribution of power. Societies which score higher in this Hofstede dimension value suggest that societal inequality is more widely accepted by those who are governed. Data for the variable of power distance was captured through Hofstede Cultural Dimension Power Distance index. The national cultural control variable for individualism (H-IDV) measures the extent to which individuals are incorporated into groups. Societies which score higher in this Hofstede dimension, value personal rights and freedoms over collectivistic values (e.g. group loyalty). Data for the variable of individualism was captured through Hofstede Cultural Dimension Individualism vs. Collectivism Index. The national cultural control variable for long-term orientation (H-LTO) measures the future orientation of a society. Societies which score higher in this Hofstede dimension are seen as more future-oriented and foster more pragmatic views such as persistence. Short-term orientation societies promote past and present values such as tradition, saving face, etc. Data for the variable of long-term orientation was captured through Hofstede Cultural Dimension Long- vs. Short-Term Orientation Index. The national cultural control variable for uncertainty avoidance (H-UAI) measures the degree of tolerance for uncertainty and ambiguity. Societies with higher scores in this Hofstede dimension generally have more rules and laws and are less tolerant to unplanned change. Data for the variable of uncertainty avoidance was captured through Hofstede Cultural Dimension Uncertainty Avoidance Index.

3.4 Data Preparation

A primary step before data analysis can be done is data preparation. One of the first steps in data preparation is examining the dataset for completeness. This examination involves reviewing the dataset for missing data and assessing the reason for such missing data. Missing data can have a significant effect on research results. Missing data analysis is not generally the main focus of scientific inquiry but must be addressed to prevent results that are “biased, inefficient (lacking in power), and unreliable.” (Schafer & Graham, 2002, p. 147). A general rule is to have no more than 10% of data missing in any column used in the data analysis; a more relaxed rule for the missing data threshold is 20% (Allison, 2001; Hair, Anderson, & Tatham, 1987; Hair, Black, Babin, & Anderson, 2010).

This study combines data elements from several multinational datasets from various sources such as the World Bank World Development Indicators, World Economic Forum Global Information Technology Report, World Bank Worldwide Governance Indicators, and Transparency International. As reported by Messner (1992), there tends to be missing data in cross-national research because national government often does not report such critical statistics consistently. Given the multinational datasets used in this study and the possibly of missing data, an analysis for missing data was conducted on the dataset. As presented in Table 3-5, the independent, mediating, and dependent variables were well within the 10% allowable missing data threshold as suggested by Hair et al. (1987). However, several Hofstede Cultural Dimension index variables exceeded both the 10% and 20% missing data thresholds. Given this amount of missing data in the Hofstede Cultural Dimension index variables, a method of handling missing data needed to be applied to the dataset.

Table 3-5. Percentage of missing data values by variable (N=605).

Variable	Percentage of missing data
Transparency	0.000%
Corruption	0.496%
Internet diffusion	1.488%
Mobile diffusion	1.653%
FDI	0.826%
NRI	1.818%
GDP per capita	0.826%
H-PDI*	38.017%
H-UAI*	38.017%
H-LTO*	28.926%
H-IDV*	38.017%

Note: '*' denotes variables with missing data values over the 10% and 20% missing data thresholds as suggested by Hair et al. (1987)

There are several ways to address missing data in the statistics literature (Allison, 2001, 2003; Enders & Bandalos, 2001; Honaker & King, 2010; Little, 1988; Little & Rubin, 1987; Olinsky, Chen, & Harlow, 2003; Roth, 1994; Schafer & Graham, 2002). The phenomenon of missing data values is known as the *missingness* of the data (Hawthorne & Elliott, 2005; Lauritzen, 1995; Little, 1988). First, the reason for the missing data must be determined in order to select the appropriate missing data treatment. There are three categorical reasons for missing data: missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR) (J.-O. Kim & Curry, 1977; Little, 1988; Little & Rubin, 1987).

The first possible categorical reason for missing data is MCAR. Missing data is considered MCAR if the data values missing are independent of the other variables of interest or some unobserved variable. MCAR is also known as uniform non-response since values are missing independently of any other variable in the study (Wang & Fitzmaurice, 2006). As the names suggests, MCAR data is *completely* missing due to random chance. Stated another way, in

MCAR, any data value has approximately the same probability of being observed or unobserved as any other data value. For example, a researcher distributes and collects 200 paper surveys and 10% of those surveys are returned completely blank. If the blank surveys were randomly not completed, the missing data from those blank surveys could be considered MCAR. Data that is MCAR reduces statistical power but does not produce bias since the missing data is not related to other variables.

The next possible categorical reason for missing data is MAR, which is an alternative to MCAR. In MAR, missing data-values are not dependent on the missing data item itself (Heitjan & Basu, 1996). A special case of MAR is known as uniform non-response within class (Robins, 1997). In the special case of MAR uniform non-response within class, data values are missing based on a particular class or group within the dataset. According to Heitjan and Basu (1996), MCAR and MAR are "ignorability conditions" (p. 1) that allow particular interpretations to be safely made without complex missing data models. For example, in MAR, unobserved data values can be intuitively based on observed data values of similar data rows (Schafer & Graham, 2002). Using the aforementioned example, a researcher distributes and collects 200 paper surveys and 10% of those surveys are returned partially blank (e.g. some questions were skipped). If the unanswered questions in the surveys were randomly not completed, this missing data could be considered MAR.

The last possible categorical reason for missing data is known as MNAR. For MNAR, the conditions of MCAR and MAR do not hold. In MNAR, data-values are missing not at random. In the case of MNAR, data is missing based on the nature or value of the missing figures. Data that is MNAR requires more complex missing data treatments and modeling. Also, determining and compensating for the underlying reasons for the missingness proves to be more problematic.

The best way to obtain estimates of the missing data without introducing additional bias is to create a model to mimic the missingness in the data (Dunning & Freedman, 2007). Using the aforementioned example, a researcher distributes and collects 200 paper surveys and 10% of those surveys are returned partially blank (e.g. some questions were skipped). The researcher reviews the surveys and discovers that a particular group (e.g. women under thirty) skipped a particular question (e.g. income). This commonality existing between the group and the unanswered question signifies that the data is MNAR.

As shown in Figure 3.5, the Hofstede Cultural Dimension data was missing for 28% to 38% of the counties in this study. The independent, mediating, and dependent variables in this study did not need a missing data treatment applied as these variables were within the 10% allowable missing data threshold as suggested by Hair et al. (1987). To determine the best method of handling the missing Hofstede Cultural Dimension data, the reason for why the data was missing must be categorized into one of the three causes as suggested by Little and Rubin (1987). In other words, were the missing cultural dimension values for countries in Hofstede's study related to the actual values of those cultural dimensions, or were they associated with some other variable of interest?

According to Hofstede (1984), the cultural dimensions data that was missing for several countries was a result of no IBM subsidiaries existing in those countries at the time of the original data collection. The missing Hofstede Cultural Dimension data could be MNAR if IBM selected countries in which to place subsidiaries based on some cultural dimension variable or other unobserved variable. It is quite plausible for a global country such as IBM to exercise diligence in placing its subsidiaries. While the explanation of selection bias by IBM is plausible, at the time of Hofstede's data collection, IBM had subsidiaries in more than seventy countries

(Hofstede, 1984). For the purpose of this study, it must be determined if there is a selection bias in the Hofstede cultural dimensions data. To determine if IBM selected countries in which to place subsidiaries based on some cultural dimension, the observed Hofstede cultural dimension data was analyzed for non-normal distribution.

A test for non-normal or asymmetrical distribution is essentially a skewness test using the adjusted Fisher-Pearson standardized moment coefficient (Doane & Seward, 2011). The test for skewness exposes whether observed data values are asymmetrically distributed around the mean. The test for skewness produces a skewness statistic that can be used to determine the degree of asymmetry in the distribution of data. A distribution of data that is relatively symmetrical produces a skewness statistic of near zero. A negative skewness statistic indicates more values lay above the mean. A positive skewness statistic indicates more data values lay below the mean. If IBM selected countries in which to place subsidiaries based on some cultural dimension, there is a high probability that such a selection bias would skew the observed data values toward the IBM-preferred bias.

Doane and Seward (2011) suggest using the adjusted Fisher-Pearson standardized moment coefficient to test for skewness. The adjusted Fisher-Pearson standardized moment coefficient includes an adjustment for sample size and is readily available in software packages such as Minitab, Excel, SPSS, SAS and (Doane & Seward, 2011). The skewness statistic (S) produced by the adjusted Fisher-Pearson standardized moment coefficient must be compared to a threshold of allowable skewness. Tabachnick and Fidell (1996) suggest calculating the "standard error of skewness – S_s" (p. 79) by using $s_s = \sqrt{6/N}$ where N is the numbers of observed data values. The probability of a large degree of skewness can be evaluated by using the z distribution of $z = (S - 0)/S_S$ as suggested in Tabachnick and Fidell (1996). A z value in excess of ±2.58 would indicate a significant degree of skewness in the distribution of data.

Presented in Table 3-6 are the results of the normal distribution test on the Hofstede cultural dimension data. These results were calculated using Microsoft Excel 2010. Other variables in this study were not tested for normal distribution as these variables were within the 10% allowable missing data threshold as suggested by Hair et al. (1987). Hofstede Cultural Dimension data was tested for symmetric distribution to determine if IBM used some selection bias in choosing countries in which to place subsidiaries. If IBM had exercised some bias in the selection of countries, the observed data values would display this bias through an asymmetric distribution of the Hofstede Cultural Dimension index data values

As presented in the results shown in Table 3-6, the Hofstede Cultural Dimension index variables of power distance index (H-PDI) and long term orientation (H-LTO) did not present a significant degree of asymmetric distribution based on the z-distribution threshold of z = ±2.58. The Hofstede Cultural Dimension index variables of uncertainty avoidance (H-UAI) and individualism (H-IDV), did present asymmetric distribution over the threshold of z = ±2.58 as suggested by Tabachnick and Fidell (1996).

Table 3-6. Results of normal distribution test on Hofstede data.

Variable	Mean	Median	St. Dev.	S	S_s	z
H-PDI	59.680	64	21.077	-0.151	0.126	-1.197
H-UAI	66.307	68	22.815	-0.361	0.126	-2.857
H-LTO	46.592	45.466	22.951	0.294	0.118	-2.485
H-IDV	42.933	38	23.4112	0.346	0.126	2.739

Note: The skewness statistic (S) was produced by the adjusted Fisher-Pearson standardized moment coefficient. The standard error of skewness S_s and z distribution calculations were produced as suggested in Tabachnick and Fidell (1996).

The findings as presented in Table 3-6 suggest that IBM subsidiaries had a tendency to be located in countries with higher values of uncertainty avoidance and lower values of individuality. The asymmetric distribution found in the two Hofstede Cultural Dimensions suggests that the Hofstede missing data values may not be MCAR. However, these findings do not necessarily demonstrate that the Hofstede Cultural Dimension missing data is MNAR. The Hofstede Cultural Dimensions index variables of power distance (H-PDI) and long term orientation (H-LTO) did not present a significant degree of asymmetric distribution.

One explanation for some of the Hofstede Cultural Dimensions indices possessing an asymmetric distribution is that some cultural dimensions are naturally asymmetrically distributed. If some cultural dimensions are naturally asymmetrically distributed, then the missing cultural dimension data values were unrelated to the unobserved value. This explanation makes the assumption that the missing Hofstede Cultural Dimensions are MAR within a class of countries. Specifically, the missing Hofstede Cultural Dimension data is unobserved for the class of countries that did not have IBM subsidiaries. As stated by Robins (1997), MAR within class data values are missing based on a particular group within the dataset.

The assumption of MAR for the missing Hofstede Cultural Dimensions data allows particular interpretations to be safely made without utilizing complex missing data models (Heitjan & Basu, 1996). A more complex missing data treatment would be required if the Hofstede Cultural Dimensions data were MNAR. Collins, Schafer, and Kam (2001) have demonstrated that under most missing data cases, even an erroneous assumption of MAR has “only a minor impact on estimates and standard errors” (p. 6). It is important to note that unobserved MAR data values can be intuitively based on observed data values of similar data rows (Schafer & Graham, 2002).

This study used two missing data treatments: removal of non-complete data rows through listwise deletion and data imputation through a modified version of mean substitution. The most common and least complex treatment of missing data is listwise deletion. Listwise deletion is also known as complete-case analysis (Schafer & Graham, 2002). This treatment requires the deletion of non-complete cases (i.e. data rows missing one or more data values) until the level of missing data is within an acceptable threshold. Statistical power may be affected by using listwise deletion as a missing data treatment due to the reduction of the sample size and introduction of bias if the data is not MAR or MCAR (King, Honaker, Joseph, & Scheve, 1998; Roth, 1994). While this treatment affects statistical power and may introduce bias, it is one of the preferable methods for addressing missing data (Olinsky et al., 2003).

The listwise deletion missing data treatment was applied to the data used in the study by removing all data rows which did not contain values for all four Hofstede Cultural Dimension index variables. This application resulted in the deletion of 145 data rows or 23.967% from the original 606 data rows in the dataset. The data treated using listwise deletion treatment was denoted as LD in this study. Presented in Table 3-7 are the resulting missing data percentages by variable after the application of the listwise deletion treatment. As presented in Table 3-7, after the listwise deletion treatment, all variables were within the relaxed 20% missing data threshold (Allison, 2001; Hair et al., 1987; Hair et al., 2010).

The two basic methods of handling missing data are removal of incomplete cases or imputation of missing data elements within incomplete cases (Little & Rubin, 2002). Although removal of non-complete cases through listwise deletion is the most common and least complex treatment for missing data, J.-O. Kim and Curry (1977), Roth (1994), and King et al. (1998) suggest that alternate methods for handling missing data should be explored.

Table 3-7. Missing data percentages after listwise deletion (N=461).

Variable	Missing data percentage
Transparency	0.000%
Corruption	0.652%
Internet diffusion	1.087%
Mobile diffusion	1.304%
FDI	1.087%
NRI	1.087%
GDP per capita	1.087%
H-PDI	18.478%
H-UAI	18.478%
H-LTO	6.522%
H-IDV	18.478%

The alternative to removing missing data from the dataset is to substitute missing values to form a complete case or data row. This process of missing data substitution is known as imputation (Schafer & Graham, 2002). As noted by Little and Rubin (2002), there are several methods of imputation. Some methods of imputation such as hot/cold-deck imputation employ random data value substitution (Sande, 1983) or intuitively-based substitution using observed data values of similar data rows (Schafer & Graham, 2002). Such substitution methods select existing data values from within the existing dataset to replace missing data values. Random data value substitution is a straightforward and less complex method for handling missing data (Reilly, 1993). In this study, however, such random substitution has a high probability of assigning Hofstede Cultural Dimensions values that may be vastly different than the actual unobserved values for a given country. A different imputation method needed to be explored that would estimate data values similar to those actual unobserved values.

Another method for handling missing data is through imputation via mean substitution (Dodeen, 2003). Typically, mean substitution is performed by calculating the mean for an entire set of values of a variable. This calculated mean is substituted for the missing values of that variable in the dataset. Using mean substitution creates a "group average" that is substituted for the missing data values. In most cases, mean substitution has proven to be more accurate than listwise deletion (Chan & Dunn, 1972; Chan, Gilman, & Dunn, 1976; Raymond & Roberts, 1987). In this study, mean substitution essentially creates world averages for each Hofstede Cultural Dimension index. These world averages would then be applied to all countries with unobserved Hofstede Cultural Dimension index values. As Hofstede Cultural Dimension values are missing for 28% to 38% of the countries used in this study, these calculated world averages would be applied to a significant number of countries. It is unreasonable to assume that up to 38% of the countries would have the same Hofstede Cultural Dimension values and those values would be the same as the world averages. Therefore, the mean substitution method has high probability of assigning world-average Hofstede Cultural Dimension values that may be vastly different than the actual unobserved values for a particular country.

Fortunately, a further examination of the Hofstede Cultural Dimension studies provides an indication on how data imputation through a modified version of mean substitution could adequately handle the missing cultural dimension data values. Hofstede's studies demonstrated that cultural similarities that influenced behavior of societies could be categorized by nations and regions (Hofstede, 1984, 1997). Some countries in the Hofstede Cultural Dimension score matrix do not have scores for all four of Hofstede cultural dimensions used in this study. However, in the Hofstede Cultural Dimension index, cultural dimension data values are provided for regional country groups as well. In these regional groups, each component country can be assigned the regional score as its individual country's Hofstede Cultural Dimension index value. For example, Nigeria did not have scores for all four Hofstede Cultural Dimension indices. However, Nigeria is classified in the regional group of West African countries. The regional group of West African countries includes Ghana, Nigeria, and Sierra Leone. Therefore, the scores for the regional group of West African countries could be used in place of the missing Hofstede Cultural Dimension data values for these three countries.

This study employed a modified version of mean substitution using the calculated mean cultural dimension scores of regional groups to address missing Hofstede Cultural Dimension index values. Countries used in this study were assigned to regional groups according to the United Nations (UN) geoscheme. This geoscheme was developed by the UN for statistical analysis of world regions (United Nations, 2000). Each UN geoscheme region has an associated area code as its identifier within the UN statistical analysis model. For the countries used in this study, there were sixteen UN geoscheme regions as presented in Table 3-8.

Table 3-8. United Nations geoscheme regions (with area codes).

Caribbean (052)	Middle Africa (017)	Southern Asia (034)
Central America (013)	Northern Africa (012)	Southern Europe (039)
Central Asia (143)	Northern Europe (154)	Western Africa (011)
Eastern Africa (014)	South America (068)	Western Asia (145)
Eastern Asia (030)	South-Eastern Asia (035)	
Eastern Europe (151)	Southern Africa (018)	

A mean score for each Hofstede Cultural Dimension was computed using available cultural dimension scores of regional component countries based on the UN geoscheme. A mean score for each UN geoscheme region was imputed for regional component countries missing data values. For example, Algeria is in the UN geoscheme for Northern Africa. Algeria did not have three of the four Hofstede cultural dimension scores used in this study. However, the Northern

Africa UN geoscheme region contained two other countries, Egypt and Morocco, which had cultural dimension scores for the four Hofstede cultural dimensions. These available scores were averaged per dimension and imputed for the missing three cultural dimension scores of Algeria.

This method of imputation using calculated regional mean scores of UN geoscheme regions produced scores for all but two UN geoscheme regions used in this study. Central Asia and Middle Africa were the only two UN geoscheme regions that did not have country-level Hofstede Cultural Dimension scores from which to compute regional cultural dimension scores through this method. The data using this modified mean substitution method was denoted as regional mean substitution (RMS) in this study. This RMS imputation method was preferable and advantageous over listwise deletion as it reduced missing data without reducing the overall sample size. The missing data percentages by variable after using RMS missing data treatment are presented in Table 3-9. As shown, all variables were well within a 10% missing data threshold as suggested by Hair et al. (1987).

Table 3-9. Missing data percentages after regional mean substitution (N=605).

Variable	Missing data percentage
Transparency	0.000%
Corruption	0.496%
Internet diffusion	1.488%
Mobile diffusion	1.653%
FDI	0.826%
NRI	1.818%
GDP per capita	0.826%
H-PDI	4.132%
H-UAI	4.132%
H-LTO	3.306%
H-IDV	4.132%

3.5 Data Validation

An analysis for multicollinearity was also performed on the data. Multicollinearity exists when correlations among two or more independent or explanatory variables are strong. When two or more variables are highly correlated, it may be an indication that variables which are supposed to measure different constructs actually measure the same construct (Kline, 2010). Multicollinearity exposes variables that may measure the same construct in a statistical model (i.e. redundant variables). While multicollinearity may not affect the reliability of a statistical model, it may not give accurate results on the significance of the effects of individual variables within such a model (Kock, 2012).

One possible indicator of multicollinearity is a high Pearson correlation coefficient (r) between two or more variables (Tabachnick & Fidell, 1996). High correlation coefficients among variables in the model may signify multicollinearity (Kock, 2012). Correlation coefficients (r) can range be from -1 to + 1. The closer the correlation coefficient is to ±1, the stronger the correlation. A correlation coefficient of zero suggests there is no relationship. A general “rule of thumb” (Farrar & Glauber, 1967, p. 82) for correlation coefficients that may indicate multicollinearity are those where $r \geq .8$. Using WarpPLS 3.0, a structural equation modeling software package discussed in greater detail in section 3.5 Data Analysis, a correlation matrix was generated with the data using both missing data treatments. WarpPLS 3.0 automatically calculated the correlation matrix as part of its data analysis (Kock, 2012).

Table 3-10 shows the correlation matrix with corresponding coefficients and associated p-values for data using regional mean substitution missing data treatment. Using the regional mean substitution missing data treatment, NRI and corruption had a correlation coefficient of r =

-0.888 with a significance level of p <.001. NRI and Internet diffusion had a correlation coefficient of r = 0.849 with a significance level of p <.001. GDP per capita and Internet diffusion had a correlation coefficient of r = 0.828 with a significance level of p <.001. Also, GDP per capita and NRI had a correlation coefficient of r = 0.829 with a significance level of p <.001. Table 3-11 shows the correlation matrix with corresponding coefficients and associated p-values for data using the listwise deletion missing data treatment. Using the listwise deletion missing data treatment, NRI and corruption had a correlation coefficient of r = -0.907 with a significance level of p <.001. NRI and Internet diffusion had a correlation coefficient of r = 0.857 with a significance level of p <.001. Analysis of the correlation matrixes using both missing data treatments showed correlation coefficients among variables greater than r = 0.800.

The presence of a high correlation coefficient between two or more variables is a possible indicator of multicollinearity. However, such high correlation coefficients do not conclusively signify multicollinearity. High correlation coefficients are generally conflated with collinearity (Douglass, Clader, Christy, Michaels, & Belsley, 2003 & Michaels, 2003; Graham, 2003). Yet, strongly correlated variables can have a low degree of collinearity (Hamilton, 1987). Also, using correlation matrices to assess multicollinearity only exposes potential bivariate collinearity. Correlation matrices only compare variables in a pairwise fashion. Often, two or more variables in a model may have collinear relationships which are not easily detected through such pairwise analysis possible from correlation matrices (Tabachnick & Fidell, 1996). While analysis of correlations provides a valuable indicator of multicollinearity, additional tests for multicollinearity need to be performed.

Another method for assessing multicollinearity is the calculation of variance inflation factors (VIFs). Unlike testing for collinearity through generating correlation matrices, the calculation of VIF value assesses the amount of multicollinearity among all variables in a model simultaneously. VIF values quantify the amount of inflation of variance due to a particular variable in the model. The VIF value for a given variable is the amount of inflation of variance caused by collinearity with other variables in the model (Kline, 2010; Kutner, Nachtsheim, & Neter, 2004).

High VIF values may signify a high degree of multicollinearity. The threshold for high VIFs is based on the type of variables used in a model. For example, the recommended VIF threshold when using formative latent variables is VIF=3.3 (Cenfetelli & Bassellier, 2009). This study does not use formative latent variable measurement, so this more restrictive threshold does not need to be applied. For studies without latent variables, such as this study, a more relaxed threshold recommendation of VIF=5 or VIF=10 has also been proposed in the multivariate analysis literature (Hair et al., 1987; Hair et al., 2010; Kline, 2010; O'Brien, 2007).

There are two forms of collinearity which can be tested through calculating VIF values: lateral and vertical collinearity. Lateral collinearity refers to predictor-criterion collinearity. Lateral collinearity occurs when independent variables (i.e. predictor variables) are collinear with the dependent variable (i.e. criterion variables) (Kock & Lynn, 2012). Vertical collinearity refers to predictor-predictor collinearity.

Vertical collinearity occurs when independent variables (i.e. predictor variables) are collinear with other independent variables. Using WarpPLS 3.0 to calculate VIF values through a full collinearity test assesses vertical and lateral collinearity simultaneously (Kock, 2012). Also, full collinearity VIF testing is a common method for testing bias that provides more conservative results than exploratory factor analyses (Kock & Lynn, 2012; Lindell & Whitney, 2001).

Table 3-10. Correlation matrix for RMS treated data.

	Transparency	Corruption	Internet diffusion	Mobile diffusion	FDI	NRI	GDP per capita	H-PDI	H-UAI	H-LTO	H-IDV
Transparency	1										
Corruption	-0.757***	1									
Internet diffusion	0.682***	-0.793***	1								
Mobile diffusion	0.495***	-0.570***	0.766***	1							
FDI	0.301***	-0.432***	0.471***	0.387***	1						
NRI	0.671***	**-0.888*****	**0.849*****	0.651***	0.555***	1					
GDP per capita	0.686***	-0.788***	**0.828*****	0.722***	0.505***	**0.829*****	1				
H-PDI	-0.614***	0.644***	-0.507***	-0.312***	-0.157***	-0.536***	-0.501***	1			
H-UAI	0.022	0.160***	0.065	0.187***	0.002	-0.125**	0.082*	0.226***	1		
H-LTO	0.212***	-0.234***	0.366***	0.289***	0.259***	0.354***	0.302***	-0.094*	0.092*	1	
H-IDV	0.547***	-0.601***	0.551***	0.380***	0.314***	0.531***	0.536***	-0.63***	-0.123**	0.303***	1
Year	-0.013	0.003	0.185***	0.299***	-0.059	0.035	-0.003	0	0	0	0

Notes: Correlations between variables higher than 0.800 are denoted in **bold**.

*** denotes p-value <0.001

** denotes p-value <0.01

* denotes p-value <0.05

Table 3-11. Correlation matrix for LD treated data.

	Transparency	Corruption	Internet Diffusion	Mobile Diffusion	FDI	NRI	GDP per capita	H-PDI	H-UAI	H-LTO	H-IDV
Transparency	1										
Corruption	-0.782***	1									
Internet Diffusion	0.740***	**-0.847*****	1								
Mobile Diffusion	0.505***	-0.486***	0.644***	1							
FDI	-0.010	-0.019	-0.009	-0.027	1						
NRI	0.714***	**-0.907*****	**0.857*****	0.545***	0.069	1					
GDP per capita	0.675***	**-0.812*****	0.774***	0.469***	-0.020	0.772***	1				
H-PDI	-0.553***	0.589***	-0.498***	-0.228***	0.005	-0.508***	-0.523***	1			
H-UAI	0.090	0.195***	-0.130**	0.083	-0.066	-0.240***	-0.152**	0.197***	1		
H-LTO	0.199***	-0.173***	0.329***	0.304***	0.011	0.307***	0.166***	-0.027	0	1	
H-IDV	0.594***	-0.593***	0.589***	0.293***	-0.016	0.525***	0.560***	-0.619***	-0.178***	0.119*	1
Year	-0.006	0.007	0.192***	0.321***	-0.084	0.013	0.010	0	0	0	0

Notes: Correlations between variables higher than 0.800 are denoted in **bold**.

*** denotes p-value <0.001

** denotes p-value <0.01

* denotes p-value <0.05

A full collinearity test was performed that calculated the VIF values of each variable. The full collinearity test was performed on the data using each missing data treatment. WarpPLS 3.0 automatically calculated the VIF values for the data as part of its data analysis (Kock, 2012). Table 3-12 presents the VIF values for each variable in the data using both missing data treatments.

The highest VIF value was 9.478 for corruption in the data using the listwise deletion missing data treatment. In general, the data using the listwise deletion missing data treatment had higher VIF values than the data using the regional mean substitution missing data treatment. Data using each missing data treatment had VIF values over the recommended threshold of VIF=5. However, using the more relaxed threshold of a VIF=10 as suggested by Hair et al. (1987) and O'Brien (2007), the VIF values for the data using both missing data treatments did not exhibit serious bias due to multicollinearity problems. Also, the variables that contribute to the high VIF values in Table 3-12 are not included in the same variable block in Table 3-13 or Table 3-14.

Table 3-12. Variance inflation factors by variable and missing data treatment.

Variable	Data using RMS	Data using LD
Transparency	2.784	3.672
Corruption	8.741	9.478
Internet diffusion	6.325	6.749
Mobile diffusion	2.523	2.059
FDI	1.045	1.036
NRI	8.004	8.089
GDP per capita	3.081	3.303
H-PDI	2.120	1.954
H-UAI	1.349	1.415
H-LTO	1.336	1.310
H-IDV	2.148	2.126
Year	1.286	1.337

Additionally, block VIF values for each missing data treatment were calculated by WarpPLS 3.0. Block VIF values measure the degree of vertical collinearity. WarpPLS 3.0 outputs the VIF values for each latent variable block. A latent variable block is each variable with two or more predictors. The calculated VIFs produced by WarpPLS 3.0 represent the latent variables on each column (predictors), with reference to the latent variables on each row (criteria). This study does not utilize latent variables, so the output from WarpPLS 3.0 comprises the VIF values produced for each variable block.

Table 3-13 presents the block VIF values for the data using the RMS missing data treatment for each variable block. Using the RMS missing data treatment, Transparency (predictor) to Corruption (criteria) showed a VIF value of 4.588. Also, Internet diffusion (predictor) to Corruption (criteria) showed a VIF value of 4.566.

All other VIF values for the data using the RMS missing data treatment were less than 3.3. Table 3-14 presents the block VIF values for the data using the LD missing data treatment for each variable block. Using the LD missing data treatment, Transparency (predictor) to Corruption (criteria) showed a VIF value of 4.769. Also, Internet diffusion (predictor) to Corruption (criteria) showed a VIF value of 4.320. All other VIF values for the data using the RMS missing data treatment were VIF less than 3.3. In the block VIF calculations, values of 3.3 or lower suggest that no vertical multicollinearity exists within the data (Kock, 2012). However, in the multivariate analysis literature, a conservative recommended threshold for VIF values when analyzing models without latent variables is VIF=5 as suggested by Hair et al. (1987). Using this recommended threshold of VIF=5, the VIF values for the data using both missing data treatments suggest that no vertical multicollinearity exist.

Table 3-13. Block VIF values using RMS.

	Transparency	Corruption	Internet Diffusion	Mobile Diffusion	FDI	NRI	GDP per capita	H-PDI	H-UAI	H-LTO	H-IDV	Year
Transparency			1.858	1.858								
Corruption	4.588		4.566	1.831				2.804	1.084	1.250	2.512	1.096
Internet Diffusion				1.886		1.886						
Mobile Diffusion												
FDI												
NRI					1.407		1.407					
GDP per capita												
H-PDI												
H-UAI												
H-LTO												
H-IDV												
Year												

Notes: These VIFs are for the latent variables on each column (predictors), with reference to the latent variables on each row (criteria).

Table 3-14. Block VIF using LD.

	Transparency	Corruption	Internet Diffusion	Mobile Diffusion	FDI	NRI	GDP per capita	H-PDI	H-UAI	H-LTO	H-IDV	Year
Transparency			1.652	1.652								
Corruption	4.769		4.320	1.606				2.009	1.104	1.143	2.228	1.154
Internet Diffusion				1.486		1.486						
Mobile Diffusion												
FDI												
NRI					1.366		1.366					
GDP per capita												
H-PDI												
H-UAI												
H-LTO												
H-IDV												
Year												

Notes: These VIFs are for the latent variables on each column (predictors), with reference to the latent variables on each row (criteria).

Additionally, Stone-Geisser Q-squared coefficients were calculated for each of the endogenous variables in the study’s path model (Geisser, 1974; Stone, 1974). The resulting Q-squared coefficients are shown for each missing data treatment in Table 3-15. The Q-squared coefficient is used to assess the predictive validity of each variable block in a path model. Endogenous variables with acceptable predictive validity have Q-squared coefficients of greater than zero (Kock, 2012). Each of the endogenous variables in the study’s model exhibited Q-squared coefficients greater than zero, thereby presenting acceptable predictive validity.

Table 3-15. Stone-Geisser Q-squared coefficients.

	Transparency	Corruption	Internet Diffusion	Mobile Diffusion	NRI
RMS	0.486	0.795	0.789	0.475	0.738
LD	0.557	0.815	0.779	0.376	0.738

3.6 Data Analysis

The theoretical model for this study as shown in Figure 2.1 was constructed based on the hypotheses as stated in Section 2.3. This theoretical model is a path model that formalized the hypothesized relationships among the macroeconomic, ICT, governance, and sociocultural variables as listed in Table 3-3. This theoretical model was statistically analyzed using path analysis with WarpPLS 3.0, a structural equation modeling software package. WarpPLS 3.0 is specially designed to identify nonlinear relationships among variables of a theorized model by conducting linear and non-linear (or “warped”) regression analysis (Kock, 2012).

Path analysis is a statistical analysis method used to explore relationships among observed variables within a defined network or model (Hatcher, 1994). Developed in the 1930s by Sewall Wright, path analysis was used in his agricultural research and has now been applied to other complex modeling fields (Dodge & Marriott, 2003; Wright, 1934). Path analysis is an extension of multiple regression analysis. In multiple regression analysis, coefficients of association are calculated among multiple independent variables and one dependent variable. These coefficients are generally in the form of standardized partial regression coefficients (Rencher, 1998; Rosenthal & Rosnow, 1991) where the corresponding P values indicate the significance of the relationship (Kock, 2011a). Indeed, path analysis extends multiple regression analysis by forming a composite structural model of several separate multiple regression models. Path analysis allows the tracing of complex paths in a model to discover how one variable affects another. This capability of path analysis allows direct and indirect effects to be explored. Also, path analysis can reveal the proportional strengths of direct and indirect relationships within a model.

Path analysis is a special case of structural equation modeling (SEM) (Maruyama, 1998). SEM is a second-generation statistical analysis technique increasing utilization in social science research due to its ability to assess theoretical models (Anderson & Gerbing, 1988; Kline, 2010). Due to its powerful predictive ability, SEM has been used in a wide variety of disciplines, including management (Cheng, 2001; Shook, Ketchen, Hult, & Kacmar, 2004), marketing (Baumgartner & Homburg, 1996; Steenkamp & Baumgartner, 2000), information systems (Gefen, 2000; Qureshi & Compeau, 2009), and finance and economics (Chang, Lee, & Lee, 2009; Titman & Wessels, 1988). In typical SEM analysis, reflective or formative manifest variables (indicators) are constituent parts of (e.g. load upon) latent variables (constructs). The observable or manifest (endogenous) variables serve as underlying components of the unobservable or latent (exogenous) variables. In SEM models, there are two or more indicators associated with each construct. SEM analysis employs a measurement model and a structural model. In SEM analysis, the measurement model assesses the loadings and reliability estimates (e.g. Cronbach's alpha) of the indictors on their associated constructs within the model. Scores for each construct are calculated based on the weighted averages of their component indicators. Once the scores for each construct are calculated, the structural model is basically a path model with constructs as variables and the association between variables as paths within the model. In path analysis, the measurement model found in SEM is excluded. The measurement model is not required since one indicator is associated upon one construct.

The software selected to conduct the path analysis for this study's theoretical model was WarpPLS 3.0. A structural equation modeling software package, WarpPLS 3.0 is specially designed to identify nonlinear relationships among variables of a theorized model by conducting linear and non-linear (or "warped") regression analysis (Kock, 2012). WarpPLS 3.0 was selected specifically for its ability to examine non-linear relationships. The majority of social and economic phenomena exhibit non-linear relationships such as the law of diminishing returns (A. Rosenberg, 1992). In fact, these types of non-linear relationships usually take the "form of U and S curves" (Kock, 2011a, p. 2). WarpPLS 3.0 utilizes algorithms that attempt to identify such non-linear or U-curve relationships between variables within a model. This study utilized WarpPLS 3.0's non-linear (denoted in the software as a Warp2) algorithm to calculate statistical results such as path coefficients (standardized betas) with related P values and R-squared (R^2) coefficients. The calculated individual path coefficients can be interpreted as standardized beta coefficients of ordinary least squares regressions. By examining these path coefficients and R^2 coefficients of the path model, the overall strength and predictive power of the model can be determined.

Path analysis has several requirements concerning the nature of the data analyzed (Hatcher, 1994). First, all endogenous (dependent) variables must be measured on a continuous interval scale and have at least a minimum of four values. However, exogenous (independent) variables can be measured on a categorical scale level, if dummy-coded. This restriction does not apply to WarpPLS 3.0 since the software uses resampling techniques (Kock, 2012). Secondly, the path model variables should be free of multicollinearity. Third, path analysis generally requires large sample sizes (n>200) (Hatcher, 1994). Data resampling techniques, for instance bootstrapping and jackknifing, remove data requirements such as large sample size and endogenous variables having a minimum of four values. As noted in the WarpPLS 3.0 software manual, the non-linear (e.g. Warp2) algorithm is sensitive to outliers present in the data. Therefore, as recommended by the WarpPLS 3.0 software manual, P values were estimated using both bootstrapping and jackknifing techniques. A good model fit generally has path coefficients with corresponding significant P values, high R^2 coefficients based on accepted thresholds, and each construct having high internal reliability above .70 (Barclay, Higgins, & Thompson, 1995).

WarpPLS 3.0 has three techniques for resampling data: bootstrapping, jackknifing, and blindfolding. Bootstrapping creates a number of resamples containing a random arrangement of rows from the original data. Bootstrapping generates stable resample path coefficients with large sample sizes and works well with non-parametric data (Nevitt & Hancock, 2001). This study's sample size falls within the acceptable limits for using the bootstrapping technique (Nevitt & Hancock, 2001). Jackknifing, an alternative to bootstrapping, resamples by removing one different row from each resample. This technique of resampling works best with small sample sizes and data with outliers (Hinkley, 1977; Osborne, 2008). Blindfolding is a resampling technique that creates resamples by replacing a certain number of rows in each resample with the means of their respective columns. Blindfolding has a tendency to perform somewhere between jackknifing and bootstrapping (Kock, 2012). In the results section, the results of the theoretical model's path analysis using data with both missing data treatments and resampling methods applied are presented.

CHAPTER IV

RESULTS

The purpose of this study was to investigate the effects of the hypothesized relationships between macroeconomic, ICT, governance and sociocultural variables using the key and control variables as listed in Table 3-3. This chapter presents the results of the statistical analysis of those variables in a path model. In the first section of this chapter, the descriptive statistics of the key and control variables are provided and explained. The second section shows results of the path analysis of the theoretical model. The third section of this chapter reports the model fit indices. The fourth section of this chapter reports the results of hypotheses testing.

The theoretical model used in this study is a path model that formalized the hypothesized relationships among the key macroeconomic, ICT, governance and sociocultural variables. The theoretical model used in this study is presented in Figure 2.1. This theoretical model was statistically analyzed using path analysis with WarpPLS 3.0, a structural equation modeling software package specially designed to identify nonlinear relationships among variables of a theorized model by conducting linear and non-linear (or “warped”) regression analysis (Kock, 2012).

4.1 Descriptive Statistics Analysis

This study examined 121 countries which are listed in Table 3-1. This study used multi-year dataset for these key and control variables collected over a period of five years (i.e. 2006, 2007, 2008, 2009, and 2010). To address the missing Hofstede Cultural Dimensions data, two missing data treatments were applied to the data in this study. The missing data treatments that were applied are listwise deletion (LD) and a modified version of mean substitution called regional group mean substitution (RMS).

This listwise deletion treatment resulted in the removal of 145 rows (23.967%) from the data. Table 4-1 presents the descriptive statistics of the data across all years for the key and control variables, including the Hofstede Cultural Dimension control variables, using the LD treatment.

Table 4-1. Descriptive statistics of data using LD.

Variable	N	Mean	SD
Transparency	460	0.332	0.873
Corruption	457	-4.843	2.303
Internet diffusion	455	40.681	26.793
Mobile diffusion	454	91.600	38.418
FDI	455	19.408	10.453
NRI	455	4.109	0.824
GDP per capita	455	17325.771	20683.797
H-PDI	375	59.680	21.077
H-UAI	375	66.307	22.815
H-LTO	375	46.592	22.951
H-IDV	375	42.933	23.411

The other missing data treatment (the regional group mean substitution) resulted in reducing missing data amounts to within recommended thresholds. Table 4-2 presents the descriptive statistics of the data across all years for the key and control variables in the study’s data, including the Hofstede Cultural Dimension control variables, using the RMS treatment. The descriptive statistics by year and in total for the key variables are also presented in Table 4-3. The results and findings in this section examine and describe the descriptive statistics of the data using the RMS missing data treatment except where noted. Microsoft Excel 2010 was utilized to calculate the descriptive statistics.

Table 4-2. Descriptive statistics of data using RMS.

Variable	N	Mean	SD
Transparency	605	0.173	0.879
Corruption	602	-4.525	2.221
Internet diffusion	596	34.148	27.372
Mobile diffusion	595	84.070	40.962
FDI	600	18.949	10.196
NRI	594	3.939	0.841
GDP per capita	600	14697.774	19686.245
H-PDI	580	61.586	18.094
H-UAI	580	65.724	20.829
H-LTO	580	41.812	22.486
H-IDV	580	40.302	20.756

The mean across all years for the governance variable of Transparency was 0.173 using the RMS missing data treatment. The data for the variable Transparency was captured through the World Bank's Voice of Accountability (VA) Governance indicator. The VA indicator, ranging from -2.5 to 2.5, measures countries' accountability and citizen participation in relation to a global average (equaling zero). Negative values in this indicator point toward less transparency through public voice and accountability. Positive values in this indicator point toward more transparency. This result of 0.173 indicated that the countries examined in the study were generally above the global average in terms of transparency. Interestingly, the mean by year for the governance variable Transparency decreased from 0.190 in 2006 to 0.160 in 2010. This signifies that the gap between the average of countries used in this study and the global average gradually became smaller over the time period examined.

Table 4-3. Descriptive statistics of the data.

Year and Statistic	Transparency	Corruption	Internet diffusion	Mobile diffusion	FDI	NRI	GDP per capita
2006							
N	121	120	119	119	120	121	120
Mean	0.190	-4.527	27.631	64.660	18.015	3.851	13366.578
SD	0.876	2.278	25.736	38.593	11.548	0.910	17875.565
2007							
N	121	120	119	119	120	118	120
Mean	0.181	-4.523	30.474	75.724	20.365	3.963	15333.754
SD	0.878	2.232	26.474	39.547	7.873	0.855	20340.096
2008							
N	121	121	119	119	120	120	120
Mean	0.170	-4.546	33.785	86.219	19.588	4.000	16806.692
SD	0.882	2.194	27.077	39.445	9.380	0.869	21973.413
2009							
N	121	121	119	118	120	119	120
Mean	0.165	-4.509	37.327	93.464	19.281	3.910	14873.445
SD	0.885	2.211	27.687	40.142	9.145	0.810	19136.946
2010							
N	121	120	120	120	120	116	120
Mean	0.160	-4.518	41.464	100.229	17.495	3.971	13108.401
SD	0.889	2.230	28.053	37.663	12.277	0.757	18952.751
Total							
N	605	602	596	595	600	594	600
Mean	0.173	-4.525	34.148	84.070	18.949	3.939	14697.774
SD	0.879	2.221	27.372	40.961	10.195	0.841	19686.275

This finding can be interpreted in a couple of different ways. The countries used in this study were a subset of the total countries examined by the VA indicator. Therefore, one interpretation is that countries used in this study became less transparent over time. Alternatively, another interpretation is that countries, on average, became more transparent over time. If countries did become more transparent, the gap between the global average and the country average calculated in this study would tend to contract.

The standard deviation for the governance variable Transparency increased from 0.876 in 2006 to 0.889 in 2010 using the RMS missing data treatment. This finding indicated that the difference between countries, in terms of transparency, increased. Indeed, in 2006, there were 52 countries below the global average. In 2010, the number of countries below the global average increased to 58. However, the mean for countries below the global average in 2006 was -0.658. In 2010 this mean was -0.657, remaining relatively unchanged for countries below the global average. This relatively small change in standard deviation by year signified very little change among countries below the global average even though additional countries fell below this average. However, there was an increase in transparency among countries that were above the global average. The mean for countries above the world average in 2006 was 0.829. In 2010, this mean increased to 0.856. One interpretation of this finding is that countries above the global average study experienced significant positive changes in the apparent level of transparency.

The mean across all years for the governance variable of Corruption was -4.525 using the RMS missing data treatment. The data for the variable Corruption was captured through the Corruption Perceptions Index (CPI) from Transparency International. The CPI ranks countries on a scale from 10 (representing a very clean/minimally corrupt government) to 0 (representing high level of corruption). Thus, higher scores on the CPI scale can be interpreted as ‘the absence of corruption'. In order to make the higher CPI values reflect the presence of corruption, a data transformation was performed. This data transformation was performed on the CPI data by multiplying the original values by negative 1. This data transformation was done to inverse the scale of the values while preserving their rank.

Therefore, the mean for the governance variable Corruption after reversing the data transformation across all years was 4.525 using the RMS missing data treatment. Between 2006 and 2010, the highest value for the CPI was 9.6 for Finland, Iceland, and New Zealand in 2006. During this same time period, the lowest value for the CPI was 1.6 for Chad in 2006 and 2007. Most country values for Corruption fall below 5.0. In this study, 64.784% of data values (390 of 602) for Corruption fell below 5.0. This signifies that several countries examined in this study have relatively medium to high levels of corruption between 2006 and 2010. The standard deviation across all years for the variable Corruption was 2.221 using the RMS missing data treatment. The standard deviation between years remained relatively unchanged ranging from 2.278 in 2006 to 2.211 in 2009. The mean for the variable Corruption between years remained relatively unchanged as well. This mean ranged from 4.527 in 2006 to 4.509 in 2009

The mean across all years for the ICT variable of Internet diffusion was 34.148 using the RMS missing data treatment. Data for the variable Internet diffusion was captured through the World Bank World Development *Internet users (per 100 people)* indicator. The mean for Internet diffusion was 34.148 which indicated that approximately one-third of the people in the countries studied had access to the Internet. Access to the Internet increased steadily during the period examined in this study. The mean by year increased from 27.631 in 2006 to 41.464 in 2010. This indicated that there was a significant increase in Internet access in the countries used in this study. In 2010, Internet access increased over 61.111% over the 2006 level. The standard deviation by year slightly increased from 25.736 in 2006 to 28.053 in 2010 using the RMS missing data treatment. This finding indicated that there was a slight increase in the variance of Internet access among countries in this study.

The mean across all years for the ICT variable of Mobile diffusion was 84.070 using the RMS missing data treatment. Data for the variable Mobile diffusion was captured through the World Bank World Development *Mobile cellular subscriptions (per 100 people)* indicator. The mean for Mobile diffusion was 84.070, indicating that approximately 5 in 6 persons (84 per 100 people), on average, had mobile cellular access/subscriptions in the countries of this study for the time period examined. Mobile diffusion increased at a significantly faster rate than Internet diffusion during the period examined in this study. The mean by year increased from 64.660 in 2006 to 100.229 in 2010. This finding indicated a large increase in the usage of mobile cellular technology in the countries during the time period of this study. Interestingly, the mean for Mobile diffusion in 2010 was over 100. Indeed, several country values for Mobile diffusion were above 100. In this study, 39.496% of data values (235 of 595) for Mobile diffusion were above 100. This signifies that several countries in this study had more than 100 mobile subscriptions per 100 people. In fact, Estonia had 202.984 mobile subscriptions per 100 people in 2009. The standard deviation across all years for the variable Mobile diffusion was 40.961 using the RMS missing data treatment. The standard deviation between years remained relatively unchanged, ranging from 38.593 in 2006 to 40.142 in 2009 and decreasing to 37.663 in 2010.

The mean across all years for the macroeconomic variable of FDI was 18.949 using the RMS missing data treatment. The data for the variable FDI was captured through the World Bank World Development *foreign direct investment, net inflows (BoP, current US$)* indicator. Since the FDI data values are quite large and varied, a logarithmic data transformation was performed. A general logarithmic transformation could not be performed as a small percentage of the FDI data values were negative. Therefore, the logarithmic transformation was performed on the absolute value of the FDI data values. Depending on the sign of the original FDI data value, a logarithmic transformed value was multiplied by a constant of +1 or -1 to represent its original sign.

The mean across all years for the macroeconomic variable FDI was 18.949 using the RMS missing data treatment (after reverse logarithmic transformation: $169,607,923.67US). This was interpreted as the average FDI inflow of the countries in the study across the years for the time period examined. The mean by year increased from 18.015 ($66,652,292.49US) in 2006 to 20.365 ($698,887,260.25US) in 2007. This finding indicated a large surge in the FDI into countries during this period. Interestingly, in 2007, FDI showed a sharp decline from its highest level of 20.365 ($698,887,260.25US) to its lowest level of 17.495 ($39,626,157.46US) in 2010. This finding was indicative of the overall global financial crisis occurring in 2007 (Crotty, 2009). The aftereffects of the global financial crises continued to affect FDI levels into 2010.

The standard deviation across all years for the macroeconomic variable FDI was 10.195 using the RMS missing data treatment ($26,769.01US). The standard deviation for the variable FDI decreased from 11.548 ($103,569.69US) to 7.873 ($2,625.43US) in 2007. This finding suggests that while the amount of FDI increased dramatically in 2007, the differences between countries decreased. After the global financial crisis of 2007, the standard deviation of FDI began to increase. The standard deviation for the variable FDI increased from 7.873 ($2,625.43US) in 2007 to 12.277 ($214,700.65US) in 2010. These findings, including the increase in standard deviation and the decrease in mean, suggest two things. First, after the global financial crisis in 2007, the amount of FDI into countries on average decreased. Secondly, differences among countries, in terms of FDI inflows, increased dramatically. These differences in FDI inflow among countries may suggest that foreign investors shifted their investments into more profitable countries.

The mean across all years for the ICT variable of NRI was 3.939 using the RMS missing data treatment. The data for the variable NRI was captured through the Networked Readiness Index from the Global Information Technology Report indices by the World Economic Forum. The NRI ranges from 1.0 (worst) to 7.0 (best) and provides a method for calculating the relative and overall development and use of ICT in countries and understanding the strengths and weaknesses of a country's ICT readiness to compete in a global environment. The finding of 3.939 for the mean across all years signifies that the average among countries in this study fell just below the midpoint mark of 4.0. The mean between all years increased from 3.851 in 2006 to 3.971 in 2010. Also, the mean between all years was at its highest of 4.000 in 2008. These findings suggest that that networked readiness among countries gradually increased from 2006 to 2010 with a slight spike in 2008. The standard deviation across all years for the variable NRI was 0.841 using the RMS missing data treatment. The standard deviation for the variable NRI decreased from 0.910 in 2006 to 0.757 in 2010. This finding suggests that differences between countries in networked readiness decreased from 2006 to 2010.

The mean across all years of the study for the macroeconomic variable of GDP per capita was 14,697.774 using the RMS missing data treatment. The data for the variable GDP per capita was captured through the *gross domestic product per capita (current US$)* indicator from the World Bank World Development Indicators. The *gross domestic product per capita (current US$)* indicator is measured in current US dollars. GDP per capita measures the gross domestic product divided by the midyear population. GDP per capita is the most widely used macroeconomic indicator of a country's standard of living and level of economic production (Ringen, 1991). The mean across all years of the study for the variable of GDP per capita was 14,697.774. This number indicated that the average GDP per capita in the countries used in this study was approximately $14,697.77US.

The mean for the macroeconomic variable of GDP per capita by year increased from 13366.578 ($13,366.58US) in 2006 to 16806.692 ($16,806.69US) in 2008. This finding indicated a 25.737% increase ($3,440.11US) in the GDP per capita between 2006 and 2008. However, GDP per capita decreased from its peak of 16806.692 ($16,806.69US) in 2008 to 13108.401 ($13,108.40) in 2010. This finding indicated a decrease in GDP per capita of approximately 22.005% ($3,698.29US) between 2008 and 2010. The average GDP per capita in 2010 was actually lower than the average GDP per capita in 2006 by $258.18. These changes in GDP were similar to the effect shown in the FDI data and are indicative of the aftereffects of the overall global financial crisis occurring in 2007 (Crotty, 2009).

The standard deviation for the variable of GDP per capita by year increased from 17875.565 in 2006 to 21973.413 in 2008 using the RMS missing data treatment. However, standard deviation decreased 21973.413 in 2008 to 18952.751. These findings indicate that the difference in GDP per capita from 2006 to 2008 increased, reflecting a wide difference between persons in different countries. These findings also indicated that differences between persons in terms of GDP per capita decreased from 2008 to 2010. However, differences between persons in different countries did not decrease at the same rate as FDI. Surprisingly, the pattern of increase and decrease were relatively the same among FDI and GDP per capita.

The Hofstede Cultural Dimensions have been utilized to examine cultural similarities or differences in various studies examining culture and technology adoption (Erumban & de Jong, 2006; Hofstede, 2001; Moghadam & Assar, 2008). Four of the Hofstede Cultural Dimension indices of Power Distance, Individualism vs. Collectivism, Long- vs. Short-Term Orientation, and Uncertainty Avoidance were used as national culture control variables to examine potential cultural factors influencing the main dependent variable in this study. The data for the cultural dimension variables used in this study were captured from the Geert Hofstede Dimension Data Matrix as presented in *Cultures and Organizations 3rd* edition (Hofstede et al., 2010). Similar to the CPI, the values of the Hofstede Cultural Dimension Indexes are best used to compare relative characteristics of countries to one another. For example, in the power distance index, Austria has a score of 11 and Malaysia has a score of 104. This disparity in score suggests that there exists a significant difference in power distance between these two countries. However, it would not necessarily signify that the power distance in Malaysia is over nine times greater than in Austria.

The national culture dimension control variables used in this study did not vary by year. The mean scores and standard deviations for each cultural dimension variable used in the study were calculated using both missing data treatments. These mean scores and standard deviations are present below.

The national culture control variable of H-PDI represented the Hofstede Cultural Dimension of power distance. Power distance measures the extent to which less powerful members of society accept and/or expect unequal distribution of power (Hofstede, 1984). Higher scores in this variable suggest that societal inequality is more widely accepted by those who are governed. The minimum score in this cultural dimension was 11 (Austria) and the maximum score was 104 (Malaysia). Using the LD missing data treatment, the mean for the variable of H-

PDI was 59.680. The standard deviation for the variable H-PDI using the LD missing data treatment was 1.088. Using the RMS missing data treatment, the mean for the variable of H-PDI was 61.586. The standard deviation for the variable H-PDI using the RMS missing data treatment was 0.751. There was a slight difference in means and standard deviations among missing data treatments. This slight difference suggests that the power distance cultural variable is consistent in both missing data treatments.

The national culture control variable of H-IDV represented the Hofstede Cultural Dimension of Individualism vs. Collectivism. Individuality versus collectivism measures the extent to which individuals are incorporated into groups. Higher scores in this variable are associated with societies valuing personal rights and freedoms over collectivistic value. The minimum score in this cultural dimension was 6 (Guatemala) and the maximum score was 91 (United States). Using the LD missing data treatment, the mean for the variable of H-IDV was 42.933. The standard deviation for the variable H-IDV using the LD missing data treatment was 1.209. Using the RMS missing data treatment, the mean for the variable of H-IDV was 40.302. The standard deviation for the variable H-IDV using the RMS missing data treatment was 0.862. There was a slight difference in means and standard deviations among missing data treatments. This slight difference suggests that the individuality versus collectivism cultural variable is consistent in both missing data treatments.

The national culture control variable of H-LTO represented the Hofstede Cultural Dimension of Long- vs. Short-Term Orientation. Long- versus short-term orientation measures the future orientation of a society. Higher scores in this variable suggest that societies are more future-oriented and foster more pragmatic views such as persistence. Lower scores in this variable suggest that societies promote past and present values such as tradition and saving face.

The minimum score in this cultural dimension was 4 (Ghana) and the maximum score was 100 (South Korea). Using the LD missing data treatment, the mean for the variable of H-LTO was 46.592. The standard deviation for the variable H-LTO using the LD missing data treatment was 1.107. Using the RMS missing data treatment, the mean for the variable of H-LTO was 41.812. The standard deviation for the variable H-LTO using the RMS missing data treatment was 0.928. There was a slight difference in means and standard deviations among missing data treatments. This slight difference suggests that the long- versus short-term orientation cultural variable is consistent in both missing data treatments.

The national culture control variable of H-UAI represented the Hofstede Cultural Dimension of uncertainty avoidance. Uncertainty avoidance measures the degree of tolerance for uncertainty and ambiguity that exists within a society. Higher scores in this variable indicate societies with more rules and laws; these societies are less tolerant to unplanned change. The minimum score in this cultural dimension was 8 (Singapore) and the maximum score was 112 (Greece).

Using the LD missing data treatment, the mean for the variable of H-UAI was 66.307. The standard deviation for the variable H-UAI using the LD missing data treatment was 1.178. Using the RMS missing data treatment, the mean for the variable of H-UAI was 65.724. The standard deviation for the variable H-UAI using the RMS missing data treatment was 0.865.

There was a slight difference in means and standard deviations among missing data treatments. This slight difference suggests that the uncertainty avoidance cultural variable is consistent in both missing data treatments.

4.2 Structural Model Analysis

The theoretical model used in this study as presented in Figure 2.1 was statistically analyzed using path analysis with WarpPLS 3.0. A SEM package, WarpPLS 3.0 possesses multiple algorithms to analyze structural models. This software is specially designed to identify nonlinear relationships among variables of a theorized model by conducting linear and non-linear (or “warped”) regression analysis (Kock, 2012).

WarpPLS 3.0 is a powerful SEM package that can be used to conduct path analysis. Path analysis is a special case of structural equation modeling (SEM) (Maruyama, 1998). In path analysis, the measurement model found in SEM is excluded. The measurement model is not required since only one indicator is associated upon one construct. The structural model found in SEM is basically a path model with constructs as variables and the association between variables as paths within the model. In order to use WarpPLS 3.0 to conduct a path analysis using the Warp2 regression algorithm, each variable used in this study was entered into the software as an indicator. Each indicator was used as a solitary indicator for each construct.

The majority of social and economic phenomena exhibit non-linear relationships (Kock, 2011b; A. Rosenberg, 1992). Therefore, WarpPLS 3.0 was utilized to do the path analysis. WarpPLS 3.0 possesses algorithms that attempt to identify such non-linear or U-curve relationships between variables within a model. This study utilized WarpPLS 3.0’s non-linear (e.g. Warp2) algorithm to calculate statistical results such as path coefficients denoted as standardized betas with related P values and R-squared (R^2) coefficients for the path model. The overall strength and predictive power of the model can be determined by examining these path and R^2 coefficients of the path model. Also, the software allows for three methods of resampling:

bootstrapping, jackknifing, and blindfolding. Bootstrapping – with WarpPLS 3.0's default setting of 100 resamples – and jackknifing resampling techniques were applied to the data using WarpPLS 3.0 before analysis. In addition, both missing data treatments were used in preparing the data for analysis.

As noted in the WarpPLS 3.0 software manual, the non-linear (e.g. Warp2) algorithm is sensitive to outliers present in the data. As recommended by the WarpPLS 3.0 software manual, P values were estimated using both the bootstrapping and jackknifing resampling techniques. Therefore, the data using two missing data treatments and two different resampling techniques was analyzed using path analysis which yielded four sets of results. Figure 4-1 presents the study's structural model with results of the Warp2 algorithm with the RMS missing data treatment and bootstrapping resampling technique applied. Figure 4-2 presents the study's structural model with results of the Warp2 algorithm with the RMS missing data treatment and the jackknifing resampling technique applied. Figure 4-3 presents the study's structural model with results of the Warp2 algorithm with the LD missing data treatment and the bootstrapping resampling technique applied. Figure 4-4 presents the study's structural model with results of the Warp2 algorithm with the LD missing data treatment and the jackknifing resampling technique applied.

Each set of results shows path coefficients as standardized betas (β) and R-squared (R^2) coefficients of explained variance. Beta values followed by three asterisks (***) are significant at $P < 0.001$. Beta values followed by two asterisks (**) are significant at $P < 0.01$. Beta values followed by one asterisk (*) are significant at $P < 0.05$. Beta values followed by no asterisk are not statistically significant. The $P=0.05$ level can be seen as the upper threshold of acceptability of significance (Rosenthal & Rosnow, 1991).

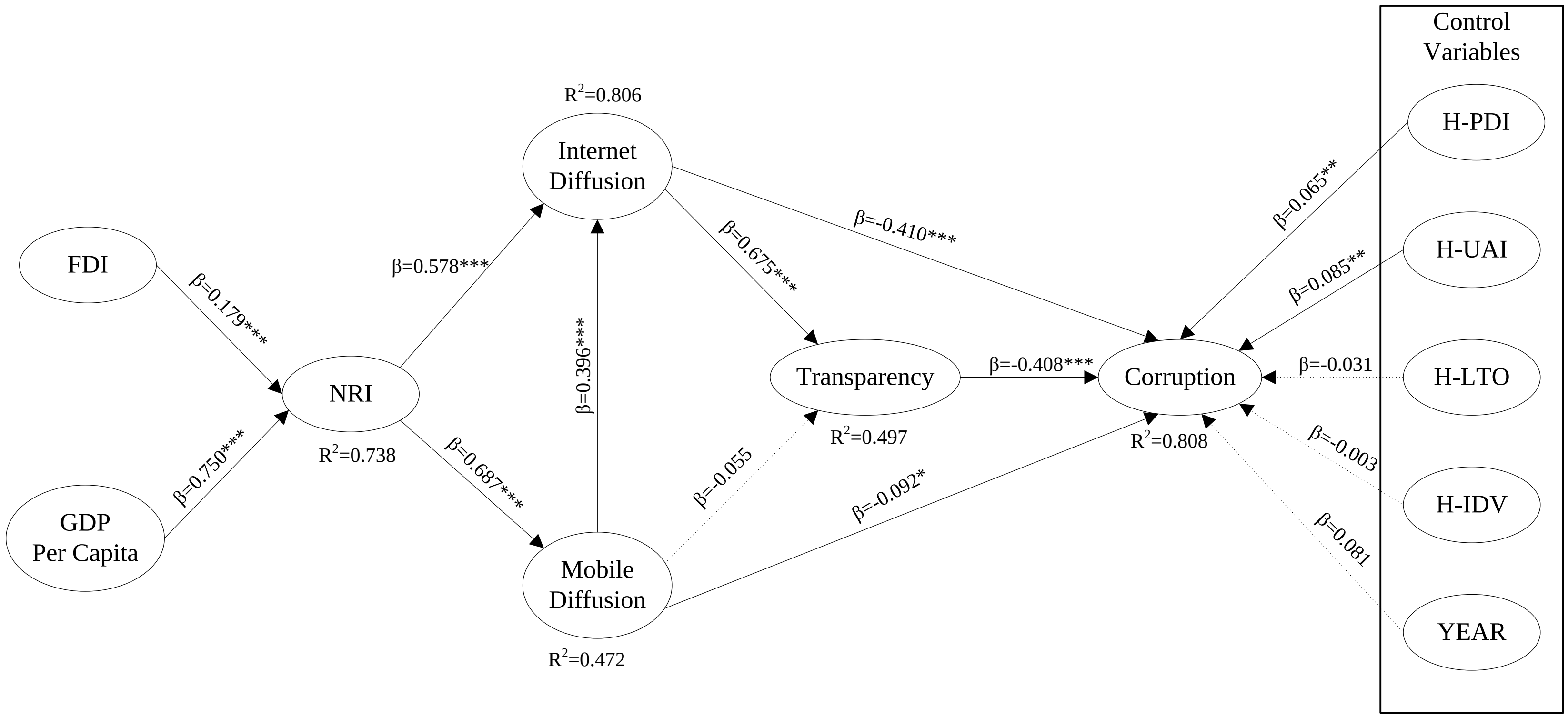

Figure 4-1. Structural model with RMS and bootstrapping.

*** indicates p-value of <0.001
** indicates p-value of <0.01
* indicates p-value of <0.05
Solid lines indicate significant paths; dotted lines indicate insignificant paths.

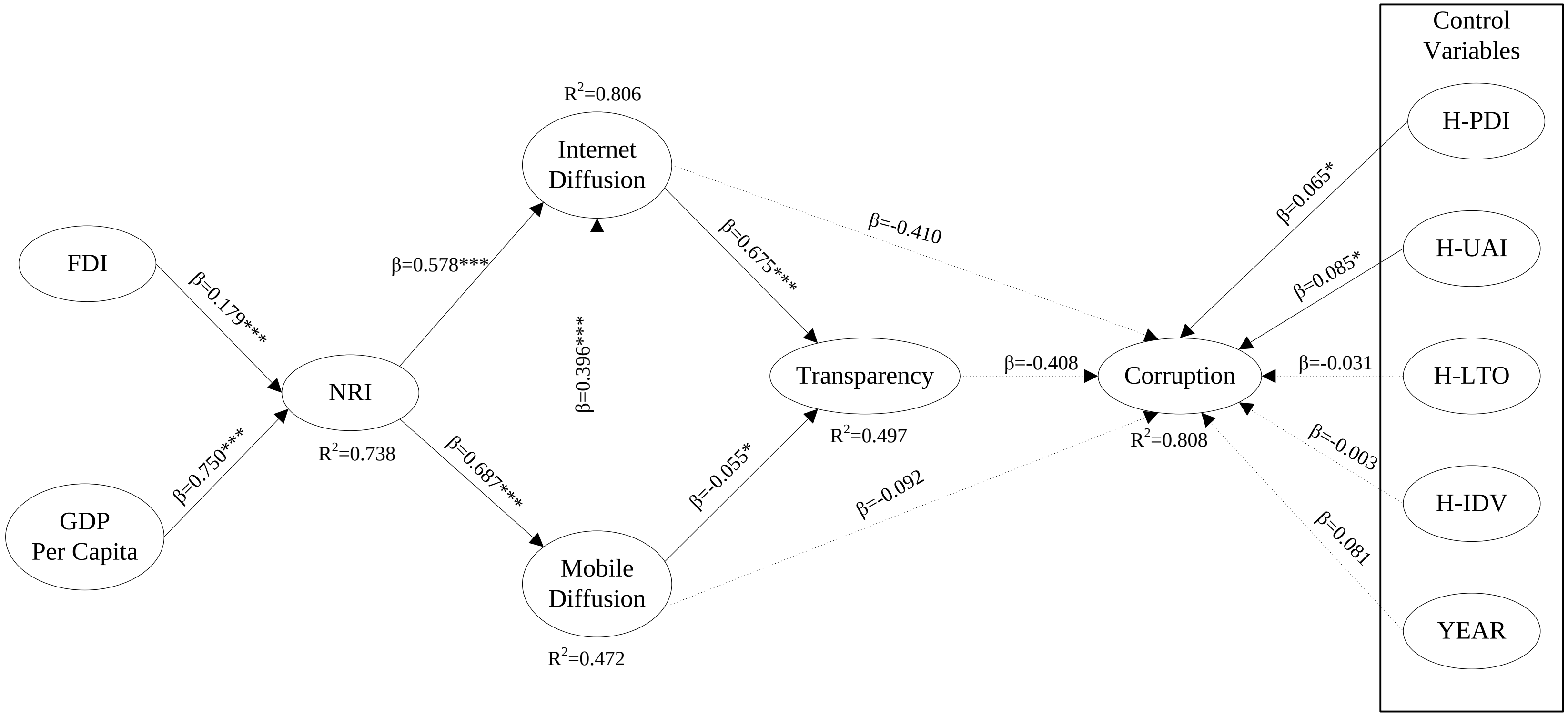

Figure 4-2. Structural model with RMS and jackknifing.

*** indicates p-value of <0.001
** indicates p-value of <0.01
* indicates p-value of <0.05
Solid lines indicate significant paths; dotted lines indicate insignificant paths.

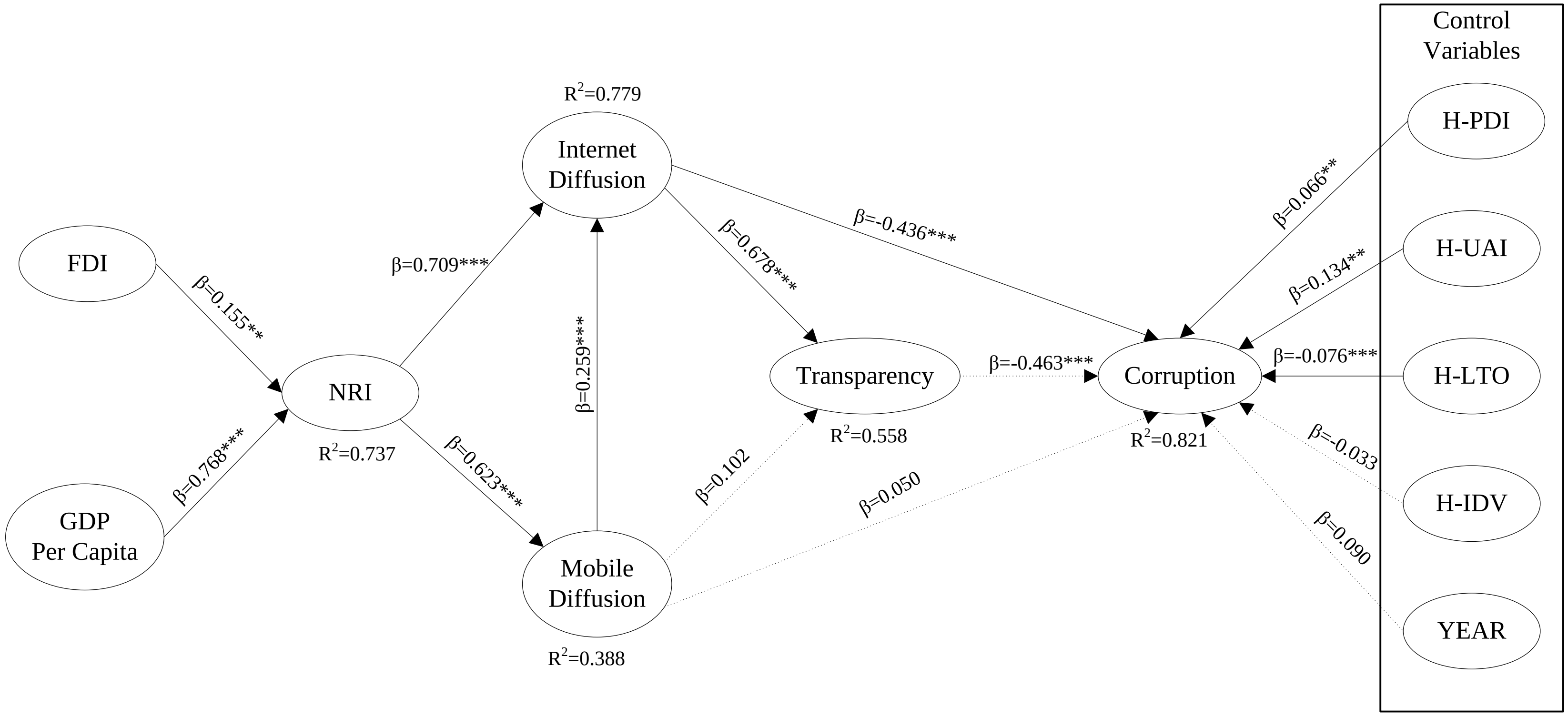

Figure 4-3. Structural model with LD and bootstrapping.

*** indicates p-value of <0.001
** indicates p-value of <0.01
* indicates p-value of <0.05
Solid lines indicate significant paths; dotted lines indicate insignificant paths.

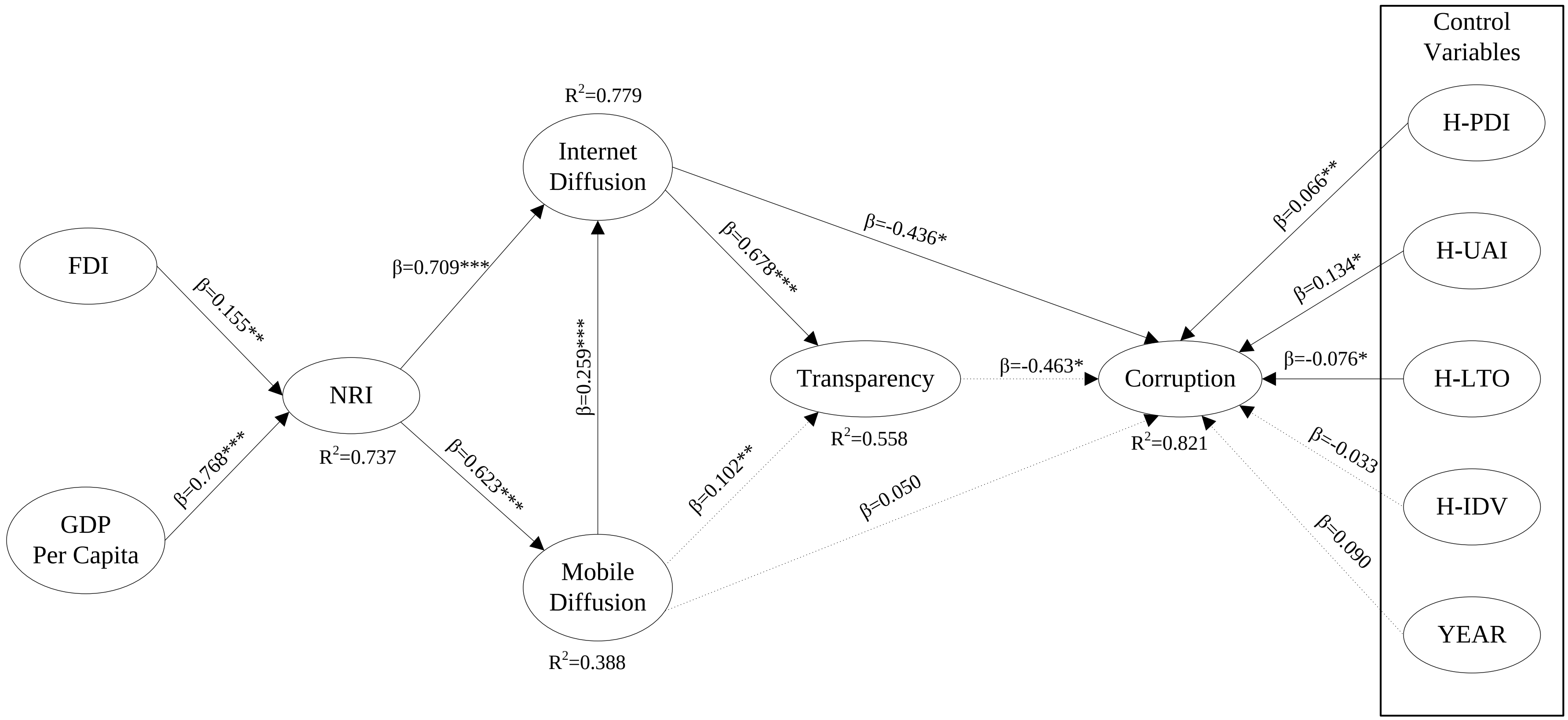

Figure 4-4. Structural model with LD and jackknifing.

*** indicates p-value of <0.001
** indicates p-value of <0.01
* indicates p-value of <0.05
Solid lines indicate significant paths; dotted lines indicate insignificant paths.

The WarpPLS 3.0 software manual recommends using "the P values associated with the most stable [path] coefficients" (Kock, 2012, p. 13). The significant path coefficients along with the related P values were estimated for each missing data treatment and bootstrapping and jackknifing resampling techniques as shown in Table 4-4.

Table 4-4. Number of significant paths by P-value level.

Significance level	**Number of significant paths**			
	RMS		**LD**	
	bootstrapping	**jackknifing**	**bootstrapping**	**jackknifing**
P<0.05	11	9	10	10
P<0.01	10	6	10	7
P<0.001	9	6	7	5

As predicted by the WarpPLS 3.0 manual, results with large samples and those that used bootstrapping resampling gave more stable path coefficients. (Kock, 2012). Consequently, the data with the RMS missing data treatment and bootstrapping resampling technique demonstrated the higher number of significant paths with stronger associated P values, indicating a higher overall predictive and explanatory quality of this particular model.

4.3 Model Fit Indices

WarpPLS 3.0 conducts a model fitness test as part of its structural model analysis. The results of these model fitness tests are outlined in this section. The following model fitness tests indices were calculated: average path coefficient (APC), average R-squared value (ARS), and average variance inflation factor (AVIF). The APC index is the average of the absolute values of the model's path coefficients. ARS index is the absolute value of the R^2 coefficients for the model.

The AVIF index is the overall measure of multicollinearity of the model. Model fit indices are useful when comparing the quality of a model with different data. In this study, the quality of the model was assessed by comparing the APC, ARS, and AVIF values of the data using different missing data treatments. The ARS and AVIF indices are more important when comparing models (Kock, 2011b, 2012).

The results of the model fitness tests along with associated P-values are shown in Table 4.3. It is recommended that APC and ARS are significant at the P<0.05 level and AVIF is less than 5 (Hair et al., 2010; Kline, 2010; Kock, 2012). The APC and ARS indices' P-values for the data with both missing data treatments were significant at the P<.001 level. The AVIF index for the data with both missing data treatments was less than 5. The model using data with the RMS missing data treatment demonstrated a higher ARS. This indicated that the study's model had more explanatory power using data with the RMS treatment. The data with the LD missing data treatment had a slightly lower AVIF index (1.953) than the data with the RMS missing data treatment (2.145). However, these AVIF indices had values below the recommended threshold.

Table 4-5. Model fit indices with associated P-values.

Fit Index	Data with LD	Data with RMS
APC	0.309*	0.300*
ARS	0.657*	0.664*
AVIF	1.953	2.145

Note: * indicates P-value < 0.001

4.4 Hypotheses Testing

The ARS values for data using the RMS missing data treatment were higher than the LD missing data treatment as shown in Table 4-5. Also, the data using the RMS missing data treatment and bootstrapping resampling demonstrated the higher number of significant paths with stronger associated P values. Given these results of the model fit and significant path tests, data with the RMS missing data treatment and bootstrapping resampling were used in the hypotheses testing. The results of the hypotheses testing are presented in Table 4-6. A detailed review of these results for each hypothesis follows.

Table 4-6: Summary results of hypotheses testing

Hypotheses	Supported
H1a: FDI has a positive effect on networked readiness.	Accept[(a)]
H1b: GDP per capita has a positive effect on networked readiness.	Accept[(a)]
H2a: Networked readiness has a positive effect on Internet diffusion.	Accept[(a)]
H2b: Networked readiness has a positive effect on mobile phone diffusion.	Accept[(a)]
H2c: Mobile phone diffusion has a positive effect on Internet diffusion.	Accept[(a)]
H3a: Internet diffusion has a positive effect on transparency.	Accept[(a)]
H3b: Mobile phone diffusion has a positive effect on transparency.	Reject
H4a: Internet diffusion has a negative effect on corruption.	Accept
H4b: Transparency has a negative effect on corruption.	Accept
H4c: Mobile phone diffusion has a negative effect on corruption.	Accept

Note: (a) Results significant at $P<0.01$ across all missing data treatments and resampling analyses.

Hypothesis 1a stated that foreign direct investment (FDI) has a positive effect on networked readiness (NRI). The results showed that FDI has a significant ($P<0.001$) and positive ($\beta=0.179$) effect on NRI. Thus, Hypothesis 1a was supported. Figure 4-5 shows the relationship between FDI and NRI in the data. As shown, the relationship between FDI and NRI was non-linear. WarpPLS 3.0 denoted such relationships as “warped” (Kock, 2012, p. 47). Such relationships are known as U-

, J- or Kuznet-curves depending on the direction of the curve and the amount of non-linearity (Selden & Song, 1995). These non-linear relationships have been found in other studies related to FDI and international trade (D. K. Backus, Kehoe, & Kydland, 1994; Rose & Yellen, 1989).

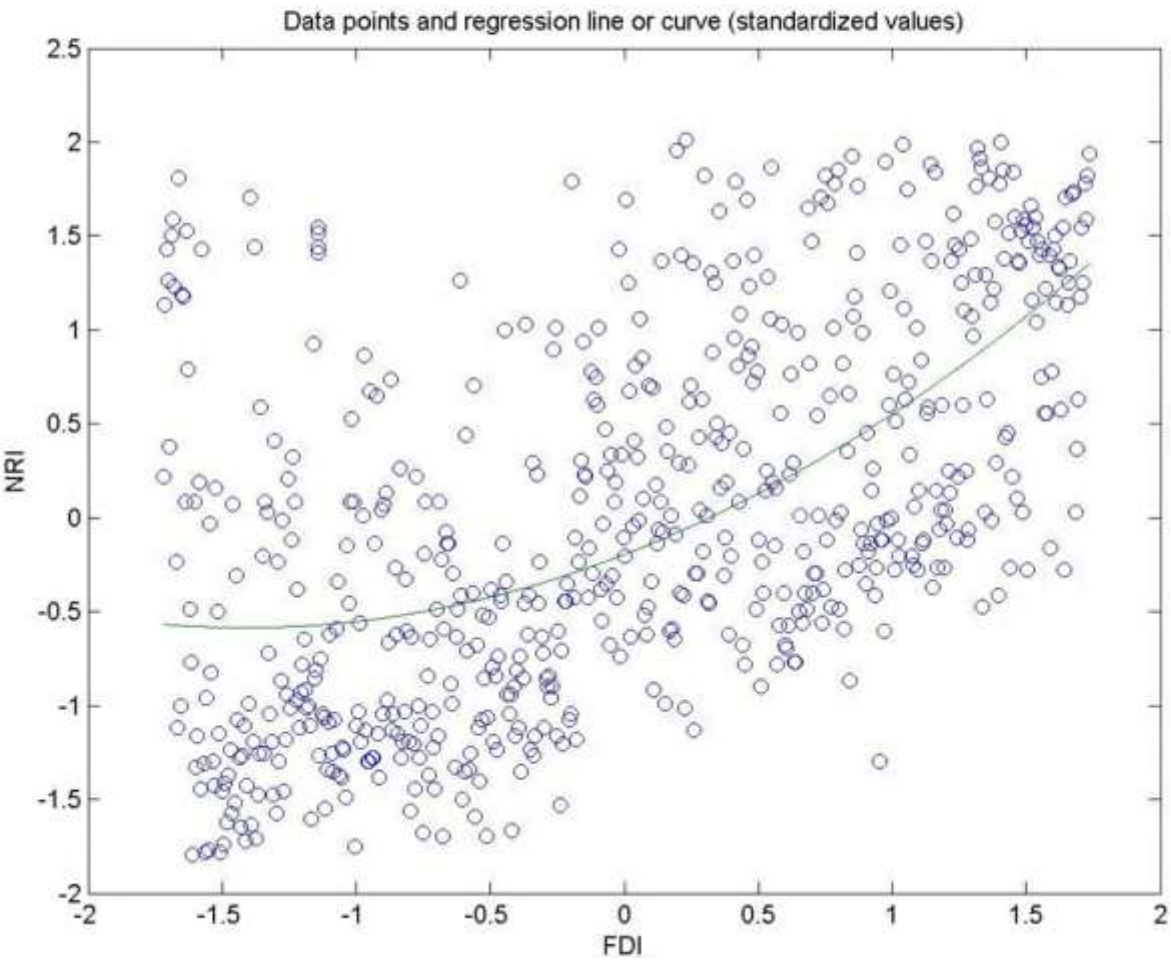

Figure 4-5. Relationship between FDI and NRI.

Hypothesis 1b stated that GDP per capita, as measured in current US dollars from gross domestic product per capita (current US$) indicator through the World Bank World Development Indicators, has a positive effect on networked readiness. GDP per capita had a significant ($P<0.001$) and positive ($\beta=0.750$) effect on corruption, as measured through the Corruption Perceptions Index

(CPI) from Transparency International. Thus, Hypothesis 1b was supported. Figure 4-6 shows the relationship between GDP per capita and NRI in the data. As shown, this relationship was non-linear.

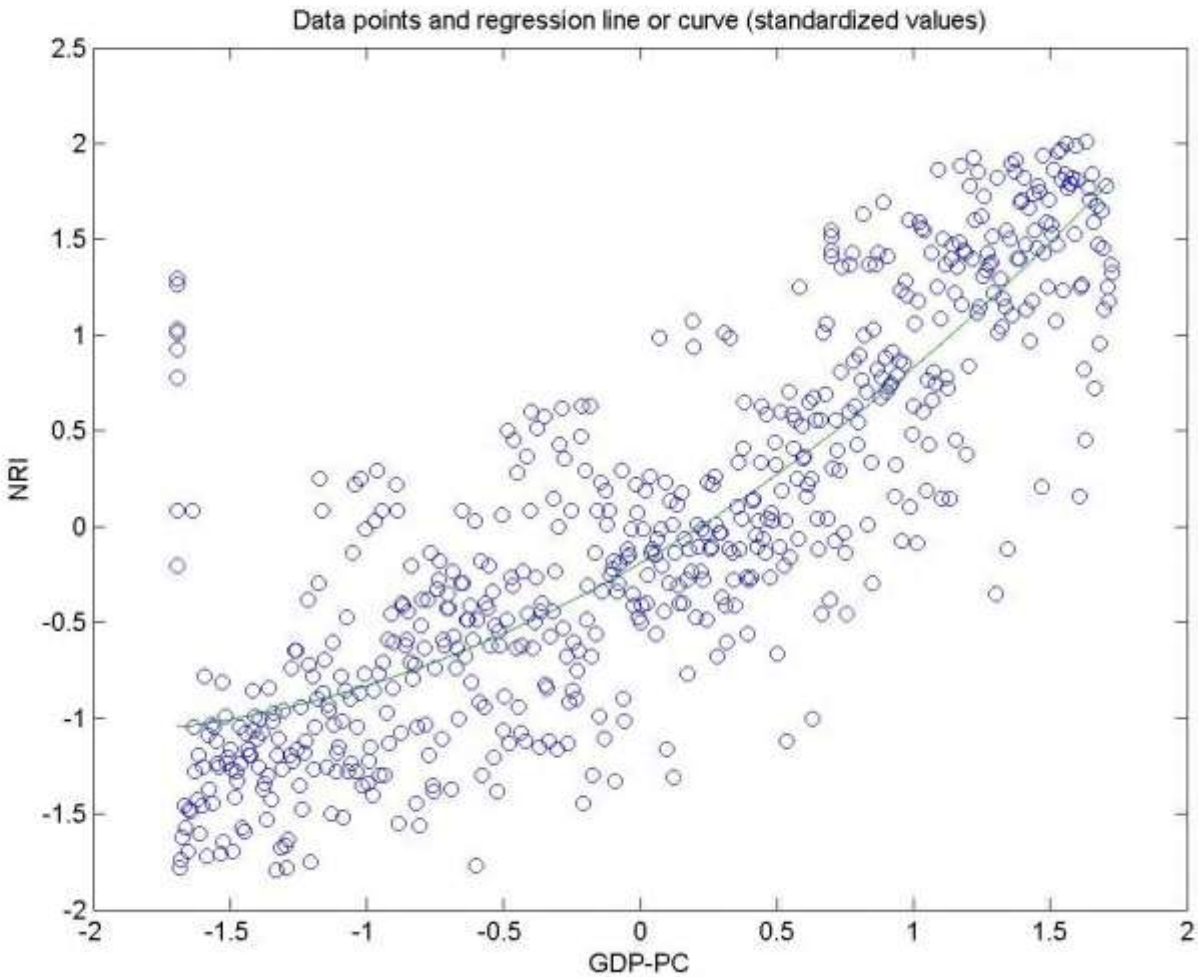

Figure 4-6. Relationship between GDP per capita and NRI

Hypothesis 2a stated that networked readiness (NRI) has a positive effect on Internet diffusion as measured through World Bank World Development Internet users (per 100 people) indicator. The results showed that NRI had a significant ($P<0.001$) and positive ($\beta=0.578$) effect on

Internet diffusion. Thus, Hypothesis 2 was supported. Figure 4-7 shows the relationship between NRI and Internet diffusion in the data. As shown, this relationship was relatively linear.

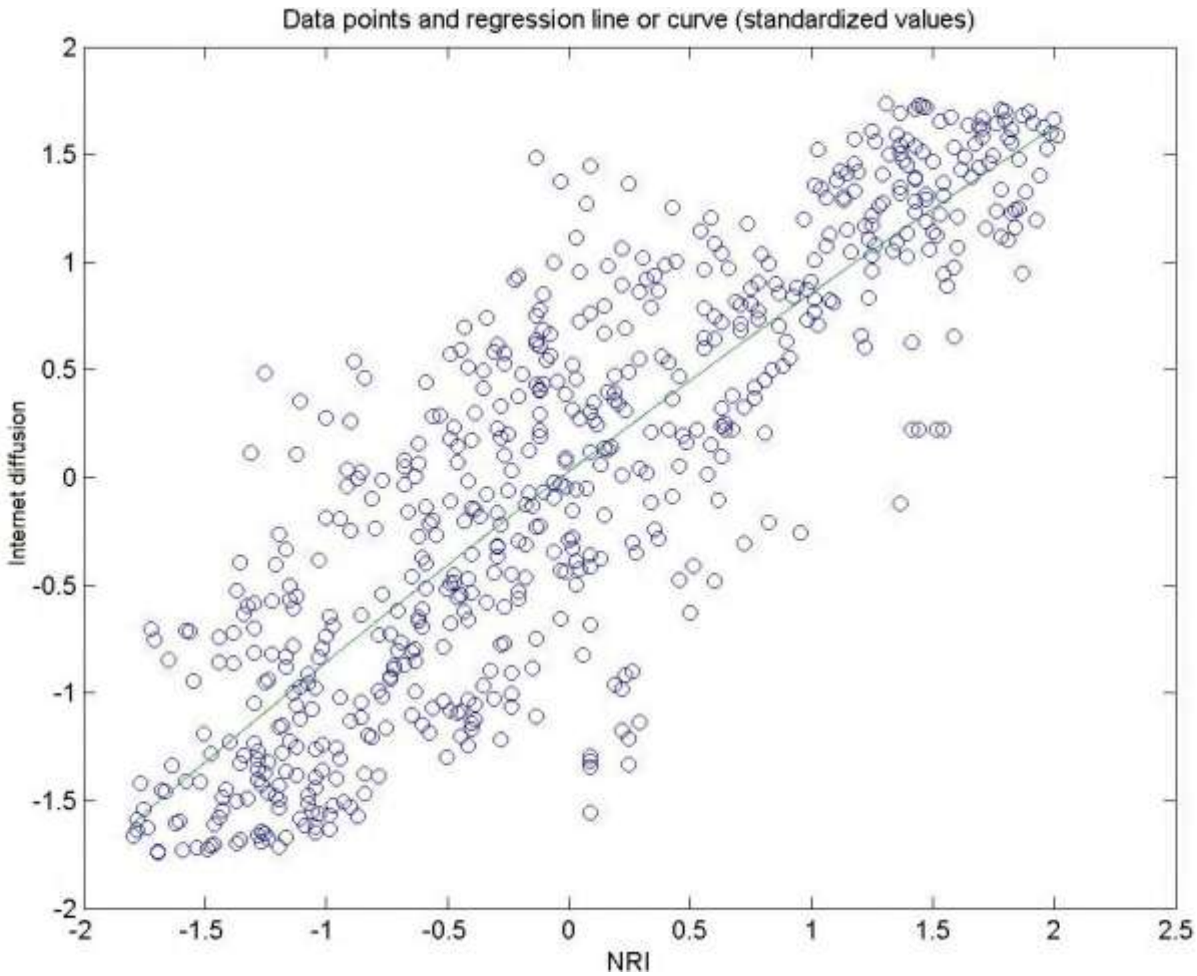

Figure 4-7. Relationship between NRI and Internet diffusion.

Hypothesis 2b stated that networked readiness (NRI) has a positive effect on mobile phone diffusion (Mobile diffusion). The results showed that NRI had significant ($P<0.001$) and positive ($\beta=0.687$) effects on mobile diffusion as measured through World Bank World Development Mobile cellular subscriptions (per 100 people) indicator. Thus, Hypothesis 2b was supported.

Figure 4-8 shows the relationship between NRI and mobile diffusion. As shown, this relationship was non-linear.

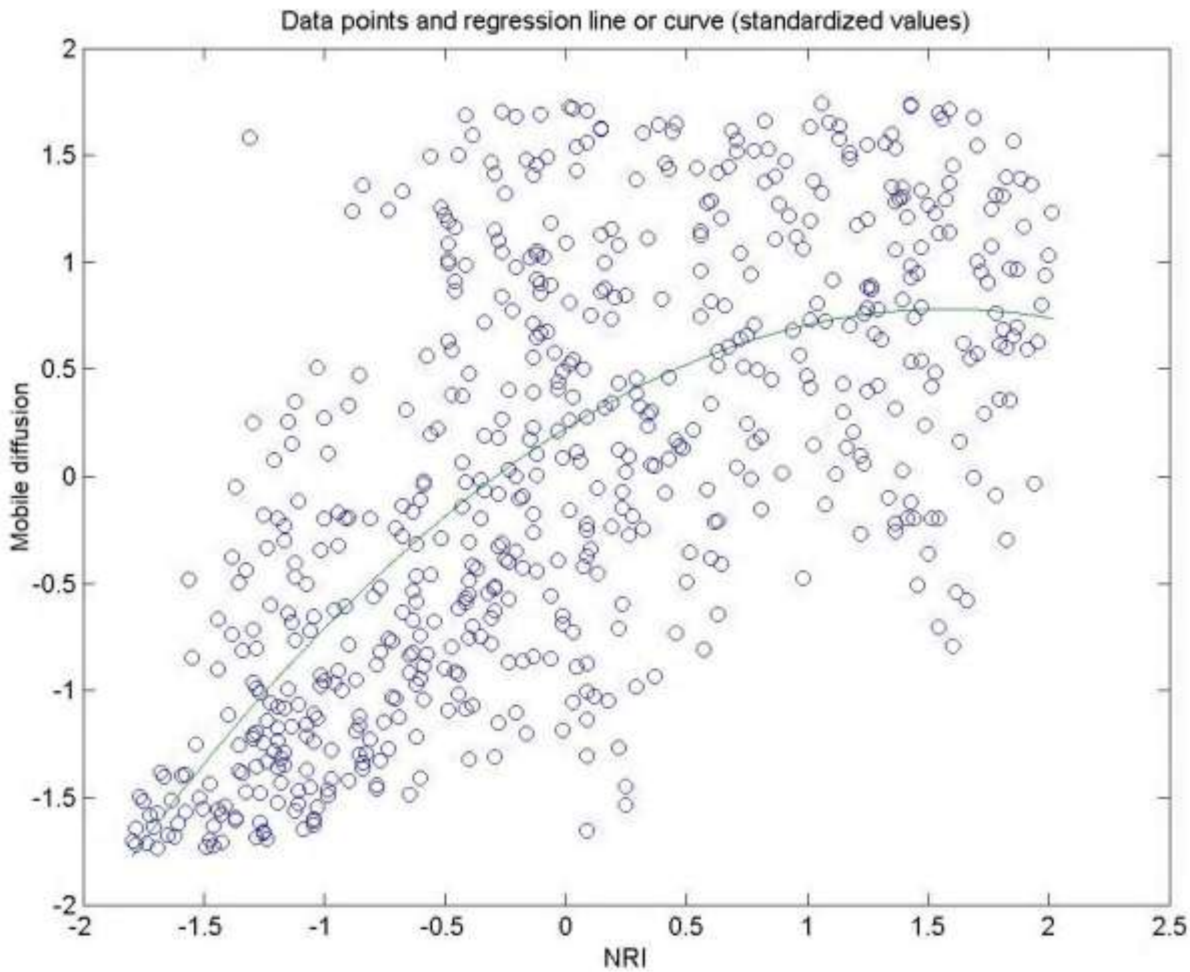

Figure 4-8. Relationship between NRI and Mobile diffusion.

Hypothesis 2c stated that mobile phone diffusion (Mobile diffusion) has a positive effect on Internet diffusion. Mobile diffusion, as measured through the World Bank World Development indicator of Mobile cellular subscriptions (per 100 people), had a significant ($P<0.001$) and positive ($\beta=0.396$) effect on Internet diffusion, as measured through the World Bank World Development indicator of Internet users (per 100 people). Thus, Hypothesis 2c was supported. Figure 4-9 shows the relationship between mobile diffusion and Internet diffusion in the data. As shown, this relationship was non-linear.

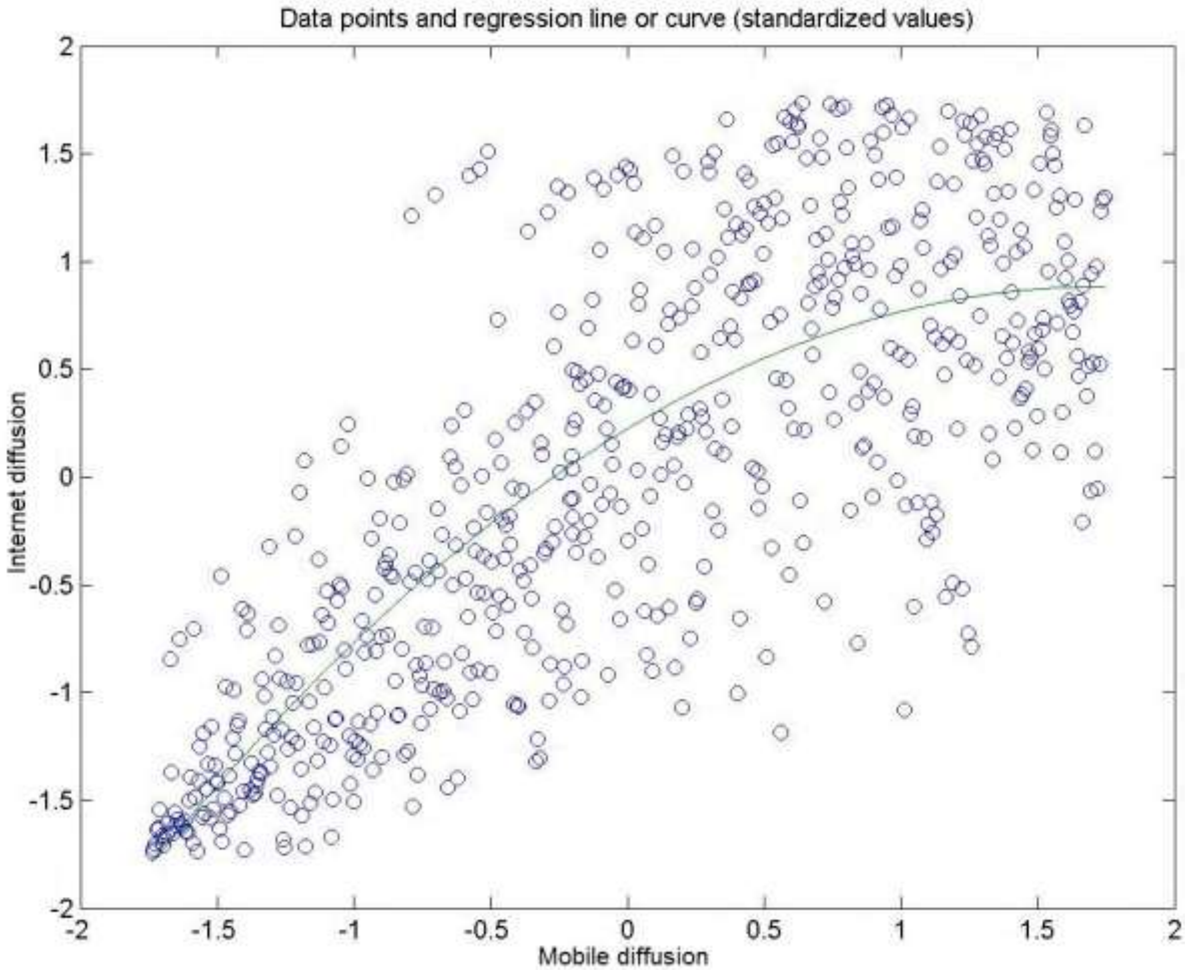

Figure 4-9. Relationship between Mobile and Internet diffusion.

Hypothesis 3a stated that Internet diffusion has a positive effect on transparency. Internet diffusion, as measured through the World Bank World Development indicator of Internet users (per 100 people), had a significant ($P<0.001$) and positive ($\beta=0.675$) effect on transparency, as measured through the World Bank Governance index of Voice of Accountability. Thus, Hypothesis 3a was supported. Figure 4-10 shows the relationship between Internet diffusion and transparency in the data. As shown, this relationship was non-linear.

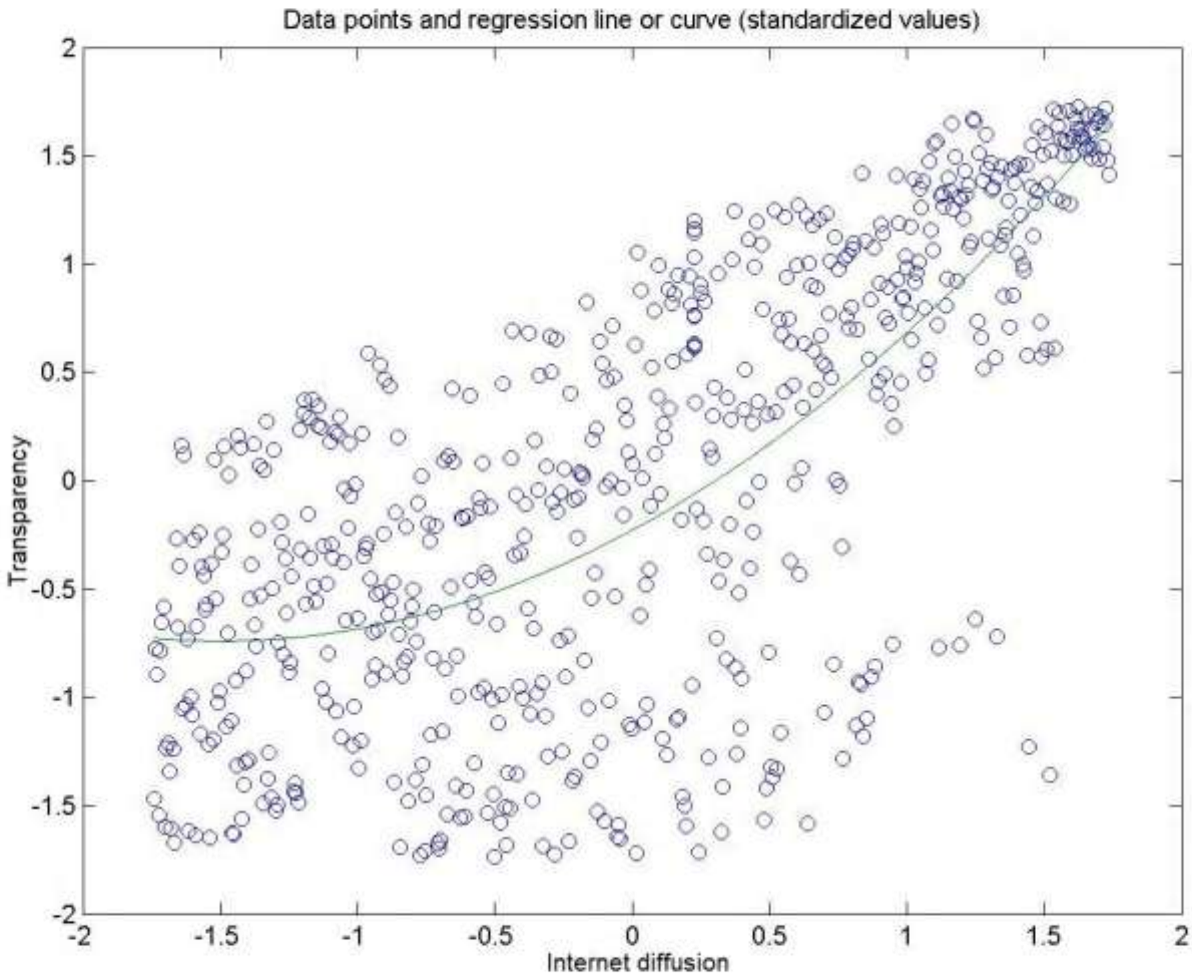

Figure 4-10. Relationship between Internet diffusion and transparency.

Hypothesis 3b stated that mobile phone diffusion (Mobile diffusion) had a positive effect on transparency. Mobile diffusion, as measured through the World Bank World Development indicator of Mobile cellular subscriptions (per 100 people), did not have a significant (P=0.182) or positive (β=-0.055) effect on transparency, as measured through the World Bank Governance index of Voice of Accountability. Thus, Hypothesis 3b was not supported. Figure 4-11 shows the relationship between mobile diffusion and transparency in the data using group-mean substitution with bootstrapping resampling. As shown, this relationship was non-linear.

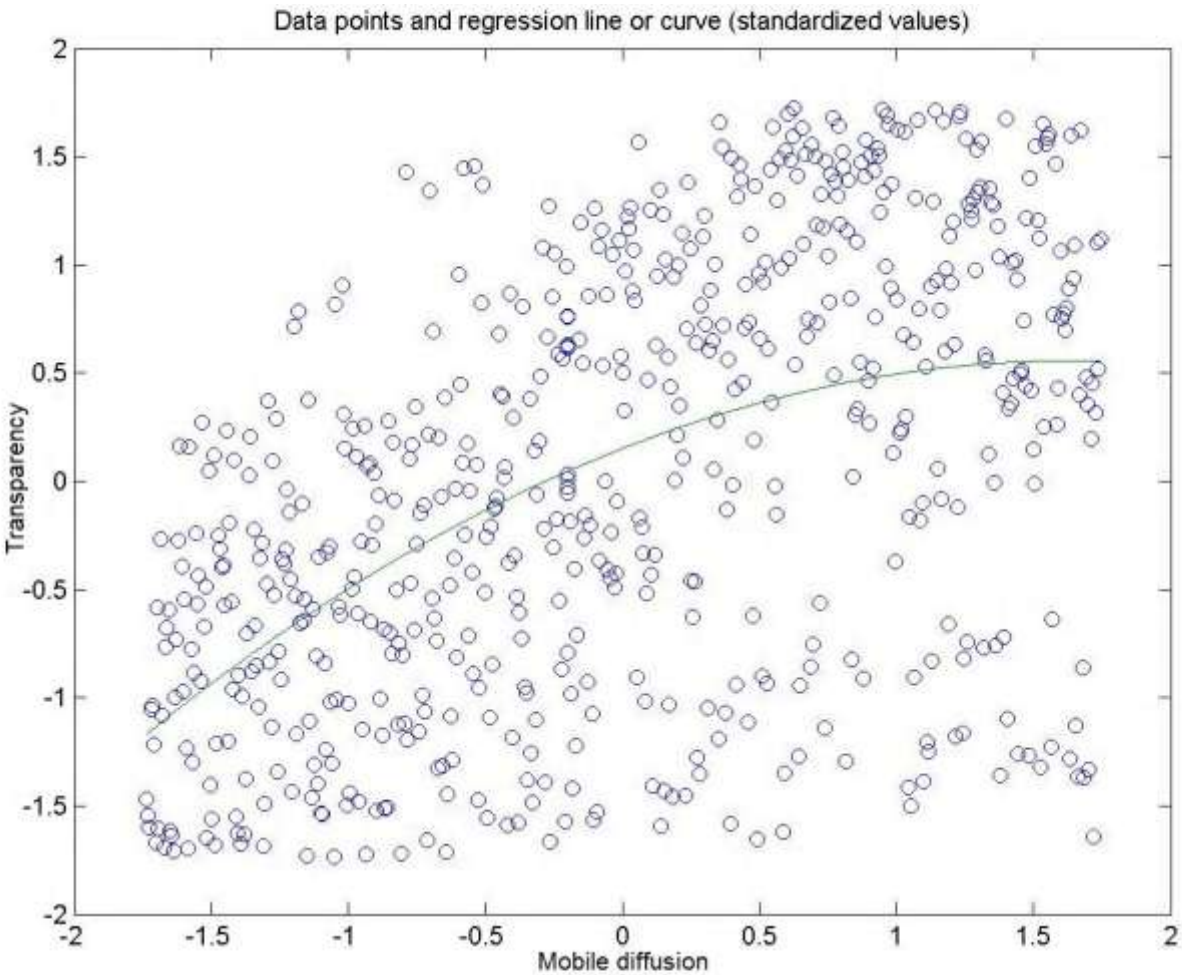

Figure 4-11. Relationship between mobile diffusion and transparency.

Hypothesis 4a stated that Internet diffusion has a negative effect on corruption. Internet diffusion, as measured through the World Bank World Development indicator of Internet users (per 100 people), had a significant (P<0.001) and negative (β=-0.410) effect on corruption as measured through the Corruption Perceptions Index (CPI) from Transparency International. Thus, Hypothesis

4a was supported. Figure 4-12 shows the relationship between Internet diffusion and corruption in the data. As shown, this relationship was non-linear.

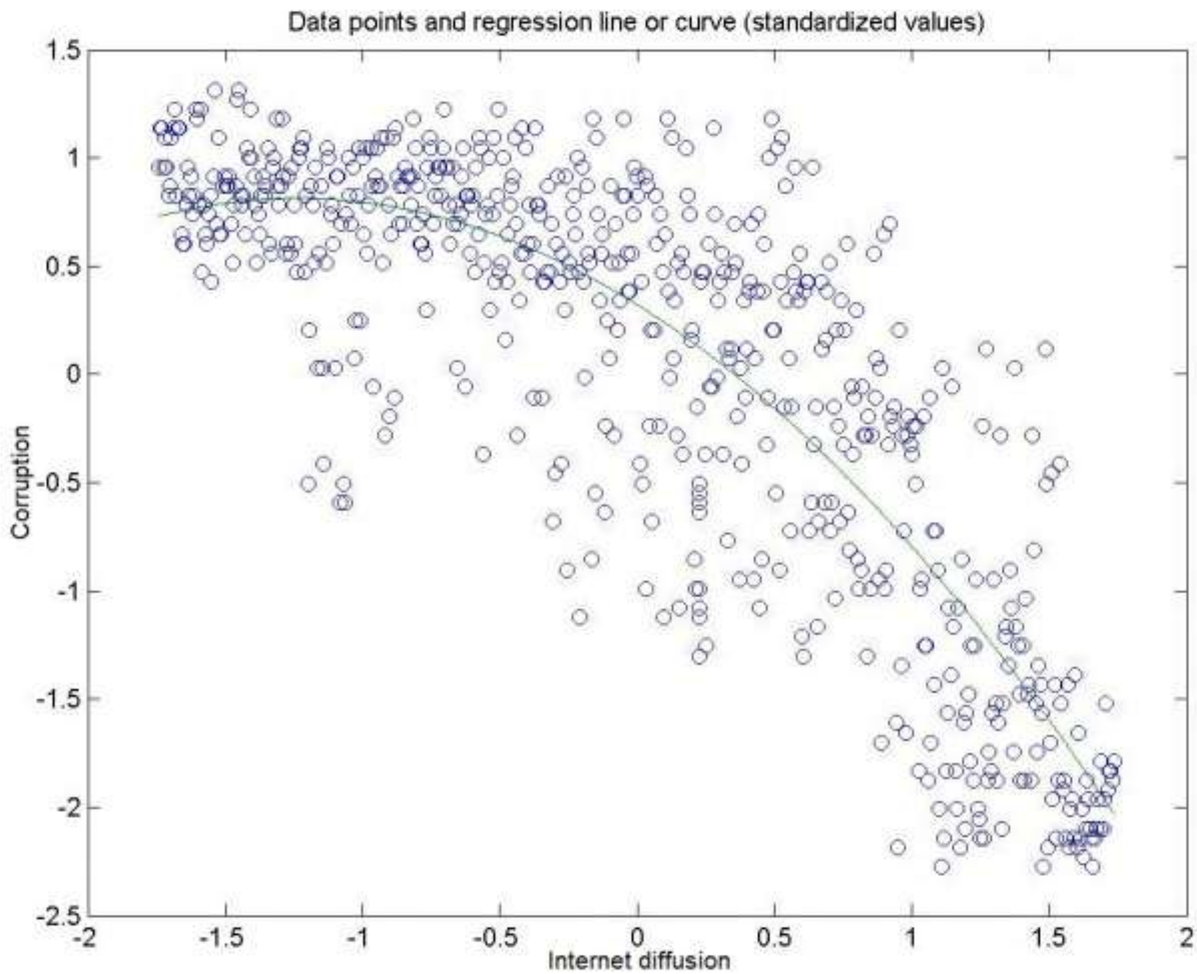

Figure 4-12. Relationship between Internet diffusion and corruption.

Hypothesis 4b stated that transparency has a negative effect on corruption. Transparency, as measured through the World Bank Governance index of Voice of Accountability, had a significant ($P<0.001$) and negative ($\beta=-0.408$) effect on corruption, as measured through the Corruption Perceptions Index (CPI) from Transparency International. Thus, Hypothesis 4b was supported.

Figure 4-13 shows the relationship between transparency and corruption in the data. As shown, this relationship was a non-linear or J-curve.

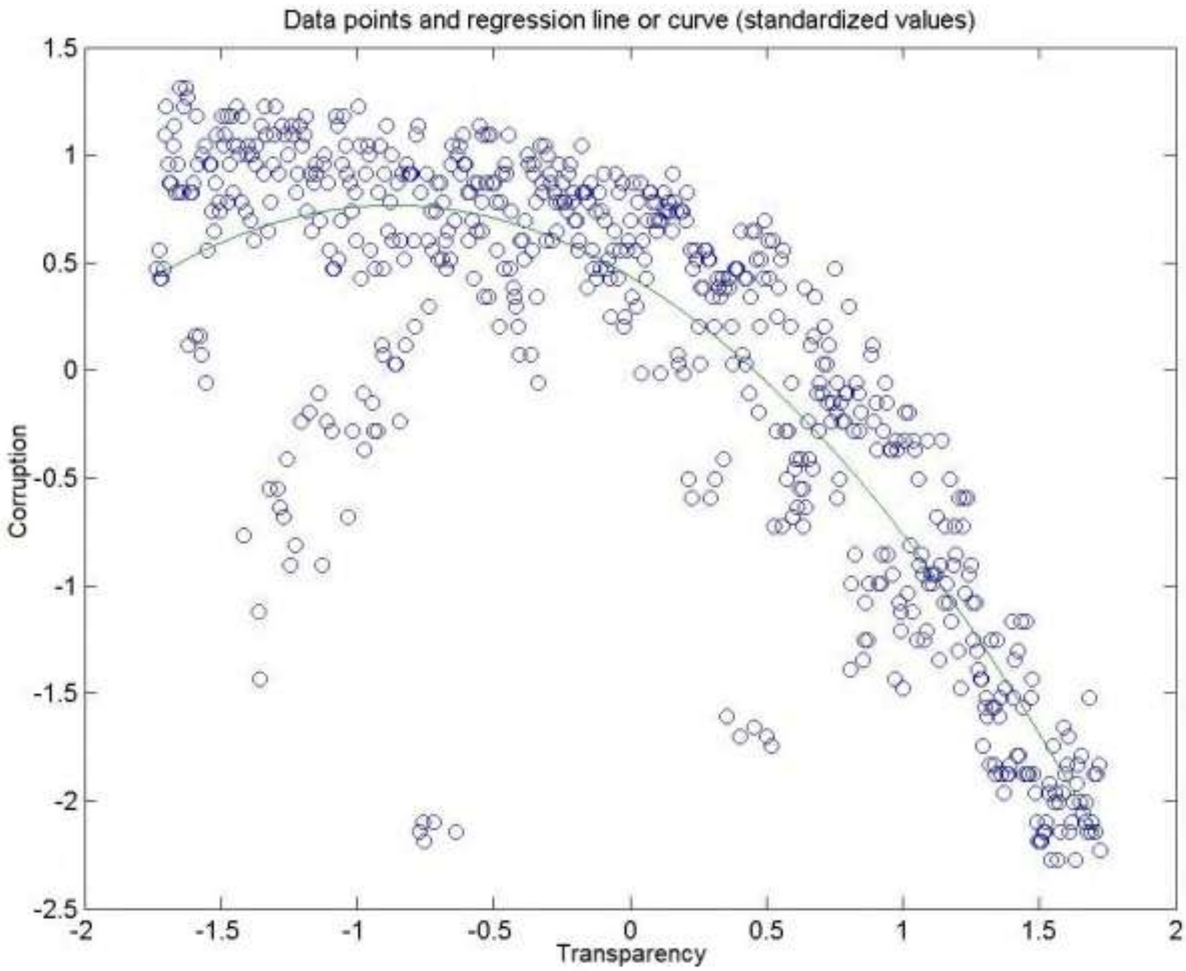

Figure 4-13. Relationship between transparency and corruption.

Hypothesis 4c stated that mobile phone diffusion (Mobile diffusion) has a negative effect on corruption. Mobile diffusion, as measured through the World Bank World Development indicator of Mobile cellular subscriptions (per 100 people), did have a significant ($P<0.05$) and negative ($\beta=-0.092$) effect on corruption, as measured through the Corruption Perceptions Index (CPI) from Transparency International. Thus, Hypothesis 4c was supported. Figure 4-14 shows the relationship between mobile phone diffusion and corruption in the data. As shown, this relationship was non-linear.

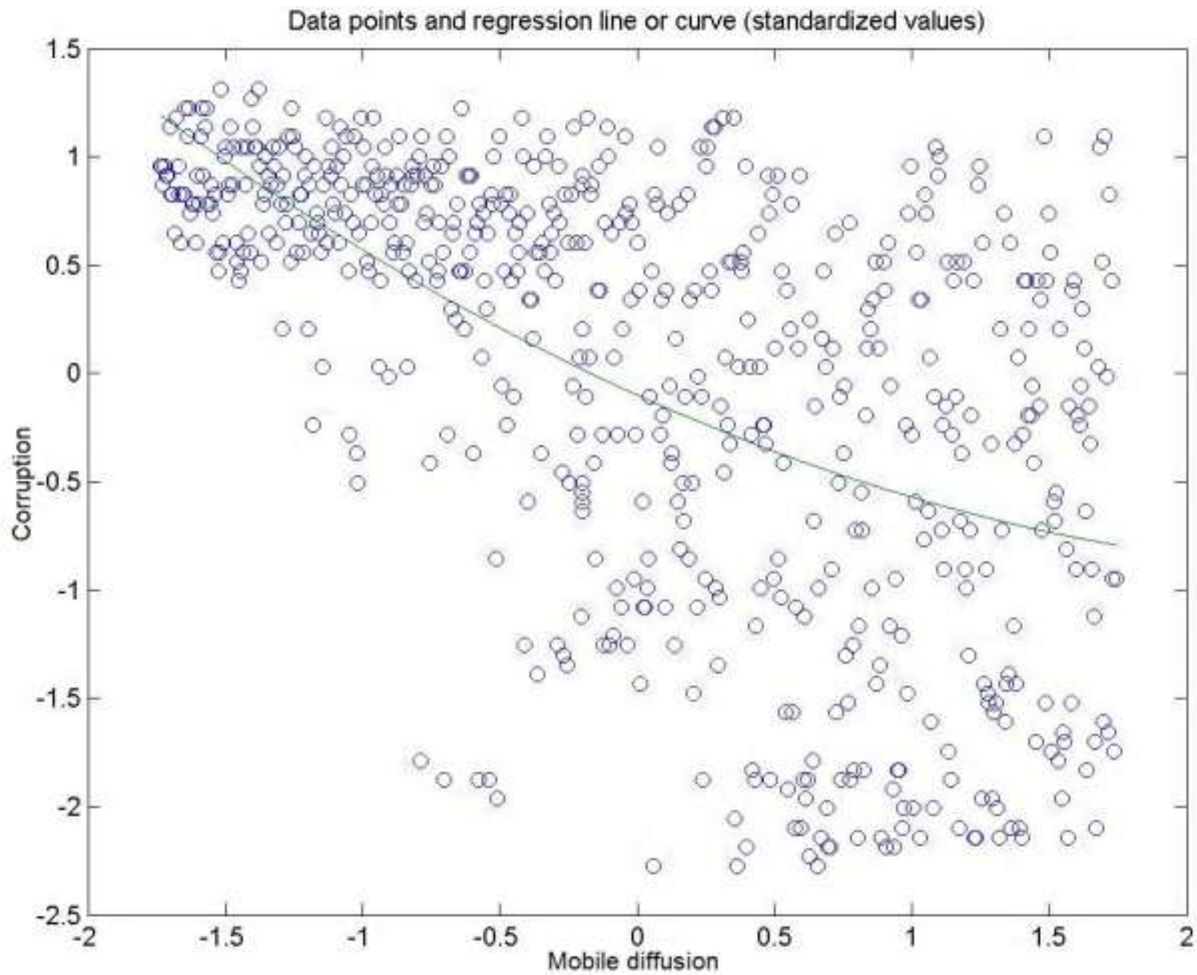

Figure 4-14. Relationship between mobile diffusion and corruption.

In this study, four control variables were used as national culture control variables to examine potential cultural factors influencing the main dependent variable. These four national culture control variables included the Hofstede Cultural Dimension indices of Power Distance, Individualism vs. Collectivism, Long- vs. Short-Term Orientation, and Uncertainty Avoidance. The year was also used as a control variable in order to control for potential multiple year effects. The year variable did not prove statistically significant (β=0.081, P=0.190) in the data analysis.

The national culture control variable of H-PDI represented the Hofstede Cultural Dimension of power distance. H-PDI had a significant ($P<0.01$) and positive (β=0.065) effect on corruption as measured through the Corruption Perceptions Index (CPI) from Transparency International. The national culture control variable of H-UAI represented the Hofstede Cultural Dimension of uncertainty avoidance. H-UAI had a significant ($P<0.01$) and positive (β=0.085) effect on corruption as measured through the Corruption Perceptions Index (CPI) from Transparency International.

The national culture control variable of H-IDV represented the Hofstede Cultural Dimension of Individualism vs. Collectivism. H-IDV did not have a significant (P=0.447, β=-0.003) effect on corruption as measured through the Corruption Perceptions Index (CPI) from Transparency International. The national culture control variable of H-LTO represented the Hofstede Cultural Dimension of Long- vs. Short-Term Orientation. H-LTO did not have a significant (P=0.072, β=-0.031) effect on corruption as measured through the Corruption Perceptions Index (CPI) from Transparency International.

4.4 Direct, Indirect and Total Effects

The J. Cohen (1988) f-squared effect size coefficients were calculated for the paths in this study's model. Direct, indirect and total effect coefficients were calculated using WarpPLS 3.0. Calculation of such indirect, direct and total effect coefficients can prove crucial to evaluating and explaining mediating effects of variables in the model. Effect size is the contribution by a predictor variable on the R^2 coefficient of a criterion variable.

WarpPLS 3.0 calculates these effects for variables linked by one or more paths in the following manner: "the path coefficients associated with the effects, the number of paths that make up the effects, the P values associated with effects (calculated via resampling, using the selected resampling method), the standard errors associated with the effects, and effect sizes associated with the effects" (Kock, 2012, p. 50). According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients (f^2) below 0.02 are considered too small for relevancy.

Direct effects for each variable relationship in the model along with the effect size with respective P values and standard error are shown in Table 4-7. Direct effects are analogous to the path coefficients for each variable-to-variable relationship. It is important to note effect size when examining direct effects. While a direct effect may be significant (P<0.001), magnitude of that effect (i.e. effect size) may be small. FDI showed a positive and significant direct effect on NRI (direct effect=0.179, P<0.001). The magnitude of the direct effect of FDI on NRI was small (effect size=0.104). GDP per capita showed a positive and significant direct effect on NRI (direct effect=0.750, P<0.001). The magnitude of the direct effect of GDP per capita on NRI was large (effect size=0.634).

NRI showed a positive and significant direct effect on Internet diffusion (direct effect=0.578, P<0.001). The magnitude of the direct effect of NRI on Internet diffusion was large (effect size=0.491). NRI showed a positive and significant direct effect on Mobile diffusion (direct effect=0.678, P<0.001). The magnitude of the direct effect of NRI on Mobile diffusion was large (effect size=0.472). Mobile diffusion showed a positive and significant direct effect on Internet diffusion (direct effect=0.396, P<0.001). The magnitude of the direct effect of Mobile diffusion on Internet diffusion was medium (effect size=0.314). Mobile diffusion showed a negative but not significant direct effect on Transparency (direct effect=-0.055, p=0.182). The magnitude of the direct effect of Mobile diffusion on Transparency was small (effect size=0.028). Mobile diffusion showed a negative and significant direct effect on Corruption (direct effect=-0.092, P<0.05, p=0.015). The magnitude of the direct effect of Mobile diffusion on Corruption was small (effect size=0.053).

Internet diffusion showed a positive and significant direct effect on Transparency (direct effect=0.675, P<0.001). The magnitude of the direct effect of Internet diffusion on Transparency was large (effect size=0.481). Internet diffusion showed a positive and significant direct effect on Corruption (direct effect=-0.410, P<0.001). The magnitude of the direct effect of Internet diffusion on Corruption was medium (effect size=0.348). Transparency showed a negative and significant direct effect on Corruption (direct effect=-0.408, P<0.001). The magnitude of the direct effect of Transparency on Corruption was medium (effect size=0.348).

The control variables were also analyzed for their direct effect on Corruption. Hofstede's power distance index (H-PDI) showed a positive and significant direct effect on Corruption (direct effect=0.065, P<0.01, p=0.008). The magnitude of the direct effect of H-PDI on Corruption was small (effect size=0.045). Hofstede's uncertainty avoidance index (H-UAI) showed a positive and significant direct effect on Corruption (direct effect=0.085, P<0.01, p=0.002). The magnitude of the direct effect of H-UAI on Corruption was small (effect size=0.045). Hofstede's long-term orientation (H-LTO) showed a negative but not significant direct effect on Corruption (direct effect=-0.031, p=0.072). The magnitude of the direct effect of H-LTO on Corruption was below Cohen's recommended effect size threshold for relevancy (effect size=0.008). Hofstede's individuality index (H-IDV) showed a negative but not significant direct effect on Corruption (direct effect=-0.003, p=0.447). The magnitude of the direct effect of H-IDV on Corruption was below Cohen's recommended effect size threshold for relevancy (effect size=0.002).

Table 4-7. Direct effects for each variable relationship.

Relationship	Total Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
FDI → NRI	0.179	<0.001	0.104	small	0.030
GDP per capita → NRI	0.750	<0.001	0.634	large	0.025
NRI → Internet diffusion	0.578	<0.001	0.491	large	0.023
NRI → Mobile diffusion	0.687	<0.001	0.472	large	0.018
Mobile diffusion → Internet diffusion	0.396	<0.001	0.314	medium	0.026
Mobile diffusion → Transparency	-0.055	0.182	0.028	small	0.061
Mobile diffusion → Corruption	-0.092	0.015	0.053	small	0.042
Internet diffusion → Transparency	0.675	<0.001	0.481	large	0.028
Internet diffusion → Corruption	-0.410	<0.001	0.347	medium	0.061
Transparency → Corruption	-0.408	<0.001	0.348	medium	0.061
H-PDI → Corruption	0.065	0.008	0.045	small	0.027
H-UAI → Corruption	0.085	0.002	0.024	small	0.030
H-LTO → Corruption	-0.031	0.072	0.008	no rel.	0.021
H-IDV → Corruption	-0.003	0.447	0.002	no rel.	0.025

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

Indirect effects are introduced when the path from an initial variable to an outcome variable has other intervening variables. The intervening variables in a model can have a mediation effect on the relationship between the initial and outcome variables. The indirect effects by number of aggregated segments and summation of indirect effects for each variable relationship in the model along with the effect size with respective P values and standard error were also calculated.

The indirect effects of initial variables on outcome variables with two aggregated segments, along with associate P values, effect size, and standard errors are shown in Table 4-8. Internet diffusion, which had one two-segment path to Corruption (Internet diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.275, P<0.001). The magnitude of the indirect effect of Internet diffusion on Corruption was medium (effect size=0.233).

Table 4-8. Indirect effects for relationships with two aggregated segments.

Relationship	Paths N	Indirect Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Internet diffusion → Transparency → Corruption	1	-0.275	<0.001	0.233	medium	0.045
Mobile diffusion → Internet diffusion → Transparency	1	0.268	<0.001	0.138	small	0.019
Mobile diffusion → Transparency → Corruption; Mobile diffusion → Internet diffusion → Corruption	2	-0.140	<0.001	0.081	small	0.031
FDI → NRI → Internet diffusion	1	0.103	<0.001	0.051	small	0.017
FDI → NRI → Mobile diffusion	1	0.123	<0.001	0.048	small	0.021
NRI → Internet diffusion → Transparency; NRI → Mobile diffusion → Transparency	2	0.352	<0.001	0.237	medium	0.047
NRI → Internet diffusion → Corruption; NRI → Mobile diffusion → Corruption	2	-0.300	<0.001	0.274	medium	0.045
NRI → Mobile diffusion → Internet diffusion	1	0.272	<0.001	0.231	medium	0.018
GDP per capita → NRI → Internet diffusion	1	0.434	<0.001	0.361	large	0.025
GDP per capita → NRI → mobile diffusion	1	0.515	<0.001	0.375	large	0.023

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

Mobile diffusion, which had one two-segment path to Transparency (Mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on

Transparency (indirect effect=0.268, P<0.001). The magnitude of the indirect effect of Mobile diffusion on Transparency was small (effect size=0.138). Mobile diffusion, which had two two-segment path to Corruption (Mobile diffusion → Transparency → Corruption; Mobile diffusion → Internet diffusion → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.140, P<0.001). The magnitude of the indirect effect of Mobile diffusion on Corruption was small (effect size=0.081). FDI, which had one two-segment path to Internet diffusion (FDI → NRI → Internet diffusion), showed a positive and significant indirect effect on Internet diffusion (indirect effect=0.103, P<0.001). The magnitude of the indirect effect of FDI on Internet diffusion was small (effect size=0.051).

FDI, which had one two-segment path to Mobile diffusion (FDI → NRI → Mobile diffusion), showed a positive and significant indirect effect on mobile diffusion (indirect effect=0.123, P<0.001). The magnitude of the indirect effect of FDI on Mobile diffusion was small (effect size=0.048). NRI, which had two two-segment path to Transparency (NRI → Internet diffusion → Transparency; NRI → Mobile diffusion → Transparency), showed a positive and significant indirect effect on Transparency (indirect effect=0.352, P<0.001). The magnitude of the indirect effect of NRI on Transparency was medium (effect size=0.237). NRI, which had two two-segment path to Corruption (NRI → Internet diffusion → Corruption; NRI → Mobile diffusion → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.300, P<0.001). The magnitude of the indirect effect of NRI on Corruption was medium (effect size=0.274). NRI, which had one two-segment path to Internet diffusion (NRI → Mobile diffusion → Internet diffusion), showed a positive and significant indirect effect on Internet diffusion (indirect effect=0.272, P<0.001). The magnitude of the indirect effect of NRI on Internet diffusion was medium (effect size=0.231). GDP per capita, which had one two-segment path to Internet diffusion (GDP per capita → NRI → Internet diffusion), showed a positive and significant indirect effect on Internet diffusion (indirect effect=0.434, P<0.001). The magnitude of the indirect effect of GDP per capita on Internet diffusion was large (effect size=0.361). GDP per capita, which had one two-segment path to Mobile diffusion (GDP per capita → NRI → Mobile diffusion), showed a positive and significant indirect effect on Mobile diffusion (indirect effect=0.515, P<0.001). The magnitude of the indirect effect of GDP per capita on Mobile diffusion was large (effect size=0.375).

The indirect effects of initial variables on outcome variables with three aggregated segments, along with associate P values, effect size, and standard errors are shown in Table 4-9. Mobile diffusion, which had one three-segment path to Corruption (Mobile diffusion → Internet diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.109, P<0.001). The magnitude of the indirect effect of Mobile diffusion on Corruption was small (effect size=0.063).

FDI, which had two three-segment path to Transparency (FDI → NRI → Internet diffusion → Transparency; FDI → NRI → Mobile diffusion → Transparency), showed a positive and significant indirect effect on Transparency (indirect effect=0.063, P<0.001). The magnitude of the indirect effect of FDI on Transparency was small (effect size=0.021). FDI, which had two three-segment path to Corruption (FDI → NRI → Internet diffusion → Corruption; FDI → NRI → Mobile diffusion → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.054, P<0.001). The magnitude of the indirect effect of FDI on Corruption was small (effect size=0.026).

Table 4-9. Indirect effects for relationships with three aggregated segments.

Relationship (aggregate paths)	Paths N	Indirect Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Mobile diffusion → Internet diffusion → Transparency → Corruption	1	-0.109	<0.001	0.063	small	0.020
FDI → NRI → Internet diffusion → Transparency; FDI → NRI → Mobile diffusion → Transparency	2	0.063	<0.001	0.021	small	0.013
FDI → NRI → Internet diffusion → corruption; FDI → NRI → mobile diffusion → corruption	2	-0.054	<0.001	0.026	small	0.012
FDI → NRI → Mobile diffusion → Internet diffusion	1	0.049	<0.001	0.024	small	0.010
NRI → Mobile diffusion → Internet diffusion → Transparency	1	0.184	<0.001	0.124	small	0.014
NRI → Mobile diffusion → Transparency → Corruption; NRI → Internet diffusion → Transparency → Corruption; NRI → Mobile diffusion → Internet diffusion → Corruption	3	-0.256	<0.001	0.233	medium	0.025
GDP per capita → NRI → Mobile diffusion → Transparency; GDP per capita → NRI → Internet diffusion→ Transparency	2	0.264	<0.001	0.186	medium	0.038
GDP per capita → NRI → Mobile diffusion → Corruption; GDP per capita → NRI → Internet diffusion → Corruption	2	-0.225	<0.001	0.193	medium	0.033
GDP per capita → NRI → Mobile diffusion → Internet diffusion	1	0.204	<0.001	0.170	medium	0.014

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

FDI, which had one three-segment path to Internet diffusion (FDI → NRI → Mobile diffusion → Internet diffusion), showed a negative and significant indirect effect on Internet diffusion (indirect effect=-0.049, P<0.001). The magnitude of the indirect effect of FDI on Internet diffusion was small (effect size=0.024). NRI, which had one three-segment path to Transparency (NRI → mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on Transparency (indirect effect=0.184, P<0.001). The magnitude of the indirect effect of NRI on Transparency was small (effect size=0.124). NRI, which had three three-segment path to Corruption (NRI → Mobile diffusion → Transparency → Corruption; NRI → Internet diffusion → Transparency → Corruption; NRI → Mobile diffusion → Internet diffusion → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.256, P<0.001). The magnitude of the indirect effect of NRI on corruption was medium (effect size=0.233). GDP per capita, which had two three-segment path to Transparency (GDP per capita → NRI → Mobile diffusion → Transparency; GDP per capita → NRI → Internet diffusion→ Transparency), showed a positive and significant indirect effect on Transparency (indirect effect=0.264, P<0.001). The magnitude of the indirect effect of GDP per capita on Transparency was medium (effect size=0.186). GDP per capita, which had two three-segment path to Corruption (GDP per capita → NRI → Mobile diffusion → Corruption; GDP per capita → NRI → Internet diffusion → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.225, P<0.001). The magnitude of the indirect effect of GDP per capita on Corruption was medium (effect size=0.193). GDP per capita, which had one three-segment path to Internet diffusion (GDP per capita → NRI → Mobile diffusion → Internet diffusion), showed a negative and significant indirect effect on Internet diffusion (indirect effect=0.204, P<0.001). The magnitude of the indirect effect of GDP per capita on Internet diffusion was medium (effect size=0.170).

The indirect effects of initial variables on outcome variables with four aggregated segments, along with associate P values, effect size, and standard errors are shown in Table 4-10.

Table 4-10. Indirect effects for relationships with four aggregated segments.

Relationship (aggregate paths)	Paths N	Indirect Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
FDI → NRI → Mobile diffusion → Internet diffusion → Transparency	1	0.033	<0.001	0.011	no rel.	0.006
FDI → NRI → Mobile diffusion → Internet diffusion → Corruption; FDI → NRI → Mobile diffusion → Transparency → Corruption; FDI → NRI → Mobile diffusion → Transparency → Corruption	3	-0.046	<0.001	0.022	small	0.008
NRI → Mobile diffusion → Internet diffusion → Transparency→ Corruption	1	-0.075	<0.001	0.069	small	0.013
GDP per capita → NRI → Mobile diffusion → Internet diffusion → Transparency	1	0.138	<0.001	0.097	small	0.011
GDP per capita → NRI → Mobile diffusion → Internet diffusion → Corruption; GDP per capita → NRI → Mobile diffusion → Transparency → Corruption; GDP per capita → NRI → Internet diffusion → Transparency →Corruption	3	-0.192	<0.001	0.164	medium	0.021

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

FDI, which had one four-segment path to Transparency (FDI → NRI → Mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on

Transparency (indirect effect=0.033, P<0.001). The magnitude of the indirect effect of FDI on Transparency was below Cohen's recommended effect size threshold for relevancy (effect size=0.011). FDI, which had three four-segment path to Corruption (FDI → NRI → Mobile diffusion → Internet diffusion → Corruption; FDI → NRI → Mobile diffusion → transparency → Corruption; FDI → NRI → Mobile diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.046, P<0.001). The magnitude of the indirect effect of FDI on Corruption was small (effect size=0.022).

NRI, which had one four-segment path to Corruption (NRI → Mobile diffusion → Internet diffusion → Transparency→ Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=0.033, P<0.001). The magnitude of the indirect effect of NRI on Corruption was small (effect size=0.069). GDP per capita, which had one four-segment path to Transparency (GDP per capita → NRI → Mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on Transparency (indirect effect=0.138, P<0.001). The magnitude of the indirect effect of GDP per capita on Transparency was small (effect size=0.097). GDP per capita, which had three four-segment path to Corruption (GDP per capita → NRI → Mobile diffusion → Internet diffusion → Corruption; GDP per capita → NRI → Mobile diffusion → Transparency → Corruption; GDP per capita → NRI → Internet diffusion → Transparency →Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.192, P<0.001). The magnitude of the indirect effect of GDP per capita on Corruption was medium (effect size=0.164).

The indirect effects of initial variables on outcome variables with five aggregated segments, along with associate P values, effect size, and standard errors are shown in Table 4-11. FDI, which had one five-segment path to Corruption (FDI → NRI → Mobile diffusion → Internet diffusion →

Transparency → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.013, P<0.001). The magnitude of the indirect effect of FDI on corruption was below Cohen's recommended effect size threshold for relevancy (effect size=0.007). GDP per capita, which had one five-segment path (GDP per capita → NRI → Mobile diffusion → Internet diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (indirect effect=-0.013, P<0.001). The magnitude of the indirect effect of GDP per capita on Corruption was below Cohen's recommended effect size threshold for relevancy (effect size=0.007).

Table 4-11. Indirect effects for relationships with five aggregated segments.

Relationship (aggregate paths)	Paths N	Indirect Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
FDI → NRI → Mobile diffusion → Internet diffusion → Transparency → Corruption	1	-0.013	<0.001	0.007	no rel.	0.003
GDP per capita → NRI → Mobile diffusion → Internet diffusion → Transparency → Corruption	1	-0.056	<0.001	0.048	small	0.011

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

The sum of indirect effects of initial variables on outcome variables in the model, along with the number of paths, the effect size with respective P values and standard error are shown in Table 4-12. Internet diffusion, which had one path to Corruption (Internet diffusion → Corruption), showed a negative and significant indirect effect on Corruption (sum of indirect effect=-0.275, P<0.001). The summative magnitude of the indirect effect of Internet diffusion on Corruption was medium (effect size=0.233).

Table 4-12. Sum of indirect effects.

Relationship	Paths N	Indirect Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Internet diffusion → Corruption	1	-0.275	<0.001	0.233	medium	0.045
Mobile diffusion → Transparency	1	0.268	<0.001	0.138	small	0.019
Mobile diffusion →…→ Corruption	3	-0.249	<0.001	0.144	small	0.033
FDI → …→ Transparency	3	0.096	<0.001	0.032	small	0.019
FDI → …→ Corruption	6	-0.113	<0.001	0.055	small	0.033
FDI →… → Internet diffusion	2	0.152	<0.001	0.075	small	0.019
FDI → Mobile diffusion	1	0.123	<0.001	0.048	small	0.033
NRI → …→ Transparency	3	0.536	<0.001	0.361	large	0.048
NRI → …→ Corruption	6	-0.631	<0.001	0.576	large	0.033
NRI → Internet diffusion	1	0.272	<0.001	0.231	medium	0.018
GDP per capita →… → Transparency	3	0.402	<0.001	0.283	medium	0.040
GDP per capita → …→ Corruption	6	-0.473	<0.001	0.406	large	0.029
GDP per capita →…→ Internet diffusion	2	0.638	<0.001	0.530	large	0.024
GDP per capita → Mobile diffusion	1	0.515	<0.001	0.375	large	0.023

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

Mobile diffusion, which had one path to Transparency (Mobile diffusion → Transparency), showed a positive and significant indirect effect on Transparency (sum of indirect effect=0.268, P<0.001). The summative magnitude of the indirect effect of Mobile diffusion on Transparency was small (effect size=0.138). Mobile diffusion, which had three paths to Corruption (Mobile diffusion → Transparency → Corruption; Mobile diffusion → Internet diffusion → Corruption; Mobile diffusion → Internet diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (sum of indirect effect=-0.249, P<0.001). The summative magnitude of the indirect effect of Mobile diffusion on Corruption was small (effect size=0.144).

FDI, which had three paths to Transparency (FDI → NRI → Internet diffusion → Transparency; FDI → NRI → Mobile diffusion → Transparency; FDI → NRI → Mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on Transparency (sum of indirect effect=0.096, P<0.001). The summative magnitude of the indirect effect of FDI on Transparency was small (effect size=0.032). FDI, which had six paths to Corruption (FDI → NRI → Internet diffusion → Corruption; FDI → NRI → Mobile diffusion → Corruption; FDI → NRI → Mobile diffusion → Internet diffusion → Corruption; FDI → NRI → Mobile diffusion → Transparency → Corruption; FDI → NRI → Mobile diffusion → Transparency → Corruption; FDI → NRI → Mobile diffusion → Internet diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (sum of indirect effect=-0.113, P<0.001). The summative magnitude of the indirect effect of FDI on Corruption was small (effect size=0.055).

FDI, which had two paths to Internet diffusion (FDI → NRI → Internet diffusion; FDI → NRI → Mobile diffusion → Internet diffusion), showed a positive and significant indirect effect on Internet diffusion (sum of indirect effect=0.152, P<0.001). The summative magnitude of the indirect effect of FDI on Internet diffusion was small (effect size=0.075). FDI, which had one path to Mobile diffusion (FDI → NRI → Mobile diffusion), showed a positive and significant indirect effect on Mobile diffusion (sum of indirect effect=0.123, P<0.001). The summative magnitude of the indirect effect of FDI on Mobile diffusion was small (effect size=0.048). NRI, which had three paths to Transparency (NRI → Internet diffusion → Transparency; NRI → Mobile diffusion → Transparency; NRI → Mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on Transparency (sum of indirect effect=0.536, P<0.001). The summative magnitude of the indirect effect of NRI on Transparency was large (effect size=0.361).

NRI, which had six paths to Corruption (NRI → Internet diffusion → Corruption; NRI → Mobile diffusion → Corruption; NRI → Mobile diffusion → Transparency → Corruption; NRI → Internet diffusion → Transparency → Corruption; NRI → Mobile diffusion → Internet diffusion → Corruption; NRI → Mobile diffusion → Internet diffusion → Transparency→ Corruption), showed a negative and significant indirect effect on Corruption (sum of indirect effect=-0.631, P<0.001). The summative magnitude of the indirect effect of NRI on Corruption was large (effect size=0.576). NRI, which had one path to Internet diffusion (NRI → Mobile diffusion → Internet diffusion), showed a positive and significant indirect effect on Internet diffusion (sum of indirect effect=0.272, P<0.001). The summative magnitude of the indirect effect of NRI on Internet diffusion was medium (effect size=0.231).

GDP per capita, which had three paths to Transparency (GDP per capita → NRI → Mobile diffusion → Transparency; GDP per capita → NRI → Internet diffusion→ Transparency; GDP per capita → NRI → Mobile diffusion → Internet diffusion → Transparency), showed a positive and significant indirect effect on Transparency (sum of indirect effect=0.402, P<0.001). The summative magnitude of the indirect effect of GDP per capita on Transparency was medium (effect size=0.283). GDP per capita, which had six paths to Corruption (GDP per capita → NRI → Mobile diffusion → Corruption; GDP per capita → NRI → Internet diffusion → Corruption; GDP per capita → NRI → Mobile diffusion → Internet diffusion → Corruption; GDP per capita → NRI →

Mobile diffusion → Transparency → Corruption; GDP per capita → NRI → Internet diffusion → Transparency →Corruption; GDP per capita → NRI → Mobile diffusion → Internet diffusion → Transparency → Corruption), showed a negative and significant indirect effect on Corruption (sum of indirect effect=-0.473, P<0.001). The summative magnitude of the indirect effect of GDP per capita on Corruption was large (effect size=0.406). GDP per capita, which had two paths to Internet diffusion (GDP per capita → NRI → Internet diffusion; GDP per capita → NRI → Mobile diffusion → Internet diffusion), showed a positive and significant indirect effect on Internet diffusion (sum of indirect effect=0.638, P<0.001). The summative magnitude of the indirect effect of GDP per capita on Internet diffusion was large (effect size=0.530). GDP per capita, which had one path to Mobile diffusion (GDP per capita → NRI → Mobile diffusion), showed a positive and significant indirect effect on Mobile diffusion (sum of indirect effect=0.515, P<0.001). The summative magnitude of the indirect effect of GDP per capita on Mobile diffusion was large (effect size=0.375).

The total effect of FDI, along with the number of paths, the effect size with respective P values and standard error are shown in Table 4-13. FDI showed a positive and significant total effect on Transparency (total effect=0.096, P<0.001). The magnitude of the total effect of FDI on Transparency was small (effect size=0.032). FDI showed a negative and significant total effect on Corruption (total effect=-0.113, P<0.001). The magnitude of the total effect of FDI on Corruption was small (effect size=0.055). FDI showed a positive and significant total effect on Internet diffusion (total effect=0.152, P<0.001). The magnitude of the total effect of FDI on Internet diffusion was small (effect size=0.075). FDI showed a positive and significant total effect on Mobile diffusion (total effect=0.123, P<0.001). The magnitude of the total effect of FDI on Mobile diffusion was small (effect size=0.048). FDI showed a positive and significant total effect on NRI (total effect=0.179, P<0.001). The magnitude of the total effect of FDI on NRI was small (effect size=0.104).

Table 4-13. Total effect of FDI.

	Paths N	Total Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Transparency	3	0.096	<0.001	0.032	small	0.017
Corruption	6	-0.113	<0.001	0.055	small	0.019
Internet Diffusion	2	0.152	<0.001	0.075	small	0.026
Mobile Diffusion	1	0.123	<0.001	0.048	small	0.021
NRI	1	0.179	<0.001	0.104	small	0.030

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

The total effect of GDP per capita, along with the number of paths, the effect size with respective P values, and standard error are shown in Table 4-14. GDP per capita showed a positive and significant total effect on Transparency (total effect=0.402, P<0.001). The magnitude of the total effect of GDP per capita on Transparency was medium (effect size=0.283). GDP per capita showed a negative and significant total effect on Corruption (total effect=-0.473, P<0.001). The magnitude of the total effect of GDP per capita on Corruption was large (effect size=0.406). GDP per capita showed a positive and significant total effect on Internet diffusion (total effect=0.638, P<0.001). The magnitude of the total effect of GDP per capita on Internet diffusion was large (effect size=0.530). GDP per capita showed a positive and significant total effect on Mobile diffusion (total effect=0.515, P<0.001). The magnitude of the total effect of GDP per capita on mobile diffusion was large (effect size=0.375). GDP per capita showed a positive and significant total effect on NRI (total effect=0.750, P<0.001). The magnitude of the total effect of GDP per capita on NRI was large (effect size=0.634).

Table 4-14. Total effect of GDP per capita.

	Paths N	Total Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Transparency	3	0.402	<0.001	0.283	medium	0.040
Corruption	6	-0.473	<0.001	0.406	large	0.029
Internet Diffusion	2	0.638	<0.001	0.530	large	0.024
Mobile Diffusion	1	0.515	<0.001	0.375	large	0.023
NRI	1	0.750	<0.001	0.634	large	0.025

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

The total effect of NRI, along with the number of paths, the effect size with respective P values and standard error are shown in Table 4-15. NRI showed a positive and significant total effect on Transparency (total effect=0.536, P<0.001). The magnitude of the total effect of NRI on Transparency was large (effect size=0.361). NRI showed a negative and significant total effect on Corruption (total effect=-0.631, P<0.001).

The magnitude of the total effect of NRI on Corruption was large (effect size=0.576). NRI showed a positive and significant total effect on Internet diffusion (total effect=0.851, P<0.001). The magnitude of the total effect of NRI on Internet diffusion was large (effect size=0.723). NRI showed a positive and significant total effect on Mobile diffusion (total effect=0.687, P<0.001). The magnitude of the total effect of NRI on Mobile diffusion was large (effect size=0.472).

Table 4-15. Total effect of NRI.

	Paths N	Total Effect	P- value	Effect Size Coefficient*	Effect Size*	Std. Err.
Transparency	3	0.536	<0.001	0.361	large	0.048
Corruption	6	-0.631	<0.001	0.576	large	0.033
Internet Diffusion	2	0.851	<0.001	0.723	large	0.010
Mobile Diffusion	1	0.687	<0.001	0.472	large	0.018

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

The total effect of Internet diffusion, along with the number of paths, the effect size with respective P values, and standard error are shown in Table 4-16. Internet diffusion showed a positive and significant total effect on Transparency (total effect=0.675, P<0.001). The magnitude of the total effect of Internet diffusion on transparency was large (effect size=0.481). Internet diffusion showed a negative and significant total effect on Corruption (total effect=-0.686, P<0.001). The magnitude of the total effect of Internet diffusion on Corruption was large (effect size=0.579).

Table 4-16. Total effect of Internet diffusion.

	Paths N	Total Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Transparency	1	0.675	<0.001	0.481	large	0.028
Corruption	2	-0.686	<0.001	0.579	large	0.042

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

The total effect of Mobile diffusion, along with the number of paths, the effect size with respective P values and standard error are shown in Table 4-17. Mobile diffusion showed a positive and significant total effect on Transparency (total effect=0.212, P<0.001). The magnitude of the total effect of Mobile diffusion on Transparency was small (effect size=0.109). Mobile diffusion showed a negative and significant total effect on Corruption (total effect=-0.341, P<0.001). The magnitude of the total effect of Mobile diffusion on Corruption was medium (effect size=0.197). Mobile diffusion showed a positive and significant total effect on Internet diffusion (total effect=0.396, P<0.001). The magnitude of the total effect of Mobile diffusion on Internet diffusion was medium (effect size=0.314).

Table 4-17. Total effect of Mobile diffusion.

	Paths N	Total Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Transparency	2	0.212	<0.001	0.109	small	0.064
Corruption	4	-0.341	<0.001	0.197	medium	0.044
Internet Diffusion	1	0.396	<0.001	0.314	medium	0.026

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

The total effect of transparency, along with the number of paths, the effect size with respective P values and standard error are shown in Table 4-18. Transparency showed a negative and significant total effect on corruption (total effect=-0.408, P<0.001). The magnitude of the total effect of transparency on corruption was medium (effect size=0.348).

Table 4-18. Total effect size of Transparency.

	Paths N	Total Effect	P-value	Effect Size Coefficient*	Effect Size*	Std. Err.
Corruption	1	-0.408	<0.001	0.348	medium	0.061

Note: * Effect size coefficients and effect size are reported. According to J. Cohen (1988), effect sizes can be small (0.02), medium (0.15), or large (0.35). Effect size coefficients below 0.02 are considered too small for relevancy (no rel.).

CHAPTER V

DISCUSSION

The purpose of this study was to investigate the effects of the hypothesized relationships of key macroeconomic, ICT and sociocultural variables on corruption and transparency. Specifically, this study explored the relationship between the ICT environment, diffusion of specific ICTs (e.g. Internet diffusion and mobile cellular diffusion), and the two macroeconomic variables of FDI and Gross Domestic Product (GDP) per capita and its potential effects on increasing transparency and reducing corruption. This chapter presents a discussion and interpretation of the statistical results and path analysis of these relationships. In the first section of this chapter, a brief overview of the study is provided. The second section provides a detailed discussion of each set of variables with their related effects.

5.1 Overview of the Study

This study tested the hypothesized relationships among the key macroeconomic, ICT, governance and sociocultural variables. These variables are listed in Table 3-3. The testing of these hypothesized relationships was statistically analyzed using path analysis with WarpPLS 3.0, a structural equation modeling software package. The path model representing these relationships is formalized as demonstrated in Figure 2.1. WarpPLS 3.0 was used to statistically analyze this path model because the software was specially designed to identify nonlinear relationships among variables. WarpPLS identifies such nonlinear relationships by conducting linear and non-linear (or "warped") regression analysis (Kock, 2012).

The data for the key variables in this study was drawn from several data sources such as the World Bank, the World Economic Forum, Transparency International and Hofstede Cultural

Dimension Data Matrix. The independent and mediating variables in the theoretical model are Foreign Direct Investment, Gross Domestic Product per capita, Networked Readiness Index, Internet diffusion, Mobile diffusion, and Transparency. The intervening or mediating variables in the theoretical model are Networked Readiness Index, Internet diffusion, Mobile diffusion, and Transparency. Finally, the main dependent variable in the theoretical model is Corruption. The national culture control variables used in this study were Hofstede Cultural Dimension indices of Power Distance, Individuality, Long-Term Orientation, and Uncertainty Avoidance.

A missing data analysis was performed prior to the statistical analysis. The independent, mediating, and dependent variables were within the 10% missing data threshold as suggested by Hair et al. (1987). However, several Hofstede Cultural Dimension indices exceed the missing data threshold. To address the missing data, this study utilized two missing data treatments: listwise deletion (LD) and a modified version of mean substitution called regional mean substitution (RMS) imputation which uses the calculated mean Hofstede Cultural Dimension scores of UN geoscheme regional groups. The LD treatment removed all data rows which contained missing data elements for all four Hofstede Cultural Dimension indices. This resulted in the removal of 145 rows (23.967% of the dataset) using the LD treatment. Using the RMS imputation treatment, all independent and dependent variables were within a 10% missing data threshold.

The data with each missing data treatment was analyzed for multicollinearity. One possible indicator of multicollinearity is a high Pearson correlation coefficient (r) between two or more variables (Tabachnick & Fidell, 1996). High correlation coefficients among variables in the model may signify multicollinearity (Kock, 2012). A general “rule of thumb” (Farrar & Glauber, 1967, p. 82) indicating possible multicollinearity is correlation coefficients where $r \geq 0.8$. Using WarpPLS

3.0, a correlation matrix was generated with the data using both missing data treatments as part of its analysis (Kock, 2012).

The correlation matrices with corresponding coefficients and associated p-values for data using each missing data treatment are presented in Table 3-10 and Table 3-11. Analysis of the correlation matrixes using both missing data treatments showed correlation coefficients among variables greater than $r = 0.800$. Based on the RMS missing data treatment, NRI and corruption had a correlation coefficient of $r = -0.888$ with a significance level of $p <.001$. NRI and Internet diffusion had a correlation coefficient of $r = 0.849$ with a significance level of $p <.001$. GDP per capita and Internet diffusion had a correlation coefficient of $r = 0.828$ with a significance level of $p <.001$. Also, GDP per capita and NRI had a correlation coefficient of $r = 0.829$ with a significance level of $p <.001$. Using the LD missing data treatment, NRI and corruption had a correlation coefficient of $r = -0.907$ with a significance level of $p <.001$. NRI and Internet diffusion had a correlation coefficient of $r = 0.857$ with a significance level of $p <.001$.

The presence of a high correlation coefficient between two or more variables is a possible indicator of multicollinearity. While high correlation coefficients do not conclusively signify multicollinearity, such high correlation coefficients are generally conflated with collinearity (Douglass et al., 2003 & Michaels, 2003; Graham, 2003). Therefore, additional tests for multicollinearity were performed.

A full collinearity test was performed on the data using each missing data treatment that calculated the VIF values of each variable. Table 3-12 presents the VIF values for each variable in the data using both missing data treatments. Using the more relaxed threshold of a VIF=10 as suggested by Hair et al. (1987) and O'Brien (2007), the VIF values for data using both missing data treatments did not exhibit serious bias due to multicollinearity problems. Additionally, block VIF values which measure the degree of vertical collinearity were calculated for each variable using each missing data treatment. Table 3-13 presents the block VIF values for each variable block with data using the RMS missing data treatment. Table 3-14 presents the block VIF values for each variable block with data using the LD missing data treatment. In the multivariate analysis literature, a conservative recommended threshold for VIF values when analyzing models without latent variables is VIF=5 as suggested by Hair et al. (1987). Using this recommended threshold of VIF=5, the VIF values for the data using both missing data treatments suggest that no vertical multicollinearity exist.

The descriptive statistics for the data using each missing data treatment were calculated using Microsoft Excel 2010. The study's theoretical model was analyzed using path model analysis with WarpPLS 3.0. The study's theoretical model was analyzed using WarpPLS's Warp2 algorithm which looks for non-linear relationships among variables. The data using both missing data treatments and two different resampling techniques (e.g. bootstrapping and jackknifing) was analyzed yielding four sets of results of the path model. The data with the RMS missing data treatment and bootstrapping resampling technique demonstrated the higher number of significant paths with stronger associated P values, indicating a higher overall predictive and explanatory quality of this particular model. The results of this model and data were used to test the hypotheses of the study. The results of the hypotheses testing are outlined in Table 4.6.

The results of the data analysis were presented in Chapter IV. In this chapter, the interpretation of the results will be provided.

5.2 Overview of Findings

The goal of this study was to investigate the relationships between the ICT environment, diffusion of two specific ICTs, and the two macroeconomic variables of FDI and Gross Domestic Product (GDP) per capita and their potential effects on increasing transparency and reducing corruption. The five main independent variables, namely Foreign Direct Investment, Gross Domestic Product per capita, Networked Readiness Index, Internet diffusion, Mobile diffusion, as well as the intervening variable of Transparency explained 80.8% (R^2= 0.808) the variance in the governance variable of Corruption. Furthermore, the five main independent variables explained 49.7% (R^2= 0.497) of the variance in the governance variable of Transparency.

5.2.1 Macroeconomic Variable Findings

One of the primary focuses of this study was to explore how the macroeconomic independent variables affected transparency and corruption. Indeed, this study did find that FDI had a significant effect on corruption and transparency. The macroeconomic variable of FDI did increase transparency and reduce corruption. For each increase of $26,795.79 (1 SD) in FDI, there was an evident increase in transparency by 1.688% (0.096 SD) and a decrease in corruption by 2.510% (-0.113 SD). This finding is congruent with similar findings from other studies. Larraín and Tavares (2004) found that FDI, as a share of GDP, is significantly associated with lower corruption levels. However, in this study, the effect sizes of FDI on these variables were relatively small. FDI accounted for the variance in transparency of only 3.2% (f^2 = 0.032) and 5.5% (f^2 = 0.055) in corruption.

The small effect of FDI on corruption and transparency may be attributed to the unique relationship between FDI and corruption. Most studies have investigated how levels of corruption affect inward FDI flows (Addison & Heshmati, 2004; Cuervo-Cazurra, 2008; Habib & Zurawicki, 2002; Wei, 2000). Generally, these studies have demonstrated that the higher levels of corruption reduce FDI inflows. Also, these studies have given this corruption-to-FDI relationship some degree of specificity. In these studies, the effect of FDI on corruption has been found to be moderated or mediated by such country factors such as resource richness (Kolstad & Wiig, 2009), concentration of bureaucratic power (Gyimah-Brempong, 2002), democratization and ICT (Addison & Heshmati, 2004), and the difference between host and source countries (Habib & Zurawicki, 2002).

On the contrary, the effect of FDI on corruption is often less studied. However, Larraín and Tavares (2004) and Pinto and Zhu (2008) studied this particular relationship. Larraín and Tavares (2004) found that FDI is associated with lower corruption levels. Their findings are harmonious with the results of this study: increases in FDI leads to decreases in corruption. However, Pinto and Zhu (2008) found that this relationship is not so straightforward. Pinto and Zhu (2008) found that FDI actually contributed to corruption in authoritarian and poor countries. However, FDI reduces corruption as countries become more democratic. Furthermore, FDI inflows had a negligible effect on more developed economies. The small effect on corruption by FDI may be attributed to the differentiated effects found by Pinto and Zhu (2008).

GDP per capita had a large effect on levels of transparency and corruption. This study found that the macroeconomic variable of GDP per capita increased transparency and reduced corruption. For each increase of $19,686.27 (1 SD) of GDP per capita, there was an elevation in transparency by 7.068% (0.402 SD) and a decrease in corruption by 10.507% (-0.473 SD). The effect sizes of GDP per capita on corruption and transparency variables were relatively large. GDP per capita accounted for the variance in transparency of 28.3% (f^2 = 0.283) and 40.6% (f^2 = 0.406) in corruption. These findings correspond with other studies investigating the relationship between

GDP per capita and corruption. Arvas and Ata (2011) found that increases in GDP per capita are significantly associated with lower levels of corruption. Paldam (2004) also found that as countries transfer from poor to rich economies, in terms of increase in GDP per capita, significant reductions in corruption are produced. These findings add confirming evidence to the suggestions by Vinod (1999) that corruption can be reduced by increasing per capita income.

This study also found that FDI and GDP per capita had a significant and positive effect on NRI. This finding is consistent with previous research which demonstrates that macroeconomic variables such as FDI and GDP per capita have a significant impact on ICT investment and capacity (Gholami et al., 2006; Kshetri & Cheung, 2002; OECD, 1991; Suh & Khan, 2003). FDI has been shown to present host countries with access to newer technology (OECD, 1991) and has increased domestic investment in ICT (Agrawal, 2003). Additionally, Gholami et al. (2006) found that increases in FDI lead to growth in ICT investment and capacity.

In this study, it is demonstrated that each FDI increase of $26,795.79 (1 SD) accounts for an increase in the NRI by 2.510% (0.151 SD). However, FDI has a small yet significant effect (f^2 = .104 or 10.4%) on explaining the variance of NRI. Similarly, FDI had small but statistically significant effects on Internet diffusion and mobile diffusion. This study found that each FDI increase of $26,795.79 (1 SD) accounts for an increase in Internet diffusion of 4.160 people per 100 persons (0.152 SD) and an increase in mobile diffusion of 5.038 people per 100 persons (0.123 SD). The effect of FDI on the explained variance of Internet diffusion was 7.5% (f^2 = 0.075). Also, FDI has explained a small amount of the variance (f^2= 0.048 or 4.8%) of Mobile diffusion. This finding is somewhat at odds with Kshetri and Cheung (2002) who showed that rapid mobile cellular phone diffusion in China was due, in part, to large FDI inflows.

FDI has been considered as an influential factor in corruption and ICT infrastructure. However, income inequality, usually measured in GDP per capita, has been put forth as important factor as well (Dasgupta et al., 2001; Erumban & de Jong, 2006). Interestingly, this study showed that GDP per capita, rather than FDI, has larger effects. In this study, it is demonstrated that each GDP per capita increase of $19,686.25 (1 SD) accounts for an increase in the NRI by 10.518% (0.750 SD). Also, GDP per capita has a large and significant effect (f^2 = 0.634 or 63.4%) on explaining the variance of NRI. Similarly, GDP per capita had a large and statistically significant effect on Internet diffusion and mobile diffusion. This study found that each GDP per capita increase of $19,686.25 (1 SD) accounts for an increase in Internet diffusion of 17.463 people per 100 persons (0.638 SD) and an increase in mobile diffusion of 21.095 people per 100 persons (0.515 SD). Furthermore, the effect of GDP per capita on the explained variance of Internet diffusion was 53.0% (f^2 = 0.530). Likewise, GDP per capita had a large effect on the explained variance (f^2 = 0.375 or 37.5%) of mobile diffusion. These findings add confirming evidence to the research by Dewan et al. (2005) and Gholami et al. (2006) which demonstrated that GDP per capita and FDI have a positive effect on NRI.

The findings in this study are consistent with existing research on the effects of GDP on ICT variables. Rasiah (2006) found that growth in GDP precedes growth in ICT. GDP per capita, considered a surrogate for the standard of living in a country (Easterlin, 2000; Ringen, 1991), increases as overall GDP rises. Dewan et al. (2005) found that GDP per capita had a positive effect on ICT diffusion. As the standard of living rises via increases in income, a large portion of disposable income becomes available. This disposable income can be used to acquire access to ICTs. Moreover, Billon, Marco, and Lera-Lopez (2009) found that, in developing countries, Internet costs have a negative impact on ICT adoption. According to ITU (2011), prices for broadband Internet access dropped, on average, by 18% from 2008 to 2010. Also, prices for mobile cellular services decreased by 22% during the same time period. The most significant price decreases occurred in African nations where prices for broadband access fell by over 55% and mobile cellular prices decreased by over 25%. It is quite likely that increases in per capita income also provide governments with more tax revenues to invest in ICT infrastructure. Singh, Das, and Joseph (2007), using a model where GDP and e-governance maturity was mediated by ICT infrastructure and other factors, found that GDP strongly influenced e-governance maturity and readiness through ICT infrastructure. Also, Billon et al. (2009) found that GDP was one of the major explanatory factors in countries with higher levels of ICT adoption.

5.2.2 ICT Variable Findings

This study investigated how three ICT variables affected transparency and corruption. The three variables included NRI, Internet diffusion, and mobile cellular diffusion. Indeed, this study did find that NRI had a significant effect on corruption and transparency. The ICT variable of NRI did increase transparency and reduce corruption. For each increase of 0.841 (1 SD) in NRI, there was a demonstrated increase in transparency by 9.423% (0.536 SD) and a decrease in corruption by 14.017% (-0.631 SD). Furthermore, the effect of NRI on the explained variance of transparency was 36.1% (f^2 = 0.361). Likewise, NRI had a large effect on the explained variance (f^2 = 0.576 or 57.6%) of corruption. This finding is congruent with similar findings from other studies. Opoku-Mensah (2000) found that ICTs such as Internet access improved access to information, thereby increasing transparency. Soper (2007) also found that ICT investments facilitate future levels of increased democracy and reduce corruption. Similarly, Charoensukmongkol and Moqbel (2012) found that increased ICT investment reduces corruption, and Sturges (2004) revealed that access to ICT promotes greater governmental transparency by removing information barriers and asymmetry.

NRI also had large positive effects on Internet and mobile diffusion. For each increase of 0.841 (1 SD) in NRI, there was an increase on Internet diffusion of 23.296 people per 100 persons (0.851 SD). This effect of NRI on Internet diffusion was large (f^2 = 0.723 or 72.3%). For each increase of 0.841 (1 SD) in NRI, there was an increase in mobile cellular diffusion of 24.141 people per 100 persons (0.687 SD). The effect of NRI on mobile cellular diffusion was large (f^2 = 0.472 or 47.2%). These findings are similar to other studies investigating ICT environment and ICT diffusion. Jakopin and Klein (2011) established that two components of the NRI, regulatory quality and market environment, significantly benefit Internet diffusion.

The ICT variable of Internet diffusion had a large and significant effect on transparency and corruption. For each increase of 27.372 per 100 persons on Internet diffusion (1 SD), there was a demonstrated increase in transparency by 11.867% (0.675 SD). Furthermore, the effect of Internet diffusion on the explained variance of transparency was 48.1% (f^2 = 0.481). Also, for each increase of 27.372 people per 100 person on Internet diffusion (1 SD), there was a marked reduction in corruption by 15.239% (-0.686 SD). Likewise, Internet diffusion had a large effect on the explained variance (f^2 = 0.579 or 57.9%) of corruption. The results of this study mirror the findings of similar studies on Internet access and transparency. García-Murillo (2010) found that several developed countries have moved toward greater transparency by publishing information on the Internet concerning governmental issues. Similarly, S. M. Johnson (1998) and Cuillier and Piotrowski (2009) showed that the Internet expands public access to government information.

Interestingly, mobile cellular diffusion had a weaker effect on transparency and corruption. For each increase of 40.961 people per 100 persons in mobile cellular diffusion (1 SD), there was a marginal increase in transparency by 3.727 % (0.212 SD). Furthermore, the effect of mobile cellular diffusion on the explained variance of transparency diffusion was 10.9% (f^2 = 0.109). Also, for each increase of 40.961 people per 100 person in mobile cellular diffusion (1 SD), there was a notable reduction in corruption by 7.575% (-0.341 SD). Likewise, mobile cellular diffusion had a medium effect on the explained variance (f^2 = 0.197 or 19.7%) of corruption. Additionally, for each increase of 40.961 people per 100 persons in mobile cellular diffusion (1 SD), there was a marginal increase on Internet diffusion by 10.839 people per 100 persons (0.396 SD). Furthermore, the effect of mobile cellular diffusion on the explained variance of Internet diffusion was 31.4% (f^2 = 0.314). These results seem to point to the fact that mobile cellular access has a greater impact on the diffusion of Internet access. Indeed, according to Kenichi (2004), mobile cellular phone diffusion leads to increased diffusion of Internet access.

However, it is important to note that for each increase of 40 people having mobile cellular subscriptions, there are only 10 additional people acquiring Internet access. Baliamoune-Lutz (2003) suggested that differences between communication technology (e.g. mobile phones) and information technology (e.g. the Internet) have become blurred. Many mobile cellular consumers can now access data and information via mobile phones (H.-W. Kim et al., 2007). For instance, in Japan, approximately 40% of the population accesses the Internet via mobile phones (Kenichi, 2004). However, this dissertation did not find strong evidence to support the convergence of these two ICTs. In fact, this dissertation shows that the two ICTs are distinctly different in their effects on transparency and corruption.

5.2.3 Control Variable Findings

Given the potential influences of national cultural differences, four dimensions of the Hofstede Cultural Dimensions framework were used as national culture control variables. Only Hofstede’s power distance index and uncertainty avoidance index demonstrated any significant effect on corruption. For each 18.094 point increase in power distance (1 SD), there was a small increase in corruption by 1.444% (0.065 SD). Furthermore, the effect of power distance on the explained variance of corruption was 4.5% ($f^2 = 0.045$). Additionally, for each 20.829 point increase in uncertainty avoidance (1 SD), there was a small increase in corruption by 1.888% (0.085 SD). Similarly, the effect of uncertainty avoidance on the explained variance of corruption was 2.4% ($f^2 = 0.024$).

The effects of these two Hofstede Cultural Dimension indices are very small compared to the effects of other variables within the study's theoretical model. These effects may be explained through their relationships with corruption and other ICT variables within the model. Some studies have found that Hofstede Cultural Dimensions of uncertainty avoidance and masculinity are associated with higher levels of corruption (Husted, 1999; Kimbro, 2002; Robertson & Watson, 2004). Similarly, Getz and Volkema (2001) showed that power distance and uncertainty avoidance were positively associated with corruption. Also, other studies have demonstrated how these two Hofstede Cultural Dimension indices affect ICT usage and adoption. For example, Erumban and de Jong (2006) showed that power distance and uncertainty avoidance influence ICT adoption. Likewise, Straub et al. (1997) suggested that power distance and uncertainty avoidance accounts for differences in e-mail usage. Lastly, de Mooij and Hofstede (2002) stated that uncertainty avoidance affects such ICT variables as embracement of the Internet and the ownership of computers and mobile cellular phones. The effect of these two Hofstede Cultural Dimension indices on corruption may be a result of their effect on the ICT variables within the model. The year was also used as a control variable in order to control for potential multiple year effects. However, the year variable did not prove statistically significant ($\beta=0.081$, $P=0.190$) in the data analysis, indicating that no multiple year effects were found in this study.

5.2.4 Transparency's effect on Corruption

One focus of this study was to augment the existing body of research on how transparency affects levels of corruption. Indeed, this study did find that transparency had a significant negative effect on corruption. For each increase of 0.879 (1 SD) in transparency, there was a demonstrated decrease in corruption by 9.063% (-0.408 SD). Furthermore, the effect of transparency on the explained variance of corruption was 34.8% (f^2 = 0.348). This finding was expected and consistent with similar findings from other studies. Initiatives that increase transparency have been shown to be an effective anti-corruption tool (Bertot et al., 2010). Similarly, Brunetti and Weder (2003) found a strong association between transparency through greater press freedom and reduced corruption. Conversely, a lack of transparency tends to exacerbate corruption-related problems (Kolstad & Wiig, 2009).

CHAPTER VI

CONCLUSION

The focus of this study was to investigate how ICTs affect levels of transparency and corruption. This study significantly adds to the existing body of research by confirming the effects of ICTs on improving transparency and governance (Avgerou, 1998; Krueger, 2002; Opoku-Mensah, 2000; Soper, 2007). Additionally, this study explores the interrelated effects of ICT, macroeconomic, and national sociocultural variables on transparency and corruption. Specifically, this study increases the existing body of research on corruption by providing confirmatory evidence of how corruption and transparency are affected by three ICT variables: NRI, Internet diffusion, and mobile cellular diffusion. In the first section of this chapter, a summary of the study's key findings is provided. The second section provides a brief discussion of the study's limitations. The third section of this chapter outlines theoretical and practical implications with directions for further research. The fourth section provides a summary of this chapter.

6.1 Summary

Indeed, this study found that the degree to which a country is positioned to use its ICT infrastructure for international competitiveness, as measured through the Networked Readiness Index (NRI) published in the Global Information Technology Report by the World Economic Forum, has a strong effect on the levels of corruption and transparency. A 0.841 increase in the NRI resulted in a decrease in corruption by 14.017%. Also, an increase in NRI by 0.841 resulted in an increase in transparency by 9.423%. These findings reinforce what other scholars have found concerning the positive effect of ICT infrastructure in reducing corruption and increasing transparency (Charoensukmongkol & Moqbel, 2012; Soper, 2007; Soper & Demirkan, 2012). ICTs have been shown to be a tool in democratization (Opoku-Mensah, 2000; Soper, 2007) and a device that facilities and improves political involvement (Krueger, 2002, 2006; Norris, 2001), thereby increasing transparency.

Not surprisingly, the NRI also had a large positive effect on Internet and mobile diffusion. Each increase in the NRI by 0.841 resulted in an increase of Internet diffusion of 23.296 people per 100 persons. Similarly, each increase in the NRI by 0.841 resulted in an increase of mobile cellular diffusion by 24.141 people per 100 persons. Kshetri and Cheung (2002) found that two components of the NRI, market openness and government initiatives, stimulated the diffusion of mobile communications in China. In this study, the NRI had large exploratory power on levels of Internet diffusion (f^2 = 0.723 or 72.3%) and mobile diffusion (f^2 = 0.472 or 47.2%). Jakopin and Klein (2011) found that two components of the NRI, regulatory quality and market environment, significantly benefit Internet diffusion. Improvements in infrastructure intensify market competition and reduce costs of goods and services (Aghion & Schankerman, 1999) such as Internet access and mobile cellular services.

Interestingly, the rate of mobile phone diffusion diminishes as units of NRI increased as shown in Figure 4.8. In the data analysis, the rate of mobile cellular diffusion plateaued and eventually began to decrease as levels of NRI increased. This behavior of mobile cellular diffusion suggests a saturation point. This mobile cellular diffusion saturation point occurs between 1.5 and 2 standard deviations above the mean of NRI. Such a saturation point suggests that countries with a higher level of NRI have barriers that prevent higher rates of mobile cellular diffusion. These barriers are most likely to be technological and market-driven. Gruber and Verboven (2001) found that spectrum capacity had a major impact on diffusion of mobile cellular communication. Additionally, Boretos (2007) found that, apart from the very young or very old, almost every European was using a mobile phone. Europe has reached an apparent saturation peak despite being one of the early adopters of mobile communication technology and leaders in active mobile accounts (Boretos, 2007).

The NRI is a composite index of three component indexes: environment, readiness, and usage. Given the amalgamated nature of such an index, it is important to examine particular elements within the index's components. In any discussion that investigates the effects of ICT infrastructure, it is important to explore how particular technologies within the ICT domain moderate or mediate such relationships. This study explored two particular ICTs: Internet diffusion and Mobile diffusion.

Internet diffusion, as measured through the *Internet users (per 100 people)* indicator from the World Bank World Development Indicators, had a significant effect on transparency and corruption. Internet diffusion had a strong positive effect on levels of transparency. By increasing Internet diffusion by 27.372 per 100 persons, there was an increase in transparency by 17.581%. In this study, Internet diffusion had large exploratory power (48.1%) on levels of transparency. Furthermore, Internet diffusion had a strong negative effect on levels of corruption. By increasing Internet diffusion by 27.372 people per 100 persons, corruption was reduced by 15.239%. Additionally, Internet diffusion had large exploratory power (57.9%) on levels of corruption. These results confirm what other scholars have found on the effects of Internet access on transparency and corruption (Cuillier & Piotrowski, 2009; García-Murillo, 2010; S. M. Johnson, 1998; Sturges, 2004).

Unexpectedly, mobile cellular diffusion, as measured through the *Mobile cellular subscriptions (per 100 people)* indicator of the World Bank World Development indicators, had much weaker effects on transparency and corruption. Increasing mobile cellular diffusion by 40.961

people per 100 persons resulted in a negligible increase in transparency by 3.727%. Likewise, increasing mobile cellular diffusion by 40.961 people per 100 persons resulted in a reduction in corruption by 7.575%. It is possible that such minor effects on transparency and corruption are related to the nature of mobile cellular use. Kenichi (2004) found that mobile Internet usage was a more time-enhancing activity (e.g. access augmented some other activity). In other words, mobile Internet usage was not primarily for information seeking. Rather, it was for entertainment. Such a postulation would explain the marginal effect of mobile cellular diffusion on transparency. Although mobile cellular diffusion has a negligible positive effect on transparency, mobile cellular diffusion has a moderate negative effect on corruption. This negative effect may be the result of mobile cellular diffusion, including mobile Internet usage on other devices such as computers, laptops, and tablets.

This study found that for each increase of 40.961 people per 100 persons in mobile cellular diffusion, there was a moderate increase in Internet diffusion of 10.839 people per 100 persons. Additionally, mobile cellular diffusion explained the level of Internet diffusion by 31.4%. This study found results similar to Beilock and Dimitrova (2003) in which openness of infrastructure—namely, densities of mobile telephones and personal computers— proved to be an important determinant of Internet usage. Many mobile cellular customers access data and information via mobile cellular technologies such as phones and cellular data cards (H.-W. Kim et al., 2007). In Japan, for instance, approximately two-fifths of the population accesses the Internet via mobile cellular technology (Kenichi, 2004). As seen in this study's results, increased access to the Internet leads to significant decreases in corruption. It is possible that the effects of mobile cellular diffusion on transparency and corruption are mediated through Internet diffusion. However, the results in this study do not conclusively demonstrate this. In this study, the effect of mobile cellular diffusion on transparency, when meditated through Internet diffusion, was slightly greater (β = 0.268, f^2=0.109) than the direct effect of mobile cellular diffusion on transparency (β = 0.212, f^2=0.138). On the contrary, the effect of mobile cellular diffusion on corruption, when meditated through Internet diffusion, was much lower (β = -0.140, f^2=0.081) than the direct effect of mobile cellular diffusion on corruption (β = -0.341, f^2=0.197).

As shown in the descriptive statistics in Table 4.3, diffusion of mobile cellular phone subscriptions has dramatically increased. Geiger and Mia (2009) detailed that, based on ITU data, mobile communications have boomed in developing countries. The data in this study mirrors the finding of Geiger and Mia (2009); mobile cellular diffusion greatly surpassed Internet diffusion. The diffusion of mobile cellular coupled with such things as mobile commerce (m-commerce) has become an important modality for receiving information (Geiger & Mia, 2009). Mobile communication has facilitated access to the Internet in developed and developing countries as well (Kenichi, 2004).

Several macroeconomic factors influence ICT infrastructure and diffusion (Gholami et al., 2006; Kshetri & Cheung, 2002; OECD, 1991; Suh & Khan, 2003). This study also examined how FDI and GDP per capita affected ICT infrastructure and diffusion. The results of this study showed that FDI has a marginal positive effect on ICT infrastructure. For example, increasing FDI by $26,795.79 only accounted for an increase in the NRI by 2.510%. Similarly, this study found that each FDI increase of $26,795.79 only accounted for marginal increases in Internet diffusion (4.160 people per 100 persons) and mobile diffusion (5.038 people per 100 persons). FDI has been shown to present host countries with access to newer technology (OECD, 1991). In addition, Gholami et al. (2006) found that increases in FDI lead to growth in ICT investment and capacity. As demonstrated by Agrawal (2003), increased foreign investment fosters domestic investment which translates to improvements in physical infrastructure and the political and business environment promoting ICT growth. However, this study did not demonstrate that the availability of newer technologies or the increase in ICT capacities through FDI inflows equate to the utilization or diffusion of such technologies.

Another important finding in this study is that GDP per capita demonstrates a larger effect on ICT infrastructure and diffusion. For example, each GDP per capita increase of $19,686.25 accounted for an increase in the NRI by 10.518%, Internet diffusion of 17.463 people per 100 persons, and an increase in mobile diffusion of 21.095 people per 100 persons. Furthermore, GDP per capita had large exploratory power on the NRI (63.4%). Similarly, GDP per capita had large exploratory power on Internet diffusion (53.0%) and mobile diffusion (37.5%). These results confirm findings by Dewan et al. (2005) and Gholami et al. (2006) which demonstrated that GDP per capita have a positive effect on ICT infrastructure and diffusion. Similarly, Billon et al. (2009) showed that GDP was a major explanatory factor in countries with higher levels of ICT adoption. Additionally, Norris (2001) stated that economic development increases civil engagement and stimulates diffusion of technologies, including the Internet.

Income inequality may be a possible cause for the strong effect of GDP per capita on ICT infrastructure and diffusion. In developing countries, Internet costs negatively impact ICT adoption (Billon et al., 2009). GDP per capita is considered a surrogate for the standard of living and economic output in a country (Easterlin, 2000; Ringen, 1991). As the standard of living rises, a greater proportion of income becomes available to acquire access to ICTs. This growth in GDP, and hence GDP per capita, precedes growth in ICT infrastructure and diffusion (Rasiah, 2006; Ringen, 1991). Furthermore, prices for broadband Internet access and mobile cellular services have dropped. According to ITU (2011), Internet access prices have dropped by 18%, on average, from 2008 to

2010. During this same time period, prices for mobile cellular services decreased by 22%. In African nations, where the most significant price decreases occurred, broadband access fell by over 55% and mobile cellular prices decreased by over 25%. Additionally, this increase in per capita income may provide more tax revenues to governments to invest in ICT infrastructure. For governments, GDP strongly influenced e-governance maturity and readiness through ICT infrastructure (Singh et al., 2007).

It has been suggested by Baliamoune-Lutz (2003) that differences between communication technology (e.g. mobile cellular phones) and information technology (e.g. the Internet) have become blurred. However, this study did not find strong evidence to support the convergence of these two ICTs in terms of their effects on transparency and corruption.

Some scholars have explored how potential influences of national cultural differences influence ICT adoption (de Mooij & Hofstede, 2002; Erumban & de Jong, 2006; Straub et al., 1997). This study found that power distance and uncertainty avoidance had a negligible effect on corruption. In this study, power distance had a marginal positive effect on corruption. Corruption increased by 1.444% for each 18.094 point increase in power distance. This finding is consistent with Getz and Volkema (2001) who showed that power distance and uncertainty avoidance were positively associated with corruption. However, in this study, power distance had a negligible explanatory power on corruption (f^2 = 0.045 or 4.5%). Similarly, uncertainty avoidance had a marginal positive effect on corruption. Corruption increased by 1.888% for each 20.829 point increase in uncertainty avoidance. Likewise, other studies have found that greater levels of uncertainty avoidance are positively associated with higher levels of corruption (Husted, 1999; Kimbro, 2002; Robertson & Watson, 2004). However, in this study, uncertainty avoidance had a negligible explanatory power on corruption (f^2 = 0.024 or 2.4%).

The effects of these two Hofstede Cultural Dimension indices on corruption may be a result of their effects on the ICT variables within the model. Other studies have demonstrated that national cultural differences have effects on ICT usage and adoption. Erumban and de Jong (2006) showed that power distance and uncertainty avoidance influence ICT adoption. Similarly, Straub et al. (1997) put forward that power distance and uncertainty avoidance accounts for differences in e-mail usage. Additionally, de Mooij and Hofstede (2002) identified that uncertainty avoidance was related to such things as embracement of the Internet and the ownership of computers and mobile cellular phones.

A secondary focus of this study was to add to the existing literature on how transparency affects levels of corruption. This study did find that transparency had a significant negative effect on corruption. Increasing transparency by 0.879 reduces corruption by 9.063%. Furthermore, the effect of transparency has moderate explanatory power on corruption (f^2 = 0.348 or 34.8%). Such a finding was expected and consistent with similar findings from other studies. Transparency makes it more difficult to hide corrupt practices (Akpan-Obong, Alozie, & Foster, 2010; Bertot et al., 2010; Cho & Choi, 2005; Kolstad & Wiig, 2009). Transparency initiatives have been shown to be an effective anti-corruption instrument (Bertot et al., 2010). Also, there is a strong association between transparency through greater press freedom and lower levels of corruption (Brunetti & Weder, 2003). On the contrary, a lack of transparency has been shown to intensify corruption-related problems (Kolstad & Wiig, 2009).

6.2 Limitations

This study examined the effects of macroeconomic and ICT variables on corruption and transparency. However, there are more avenues of research on this topic. This study did not separate the countries into distant clusters by geographic region, languages, Hofstede Cultural Dimension rankings, or other sociocultural variables such as levels of literacy or poverty. Such factors, in addition to ICT infrastructure and diffusion, could have an effect on transparency and corruption. Vinod (1999) found that schooling and income inequality are more relevant in fighting corruption rather than Internet use. Corruption is not merely a factor of available information. However, the finding of Vinod (1999) did not diminish other studies which found that access to information via the Internet was effective in reducing corruption (DiRienzo, Das, Cort, & Burbridge, 2007; García-Murillo, 2010). It does suggest, however, that the Internet and similar information technologies provide some intervening effect on corruption (Schroth & Sharma, 2003). It is possible that the reduction of corruption requires more fundamental changes in other aspects of a society coupled with improvements in ICT infrastructure and diffusion.

In this study, extra statistical and explanatory power may have been achieved by examining additional years of the Networked Readiness Index; however between 2004 and 2005, the method for calculating the NRI changed significantly. Additionally, other ICT indicators could have been added for robustness such as number of radios, televisions, or personal computers per inhabitants. Since this study focuses on Internet and mobile cellular diffusion indicators, it was decided not to use other such indicators. In future research on this topic, the use of other such indicators may increase additional understanding of the relationships between ICT variables, transparency and corruption.

6.3 Implications and Future Research

The results of this study lead to several practical implications. As stated by Vinod (1999), the Internet's potential for increasing transparency and reducing corruption is "promising and obviously vast" (p. 10). Similarly, Soper (2007) found that ICT diffusion, which includes Internet access, is negatively related to levels of corruption. This study has shown that ICT infrastructure and diffusion of Internet access does reduce corruption and increase transparency. Government officials and citizens wishing for more transparency in their governance should campaign for development in their country's ICT infrastructure with a focus on providing access to information via the Internet.

Vinod (1999) put forth that the top five actions in reducing corruption, in order of importance, are as follows: 1) reducing bureaucratic overhead (e.g. red tape), 2) increasing judiciary efficiency, 3) increasing GNP per capita, 4), increasing education and economic freedoms, and 5) reducing inequalities in income. Government officials can use ICTs in the following ways to achieve some of the actions suggested by Vinod (1999) to promote increases in transparency and reductions in corruption.

First, the diffusion of ICTs can reduce bureaucratic overhead through such initiatives as e-governance (Bertot et al., 2010). Specifically, the Internet expands public access to government information (Cuillier & Piotrowski, 2009; S. M. Johnson, 1998). Secondly, reduced judiciary efficiency impacts economic growth and infrastructure development by adding additional costs to private transaction disputes (Buscaglia & Ulen, 1997). One way ICTs can improve judiciary efficiency is by modernizing (e.g. computerizing) the court case system, thereby giving litigants better access to the status of their cases (Buscaglia & Ulen, 1997). Diffusion of ICTs coupled with computerization of the judicial system can also assist attorneys and other legal representatives in accessing case law and legal opinions of the courts (Shuldberg, 1997).

Diffusion of ICTs may have some effect on increasing GNP per capita. ICTs have been found to be a contributing factor in economic growth (Avgerou, 1998). For example, mobile phone diffusion has been shown to have a positive effect on economic growth and poverty reduction (Geiger & Mia, 2009). ICTs can not only reduce poverty, but they can also meditate the effects of poverty by reducing information asymmetry (Sturges, 2004) and improve the quality of life (Forestier et al., 2002) of the poor. The diffusion of ICTs can also increase education and economic freedoms by informing citizens of relevant information on government and society. ICTs facilitate and improve political involvement (Krueger, 2002, 2006; Norris, 2001), and they foster civil and political freedoms (Baliamoune-Lutz, 2003). Access to ICTs allows citizens to become lifelong learners who can acquire new skills to meet the demands of changing economic markets (Noe & Peacock, 2002).

Additionally, Kiiski and Pohjola (2002) found that, in OECD countries, GDP per capita and Internet access cost explained most of the growth in computer hosts per capita. Beilock and Dimitrova (2003) also found that Internet usage rates were significantly determined by per capita income. Future studies should explain GDP per capita as an independent variable effecting the NRI and Internet and mobile diffusion.

In this study, mobile cellular diffusion did find a negligible negative effect on corruption and a moderate positive effect on transparency. However, Akpan-Obong et al. (2010) and Bailard (2009) found that mobile communication technologies significantly accounted for political development in Africa. Future research should use geographical region as a control variable.

6.4 Conclusion

The findings presented in this study are mostly consistent with those of other scholars on the effects of ICTs on improving transparency and governance. (Avgerou, 1998; Krueger, 2002; Opoku-Mensah, 2000; Soper, 2007). There is no doubt that corruption and transparency need to be addressed worldwide. As countries and their citizens rapidly adopt ICTs, there is hope that corruption will be exposed and eradicated through the increased transparency brought about by access to information. Increased transparency offers the promise of participatory governance, and technology is one avenue in fulfilling this promise. The results of this study should be taken as a positive message that ICT diffusion and adoption can decrease corruption and increase transparency as citizens have access to more information via the Internet.

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