Managing E-Government Development for Reducing Corruption via Effective Policymaking: Empirical Evidences from Cross-Country Analyses

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***Abstract*—Internationally E-Government (E-GOV) has been broadly demonstrated as an anti-corruption instrument in extant research, based on the extensive analyses of E-GOV Development Index (EGDI) against Corruption Perceptions Index (CPI). EGDI's effectiveness in combating corruption ideally involves country-specific appropriate policy-driven development along its three constituent components: Human Capital Index (HCI), Telecommunications Infrastructure Index (TII), and Online Services Index (OSI). However, we argue that, while considering EGDI's impact on lowering corruption, existing studies do not consider the heterogeneity among the countries in terms of their EGDI maturity levels. Also, past research does not delve into the analysis of the relative contribution of EGDI components in controlling CPI, which may very well vary with EGDI maturity level. We posit that, unless these determinants are explored, countries would lack in formulating right policies to strengthen the enablers they are currently weak in to fight against corruption. So, this paper aims to understand the exact role HCI, TII, and OSI play individually in alleviating corruption vis-à-vis how these index values vary across cohorts of countries having similar EGDI trajectories. Using longitudinal clustering based on EGDI, we first identify temporal country cohorts and then perform cohort-wise panel regression to analyze the individual effects of HCI, TII and OSI on CPI. As expected, the three components do not contribute uniformly in lowering corruption, and more importantly, each assumes significance only under different contingent internal factors. So, based on our results, we recommend, for each cohort, a set of specific E-GOV development policies targeted for combating corruption, thereby helping countries formulate long-term and short-term measures toward moving up the E-GOV maturity stages too.**

Keywords*— *E-Government; EGDI; Corruption; CPI; E-Gov Strategies; Longitudinal clustering; Panel regression.

I. INTRODUCTION

Corruption is a social menace that corrugates the foundations of a government machinery, thereby undermining the socio-economic welfare and well-being of the citizens nation-wide. Elbahnasawy [1] defines corruption as "*a manifestation of the principal-agent problem owing to information asymmetry and non-alignment of incentives"*. It has proved to be a major barrier for countries seeking to achieve the Sustainable Development Goals (SDGs) set by the United Nations Development Programme (UNDP) [2]. Extant research provides substantial evidence of the negative externalities, such as lowering of economic prosperity, increased environmental degradation, growing resource wastage, increased income inequalities, and growing poverty, propagated by corruption [3]. Taking cognizance of these negative externalities, controlling corruption has become imperative for governments all around the world. E-Government (E-GOV), which advocates the use of Information and Communication Technologies (ICT) in the delivery of public services, has been demonstrated in past studies as an effective anti-corruption tool [4] to reduce information asymmetry and bring transparency in government service delivery [1][5][6]. In literature, E-GOV [5] is defined as "*the use of ICTs to enable and improve the efficiency with which government services are provided to citizens, employees, businesses and agencies*".

Corruption level of a country is usually estimated with the help of the well-known measure, called Corruption Perceptions Index (CPI), published annually by Transparency International [7]. Countries are given a score between 0 and 100, where "0" signifies highest corruption and "100" signifies lowest corruption [7]. On the other hand, E-GOV development of countries is assessed through the measure, called E-GOV Development Index (EGDI), published by the United Nations on a bi-annual basis from 2008 onwards (earlier published annually during 2003-2005) [6]. EGDI is a composite metric consisting of three components: (i) Human Capital Index (HCI) – that assesses the human capabilities (HC) and skill levels, (ii) Telecommunications Infrastructure Index (TII) – which assesses development levels of telecommunications infrastructure (TI), and (iii) Online Services Index (OSI) – which assesses the scope and quality of government's e-services or online services (OS) [6].

Although recent research works [3]–[5] in the "*E-GOV–Corruption*" discourse provide substantial evidence regarding the potential of E-GOV development in combating corruption, we have identified two inter-related research issues that have not been adequately addressed in the literature: (i) how the impact of E-GOV development on lowering corruption varies with the heterogeneity among countries through their temporal EGDI evolutions, due to the differing HC/TI/OS capabilities and differing levels of internal factors, and (ii) how the relative contribution of HC, TI and OS matters in managing corruption at various levels of E-GOV maturity across countries. The previous studies on *E-GOV–Corruption*, therefore, do not consider adequately the context-specific component-wise variations in the *EGDI-CPI* relationship. Hence, the policy recommendations mentioned in these studies are not complete and sufficient to a large extent, rendering such policies not

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readily operationalizable at the country-level [8][9]. Consequent to such scant research focus and insufficient empirical guidance, countries may incorrectly estimate the exact impact of the three components, namely HC, TI, and OS, in reducing corruption, which could lead to incorrect prioritization and inefficient resource allocation and hence, sub-optimal outcomes thereof [10].

Our primary focus in this paper is on the context-specific role that HCI, TII and OSI play within EGDI in increasing CPI; to be more specific, the relative contribution of HC/TI/OS in reducing corruption. In order to avoid any over-estimation of HC/TI/OS's impact, we have controlled for the effect of governance quality and economic factors on corruption. Towards this, firstly we have taken help of longitudinal clustering technique to group the countries into clusters (referred to as *cohorts* henceforth), based on the similarity of their EGDI trajectories across time; secondly, we have employed panel regression to understand the quantum of individual impact of HCI/TII/OSI on CPI for each of the cohorts. Finally, based on the above findings, we recommend context-aware cohort-specific E-GOV policies to provide guidance regarding the HC/TI/OS prioritization by countries and the enabling factors that the countries should take cognizance of, in order to harness the full potential of E-GOV development in combating corruption.

Therefore, the paper contributes to the "*E-GOV–corruption*" discourse in the following four ways: (i) we account for the heterogeneity among countries in their temporal EGDI evolution, taking cognizance of the dynamic similarities of countries across time, (ii) we identify the individual roles of HC, TI and OS in controlling corruption and the enabling conditions under which the effect of HCI/TII/OSI on CPI is significant, (iii) we combine the above two analyses by relating *country-wise heterogeneity* with *E-GOV-corruption correlation*, and (iv) we recommend, based on our unique combination of analyses, long-term and short-term E-GOV strategies closely aligned with the objective of lowering CPI.

The rest of the paper is organized as follows: The following section reviews the relevant literature, Section III outlines the research framework and methodology, Section IV presents the results and discussions. Section V finally concludes the paper.

II. Literature Review and Background

Since our study draws from two distinct streams of literature: (i) Country-wise heterogeneity, and (ii) E-GOV-corruption discourse, we begin with short introduction of each followed by brief survey of relevant works in each domain.

A. Country-wise Heterogeneity

We extend the definition of a firm's competitive advantage, as defined in the Resource-Based View literature [11], to define country-level heterogeneity as "*the distinct and unique characteristics inherent in countries due to their access to a unique bundle of resources and the subsequent development of capabilities and knowledge, not easily duplicated by other countries*." In the context of its influence on longitudinal E-GOV development of countries, extant research provides evidence for two broad categories of variables to handle country-level heterogeneity - (i) Internal Capabilities, and (ii) Country-level Governance and Economic factors [3][10][11]. Adapting the definition of organizational capabilities [12], we define internal capability of a country as its ability to derive utility through deployment of valued resources, either in combination or copresence. Borrowing from the arguments in [11], internal capabilities differentiate countries in terms of their absorptive capacity, i.e., their ability to assimilate and make use of available knowledge or technology (including ICT which leads to E-GOV). This, in turn, highlights the importance of internal capabilities in creating unique country-level attributes. At the same time, there exists sufficient empirical evidence of governance and economic factors, such as judicial independence, economic prosperity, institutional strength, and press freedom, having a significant role in fostering E-GOV development in a country [13]. Hence, it becomes imperative that, while using EGDI, one should take country-wise heterogeneity into consideration properly.

However, to the best of our knowledge, no previous study on explaining E-GOV-corruption connect has longitudinally incorporated such country-wise heterogeneity, arising out of the combined effect of internal capabilities and governance/economic factors acting over time. Few studies that try to differentiate among countries, however, either attribute such differences to geographical affiliations [9] or confine to single time-period, thereby ignoring the underlying structural differences among countries over temporal domain. To circumvent these limitations, we invoke longitudinal clustering – a technique that captures the underlying dynamic structural similarities of countries by grouping countries based on some variable (EGDI in this study) over a time-period, as explained in details in Section III.

B. E-GOV and Corruption Discourse

Existing studies in the E-GOV-corruption discourse have demonstrated the ability of E-GOV in lowering corruption at the broader index level [1][5][13], as well as at the individual resource levels, such as Internet diffusion, citizens' educational capability, or mobile phone penetration [8][9]. However, extant studies are silent on taking the country-wise heterogeneity into proper consideration while analyzing the E-GOV-corruption relationship. Furthermore, these studies have missed out on the possibility that the said heterogeneity may stem from the variations in HC/OS/TI capabilities of countries. Extant studies [5][13]–[16], therefore, have not empirically studied the effect of HCI/OSI/TII on corruption. Consequently, the EGDI-corruption relationship has never been explored at the sub-index level (i.e., at the level of HCI, TII and OSI), to the best of our knowledge. However, unless such understanding is explored, countries would be unable to leverage on the strength of their internal capabilities, meanwhile lacking in policies to strengthen the sub-index they are weak in. Moreover, the use of the broad index EGDI masks the inter-country differences in their sub-index prioritizations. For example, Chile and Czech Republic have almost identical EGDI viz. 0.60137 and 0.60695 in 2010 and 2014, respectively [6]. However, there are marked differences at the levels of their EGDI components. While Chile is much superior to Czech Republic in terms of OSI (0.60952 vs 0.37007), it lags Czech Republic in terms of TII (0.27109 vs 0.57532). As existing literature does not clearly spell out the relative contribution of each of the three components of EGDI on CPI, countries, therefore, face decision uncertainties while formulating their E-GOV development strategies. Due to resource limitations, which is a reality in many countries, some countries may choose to provide more emphasis on one or two of the critical components at the expense of other less significant component(s), thereby failing to utilize their limited resources effectively [10].

Our motivation behind delving deeper into the sub-index level comes from the following observation. Despite lack of studies probing HC/TI/OS's effect on corruption individually, there exist empirical evidences that point towards the possibility of each component having its own significant effects in lowering corruption. Education levels and access to education have been shown to lower corruption [13], thereby building a strong case for HCI's significance in increasing CPI. In support of TII, Internet diffusion and cellphone subscription [8] (both being sub-components of TII) have been shown to have significant influence in lowering corruption. In support of OSI, digitalization of government services has been shown to increase transparency, which is an antecedent of reduction in corruption. Furthermore, enablers of E-GOV service usage, such as Internet adoption has been shown to lower corruption levels [8]. We, therefore, posit that the three EGDI components – HCI, TII, and OSI – have significant effects in increasing CPI in their own capacities alone.

III. Research Framework And Methodology

As mentioned earlier, we first account for country-wise heterogeneity by employing longitudinal clustering to group countries with similar EGDI levels. Next, within each group, we use panel regression for testing the effects of HC, TI, and OS in lowering corruption as per the model of Figure 1, which captures the overall structure of the conventional research framework used in this kind of study [3]–[5]. We assume that HCI, TII and OSI (on the left part of Figure 1) are the three basic capabilities derived out of EGDI that contribute to CPI, subject to the internal factors (on the right part) explained below in details.

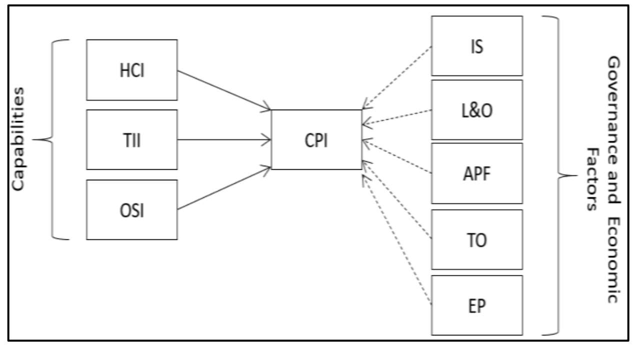

Figure 1. Model for testing EGDI components on CPI

A. Research Model

Our model (Figure 1) aims to draw upon the resource-based view of countries to understand how the unique mix of HC/OS/TI capabilities, subject to governance and economic factors, contribute to corruption control. We control for the effects of governance and economic factors on corruption in order to avoid over-estimation of HC/TI/OS's effects on corruption. Regarding the control variables, though there is no universally agreed upon set as determinants of corruption, based on the existing literature [1], we make use of five control variables, namely Government Effectiveness (GE) [17], which operationalizes Institutional Strength (IS), Rule of Law (RL) [17], which operationalizes Law and Order (L&O), Anti Press Freedom (APF) [18], Trade Openness (TO) [17], and Economic Prosperity (EP) [17], which represent the degree of political and economic freedom enjoyed by the citizens of a country. Causes of corruption have been consistently found, in extant research, to be deeply rooted in these governance (that contribute to political freedom [13]) and economic factors [1][3][13], and have therefore been extensively used as control variables. We consider IS as the variable that captures GE, as shown in Table I, which provides a summary of all variables used in our study.

B. Data Sources

Our study uses a balanced panel dataset consisting of 102 countries with data ranging from 2003 to 2016. The dataset comprises 8 time periods with consecutive time-period data from 2003 to 2005 and alternative year's data from 2008 onwards due to non-availability of EGDI data (the United

TABLE I. SUMMARY OF VARIABLES USED

Sl. No.	Variable	Measure / Description	Scale	Source	Years
1	CPI	Corruption Perceptions Index	0 to 100	Transparency International	2003-2005: 2008-2016
2	EGDI	E-government Development Index	0 to 1	United Nations E-government Global Survey	2003-2005: 2008-2016
3	HCI	Human Capital Index	0 to 1	United Nation E-government Global Survey	2003-2005: 2008-2016
4	TII	Telecommunications Infrastructure Index	0 to 1	United Nation E-government Global Survey	2003-2005: 2008-2016
5	OSI	Online Services Index	0 to 1	United Nation E-government Global Survey	2003-2005: 2008-2016
6	IS	Government Effectiveness	-2.5 to +2.5	World Bank World Governance Indicators	2003-2005: 2008-2016
7	L&O	Rule of Law	-2.5 to +2.5	World Bank World Governance Indicators	2003-2005: 2008-2016
8	APF	Press Freedom from political influence	0 to 100	Freedom House	2003-2005: 2008-2016
9	TO	(Imports + Exports) of goods and services (as % of GDP)	Actuals (%)	World Bank World Development Indicators	2003-2005: 2008-2016
10	EP	GDP per capita (constant 2010 US$)	Actuals ($)	World Bank World Development Indicators	2003-2005: 2008-2016

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TABLE II. DESCRIPTIVE STATISTICS OF THE VARIABLES

Variable	Obs.	Mean	Std. Error	Min	Max
CPI	816	47.47	21.72	13.00	97.00
EGDI	816	0.54	0.19	0.09	0.95
HCI	816	0.80	0.17	0.17	1.00
TII	816	0.34	0.25	0.00	0.94
OSI	816	0.49	0.24	0.01	1.00
IS	816	0.36	0.92	-1.53	2.44
L&O	816	0.27	0.96	-1.82	2.10
APF	816	41.77	21.49	8.00	90.00
TO	816	88.63	52.77	20.59	441.60
EP	816	17904.47	21463.99	307.03	108600.93

Nations did not publish the same for the other years). EGDI data contain the three component level data too for HCI, TII and OSI. All the four measures viz. EGDI, HCI, TII and OSI score countries on a scale of 0 to 1, where "0" signifies low and "1" signifies high. The outcome variable, namely corruption, has been operationalized using CPI, published annually by Transparency International [7]. Table II provides the descriptive statistics of all the variables. Our dataset provides a total of 816 observations for every variable.

C. Methodology

Our methodology consists of two primary sequential steps: (i) longitudinal clustering based on EGDI trajectory, and (ii) panel data regression within each cluster.

a) EGDI Trajectory based Clustering

Although there are several clustering techniques available [19], our study employs the commonly used *k*-means clustering technique to create longitudinal cohorts of countries in order to capture the dynamic similarities of some countries across time. The *k*-means based algorithm, being an unsupervised learning technique, does away with the need to pre-specify the number of clusters, hence being appropriate for our exploratory study, where the number of clusters is unknown. Some related works have done region-specific studies using single time-period data [9]. However, they have not used any clustering technique per se. So, our paper is the first of its kind to use multi-time period clustering employing *k*-means technique. As mentioned earlier, the factor we have used for the longitudinal clustering is the EGDI trend from 2003 through 2016. We have used the "kml" package present in the open source statistical programming language "R" for conducting the clustering analysis. After testing with various values of *k*, we have narrowed down to four cohorts, namely A, B, C and D, (Figure 2) because four clusters maximize the Calinski-Harabasz Index [20] in the case of EGDI. Table III provides the list of countries included in each cohort post our analysis. Cohort A represents the largest group with 34 countries, while cohort D represents the smallest group with 20 countries.

TABLE III. COHORT WISE COUNTRY LIST

Cohort	Countries
D	Bangladesh, Cameroon, Algeria, Ghana, Gambia, Honduras, Kenya, Morocco, Madagascar, Mali, Mozambique, Malawi, Namibia, Nigeria, Nicaragua, Pakistan, Senegal, United Republic of Tanzania, Uganda, Zimbabwe. (20)
A	Albania, Armenia, Azerbaijan, Bolivia, Botswana, China, Costa Rica, Dominican Republic, Egypt, Georgia, Guatemala, Indonesia, India, Jamaica, Jordan, Kyrgyzstan, Kuwait, Sri Lanka, Republic of Moldova, Macedonia, Mauritius, Panama, Peru, Philippines, Paraguay, Qatar, Saudi Arabia, El Salvador, Thailand, Trinidad and Tobago, Turkey, Ukraine, Vietnam, South Africa. (34)
B	United Arab Emirates, Argentina, Bulgaria, Brazil, Chile, Colombia, Cyprus, Czech Republic, Spain, Greece, Croatia, Hungary, Italy, Kazakhstan, Lithuania, Latvia, Mexico, Malaysia, Poland, Portugal, Romania, Russian Federation, Slovakia, Slovenia, Uruguay. (25)
C	Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Estonia, Finland, France, United Kingdom, Ireland, Iceland, Israel, Japan, Republic of Korea, Luxembourg, Netherlands, Norway, New Zealand, Singapore, Sweden, United States of America. (23)

b) Panel Data Analysis

Compared to only cross-sectional data or pure time series data, panel data includes the inter-individual, as well as the intra-individual differences, besides containing information along both cross-sectional and temporal dimensions. This suits our research requirement perfectly. Moreover, panel data analysis has several advantages including: (i) the ability to model and/or test more complex behaviors and/or hypotheses [21], (ii) the ability to control the effect of omitted variable biases, and (iii) the ability to handle the effect of inter-individual dependencies as well as correlation (aka dependency) across time. This is not possible in other techniques (like Ordinary Least Squares [21]) due to violation of independence assumption [21].

Our research model uses two approaches for fitting the panel data: (i) Within Group Fixed Effects Regression, and (ii) Random Effects Regression [21]. We have used Hausman test [21] to identify the appropriate model for each cohort. Prior to running the models, the dataset was tested for the presence of fixed effects using Chow test, post which the time effect and the individual effects were tested using the Lagrange Multiplier test developed by Breusch and Pagan [21]. The Random Effects model have been run using either the Swamy Arora's Transformation [21] or the Wallace-Hussain Transformation [21]. Heteroskedasticity was tested using Breusch Pagan test [21] and was detected in majority of the models. Therefore, we have calculated heteroskedasticity robust estimates, using Arellano's and White's method [21], for Fixed Effects and Random Effects regression, respectively. The dataset was tested for stationarity using the Augmented Dickey Fuller test [21], where all variables were found to be stationary.

IV. RESULTS AND DISCUSSIONS

We present here our findings, which provide substantial evidence regarding the existence of cohort-wise differences in the EGDI levels, as well as cohort-specific roles of the different EGDI components in lowering corruption.

A. Cohort-specific Characteristics

Our findings provide evidence of significant inter-cohort differences regarding their EGDI trajectories. Figure 2 shows the result of the EGDI-based longitudinal clustering, where the vertical axis in the right side of the figure denotes EGDI levels

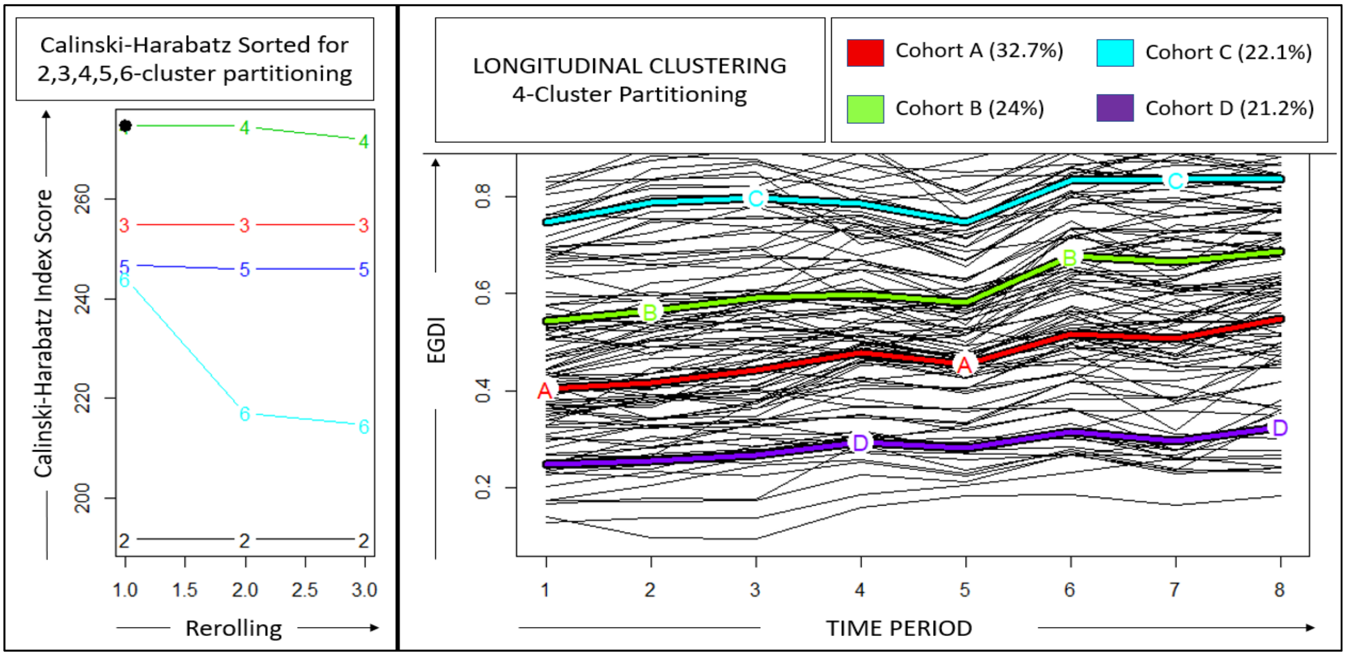

Figure 2. Results of EGDI Longitudinal Clustering

while the horizontal axis denotes the time period. Table IV provides a descriptive summary of the four cohorts (Table III) identified therefrom. Cohort C represents the countries at the higher end of the spectrum across all the variables used in the study, while cohort D represents the countries at the lower end of the spectrum across all the variables. In between, we have cohorts B and A. It can be observed that countries with similar levels of governance levels (IS/L&O/APF), internal capabilities (HCI/TII/OSI), and economic factors (TO/EP) have similar longitudinal EGDI trajectories demonstrated by their automatic affiliation to distinct cohorts (Table IV). Countries are identically clustered for all the variables considered in this study. In other words, cohort D is the cluster with the lowest average value for all the variables, cohort C is the cluster with the highest average value for all the variables, with cohorts B and A in between. Our results provide evidence regarding (i) heterogeneity among countries in terms of their EGDI evolution trajectories, and (ii) the heterogeneity being contingent on the level of internal capabilities and governance quality/economic development levels of countries. As posited, our clustering result provides sufficient evidence of country-wise heterogeneity in EGDI evolution trajectories.

B. *EGDI Components and CPI*

The panel regression summary indicates some cohort-wise variations in the way EGDI components affect corruption. As observed in Table V: (i) cohorts A and B, both with relatively steeper EGDI trajectories, have TII as the only EGDI component having a significant effect on CPI. Besides TII, governance factors, namely IS, and L&O, are significant for both cohorts, while TO and EP differentiate the two cohorts, (ii) cohorts C and D, both with relatively flat EGDI trajectories have HCI as the only EGDI component having a significant effect on CPI. Besides HCI, IS has a significant effect on CPI for both the cohorts, and (iii) OSI does not have a significant effect on CPI for any of the cohorts. Thus, our findings indicate that the three EGDI components are not uniform in their contribution in lowering corruption. The roles of HCI and TII in lowering corruption assumes significance only under specific contexts, while OSI has no significant effect on CPI.

C. *Temporal Analysis of E-GOV Trajectories*

In terms of the EGDI trajectory and the relationship between EGDI components and CPI, the four cohorts can be grouped under two broad categories: (i) an unstable transitionary trajectory observed for cohorts A and B, where TII has a significant effect in lowering corruption, and (ii) a stable flat trajectory observed for cohorts C and D, where HCI has a significant effect in lowering corruption. From these observations, we draw short-term E-GOV policy measures for combating corruption. For cohorts with flat trajectories, HCI needs to be given focus in order to lower corruption, whereas

TABLE IV. DESCRIPTIVE STATISTIC OF THE FOUR EGDI TRAJECTORY COHORTS

Cohort	Ave. CPI	Ave. EGDI	Ave. HCI	Ave. TII	Ave. OSI	Ave. IS	Ave. L&O	Ave. APF	Ave. TO	Ave. EP
D	28.89	0.29	0.55	0.08	0.24	-0.61	-0.60	54.10	68.16	1437.98
A	36.29	0.47	0.79	0.21	0.41	-0.10	-0.23	52.51	85.99	7842.92
B	47.47	0.61	0.88	0.40	0.56	0.55	0.38	38.42	89.89	16502.06
C	80.17	0.80	0.94	0.70	0.75	1.69	1.65	18.80	108.96	48621.10
Overall	47.47	0.54	0.80	0.34	0.49	0.36	0.27	41.77	88.63	17904.47

TABLE V. SUMMARY OF PANEL REGRESSION ANALYSIS

Cohort	HCI	TII	OSI	IS	L&O	APF	TO	EP
D	23.061 (***)	ns	ns	4.491 (***)	ns	ns	ns	ns
A	ns	13.368 (***)	ns	9.058 (***)	7.168 (***)	ns	ns	0.0002 (*)
B	ns	9.542 (***)	ns	6.703 (***)	9.375 (***)	ns	0.374 (**)	ns
C	32.046 (***)	ns	ns	10.938 (***)	17.114 (***)	-0.140 (*)	0.031 (***)	ns

*p<0.1; **p<0.05; ***p<0.01; ns: not significant

countries in cohorts where EGDI is transitioning towards mature levels need to prioritize TII in order to lower corruption. As expected, IS has significant effects in lowering corruption for all four cohorts; so overall IS cannot be ignored if corruption control is desired. L&O has a significant role to play only after countries begin the transition, as can be deduced from L&O's insignificance on corruption for cohort D. EP influences corruption only for countries which are at the initial transition stage (cohort A), which highlights the importance of purchasing capacity of citizens to avail the ICT services. For cohorts at higher maturity levels, EP's effect in lowering corruption loses significance. As EGDI levels mature (cohorts B and C), TO and APF, which foster greater transparency in trading practices, as well as information dissemination, start assuming greater importance in lowering corruption.

On a longer term, countries need to plan how they can transition towards cohorts with higher maturity in terms of their EGDI and corruption levels. Although countries need to develop their overall levels for all variables used in this study to gain membership to the next mature cohort, there are certain factors that should receive higher prioritization on a long-term basis as deduced from the panel regression analysis. Accordingly, we have recommended adequate short-term and long-term prioritization of EGDI components, governance and economic factors for each cohort as summarized in Table VI. By focusing on the appropriate factors that have significant effects on corruption, countries could hasten their shift to the next higher mature cohort, while their EGDI strategy being in close alignment with corruption reduction.

TABLE VI. SUMMARY OF RECOMMENDATIONS

Cohort	Short-term Measure	Long-term Measure
D	HCI, IS.	TII, L&O, EP
A	TII, IS, L&O, EP	TO
B	TII, IS, L&O, TO	HCI, APF
C	HCI, IS, L&O, TO, APF	Maintain current levels

V. CONCLUSIONS

The relationship between E-GOV and socio-economic welfare has received major focus in extant research. This line of research helps justify the investments that go into building the requisite infrastructure for E-GOV, and therefore the importance on national E-GOV strategy formulation. Our study also falls in this line of inquiry, where we explore the impact of E-GOV development on corruption, while taking cognizance of associated country level factors, such as IS, L&O, APF, TO and EP. We have found that countries are not homogeneous in their EGDI maturity, and heterogeneity is due to the combined effects of internal capabilities, as well as governance and economic factors. Furthermore, the EGDI components that have significant effects on lowering corruption are different for the different cohorts of countries. So, there is a need for a context-aware prioritization of EGDI components in order to harness the benefits of EGDI in controlling CPI. Towards this, we have derived short-term and long-term E-GOV policy measures, for each of the cohorts, geared towards lowering of corruption, as summarized in Table VI. For instance, let us consider cohort D, which is at the lowest EGDI maturity level primarily due to the absence of adequate capabilities in terms of TII, as well as EP (Table IV). This warrants cohort D to emphasize on TII and EP as part of their long-term policy measures.

Some limitations of this study include unavailability of data for all countries thereby limiting our dataset, and the use of perception-based measures that suffer from subjectivity. Alternative measures could be derived based on the sentiment data mined from social media, or online discussion forums. Our plan for future works goes like this. Additionally, survey instruments capturing perception measures could be administered using these online communities or social media, thus leveraging on new avenues for data collection. We have used the *k*-means longitudinal clustering for grouping the countries. We intend to repeat this work using other clustering methods and compare the results for robustness. Additionally, we wish to further work on uncovering the additional reasons for the decreasing CPI despite increasing EGDI observed for cohort C.

TABLE VII. SUMMARY OF ABBREVIATIONS

Abbreviation	Full form
E-GOV	E-Government
EGDI	E-Government Development Index
CPI	Corruption Perceptions Index
HCI	Human Capital Index
TII	Telecommunications Infrastructure Index
OSI	Online Services Index
SDG	Sustainable Development Goals
UNDP	United Nations Development Programme
ICT	Information and Communication Technologies
HC	Human Capabilities
TI	Telecommunications Infrastructure
OS	Online Services
GE	Government Effectiveness
IS	Institutional Strength
RL	Rule of Law
L&O	Law and Order
APF	Anti Press Freedom
TO	Trade Openness
EP	Economic Prosperity

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