Tax-evading Politicians, Public Goods Provision and Public Health

Moogdho Mim Mahzab
Dhaka, Bangladesh

M.A. Economics, University of Virginia, 2016
M.A. Policy Economics, Williams College, 2014
M.S.S. Economics, University of Dhaka, 2011
B.S.S. Economics, University of Dhaka, 2010

A Dissertation presented to the Graduate Faculty
of the University of Virginia in Candidacy for the Degree of Doctor of Philosophy

Department of Economics

University of Virginia
May, 2021

Committee Members
Sandip Sukhtankar
Sheetal Sekhri
Molly Lipscomb
Gaurav Chiplunkar

Abstract

Elected politicians are instrumental in providing public goods to their constituencies. On one hand, dishonest politicians can expropriate public funds for personal use, thus reducing the funds available for public goods provision. On the other hand, through clientelistic and patronage politics, dishonest politicians can give appropriated funds back to citizens.

In the first chapter, I study how dishonest politicians affect public goods provision in their constituencies. To identify dishonest politicians, I determine whether they evaded income taxes conditional on their minimum earnings and occupation, using a unique dataset based on the asset disclosure and tax forms candidates submit prior to elections in Bangladesh. Directly comparing constituencies represented by dishonest and honest politicians will not reveal the causal effects on public goods provision and economic development, since constituencies that elect dishonest politicians may systematically differ from the ones that do not. I rely on close elections, in which a dishonest politician narrowly defeats an honest one, and a regression discontinuity design to examine the effects of dishonest politicians on public goods provision and economic progress. Between 2009-10 and 2014-15, I find that in sub-districts that narrowly elected dishonest politicians, 27.3% fewer households received social safety net benefits compared with sub-districts that narrowly elected honest politicians. To analyze the effect between 2014-15 and 2019-20, I use a number of health and infrastructure variables at the sub-district level to develop an index of public goods provision using principal component analysis. I find that constituencies with dishonest leaders have a 0.74 standard deviation lower index value than constituencies with honest leaders. Results are quantitatively similar under the choice of different bandwidths and are robust to various specifications. Furthermore, categorizing sub-districts by wealthy dishonest versus wealthy honest leaders, measured by politicians' total assets above the mean value in 2014 -

compare long-term economic development, proxied by growth of nighttime light brightness. I find that sub-districts with wealthy dishonest leaders have 5.75% point lower growth in night-time light brightness. Using my own estimates to convert night-time light brightness to GDP growth, I find 0.94% lower yearly GDP growth per sub-district under wealthy dishonest leaders.

In the second chapter, to understand the mechanism, I provide evidences from sub-district-level budgets showing statistically significant lower constituency-wide expenditure by dishonest politicians. I found local-level tax revenues do not differ significantly between upazilas with honest versus dishonest politicians. I also show empirically that public goods provision does not depend on the ability of politicians, as measured by years of education, and politicians' honesty and ability are independent of each other. Furthermore, I provide evidence that the central government resources allocation also does not differ significantly, it suggests that honest politicians are not favored by the central government. I provide further evidence that dishonest and honest politicians' occupation choices are not statistically different. Lastly, I show that re-election probability of dishonest politicians also does not influence public goods provision differentials.

Third chapter is a conjoint work with Abu S. Shonchoy (Florida International University) and Towhid I. Mahmood (Texas Tech University) on public health concerns in Bangladesh arising from infectious diseases. Bangladesh is among the top fifteen SARS-CoV-2 (COVID-19) affected countries in the world. However, the country has the lowest testing capacity per million in that group. Faced with growing pressure to continue livelihoods, Bangladesh government lifted the lockdown abruptly in 2020, costing an immediate surge in the virus caseload. Against this backdrop, there is a dire need to derive data-driven planning, for mitigation and management of COVID-19 cases in Bangladesh – prioritizing

the efficient allocation of limited resources. Utilizing publicly available and administrative data, this paper introduces a contagion risk (CR) index, which can work as a credible proxy to detect potential virus hotspots – aiding policymakers with proper planning. Grounded on disease spreadability vectors, we derived the CR-Index at the district level, based on nine variables across five domains: socio-economy, demography, occupation, migration, and health infrastructure. The CR-Index is validated against the district wise COVID-19 cases across the study period. CR-Index is positively correlated with district-wise COVID-19 cases across the pandemic period (average correlation is 0.65, p-value 0.001). We found that one percent increase in the CR-index predicts a 3.8 percent daily change in the increase of COVID-19 cases across districts. The proposed CR-Index can predict seven out of the top ten COVID-19 caseload districts of Bangladesh.

JEL codes: C31, C43, D73, D72, I18, I25.

Keywords: Regression Discontinuity, Dishonest Politicians, Tax Evasion, Vote Margin, Bangladesh, Election, Contagion Risk, Index, COVID-19.

Acknowledgements

Firstly, I would like to show my wholehearted gratitude to my thesis advisor, Sandip Sukhtankar. This thesis and my intellectual journey as a Ph.D. candidate has been rewarded immensely by his wisdom and support. I would like to thank my second advisor, Sheetal Sekhri for her invaluable support throughout the process.

I want show my appreciation to Molly Lipscomb and Gaurav Chiplunkar for taking the time to make important comments and observations on my thesis, which have enriched my research greatly. I also want to show my appreciation to John Pepper and Leora Friedberg; Their guidance and intellectual inputs helped me throughout the graduate years. Marc Santugini and Karim Chalak have helped me to become a better teacher, I want to thank them both as well.

My dissertation has improved significantly from the comments I have received from the following conferences—New York University (YES), Philadelphia Fed (UEA), World Bank-SANEM Workshops, UC-Berkeley (Pac-Dev), Bangladesh Institute of Development Studies, and Political Economy of South Asia (WPESA) and Development seminars at University of Virginia (UVa).

I am extremely grateful to the following persons and institutions to help me with data collection and management from Bangladesh— Dilip Sarker and Badiul Alam (SHUJAN); Mehrab Ali and Zahirul Islam (ARCED foundation). I would like to show my gratitude to my undergraduate teacher from University of Dhaka, Selim Raihan for his continuous support to my research career. I am also indebted to Peter Pedroni and Jessica Leight from Williams College for their support to pursue my Ph.D. journey.

I wholeheartedly thank my classmates at UVa for the six years journey together and their support - Seunghyeon Lee, Hanna Charankevich, Jeaki Jang, Divya Pandey, Grace

Toufeili and Ramiro Burga.

I am very grateful to my parents—Umme Muslima and Aapel Abdullah, not only for their support throughout my academic career, but for personally helping me to build relation with different government agencies in Bangladesh to support my research. I can't thank enough my wife, Sadia Shaheed and my sons, Shahitto Sabin and Sharthok Meerab for bearing with me and encouraging me every step of the Ph.D. journey. I want to thank my sister, sistrer-in-law, and mother-in-law for their support as well.

Last but not the least, I show my full appreciation to Bankard Fund for Political Economy, Quantitative Collaboration fund, and Economics department research fund of UVa to support my thesis.

This dissertation is dedicated to my mother, Umme Muslima, I owe her for everything; Its must have been very hard to raise a mischievous boy like me...

Contents

List of Figures

List of Tables

Chapter 1

Dishonesty and Public Goods Provision—A Tale of Tax-evading Politicians

1.1 Introduction

In a democratic society, elected politicians have the discretion, as a result of public mandate, to allocate and manage development expenditure. The "honesty" of a politician standing for elected office is typically scrutinized and debated in elections around the globe. Despite this, dishonest politicians get reelected; prior research attributes this to strong clientelism or patronage politics (Chandra 2013; Vaishnav 2017). However, there is relatively scarce evidence on how the election of a dishonest politician affects public goods provision and, more broadly, economic development. This question is particularly salient in developing countries, where local elected representatives wield great discretion in the provision of public goods and institutions to keep them in check are weak. Dishonest politicians are likely to embezzle public funds (Fisman et al. 2014, Pande et al. 2012) for their personal use, which hinders public goods provision and their constituencies' economic progress. The impact of electing a dishonest politician on public goods provision and economic development is not obvious for two reasons: First, dishonest politicians may redistribute appropriated public funds to their constituents privately (Menes 1999, Banerjee 2014), and second, they may be more competent than honest ones (Caselli and Morelli 2004, Messner and Polborn 2004) and hence better at resource allocation despite appropriating funds[1]. Moreover, identifying the causal effects of a dishonest politician is challenging, because constituencies that elect dishonest and honest politicians may differ systematically from each other in many ways. With this backdrop, in this paper I investigate whether a constituency performing better if the elected politician is honest compared to one with a dishonest politician. I construct a unique dataset from the asset disclosure and tax forms of politicians in Bangladesh, which include the politician's actual income, assets, educational and criminal records and whether they have paid income taxes. I assess a politician as dishonest if his income falls within the bracket that qualifies for the income tax, but he[2] has not claimed it. Bangladesh presents a unique setting to study this question. In 2009, a law was enacted in Bangladesh that requires every candidate running for any public office to disclose their income, assets, educational and criminal background, and information on dependents. I use this data to define dishonest politicians.

As stated above, directly comparing constituencies represented by dishonest and honest politicians will not reveal the causal effects on public goods provision and economic devel-

[1] In parallel research, I will conduct a field experiment in Bangladesh. This will consist of an information intervention to examine voters' perceptions of politicians' competency and honesty and identify the relative weights voters place on those characteristics when voting.

[2] I use "he" for politicians because the elected chairman are all male. There is reserved vice-chairman post for women politicians.

opment, since constituencies who elect dishonest politicians may systematically differ from those that do not. I rely on close elections, in which a dishonest politician narrowly defeats an honest one, and a regression discontinuity design to examine the effect of dishonest politicians on public goods provision and economic progress[3]. My identification assumption is that otherwise similar constituencies elect a dishonest politician versus an honest one by chance. The running variable in my RD estimation is the winner's vote margin. Using this randomness at the cutoff, I show the causal effects on public good measures. My analysis is at the local government level of Bangladesh, which are called *upazilas* (subdistricts). Capturing public goods provision that depends on politicians' characteristics, especially dishonesty, is more effective at lower administrative levels of government.

In 2009, after 19 years of not having upazila elections, the third upazila election was held in Bangladesh. All of the major political parties agreed to decentralize power and grant more leverage to local governments in order to play a more inclusive role in terms of local development. In this regard, an upazila chairman who is elected by voters for a 5-year term—becomes indispensable for public goods provision and economic progress for the upazila. Social safety net programs serve as an excellent proxy for a public goods measure in Bangladesh. Twelve percent of all households in Bangladesh[4] are included in these programs[5]. Specifically in rural areas of Bangladesh, the most economically challenged households receive support from the central government under the social safety net measures. Around 63% of the population live in rural areas in Bangladesh, where the poverty rate is currently 35.2%. Social safety net programs mainly targeted to non-urban areas to reduce

---

[3]Lee (2008) pioneered the method; recent papers in India that focus on electoral competition, have used an RD design to elicit causal estimates (Asar & Novosad 2015; Prakash et al. 2015; Bhavnani 2014);

[4]Bangladesh is the eighth largest country in the world in terms of population (170 million).

[5]Scholarship programs for education at the primary and secondary levels, different kinds of food programs, household benefit programs for the elderly, women's empowerment programs, food for work, freedom-fighters benefits, etc., are examples.

poverty and the vulnerabilities of a socially and economically challenged population. The government of Bangladesh declared social safety net programs one of the main anti-poverty strategies (Khuda 2011). On average, 2.5% of GDP and 13.2% of the total national budget goes to social safety net programs. I use two main measures of social such programs[6]: total number of households in an upazila under the programs and total cash value of the programs. Local leaders are instrumental in providing and managing social safety net programs in the upazilas, and reports of serious misallocation of the programs have been revealed (Carlo del Ninno 2001).

Between 2009-10 and 2014-15, I find that in subdistricts that narrowly elected dishonest politicians, 27.3% fewer households received social safety net benefits compared with subdistricts that narrowly elected honest politicians. Results are quantitatively similar under the choice of different bandwidths and robust to various specifications. The effects on cash values received by households are also negative but statistically insignificant in close elections comparison[7]. It could be the case that dishonest politicians are reaching out to fewer households thus expropriating from the social safety net funds, but due to a clientalistic nature are not taking money back from a certain number of households. To analyze the effect between 2014-15 and 2019-20[8], I use a number of health and infrastructure variables at the subdistrict level to develop an index of public goods provision using principal component analysis (PCA)[9]. I use information on the number of community clinics in an upazila, the

[6]Household income and expenditure survey of Bangladesh (2015-16) is used for the variables; weights adjusted according to upazila level population

[7]Including all the upazilas—simple OLS shows statistically significant negative effect; however, many households did not respond in the survey about exact monetary value of the benefits they received. So in the close vote margin, number of observations shrinks rendering lack of power to detect the any statistical effect.

[8]Information on social safety net programs are only available in 2015-16 as it was the last national level household survey conducted in Bangladesh.

[9]Information on all of the health and infrastructure variables were not available for the period between 2009 and 2015.

number of sanctioned beds in the upazila health complex, and the average length of stay of a patient in a upazila health complex; I also use a phone survey to collect the number of Covid-19 patients reported to the community clinics. Each of the variables is indicative of upazila-level health performance, in which the upazila chairman plays a vital role. Additionally, I use growth of paved roads between 2016 and 2020 at the upazila level as an indicator of infrastructure development. I find that upazilas with dishonest leaders have a 0.74 standard deviation lower index value than constituencies with honest leaders. Comparing the means, this translates into 125% lower index value in upazilas with dishonest leaders.

To measure the long-term impact of economic development, I used nighttime light images from the NOAA National Center of Environmental Information and the Visible Infrared Imaging Radiometer suite (VIIRS), andprocessed GIS data for all upazilas in Bangladesh for the years 2007, 2010, 2013, 2015 and 2019. I find a close to zero but statistically insignificant impact on the growth of nighttime light over the period of 2015 to 2019. However, categorizing subdistricts by wealthy dishonest versus wealthy honest leaders—measured by politicians' total assets above the mean value in 2014—I compare long-term economic development proxied by the growth of nighttime light brightness. I find that subdistricts with wealthy dishonest leaders have 5.75% point lower growth of nighttime light brightness. There are no available estimates to convert night-time light brightness in GDP growth in Bangladesh; however, Michalopoulos and Papaioannou (2013) provide an estimate using more than 100 developing countries: 1% growth of night-time brightness is equivalent to 0.3% growth of yearly GDP. Using satellite and GDP data on Bangladesh, I estimate the elasticity to be close to 0.165%. Using both estimates to convert nighttime light brightness to GDP growth, I find (0.94∼1.72)% points lower yearly GDP growth per sub-district under a wealthy dishonest leader. It is important to note that heterogeneous effect is persistent for public goods provision as well. I also find a stronger negative impact on the public goods index as well in upazilas with wealthy dishonest leaders.

Furthermore, I show that my results are not driven by politicians' ability. The political economy literature on politicians' quality indicates that education is a good proxy for ability. I use politicians' years of education and show that there is no effect on public goods provision using a similar regression discontinuity design. Moreover, I provide evidence that ability, as measured by education, and level of dishonesty, as measured by the asset growth of incumbent politicians, are not correlated. Thus, the ability of politicians does not render the main results endogenous. The impact on economic development, as measured by nighttime light is mixed. Plausible explanation could be that local level leaders do not have the influence to spur economic growth in his constituency within a short period of time.[10] This can also explain why dishonest politicians are not severely punished in terms of getting reelected, which I show with my data in second chapter.

My paper mainly adds to four strands of the political economy and comparative politics literature. The first strand shows that traits such as ability, measured mainly by education, and the criminality of politicians affects the economic progress of their constituencies (Callen et al. 2015; Alcántara 2009; Prakash et al. 2015). It is empirically difficult to identify dishonesty traits of politicians due to lack of information. To my knowledge this is the first paper that uses tax evasion as a dishonesty indicator and find the causal affect on public goods and economic progress. Tax-evading politicians are not limited to Bangladesh; this approach can be used in other democratic countries given the possibility of having such a disclosure law.

The second strand of literature I contribute to is the mostly theoretical work on the

[10]Alternatively, it could be possible that politicians might be giving away some of the appropriated funds to maintain a solid vote bank for getting reelected thus mitigating the negative effects; this effect can only be profound in public goods provision, not in economic development.

with ability and dishonesty of politicians and their selection mechanism (Besley, Pande and Rao 2003; Messner and Polborn 2004; Caselli and Morelli 2004; Vaishnav 2017). Papers have shown that criminally accused politicians have in fact some positive probability of getting reelected, I provide empirical evidence regarding how dishonest politicians economically affects their constituencies.

Third, my paper contributes to recent literature focuses on politician's income and asset in developing countries (Fisman et al. 2014; Bhavnani 2016; Asher and Novosad 2015), mainly in India. The major finding is that the winner of a close election is using the power of the office to earn money illegally, which is a clear sign of corruption. I add to this literature by asking whether constituencies in which elected politicians are dishonest have less public goods provision.

Fourth, I contribute to the vast literature on comparative politics, which deals with distributive politics and public goods provision within a country (Golden and Min 2013; Chandra 2013). My paper expands this literature by providing empirical evidence and an ex ante measure of dishonesty, as measured by tax-evasion of politicians.

The rest of the chapter proceeds as follows. In section 1.2, I propose a simple theory of public goods allocation by local governments that generates empirically testable claims. In section 1.3, I discuss disclosure laws and forms and the specifics of upazila elections in Bangladesh. In section 1.4, I describe my data in detail. In section 1.5, I describe my definition of dishonest politicians using information from asset disclosures and tax forms. In sections 1.6 and 1.7, I discuss the validation of my RD design and estimation strategy. Results and robustness checks are elaborated on in section 1.8. I conclude in section 1.9, by summarizing my overall insights and connecting my future research with this paper.

1.2 Theoretical Framework

I start with the following simple model to explain the mechanism of expected relative level of public goods provision at local governments (upaizlas) depending on politicians' characteristics — specifically, honesty and clientelism.[11]

There are two constituencies (*upazila*s) in the model denoted by $j \subset (1, 2)$. In each upazila there are two groups of tax-paying voters $k \subset (A, B)$. We can think these two groups are divided in terms of their support for the candidates. In a practical setting—this is similar to voters who are divided into two major political parties in Bangladesh. The share of group k in upazila j is π_k^j.

Let $g_k^j \subset (0, G)$ be the amount of public good provided in upazlia j for voter group k. There is no spillover of public goods between two sub-districts, this is true in Bangladesh, as an upazila chairman only manages public good provision in the upazila he represents. Thus in upazila 1, $g_A^1 + g_B^1 = g^1$, and in upazila 2, $g_A^2 + g_B^2 = g^2$.

Now, politicians clientelism will enter in the individuals' utility in the following way:

$$V_k^j(g_A^j, g_B^j) = \lambda^j log(g_A^j) + (1 - \lambda^j) log(g_B^j) + y_k^j \tag{1.1}$$

$\lambda^j \subset (0, 1)$ indicates the degree of clientelism of the chairman in upazila j. So if $\lambda^j > 1/2$, then the chairman belongs to the party that matches with voter group $k = A$. Due to this match, because of clientelism, voter group $k = A$ will have more share of public goods than voter group $k = B$. If $\lambda = 1$, then due to extreme form of clientelism, only voter group $k = A$ is provided with public goods and voter group $k = B$ does not get any provision. y_k^j captures the private good for group k in upazila j.

[11]Model is motivated by Besley and Coate (2003), and Besley, Rahman, Pande & Rao (2004)

In the model, public goods for upazila j is funded by the individuals' tax amount T^j. For simplicity, price of public goods is assumed to be one. Honesty of the politicians is shown in the model through budget constraint in the following way:

$$g_A^j + g_B^j = \theta^j T^j \tag{1.2}$$

$\theta^j \subset (0,1)$ measures the honesty of the elected upazila chairman. On one hand, if $\theta^j = 1$ then chairman is completely honest and he does not expropriate any tax income for his personal uses. On the other hand, if $\theta^j = 0$ then chairman is completely dishonest and expropriates the full possible tax fund, leaving nothing for the voters as public goods. In the two upazilas the chairmen will vary in terms of their measure of honesty— $\theta \subset (\theta^1, \theta^2)$. With the above mentioned setting, public goods allocation will solve the following problem:

$$\max_{\{g_A^j, g_B^j\}} \lambda^j log(g_A^j) + (1-\lambda^j) log(g_B^j) + y_k^j \tag{1.3}$$

subject to

$$g_A^j + g_B^j = \theta^j T^j \tag{1.4}$$

Solving the model yields the following optimal values of public goods provision for four groups in two upazilas:

$g_A^1 = \lambda^1 \theta^1 T^1$

$g_B^1 = (1-\lambda^1)\theta^1 T^1$

$g_A^2 = \lambda^2 \theta^2 T^2$

$g_B^2 = (1-\lambda^2)\theta^2 T^2$

These results show that public good provision for a group of voters will depend on the honesty and clientelism of the upazila chairman.

$\frac{\partial g_A^j}{\partial \theta^j} = \lambda^j T^j > 0$, indicates that as honesty increases, public good provision increases for voter group A.

$\frac{\partial g_B^j}{\partial \theta^j} = (1 - \lambda^j)T^j > 0$, indicates that as honesty increases, public good provision increases for voter group B.

$\frac{\partial g_A^j}{\partial \lambda^j} = \theta^j T^j > 0$, indicates that as clientelism increases, public good provision increases for voter group A. In the model, as mentioned earlier $\lambda > 1/2$, indicating the match between the chairman and clientelistic voter group A.

$\frac{\partial g_B^j}{\partial \lambda^j} = -\theta^j T^j < 0$, indicates that as clientelism increases, public good provision decreases for voter group B. In the model, as mentioned earlier $\lambda > 1/2$, indicating that the non-aligned voters of group B are getting punished for non-compliance with the chairman.

Comparing public goods provision across groups and sub-districts will give the following empirically testable predictions:

Proposition 1: honesty hypothesis: If $\theta^1 > \theta^2$ then public goods provision will be higher in upazila-1 compared to upazila-2, and vice versa.

Proposition 2: clientelistic hypothesis: If levels of (dis)honesty are the same in two upazilas $\theta^1 = \theta^2$, then $g_A^1 > g_A^2$ and $g_B^1 < g_B^2$, if $\lambda^1 > \lambda^2$.

Model mechanism asserts that if $\theta^1 > \theta^2$, then $\lambda^1 < \lambda^2$. This is saying that if the chairman of upazila-1 is more honest than the chairman of upazila-2, then the upazila-1 chairman will be less clientelistic than the upazila-2 chairman. I will be able to test 'proposition-1' empirically with the data. There are limitations in the data to decompose the effects of honesty into the voter groups of each upazila, as I do not empirically observe public goods provision for each groups mentioned in the model. Also, I can only pseudo-test 'proposition-2', as no direct measure of clientelism is available[12]. It is important to note

[12]With some restrictions on the parameters, I will be able to structurally estimate the effects of honesty and clientelism on public goods provision. However, in this paper, I do not take that approach rather I

that the empirical results of the effects of honesty will be on the conservative side, as it also captures the effects (if any) of clientelism. Effects of honesty and clientelism run in opposite directions as shown in the model.

1.3 Institutional Background

1.3.1 Asset Disclosure Law and Upazila Elections

In 2009, a new law regarding asset disclosure of the candidates competing in elections was passed in Bangladesh. This law makes it mandatory for every candidate competing in national or local government elections to declare their own and as well as their family's asset information, along with education, criminal records, occupation and other related information. The motivation behind the law was to curb corruption of politicians and also to enrich the voters' selection procedure by providing more information about the politicians. But it still remains an open question in Bangladesh— whether voters have access to this information and whether they actually use it to make ballot decisions.

Figure-A1 (see appendix) shows the administrative geography of Bangladesh. The focus of the paper is on the sub-districts (upazilas), where the elected politician is known as the upazila chairman. Upazila Cahirmen hold office for 5 year terms and are supported by an upazila executive committee, where the other members are also elected.[13,14] The following

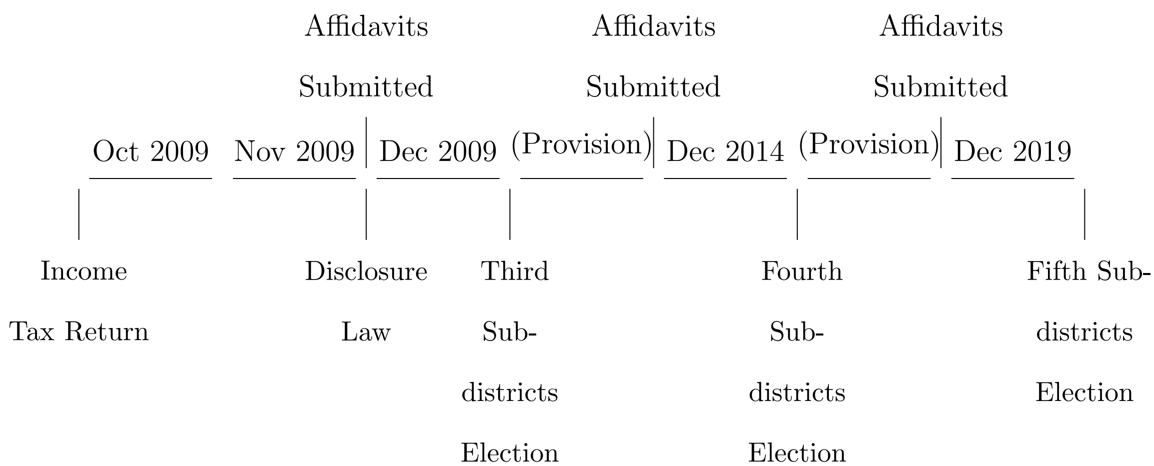
present the model to provide better understanding of the empirical results of my regression discontinuity design.

[13]Under the law, a candidate can not run under the political banner of the national parties. I have 2009 and 2014 in my sample under this law. Then it got changed recently and 2019 election was under major political parties' selected candidates. However, voters do know their ideological preferences given these candidates do have history to work with some particular political party.

[14]In general, Bangladesh has two major parties, the ruling government (AL) is the central-left party and the main opposition is the center-right party (BNP).

timeline figure summarizes: times of the elections, tax-return periods, affidavit submission time, data collection time, and the duration of the tenure of the local leaders, in which public goods provision is estimated.

Figure 1.1: Timeline of disclosure law, tax-returns, elections and, tenure



Before 2009, the last upazila election was held nineteen years earlier, the first ever upazila election was held in 1985 for all 460 upazilas in Bangladesh. After a long political debate over strengthening local government and decentralizing power, the major parties finally decided on upazila election in 2009. The motivation was to give more power to local government to implement effective development programs at the community level. An upazila chairman, initially running without affiliation of national political parties, is elected by the local voters, he is expected to deliver pubic goods and lead the upazila for more economic development. In 1998, Parliament passed the act (ACT no. XXIV of 1998) indicating "provisions relating to administrative powers, functions, and authorities to the upazila parishad which has been laid down in the third schedule of the said Act". The legislation was further amended in 2011.

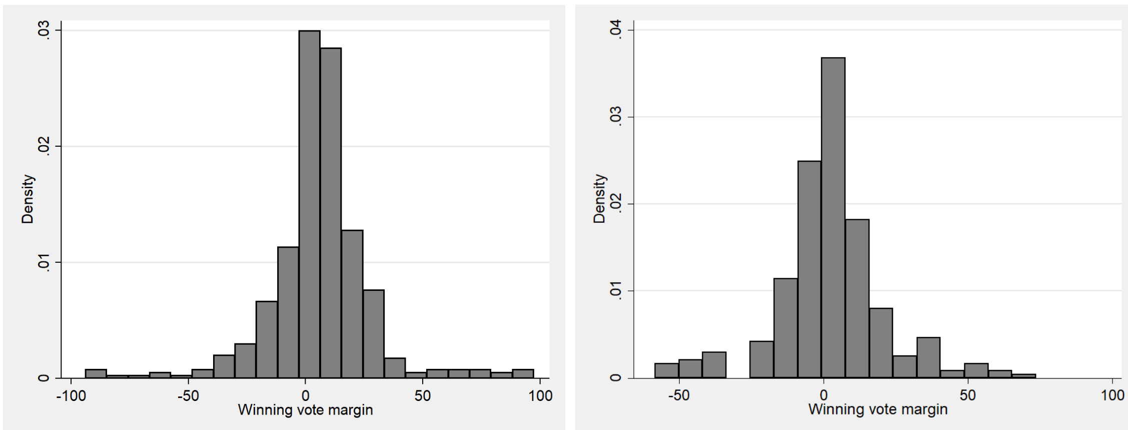
It is evident from the law that an upazila Chairman has discretion over the government fund allocated to those upazilas under each fiscal year's budget. Any development-related work done at this administrative unit has to be overseen by the Upazila chairman. Thus, whether a Chairman is dishonest or not can have a significant bearing on the economic progress of the Upazila.

1.3.2 Close Elections

The following histograms show the distribution of upazilas under winning margins in the 2009-10 and 2014-15 upazila elections, respectively. It is important to note that the local government election in general is very competitive, more than the national level parliamentary elections in Bangladesh. On average, according to the distribution, 35.1%, 60%, 82.2% of upazilas fall under 5%, 10%, and 20% winning vote margins, respectively[15]. Close elections also suggest that elections are not rigged by the incumbents. Having close elections is a prerequisite to run regression discontinuity design (RDD). Given the distribution that I have for the winning margin, empirically it is feasible to use vote margin as a running variable in the RDD.

[15] Participation rate is also very high in local level elections. In third and fourth upazila elections, on average, around 70% legitimate voters participated. The number is less in the last (2019) election as one major political party did not participate due to political reasons

Figure 1.2: The left panel shows the distribution of 2009-10 winning vote margin, and the right panel shows the distribution of 2014-15 winning vote margins



Note: For both panels, left of the cutoff 0 are the vote margins of upazilas in which dishonest candidates won over honest candidates. On the right side of the cutoff 0 are the vote margins of upazilas in which honest candidates won over dishonest candidates.

1.3.3 Asset Disclosure and Tax Returns Forms

There are essentially three different forms that a candidate has to submit to the election commission to get a nomination. One is a form of affidavit, where the candidate reports his and his family's income, occupation, education and criminal background-related information. The second form provides sources of income and assets. The candidate discloses all the sources of income and different categories of tangible and intangible assets and their values. He also mentions all related information about income and assets of his family members in this form. The last form is about his tax return. In this form, given that he has submitted income taxes, there is information about his total asset, income and total tax that he has given. Examples of these forms are provided in the appendix (Figure-A2 and Figure-A3).[16]

[16] I have hidden some of the information in the Appendix that could be sensitive.

These forms are only available to the election commission exactly the way it is shown in the Figure section. I have manually extracted all the relevant information and digitized it.

Most importantly, I use the affidavit form to find the reported individual income of the politician and that of his family. In this form, politicians have a tendency not to hide their true income. It is motivated by the fact that they might believe that politicians are giving signals to voters with their higher assets, and voters will choose a wealthier politicians believing that he will not need to expropriate public funds. On the other hand, a dishonest politician will under-report his income on the tax forms to evade income taxes. Interestingly, I found a bunching around the minimum income to pay taxes, another indication of under-reporting income to evade income taxes. So I use the affidavit form to track the income of the politicians and then use the tax forms to check whether the politicians have returned income taxes and whether the amount returned is appropriate or not. Interestingly, by the time the law of mandatory disclosure was passed in 2009, the deadline of tax return was over. So even if dishonest politicians tried to cook their tax forms, it was not practically possible.

1.4 Data

1.4.1 Politicians' Information

Affidavits Forms

I have collected all the relevant information of politicians from the election commission of Bangladesh. After a certain period of time after election, the election commission of Bangladesh removes all the candidates' information from the website. I was able to obtain the hard copies of the affidavits forms and tax forms with the help of an NGO. I have collected profile information of the winners and runner-ups for the 2009, 2014 and 2019 of the upazila elections and digitized them to create the dataset. The dataset includes candidates' own and dependents' information on different sources and values of income; tangible and intangible assets; educational qualifications[17]; past and current criminal records.

Income Tax Returns

All the candidates had to submit their income tax return forms along with their affidavits forms prior to the election. It also mentions whether each candidate has claimed income taxes or not. From the tax form, I am able to observe the reported income and asset information of the candidates and also the exact amount of income taxes the candidates paid.

1.4.2 Election Results

Election results from the 2009 and 2014 upazila elections are also not clearly documented by the election commission. Only the winner's voting results are gazetted as per law. The 2009 and 2014 elections were non-political party elections under law; again for this reason there was some reluctance from the election commission to document the results clearly. For this reason, I collected and cross-validated the election results from three sources. First, the election commission; second, from newspaper articles immediately following the election dates. Third, from an NGO which keeps record of the election results to some extent. I needed to use the last two methods as it is obligatory for my research purpose to

[17] I have converted the reported qualifications to years of education in following way: no education=0, grade 1 to grade 9 = 1 to 9 years, secondary school certificate= 10 years, higher secondary school certificate = 12 years, honors degree = 15 years, post-graduate degrees = 16 to 20 years, self-educated: 1 year

know the vote counts of the runner ups and the total number of votes within an upazila.[18]

1.4.3 Public Goods Measures

Social Safety Net Programs

My main public goods provision indicator is social safety net measures for the 2009 to 2014 period. As mentioned earlier, an upzaila chairman has control over allocation and use of funds related to social safety net programs. The Bangladesh government uses these programs as one of the pillars to support the most poor and vulnerable population. These programs are broadly defined in four categories: 1. special allowances to tackle poverty; 2. employment generations through micro-credit initiatives; 3. food security-based activities; 4. health, education and training programs (Khuda 2011). I have collected information on social safety net programs from a recent household income expenditure survey of Bangladesh (2016). The survey has a total of 186,546 respondents, out of which 48,355 have participated in social safety net programs.

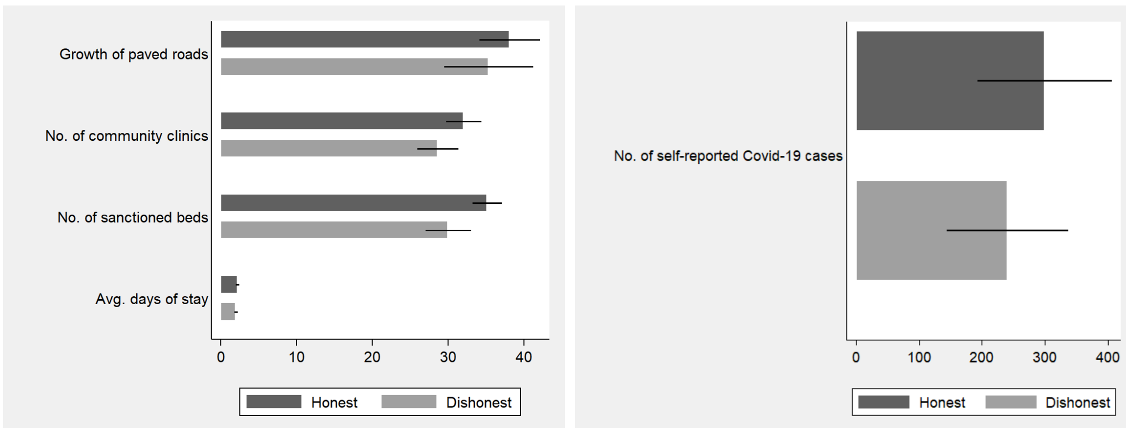
Health and Infrastructure Measures

To analyze the impact of upazila chairmen between 2014-15 to 2019-20 political cycle, I came up with a number of health and infrastructure measures. I do not have information on social safety net programs, as the next survey will take place in 2021-22. From a phone survey, I have collected health-services related information from a sample of upazilas. Using web-scrapping from the website of Ministry of Local Government, I have collected information on paved roads of upazilas. Allocations and progress of all the variables mentioned below

[18] In 2019, due to non-participation of one of the major political opposition parties, many of the upazila chairman won uncontested.

are dependent on upazila chairmen's discretion. I use all of them to come up with an index on public goods.[19]

Figure 1.3: Bar charts show the average values of health and infrastructure variables between upazilas with honest and dishonest leaders



Note: Left and right panels show average values of the 5 variables used to construct the public good provision index using principal component analysis. It shows that in all of the health and infrastructure indicators, on average, upazilas with dishonest leaders perform worse than upazilas with honest leaders.

1.4.4 Economic Development Indicator: Night-time Light

In the development literature, night-time light brightness has been used as a proxy for economic development for the last few years (Michalopoulos and Papaioannou 2013, Prakash et al. 2019)) . There is no data source in Bangladesh that can provide data to calculate upazila-level gross domestic product. Instead I use satellite images of night time light to proxy for long run economic development. I have used the satellite images of Bangladesh for 2007, 2010, 2013, 2015 and 2019. I have collected the GIS data from NOAA National Center for Environmental Information for 2007, 2010, and 2013. There is some discrepancy among

[19]I can not use each variable separately to measure the impact due to lower coverage of upazilas under different variables.

this data due to resolution differences and images that are not cloud free. GIS data from 2015 and 2019 are more compatible, which I have collected from Visible Infrared Imaging Radiometer Suite (VIIRS) data, are more compitable and provide cloud-free images. For 2015, the yearly average image is provided, but for 2019 it is only on a monthly basis. Because of this, I have used the January 2019 image. I have used the night-time lights images to calculate the light intensity for each of the 485 upazilas.

1.4.5 Upazila-level Budget

Upazila expenditure

There are number of sources from which a upazila chairman receives funds. He receives them from an allocation to Member of Parliament (MP) of the constituency. There are a number of development projects run by donor agencies in cooperation with the Ministry of Finance, Ministry of Local Government and Rural Development, and some other ministries from which an upazila receives development funds. Upazilas also have there own revenue and development budgets; only in recent years, they are formally documenting those. There are local level tax collections done by the upazila chairman office. There is no public database or source from which I can collect upazila specific income and expenditure by the local governments. I use a sample survey by UNDP-BIDS conducted in 2014-15 to decompose the local level income and expenditure of the upazilas. I use this sample survey to explain the mechanism of negative effects on upazilas with dishonest politicians.

Central-fund allocation

To understand the mechanism, specifically whether or not the upazila level development is explained by the variations in the funds received from the central government, I have collected administrative documents from the Ministry of Finance for the last two fiscal years—2018-19 and 2019-20. From the documents, I have digitized the data for my analysis. They do not have any previous years' information disaggregated at the upazila-level to their disposal.

Finally, to generate upazila level weight, and analyzing per capita development of the upazila, I have used population census of 2011 to have the upazila level population.

1.5 Dishonest Politicians

1.5.1 Definition

My objective in this paper is to find the causal impact of dishonest elected politicians' tenure on the economic progress of that constituency and compare them with constituencies represented by honest politicians. I am using tax evasion based on the income the politician has stated in the affidavit forms.[20] I need to have ex ante information on politicians to figure out whether he is dishonest or not.

The declaration of the disclosure law in 2009 came as a surprise that can help me use tax evasion to find dishonest politicians. In September-October 2009, the income tax return was due, and in December 2009 the election was held. Thus, the affidavits of income and asset came after the tax submission. Dishonest politicians evaded tax and could not change it later on. The mandatory law of disclosures came to effect for the first time that year, so politicians were caught off-guard[21]. With this motivation, I use the following definition to

[20]Definition based on asset growth of politicians to see the impact on constituency level development used in previous literature has the problem that asset growth may be due to economic progress thus endogenous, which is the outcome I am interested in.

[21]The punishment of not paying the tax is not that heavy and being a Upazila Chairman, a person can use his position to avoid any legal consequences.

figure out dishonest politicians.

Definition 1: A politician is dishonest if he has more than or equal to Taka 265,000/300,000 but did not submit his mandatory Income Tax, subject to occupations.

By definition, if income is Y and tax amount is t, the variable $dishonest = 1$ if $Y > 265,000/300,000$ and $t = 0$, otherwise $dishonest = 0$.

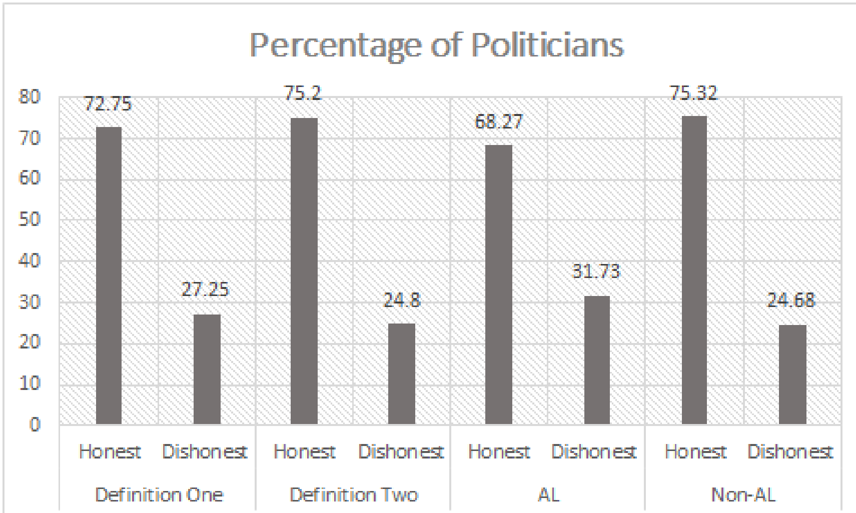
According to the income tax law in 2008-09, a person is exempted from income tax if his or her income is less than Taka 265,000/300,000[22,23]. Thus, in my sample of 493 upazila chairmen, if someone did not have an income over Taka 265,000/300,000 and did not submit his tax return, then he is not identified as dishonest. I have incorporated family income in the equation because the dishonest politicians can avert taxes by transferring income to family members, for example—he might own a business in his wife's name. The latter is my definition-two for dishonest politicians.

According to definition, I have the following distribution:

[22] USD 1 was equivalent to Taka 70 in 2009.

[23] The Taka 25,000 range is allowed depending on occupation categories.

Figure 1.4: Honest versus Dishonest Politicians in 2009-10



Note: Four categories are shown above; from left to right— overall percentage of dishonest and honest leaders using only individual reported income, overall percentage of dishonest and honest leaders using diverted income to dependants, percentage of dishonest and honest leaders in major party Awami League (AL), percentage of dishonest and honest leaders in other major political parties.

As mentioned earlier, the 2009 upazila election was a non-party one. Candidates were not allowed to run under national political party banners. However, it became a common knowledge to voters prior to the election about the affiliation of the candidate with any one of the national political parties. Election commission, by law, cannot tag a candidate under a political party. I went back to newspaper articles published right after each round of 2009 election. From there, I collected information of political affiliation of the winners of the 2009 elections. It is important to understand whether the number of dishonest politicians varies according to the political parties. Bangladesh has two major political party— Awami League (AL) and Bangladesh Nationalistic Party (BNP). AL is middle-left in political ideology, and BNP leans to the right. Many leftist parties have coalition with

AL and right-wing parties including Islamic religious political parties ally with BNP. I found that in 2009, around 57.46% of upazila charimen were from AL and 42.45% were from BNP and others.[24] It is evident from this distribution that dishonest politicians are not skewed towards any major parties.

Further check of the definition

In the RD design, I use dishonest winners over honest winners on the left of the cutoff and honest winners over dishonest winners on the the right of the cutoff[25,26]. I track the 2009 runner ups, who have competed in the 2014-15 upazila election. Among these candidates, 118 competed in the 2014-15 election. Also, I have found that out of 249 winners (within 10% winning margin) in 2009-10, 127 have competed in the 2014-15 upazila election. I collected both of these two groups' asset information from 2014-15. Table-1.2 shows that the winners, on average have higher total income and total asset compared to the runner ups. This validates the results of Fisman et al. (2014) and Bhavnani (2012), which states that in close elections winners accumulate higher wealth compared to the runner ups.

[24]Parliament is also currently controlled by AL. AL have won majority of the seats on the last three parliamentary elections. However due to political turmoil and disbelief between the two major parties, BNP did not participate in the last two parliamentary elections. Interestingly in 2009 an 2014, in both times candidates backed up by BNP participated in upazila elections.

[25]For 2014-15 election this requirement is met as I was able to collect information on all the runner-ups

[26]For 2009-10, election commission could not retrieve all runner ups information. I only have 103 runner ups profile to understand whether they are dishonest or not. Using this truncated sample hinders me to have enough statistical power to run the RDs. However I have one with the small sample, and signs of the main results remain intact, although I lose statistical significance.

Table 1.1: Income and Asset information in 2014 of Winners and Runner-Ups from 2009

Variable	Winners of 2009	Runner-Ups of 2009	Difference
Total Income in 2014	2.2	0.71	1.52
	(1.3)	(1.4)	(1.47)
Total Asset in 2014	8.2	7.08	1.12
	(2.5)	(1.4)	(3)

Notes: In million of Taka. 1 USD = Taka 70 in 2010. Standard errors in the parentheses.

Dishonest vs. Honest winners

In Table-1.2, I show that in 2014-15 the dishonest winners from 2009-10, on average, have more income and assets compared to honest winners from 2009. Specifically, in terms of total assets, the dishonest winners have around \$124,025 more than honest ones. This result clearly bolster the definition of dishonest politicians that I have used for my analysis. More importantly, I followed the set of dishonest and honest winner in 2019-20 elections. The last row of the table shows that there is 3.6% higher asset growth of dishonest woinners compared to honest winners.

Table 1.2: Income and Asset information in 2014 of dishonest and honest winners from 2009

Variables	Dishonest Winners	Honest Winners	Difference
Total Income in 2014	5.2 (4.1)	0.77 (0.2)	4.51 (2.9)
Total Asset in 2014	15 (8.0)	5.08 (0.7)	9.97* (5.5)
Asset Growth (2014-2019)	27.78 (12.51)	24.28 (11.15)	3.6 (5.5)

Notes: In million of Taka. 1 USD = Taka 75 in 2014. Standard errors in the parentheses.

Ex ante characteristics of politicians

The second set of tests deals with ex ante characteristics of the honest and dishonest politicians. According to my definition of dishonest politicians, it is important to find some meaningful differences in their income and asset records. The following table provides this evidence. I find that the income and assets of the dishonest politicians are higher on average and that it is statistically significant. This also gives validation to the definition of dishonesty that has been used in the paper. Interestingly, the wealth record that has been collected from the tax-return document shows that the honest politicians have more wealth than the dishonest, unlike in the affidavit form. However, the difference is insignificant. This also implies that there is a high possibility that the dishonest politicians have misreported about their wealth in the tax returns forms.

There are other statistically different features between honest and dishonest politicians.

Average income reported by dishonest politicians in the tax return form is 61.4% less than the amount declared in the affidavit forms. This shows the that dishonest politicians are under-reporting their income to evade taxes and over-reporting their wealth and income on affidavits to show off to the voters. On the other hand, honest politicians are reporting more income on tax return compared to affidavit forms.

Table 1.3: Pre-determined Characteristics of Candidates

Variables	Honest	Dishonest	Difference
Individual income from affidavits	.607	.960	$-.352^{*}$
Family income from affidavits	.651	1.056	$-.404^{*}$
Total Asset in self-declared form	4.043	5.481	-1.438
Total Income in tax return form	.942	.370	.572
Tax Paid (in Taka)	91990.09	0	91990.09^{***}
Years of Schooling	13.78	13.57	.217
Past Criminal Records	.494	.548	-.054
Current Criminal Records	.230	.338	$-.108^{*}$
Number of observations	351	133	-

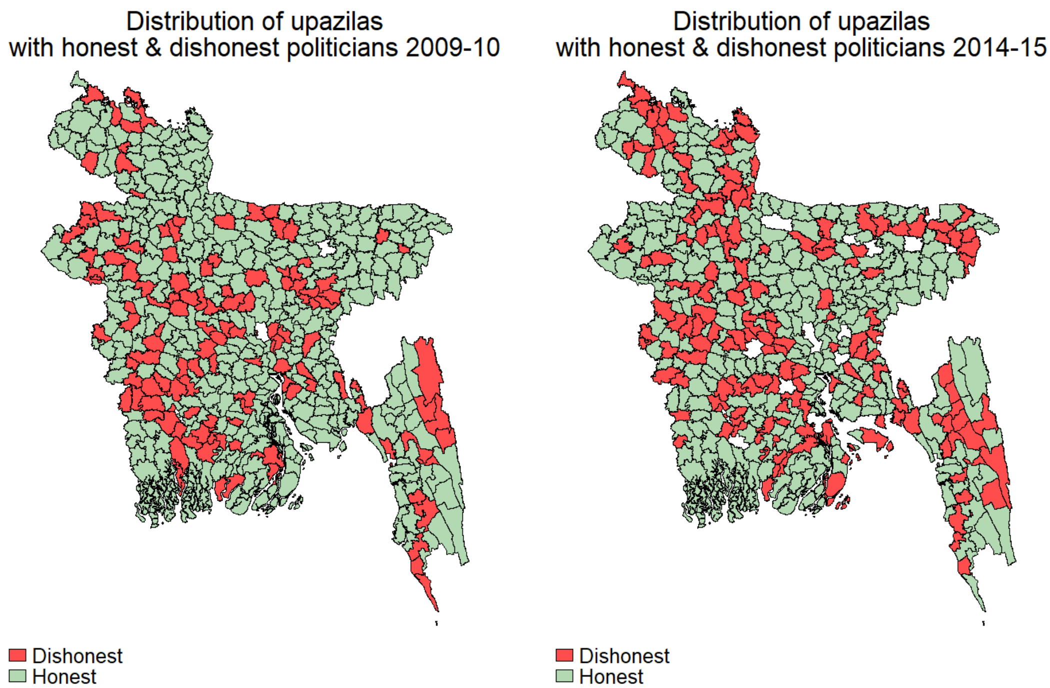
Note: ***, **, * denote 1 percent, 5 percent and 10 percent level of significance, respectively. The unit of monetary measure in this paper is Taka (BDT). USD 1 = Taka 70. Information on the variables are collected from candidates' reported affidavits and income tax returns from the upazila elections in 2009 & 2014. First four entries are in million Taka.

Another important finding from this table is that dishonest politicians are just as educated as honest politicians. It also confirms that the main results of the paper are not driven by competence of the politicians, which I expand on in second chapter. The second to last row in the table shows that compared to honest politicians, dishonest politicians had 10% more criminal records and this is statistically significant. Therefore, there is a fairly a loose correlation between politicians having criminal records and being dishonest.

1.5.2 Spatial distribution of upazilas

The following set of maps demonstrates the spatial distribution of constituencies with dishonest versus honest politicians. There is significant spatial variation in income and education in the east and west of Bangladesh. It is notable, however, that dishonest politicians are not selectively represented in east or west. It is also noticeable that compared to 2009, few upazilas in 2014 are changing from honest to dishonest, and vice versa.

Figure 1.5: Geographical distribution of upazilas with dishonest and honest elected politicians in 2009-10 & 2014-15



Note: Left map shows the spatial distribution of upazilas with honest (green) and dishonest (red) upazila chairmen between 2009-10 and 2014-15. Right map shows the spatial distribution of upazilas with honest (green) and dishonest (red) upazila chairmen between 20014-15 and 2019-20.

1.6 Empirical Strategy & Validity of RD

1.6.1 Identification under Regression Discontinuity (RD)

The following strategy is used to have the causal estimate under regression discontinuity design:

In my analysis, the treatment is, if a politician is dishonest, he gets a value of 1, otherwise he gets a value of 0. Lets say, $D = 1$ if politician is dishonest and $D = 0$ if he is honest. Let X_i be the margin of votes for victory in the 2009/2014 Upazila elections. $c = 0$ is the cut-off point. Then,

$$D_i = \begin{cases} D_i = 1, & \text{if } X_i \geq c \\ \\ D_i = 0, & \text{if } X_i \leq c \end{cases}$$

Lets say, Y_1 and Y_0 are the provision of public goods in dishonest and honest constituencies, respectively. Then, at the vicinity of the cut-off, I am able to identify the causal effect of treatment according in following way:

$$\beta_{RDD} = E[Y_1 - Y_0|X = c]$$
$$= E[Y_1|X = c] - E[Y_0|X = c]$$
$$= \lim_{x\to c} \uparrow E[Y_1|X = c] - \lim_{x\to c} \downarrow E[Y_0|X = c]$$

The following are the identifying assumptions that I need to make the causal estimate:

$Y_1, Y_0 \perp\!\!\!\perp D|X$

and

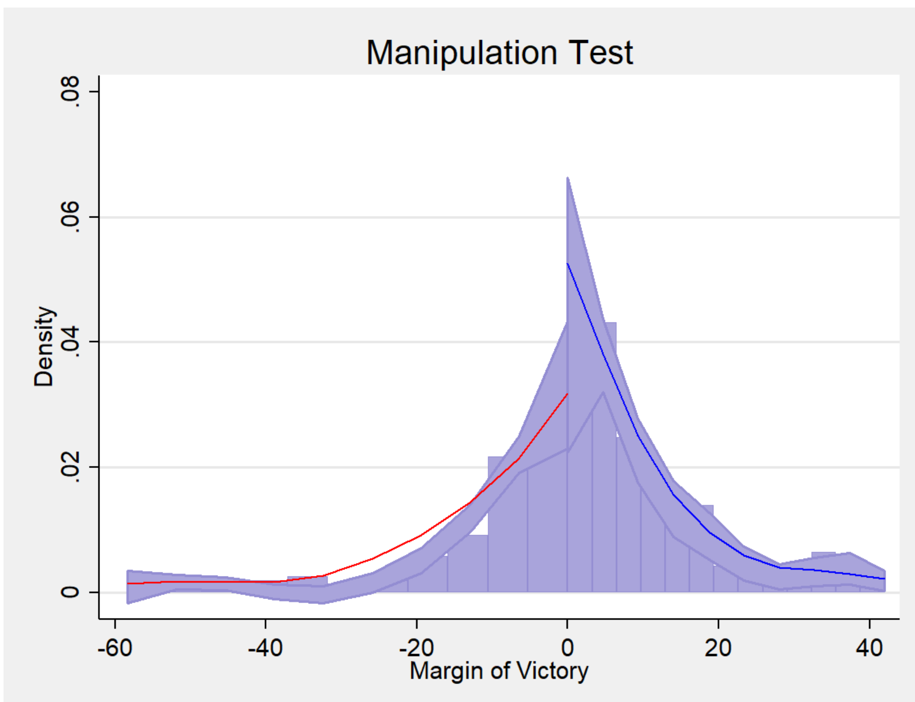
$0 < P(D = 1|X = x) < 1$ [In my case of Sharp RD, this assumption is met]

As mentioned above, there are two main concerns regarding the validity of RD design, in the following section I discuss them in detail.

1.6.2 Manipulation test: Density estimate at the cutoff

The first test of validity is the test for a jump at the cutoff of in the density of the running variable. The concern is that the vote margin is non-smooth at the cutoff due to the rigging of elections by the dishonest politicians.[27] This test implements a check at the cutoff, whether there is a statistically significant discontinuity of the forcing variable. The running variable is the winning margin of votes. On the right side of the cutoff is the difference as a percentage of total votes of an honest winner over a dishonest runner up. On the left hand side of the cutoff is the difference as a percentage of total votes of dishonest winners over an honest runner up.

Figure 1.6: McCrary test of Density around the cutoff of the Forcing variable, Margin of Victory



Note: The p value is : 0.40 - failed to reject the null of continuity at the cutoff.

The above figure shows that the discontinuity is not statistically significant above and below the cutoff.[28].

[27]Previously, in RD literature, it was known as the McCrary (2008) density test. In recent development, the most popular test is known as the Cattaneo, Jansson, and Ma (2017a) density test.

[28]This test employs a polynomial order of 2 and the bandwidth is selected by the following criterion

1.6.3 Balance Test

The second test is to see whether the known characteristics of the upazilas are continuous at the cutoff. This is primarily the second test of validity of RD design (Imbens and Lemieux 2008). The objective of this test is the characteristics of constituencies with dishonest chairmen could be different from the constituencies with honest chairmen in the overall sample, but they should not be discontinuous around the cutoff. The only exception is the treatment itself, which in this case jumps from 0 to 1 from moving right from the left of the cutoff (Sharp RDD). Table-1.4 shows the differences of the characteristics of honest and dishonest constituencies in the pre-election period. As shown, mostly all the variables' differences are statistically insignificant besides literacy rate.

(Cattaneo, Jansson, and Ma (2017a)) for the restricted model (where h is the bandwidth): $h^{\hat{R}}_{comb,p} = \min[h^{\hat{R}}_{diff,p}, h^{\hat{R}}_{sum,p}]$

Table 1.4: Descriptive Statistics of Pre-determined Characteristics of Upazilas

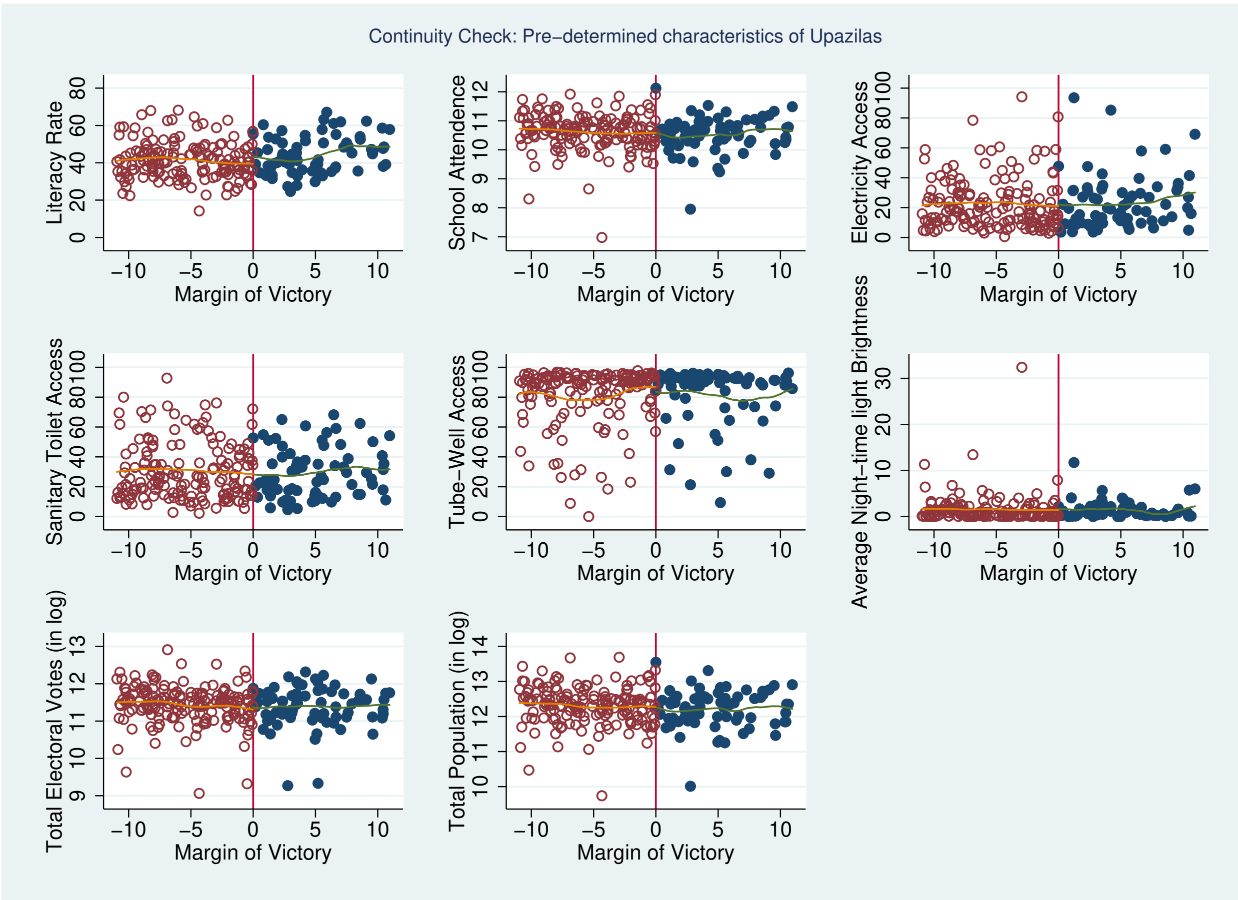
Variables	Honest	Dishonest	Difference
Total Population	240,661	223,204	17,456
	(11115)	(14247)	(19258)
Literacy Rate	41.2	44.23	-2.9*
	(.7)	(1.1)	(1.4)
Electricity access	22.4	23.3	-.87
	(1.3)	(2.09)	(2.4)
Tube-well access	81.7	81.9	-.16
	(1.5)	(2.3)	(2.7)
Sanitary-Toilet access	30.6	29.6	.95
	(1.5)	(1.9)	(2.5)
School Enrollment	48,465.2	44,364.4	4,100.8
	(2127.7)	(3046.3)	(3772.3)
Average Night-time light Brightness	1.53	1.46	.071
	(.26)	(.22)	(.41)
Number of Observations	351	133	

Notes: ***, **, * denote 1 percent, 5 percent and 10 percent level of significance, respectively. Standard errors are in parentheses.

The eight separate variables are used and presented in the following figure to check for the continuity at the cutoff. Every dot represents an upazila and the lines are local linear regression fit. There are two curves separated by the cutoff. The curves are derived using thr triangular kernel and optimal bandwidth calculator proposed by Imbens and Kalayanaraman

(IK)(2012). So, Upazila level characteristics, measured by literacy rate, school attendance, percentage of households with electricity access, percentage of households with sanitary toilet access and percentage of households with tube-well water access, do not vary at the cutoff and the change at the cutoff is not statistically significant.

Figure 1.7: Balance check test of density around the cutoff of the Forcing variable, Margin of Victory for eight variables



Note: Eight variables are presented above: literacy rate, school attendance, percentage of households with electricity access, percentage of households with sanitary toilet access and percentage of households with tube-well water access, total electoral votes, total populations, and average night-time light brightness prior to the 2009-10 election. There are no discontinuous jumps of any of the variables at the cutoff. On the left of the cutoff are upazilas with dishonest winners, and on the right side of the cutoff are upazilas with honest winenrs.

Also, the average luminosity that I have captured from GIS data do not vary at the cutoff and this for 2007, which is right before the Chairman got elected for a particular

Upazila. The last two figures are of total electoral votes (taken in log) in the 2009-10 upazila election and total population (taken in log) of the Upazila. These two variables are also not statistically different at the cutoff. These validity checks confirm that the identification under RD should elicit the causal effect of having a dishonest politician on constituency level public goods provision.

1.6.4 Regression Discontinuity Design

In my RD design, on the right side of the cutoff of the running variable, I have the constituencies where there were honest winners in the 2009 election. On the left side of the cutoff are the constituencies of dishonest winners of 2009 election, and winning margins are denoted as negative. My major dependent variable here is the provision of social safety net programs adjusted for the total population of the Upazila. I have generated upazila weights from population census and have used them to remove any bias that might be generated from the household survey sampling. If the dishonest politicians under-provide public goods, there would be a discontinuous jump at the cutoff. But if the alternative hypothesis holds, then there could be no jump or fall, suggesting dishonest politicians did not negatively effect the outcome or could have had even positive effects. So here at the cutoff, the status of the politicians gets changed from dishonest to honest (1 to 0). Closer to the cutoff, the margin of victory becomes very small, thus the outcome of the election becomes as good as random. As a result, constituency that has voted for a honest politician becomes a counter-factual for a constituency that has voted for an dishonest politician at the small margin of votes. Connecting the expected results with the theoretical framework I provided in section-2, we can think the variable 'dishonest' as θ and Y_{dt} as the level of public goods provision denoted by g_j in the model.

I use the following regression equation to estimate the RD effect of electing a dishonest politician compared to an honest one.

$$Y_{dt} = \alpha_d + \beta dishonest_{idt-1} + f(VoteMargin_{idt}) + \epsilon_{dt}, \tag{1.5}$$

where, $\forall VoteMargin_{idt} \subset (c - h, c + h)$

Here $(Y_{dt}) = logY_{dt+1}$ - $logY_{dt}$, which measures the number of families getting social safety net programs in a constituency over the period from 2010 to 2015 for SSNP. h would be the bandwidth choice that will determine the neighborhood around the cutoff, c. $f_{VoteMargin}$ is a semi or non-parametric continuous function. In this setup, β will give me the causal impact of electing dishonest politicians relative to honest ones on the public goods provision of constituencies.

1.7 Results

1.7.1 Dependent variable: Social Safety Net Programs

To evaluate whether dishonest politicians are having a negative impact on development of his constituency, I need to come up with variables that are closely related to the activities of an upazila chairman. Social safety net programs (ssnp) are an accurate measure of public goods provision in the case of Bangladesh. 12 % of all the households in Bangladesh are receiving social safety net support from the government, especially the poorer households in rural areas. On average, 2.5 % of GDP & 13.2 % of total budget of Bangladesh go to ssnp. There are 50 different programs running under ssnp. Scholarship programs for education at the primary and secondary level, different kinds of food programs, household benefit programs for elderly, women empowerment programs etc are under ssnp. Among these programs, many fall under direct jurisdiction of the upazila chairman. Dishonest politicians can severely misuse these funds for their own benefits, leaving the households under the program vulnerable. I use two main variables related to ssnp to understand the impact of having dishonest politicians—total households under ssnp in a upazila and total value (cash and in-kind) of the transfer to a household in upazila. Following table shows the descriptive statistics of the two variables. I use the Bangladesh household income expenditure survey (2015-16) for the data on ssnp.

Table 1.5: Descriptive Statistics: Social Safety Net Programs

Social Safety Net Programs	Mean	Std. Dev	Min	Max	Observations
No. of households receiving social safety nets	15.74	29.53	0	249	480
Average value (in Taka) of social safety nets per household	1773.196	1883.80	300	21750	335

On average, around 16 households are receiving ssnp in each upazila. The average value per household of the programs is Taka 1773.2 [29]. More importantly, both of the variables vary significantly in upazilas with dishonest versus honest leaders.

[29] In 2015, \$1 = Taka 75

Table 1.6: OLS results of social safety net programs

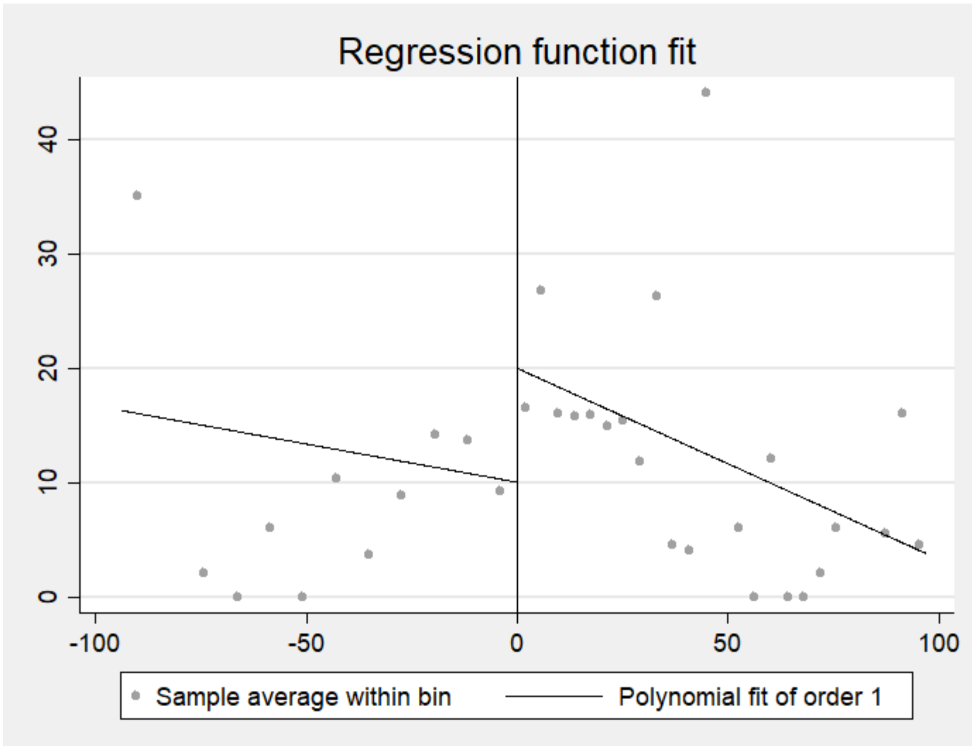
	No. of households	Value of the programs per household
Dishonest	-5.969** (2.4)	-282.7* (163.7)
Constant	17.37*** (1.78)	1855.9*** (141.3)
No. of upazilas	480	335

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Before moving to the RD estimates, I want to show that the above table provides OLS estimation of having dishonest upazila chairman as opposed to an honest one. As discussed before, simple OLS results are not causal evidence of having dishonest politicians, as constituencies that elected dishonest politicians can be systematically different from the ones that do not. Nonetheless, it provides general evidence that upazilas with dishonest leaders have 6 fewer households receiving ssnp and Taka 283 less in terms of average value of the programs. I will use the number of households as the main dependent variable to run the RDD because it has been observed in Bangladesh that local leaders reached out to fewer households in many development initiatives, mainly because of corruption (Khuda 2011). Also, many households in the survey did not mention the value of the program received, thus I lose statistical power for RDD if I use the value of the ssnp as dependent variable.

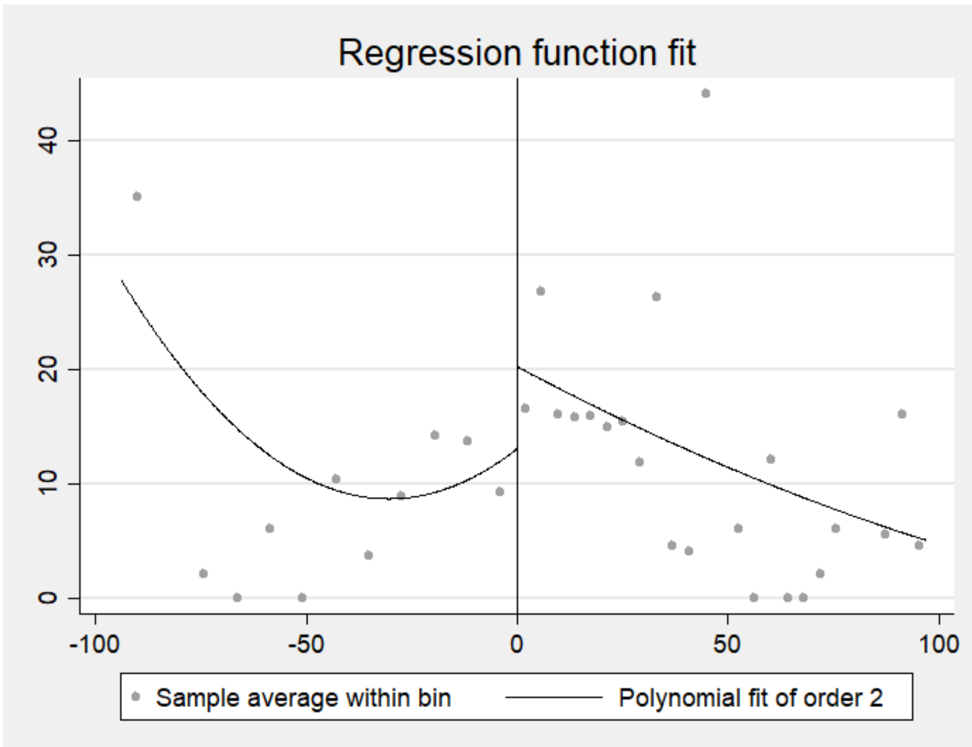
Figure-1.9 and figure-1.10 provide prima facie evidence of my results. The Y axis of the figure is the number of households receiving ssnp (adjusted for the population of the upazila) in constituencies over the period from 2009-2015 at the upazila-level. The running variable in the X axis is the margin of votes for the winner in percentage term of total votes in the election of an upazila in 2008-09. The cutoff is at 0 and on the right hand side of the cutoff are the constituencies which had honest elected politicians. On the left side of the cut off are the constituencies which had dishonest politicians as their elected chairmen. Each dot represents the sample average of a bin. The solid lines depict a polynomial regression function that uses triangular Kernel and the optimal bandwidth formula proposed by CCT(2016). The RD figure shows a sharp discontinuity at the cutoff. On average, an upazila with a dishonest politician has 12 fewer households in terms of social safety net provision compared to honest upazilas. In the upazilas with honest chairmen, an average of 44 households recieve social safety net programs. So 27.27 percent less households are provisioned in the dishonest constituencies.

Figure 1.8: Number of households receiving social safety net support



Notes: Regression discontinuity with polynomial order of one with dependent variable: number of households receiving social safety net programs. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Margin of victory in the election is on the x-axis as the running variable of the RD.

Figure 1.9: Number of households receiving social safety net support



Note: Regression discontinuity with polynomial order of two with dependent variable: number of households receiving social safety net programs. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Margin of victory in the election is on the x-axis as the running variable of the RD.

Table 1.7: Effect of having a dishonest politician on social safety net provision

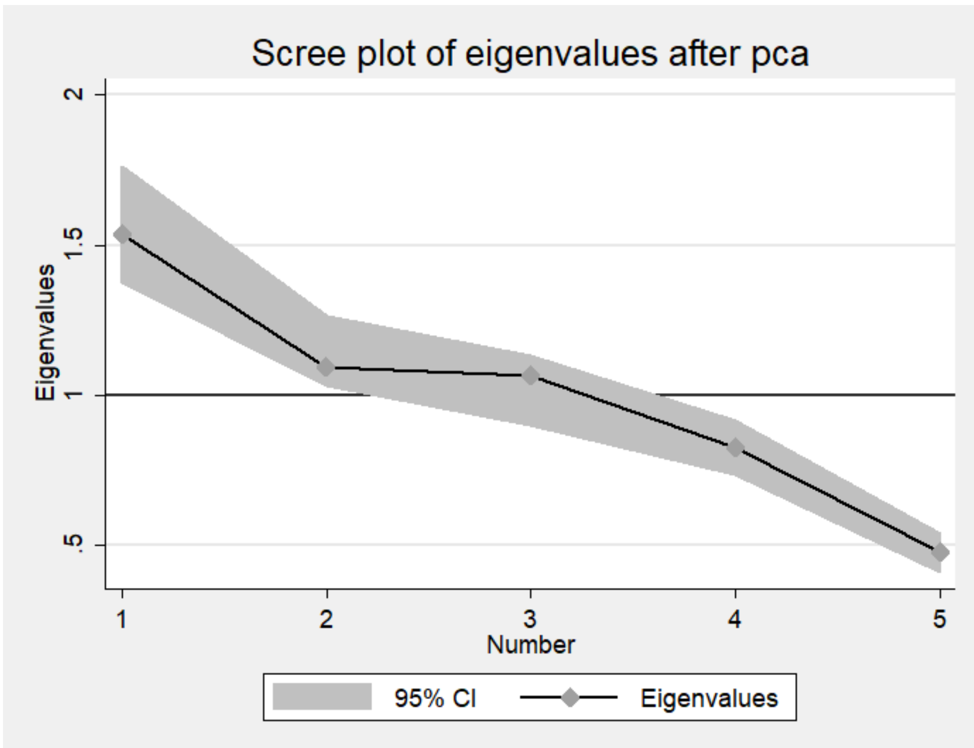
No. of households	(1)	(2)	(3)	(4)
Honest Constituencies	12.69***	12.03**	12.82**	11.46*
	(4.93)	(5.86)	(5.33)	(6.5)
Kernel	Triangular	Triangular	Uniform	Uniform
Bandwidth (CCT)	14.7	20.06	11.3	18.04
Polynomial	one	two	one	two
No. of Observations	485	485	485	485

Note: ***, **, * denote 1 percent, 5 percent and 10 percent level of significance, respectively. Standard errors in parentheses. RD estimates of the number of households are reported in all the four columns using different specifications.

1.7.2 Results: Analysis of 2015-20 political cycle

The fourth upazila election took place in 2014-15 and there were six rounds of elections taking five months of time. To test whether dishonest politicians have a negative effect on public goods provision in 2015-2020, I apply similar methods but with different dependent variables. I do not have information on social safety net programs provision for years after 2015. Using a set of health and infrastructure variables at the upazila level, I construct a public goods provision index using principal component analysis. The health indicators that I have used are: No. of community clinics, No. of self-reported Covid-19 patients at upazila facilities, No. of sanctioned beds at upazila health complexes, and average length of stay of a patient in the hospital. The infrastructure indicator used for the index is the growth of paved roads from 2014-15 to 2019-20.

Figure 1.10: Scree plot of the Eigenvalues

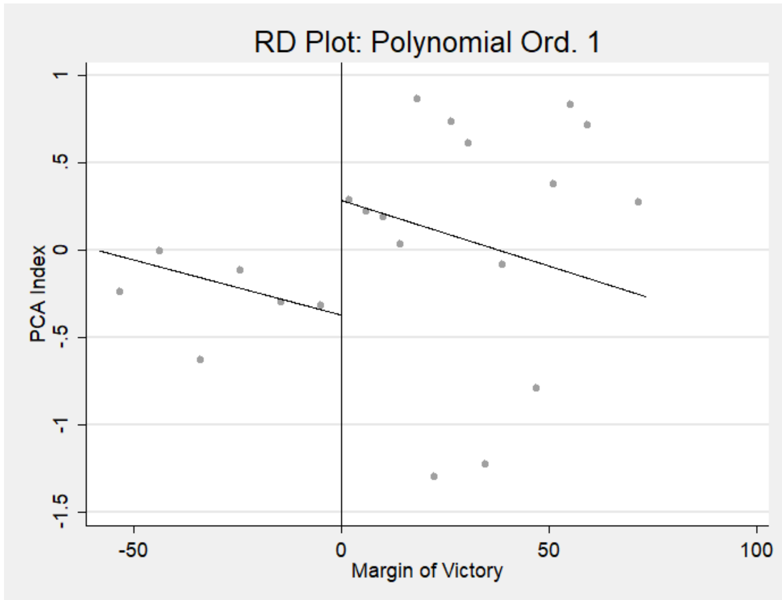


Note: Screepolot of eigenvalues of the components is shown in above figure. First three components explain 73% variations

The screeplot of the eigenvalues generated from the principal component analysis show that the first three components explain 73% variaton in the data. Using the components, I generate the score for each upazila, which serves as the public goods provision index. The following figures provide the result of the RD design, where the dependent variable is the public goods provision index. In the appendix (Table A.1), I provide the top-20 and bottom-20 upazilas in terms of the index values.[30]

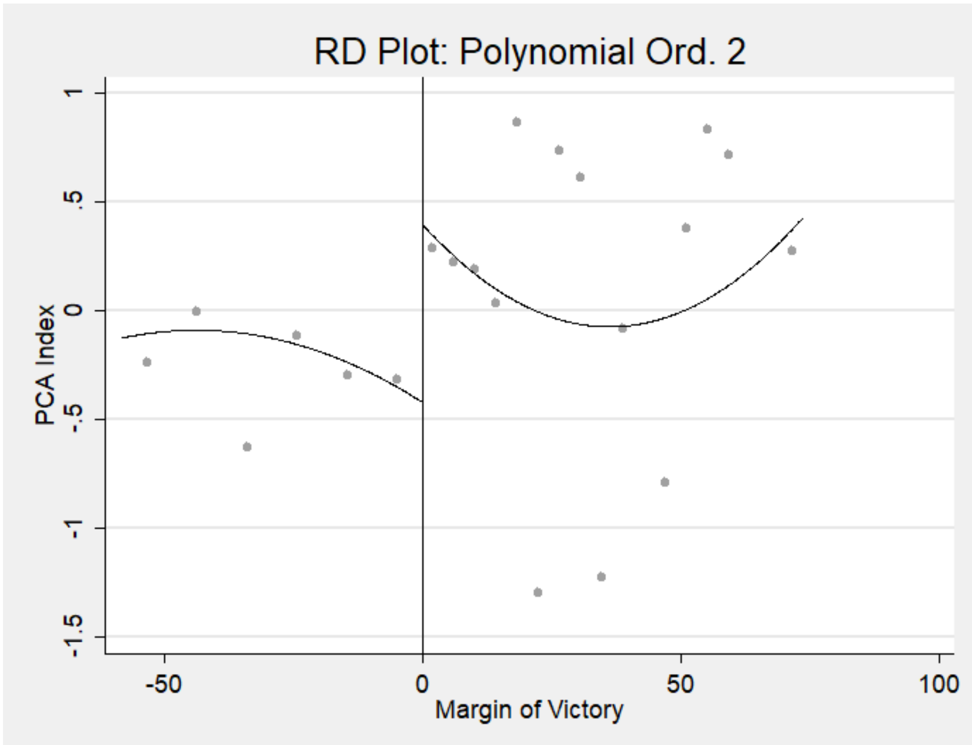
[30]To my knowledge, I provide the first recent ranking of upazilas in terms of public goods provision in Bangladesh. This is going to immensely helpful for the policy makers of Bangladesh. Full ranking available on request.

Figure 1.11: PCA Index



Note: Regression discontinuity with polynomial order of one with dependent variable: public good provision index constructed using principal component analysis. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Margin of victory in the election is on the x-axis as the running variable of the RD.

Figure 1.12: PCA Index



Note: Regression discontinuity with polynomial order of two with dependent variable: public good provision index constructed using principal component analysis. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Margin of victory in the election is on the x-axis as the running variable of the RD.

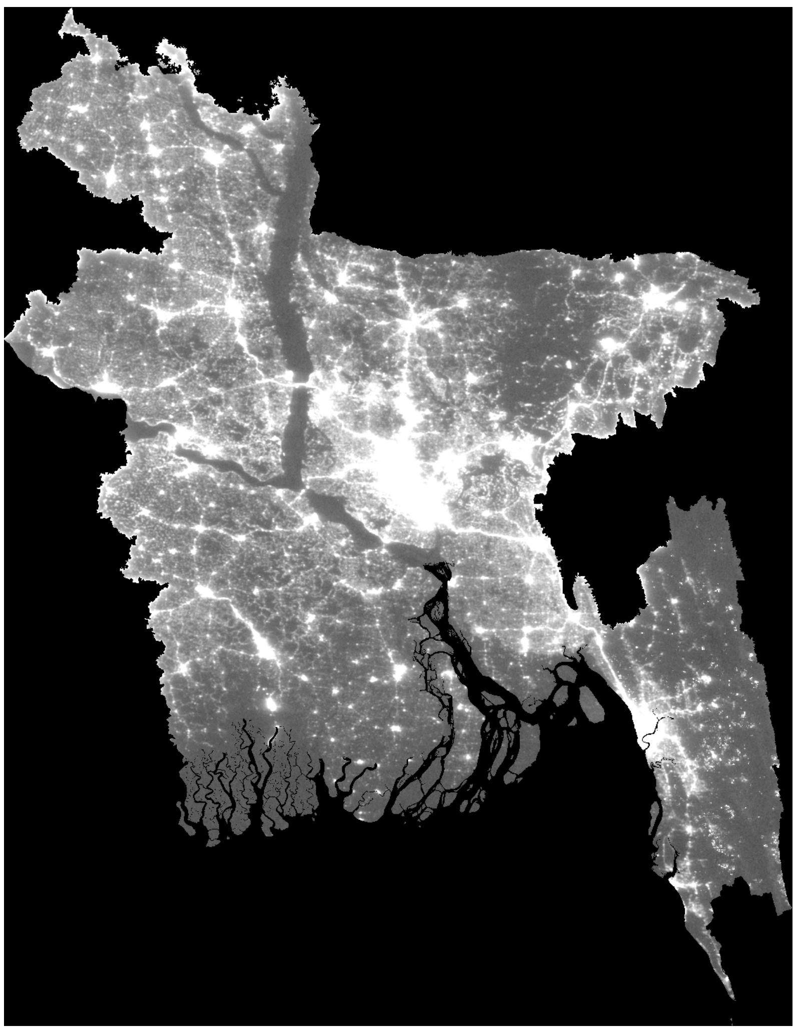
A median value of the index is 0.27 with a standard deviation of 1.23. The RD estimate is 0.94, which means that the upazilas with honest leaders have a 0.74 standard deviation higher index value compared to upazilas with dishonest leaders.[31]

[31] In appendix, Figure-A4 coefficients plot shows that in all the three dimensions of growth of roads, dishonest politicians' constituencies are doing worse than the upazilas with honest politicians.

1.7.3 Economic Development: Nightime light luminous

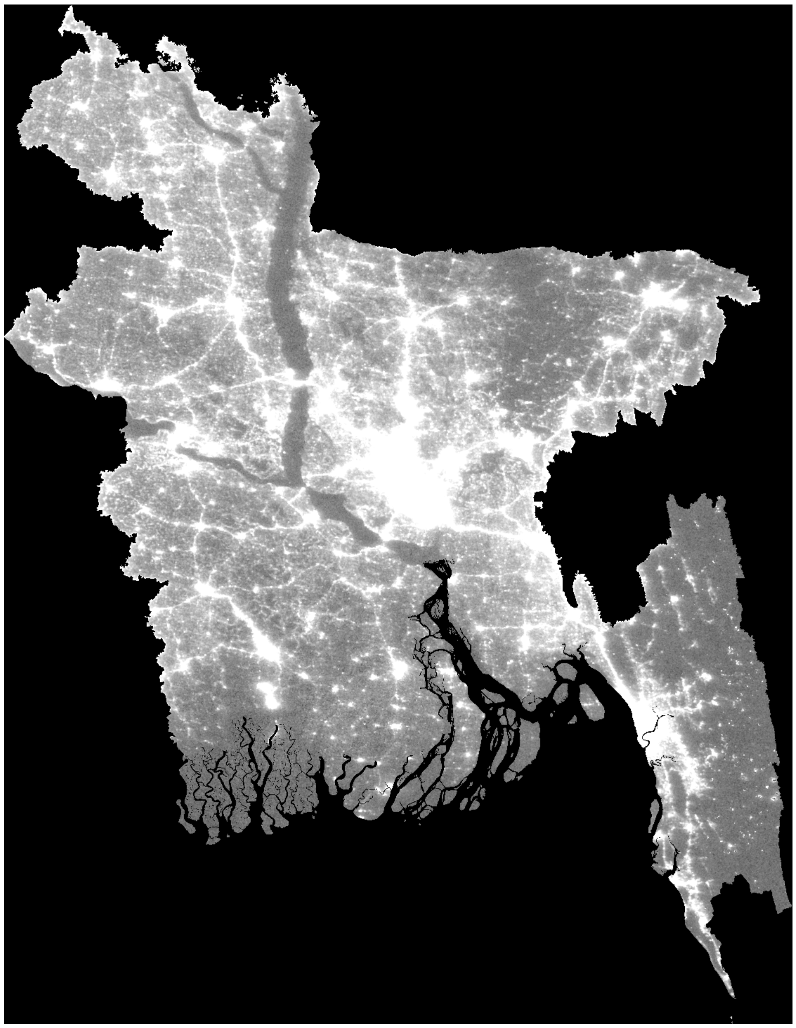
Using the satellite images from NOAA National Centers for Environmental Information and the visible infrared imaging radiometer suite (VIIRS), I have created a datatset of night-time light brightness of Bangladesh in 2015 and 2019. The following two pictures show the images that have been converted to numerical values for my analysis.

Figure 1.13: Night-time light image of Bangladesh:2015



Note: Pixel values of the night-time light brightness is used to measure economic development.

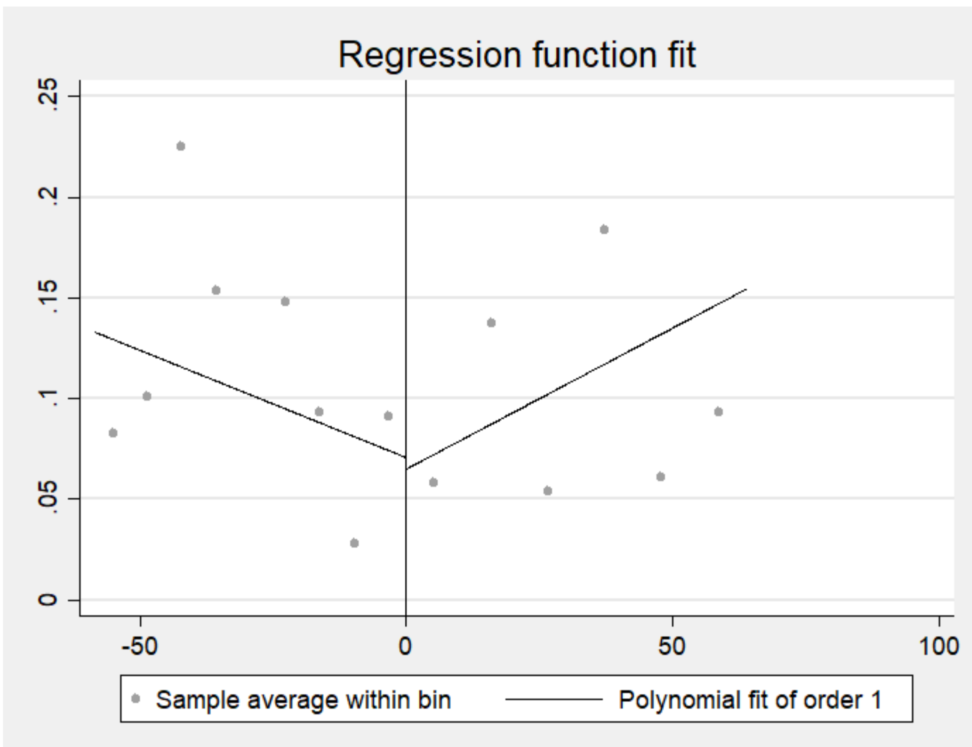
Figure 1.14: Night-time light image of Bangladesh:2019



Note: Pixel values of the night-time light brightness is used to measure economic development.

In 2015, the average night-time light brightness for an upzaila was 1.92 and 2.27 in the year of 2019. Over this period of this time, the growth was 9.1%, with an annual growth rate of 2.3%. Indeed, GDP growth of Bangladesh within this period was around 7 to 8% per year. However, the growth was not evenly distributed among all the districts. To address this issue, I apply regression discontinuity where the dependent variable is the growth of night-time light. Using the full sample, the following RD plot shows that there is almost no statistical difference between the growth of night life between the upazilas with honest and dishonest politicians.

Figure 1.15: RD result: Growth of Night time light



Note: Pixel values of the night time light brightness is used to measure economic development. Regression discontinuity with a polynomial order of one with dependent variable: growth of nighttime light brightness over the period from 2015 to 2019. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Margin of victory in the election is on the x-axis as the running variable of the RD.

The following table shows the RD estimates with different bandwidth choices and polynomial orders; We can see that the estimates are essentially zero.

Table 1.8: Effect of having a dis(honest) politician on Growth of night-time light

Growth of NL	(1)	(2)	(3)	(4)
Honest Constituencies	-.03353	.00687	-.00445	.0224
	(.0463)	(.07215)	(.05763)	(.07363)
Kernel	Triangular	Triangular	Uniform	Uniform
Bandwidth (CCT)	12.9	13.3	6.8	10.18
Polynomial	one	two	one	two
No. of Observations	485	485	485	485

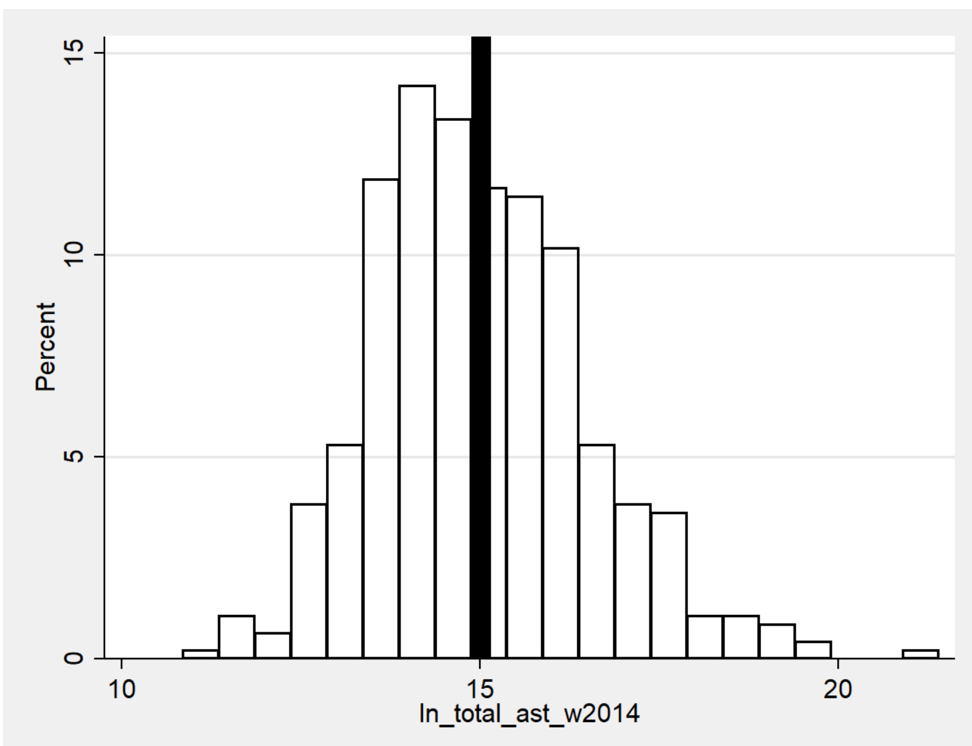
Note: ***, **, * denote 1 percent, 5 percent and 10 percent level of significance, respectively. Standard errors in the parentheses. RD estimates of growth of nighttime light over the period from 2015 to 2019 are reported in all four columns using different specifications.

One plausible explanation of this null result is that the local level leaders might not have the power to spur overall economic growth.

1.8 Heterogeneity test: Wealthy politicians

One natural question could arise—Whether public goods provision and economic development can vary by the degree of dis(honesty). So far, throughout the analysis, my definition of dishonesty is a binary measure (0 vs.1). Given the data I am using to measure dishonesty, it is difficult to come up with a method to measure degree of dishonesty. One way to measure this is to use the growth of assets of a politician (the higher the growth, higher the dishonesty if he evaded income taxes). However, it is problematic to use asset growth as a measure of dishonesty and analyze its effect on public goods provision and economic development because the development of an upazila and the growth of wealth of politicians could be correlated. This can make the results endogenous. I introduce a measure to check the effects on public goods provision and economics development of wealthy dishonest politicians. The following histogram shows the distribution of candidates' assets (log) reported in 2014-15. I take the mean value of log asset (15.01) and truncate the sample to the right of the line.

Figure 1.16: Asset Distribution



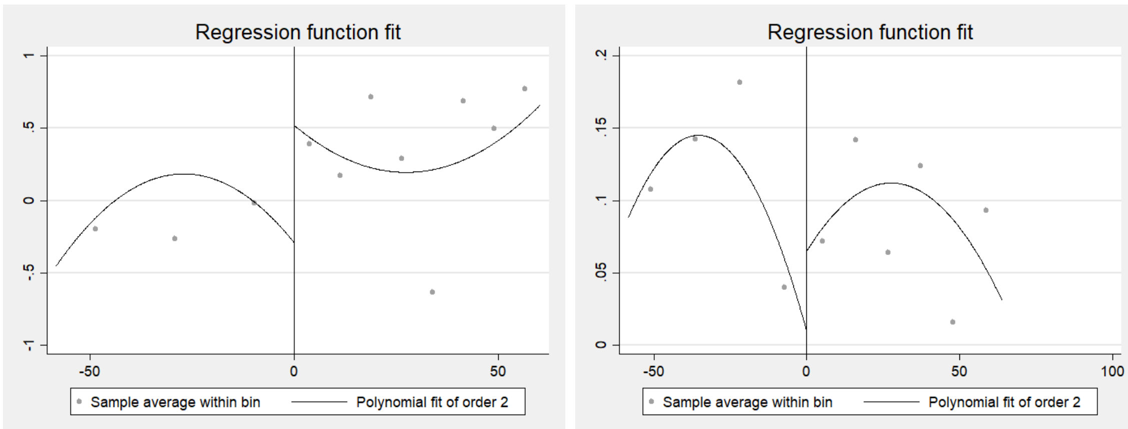
Note: Distribution of total assets of politicians in 2014-15. Mean value of log asset (15.01), indicated by the dark line. Sample of relatively wealthy leaders on the right side of the dark line.

I will be comparing dishonest wealthy politicians to honest wealthy politicians in the following RD plots. Are the wealthy politicians more dishonest? I am not able to provide a direct link between wealth and dishonesty. What I am claiming here is that politicians with higher assets, who are tax-evaders, are relatively more dishonest than tax-evaders with lower assets holding. On the other hand, politicians with higher wealth, that do return their income taxes properly can be a signal of politicians with a relatively higher level of honesty. I have already shown in section 5 that occupation-wise there is not fundamental differences between honest and dishonest elected leaders. I have also provided evidence that, on average, dishonest politicians have higher growth of assets than honest politicians in their five-year tenure.

In the RD plots, on the left of the cutoff, I now have a upazilas whose dishonest leaders have a higher than average value of assets. On the right of the cutoffs are upazilas whose honest leaders have a higher than average value of assets[32].

[32]Growth of assets between 2009-2015 cannot be a good measure of degree dis(honesty) for two reasons:First, conceptually, asset growth can be endogenous to economic development growth of the upazila. Second, practically, I only observe a very small sample of politicians in 2014-15 to compare the asset growths.

Figure 1.17: RD result: Public Goods Index and Growth of Night time light in upazilas with wealthy politicians



Note: The left panel shows the discontinuous jump on public good index from wealthy dishonest to wealthy honest leaders. The right panel shows the discontinuous jump on growth of night-time light from wealthy dishonest to wealthy honest leaders. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Margin of victory in the election is on the x-axis as the running variable of the RD.

The left figure shows the discontinuous jump of the public goods provision index and the right one is for growth of night-time light brightness. We can observe that upazilas with wealthy honest leaders are performing better than upazilas wealthy dishonest leaders in terms of public goods and economic development.

Table 1.9: Effect of having wealthy dis(honest) politicians on public goods index

Public Goods Index	(1)	(2)	(3)	(4)
Honest Constituencies	1.23*	1.4*	1.01	1.3
	(.71)	(.82)	(.70)	(.90)
Kernel	Triangular	Triangular	Uniform	Uniform
Bandwidth (CCT)	14.4	24.1	10.5	16.6
Polynomial	one	two	one	two
No. of Observations	190	190	190	190

Note: ***, **, * denote 1 percent, 5 percent and 10 percent level of significance, respectively. Standard errors in parentheses. RD estimates of public good index from 2015 to 2019 are reported in all four columns using different specifications.

The RD estimates of public goods index are bigger than what I found in the regular full sample.

Table 1.10: Effect of having wealthy dis(honest) politicians on growth of night-time light

Growth of NL	(1)	(2)	(3)	(4)
Honest Constituencies	.17*	.23*	.13	.21*
	(.10)	(.13)	(.102)	(.12)
Kernel	Triangular	Triangular	Uniform	Uniform
Bandwidth (CCT)	12.7	15.5	11.62	15.6
Polynomial	one	two	one	two
No. of Observations	190	190	190	190

Note: ***, **, * denote 1 percent, 5 percent and 10 percent level of significance, respectively. Standard errors in parentheses. RD estimates of growth of nighttime light from 2015 to 2019 are reported in all four columns using different specifications.

Table-1.10 shows the RD estimates of growth of night-time light. On average, there is 23% higher growth of night-time light brightness in upazilas with honest leaders over the period from 2015 to 2019. I use elasticity from literature and my own estimate to convert night-time light brightness growth to GDP growth in upazilas. One % night-time growth is equivalent to 0.3 GDP growth (Henderson et al. 2015) I use following equation to measure elasticity:

$$\epsilon = \frac{Average \Delta GDPGrowth}{Average \Delta NightlightGrowth} * 100$$

Using available night-time light data from 2007, 2010, 2013, 2015 & 2019, I find $\epsilon =$ 0.165%. Previously, from the RD estimate, I find yearly night-light growth—honest versus dishonest is, on average, 5.75%. Using both the elasticites as higher and lower bounds, I find

GDP growth: 0.94%∼1.72% lower in upazilas with wealthy dishonest leaders.

1.9 Conclusions

I use a novel approach to define dishonest politicians and find using regression discontinuity design that there is an economic cost associated with electing tax-evading politicians in closely contested constituencies. I find that 27.3% fewer households in upazilas with dishonest politicians do not receive social safety net programs. Furthermore, in terms of cash benefits under the programs, there is not much of a statistical difference, indicating the possible presence of some sort of clientelestic behavior by the dishonest politicians. In terms of long-term economic progress, measured by night-time light brightness growth, I find a close to zero but statistically insignificant impact. This indicates that local-level elected leaders do not have the influence to spur overall economic growth for the upazilas within a short period of time. Interestingly, among the wealthy dishonest leaders' upazilas, I find a 0.94% to 1.72% lower growth in terms of yearly GDP in comparison with wealthy honest chairmen's upazilas.

One of the major contributions of my work is to use the self-reported information provided by the politicians to come up with a measure to identify dishonest politicians, ex ante of his office term. With administrative and political backlashes, I was able to collect the raw information from the asset and tax disclosure form in order to use them in my research. There are other developing countries which have similar disclosure laws. If information is accessible in those countries, then a similar approach could be applied to identify the dishonest politicians. In many instances, using a third-party audit system to find corrupted politicians might not be successful due to political backlashes; additionally, third-party uses ex post measues, which can be endogenous to the economic progress of the constituency. Using self-reported information provides an easier opportunity to track down dishonest or corrupted politicians.

Chapter 2

Tax-evading Politicians and Public Goods Provision—Understanding the Mechanism

2.1 Introduction

In this chapter, I shed lights on the possible mechanism of the negative effects on public goods provision in the constituencies governed by dishonest politicians. I have explored a number of possible channels to understand the effects. First and foremost, it makes sense to see if there is any significant differences in local level budget—income and expenditure. Unfortunately, there is no central repository that collects upazila-level budget details. I used a study conducted by BIDS[1] and UNDP in 2014-15 on 40 randomly selected upazilas. I have used the yearly budge information from the upazilas in the sample, and found out that

[1] Bangladesh Institute of Development Studies; Project was conducted in 2015, I was a part of the research team.

the local level development expenditure is on average 3.1 million Taka less in the upazilas run by dishonest politicians. I also further found that the difference is not explained by lack of revenue, as there is no statistically significance difference in local-tax revenues. It is important to mention that I was not able to implement regression discontinuity as I do not have enough statistical power to do so.

Political economy literature emphasized on politician's ability to understand variations in economic development and public goods provision. I have used years of education of politicians as a measure of ability. I run similar regression discontinuity, changing the running variable to years of education. I found no statistically significant impact of having higher years of education on public goods provision.

Next, I look into whether politician's dishonesty is correlated with ability. The hypothesis here is that the politicians who are more dishonest could be more able thus the results are not fully driven by politician's' dishonesty. I found no evidence of correlation between politician's dishonesty and ability, where ability is measured by years of education.

Furthermore, I also provide evidence that the resources allocation from the central government does not significantly vary between upazilas with dishonest versus honest politicians. Lastly, I show that dishonest politicians' re-election probability is not significantly lower than that of honest politicians. It means that dishonest politicians maximize their utility (appropriating funds) by not taking into consideration of getting elected in the next term.

2.2 Upazila-level expenditure: A sign of embezzlement

The results in first chapter shows that dishonest politicians have negative effects on social and economic development indicators of their upazilas. It is important to know whether these results correspond to the first-stage impact on upazila-specific annual income and development expenditure. I was only able to collect information on 60 upazilas from the local upazila executive offices about their local level income and expenditure (from 2011-15). Data came from a survey by UNDP-BIDS[2] project on local government development. With the limited data, the following table shows that upazilas with dishonest politicians are having lower mean income and also lower development expenditures, although having similar local-level revenue. Dishonest politicians, either by direct embezzlement or by some other measures, are inflicting lower income and also expenditure on the upazilas they are representing. This is an indication of why, in terms of public goods provision, constituencies under dishonest politicians lag behind in comparison to the upazilas with honest representatives.

[2]Bangladesh Institute of Development Studies (BIDS).

Table 2.1: Upazila Income and Expenditure

	Annual Income	Development Expenditure	Local tax Revenue
Dishonest Constituencies	-32.9* (13.4)	-3.1* (1.3)	-15.3 (15.6)
Constant	42.3** (13.73)	34.9* (13.47)	25.5 (16.9)
Upazila Specific Control	Yes	Yes	Yes

Note: In million Taka; 1 USD = 75 Taka.

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

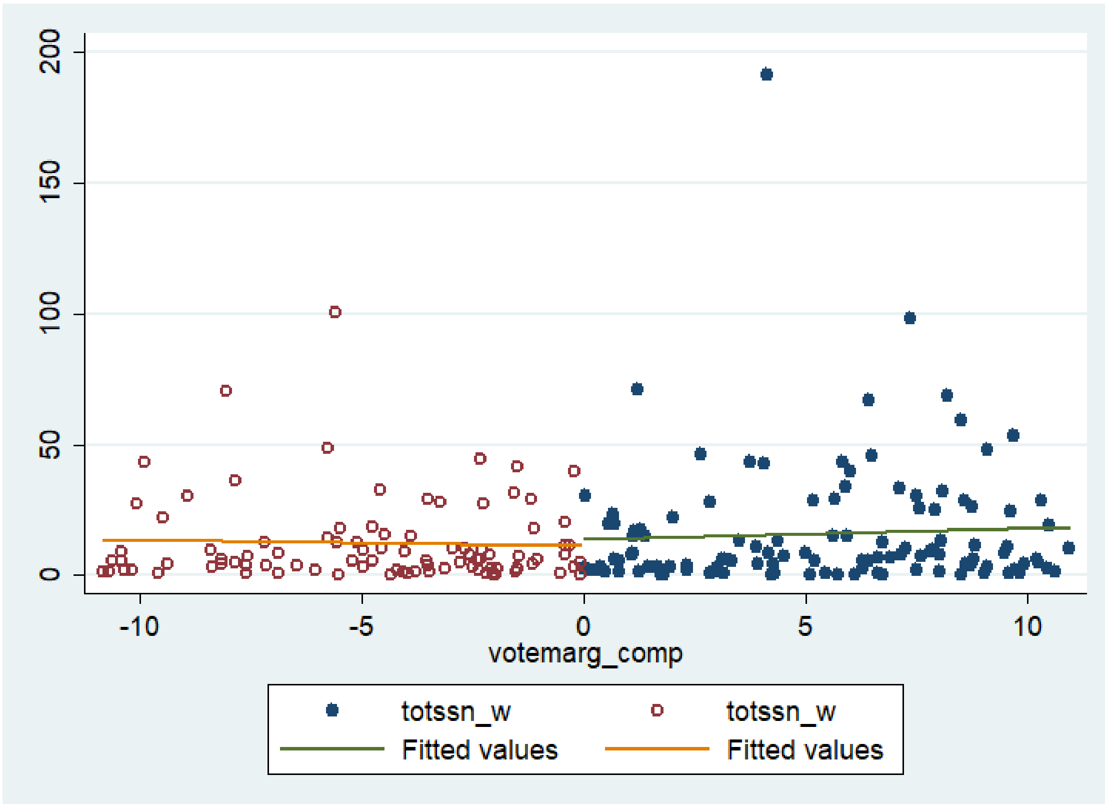
2.3 Alternative hypothesis: Ability of politicians

2.3.1 Years of education as a measure of ability

What if the negative affect on public goods can be explained by the ability of politicians rather than honesty? A good number of papers have used education as the proxy of ability of politicians (Besley et al., 2005; De Paola and Scoppa, 2010 ; Callen et al., 2015). A nation-wide campaign by a NGO (SHUJAN) in Bangladesh also found that voters considered education to be one of the most important traits they want in a politician.

To test whether the education of a politician can translate into high competency and that could in effect have positive impact on public goods provision, I employ a similar regression discontinuity design. The median years of education of a politician is sixteen years. Sixteen years of education implies at least a bachelor degree. I have termed politicians with sixteen or more years of education as highly able politicians, and politicians with lower years of education than the median are considered low ability politicians. The following graph has my main indicator of public goods provision: households receiving social safety net programs. Blue dots represent the average number of households receiving social safety net support in the upazilas where the chairman is highly able. On the other side, red dots represent the same variable but for upazilas deemed low ability chairmen. As we can see, there is no significant difference between the two groups in closely contested upazilas.

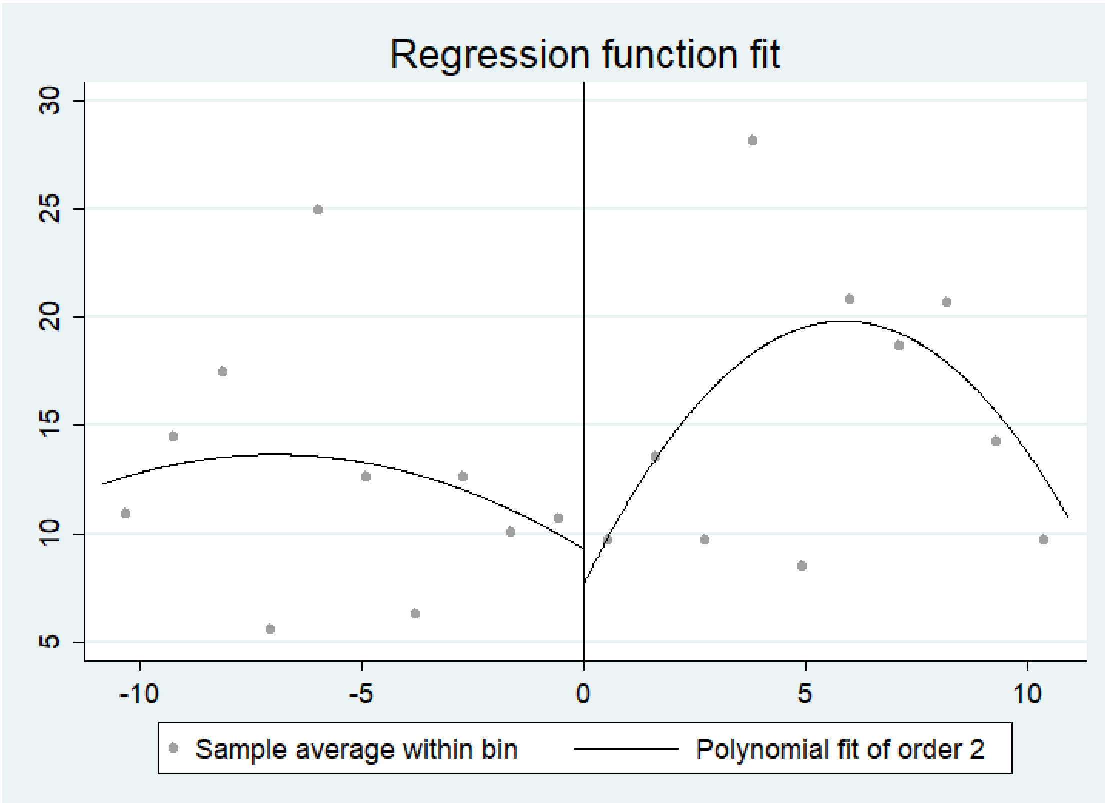
Figure 2.1: Results: whether ability (education) matters for social safety net allocation



Note: Dependent variable: total number of households getting social safety net programs. Scatter plot with fitted line polynomial order one is shown above.

The following is the result of regression discontinuity with the same setting as above. We can clearly see that there is no discontinuous jump of the dependent variable at the cutoff. Running variable is the winning vote margin of the low ability politicians and after the cutoff shows the winning vote margin of the highly able politicians.

Figure 2.2: Results: RD plot



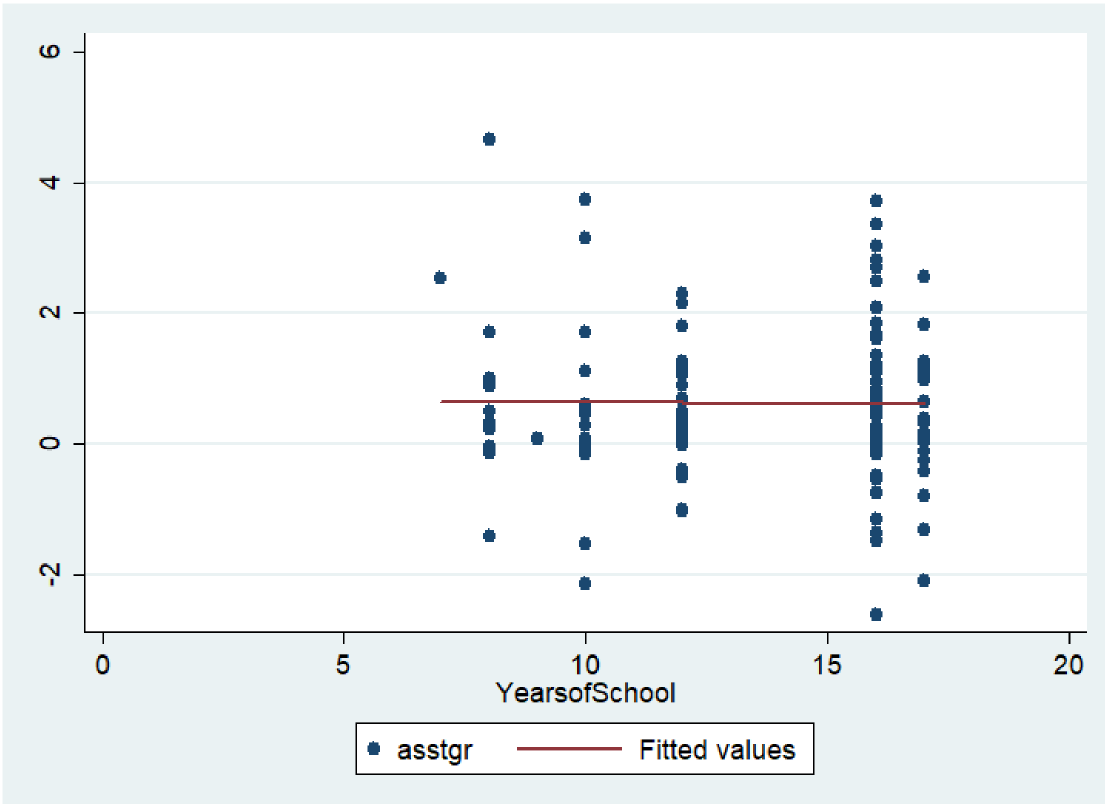
Note: Regression discontinuity with a polynomial order of two with dependent variable: total number of households receiving social safety net programs from 2010 to 2015. On the left of the cutoff 0 are the upazilas with dishonest upazila chairmen, and on the right of the cutoff 0 are the upazilas with honest chairmen. Running variable is the winning vote margin of the low ability politicians and after the cutoff shows the winning vote margin of the highly able politicians.

2.3.2 Honesty and ability: Are they correlated?

Another important aspect is whether ability can predict the honesty of politicians. The previous two graphs showed that ability is not able to explain the difference between public goods provision in the upazilas. However, if ability is highly correlated with dishonesty or honesty, then my main results could be endogenous. Throughout the paper I have maintained a binary definition of dishonesty coming from tax evasion. Another way to see the dishonesty can be to check the asset growth of the politicians. I have shown before that dishonest politicians are having dis-proportionally more asset growth than honest politicians. The following scatter has years of education as the measure of ability on the horizontal axis and asset growth of all the politicians, regardless of honesty on the vertical axis. It clearly shows that there is no relation between asset growth over the tenure of office and ability, as measured by education[3].

[3]Same is true if I take just level of Asset to measure degree of dishonesty

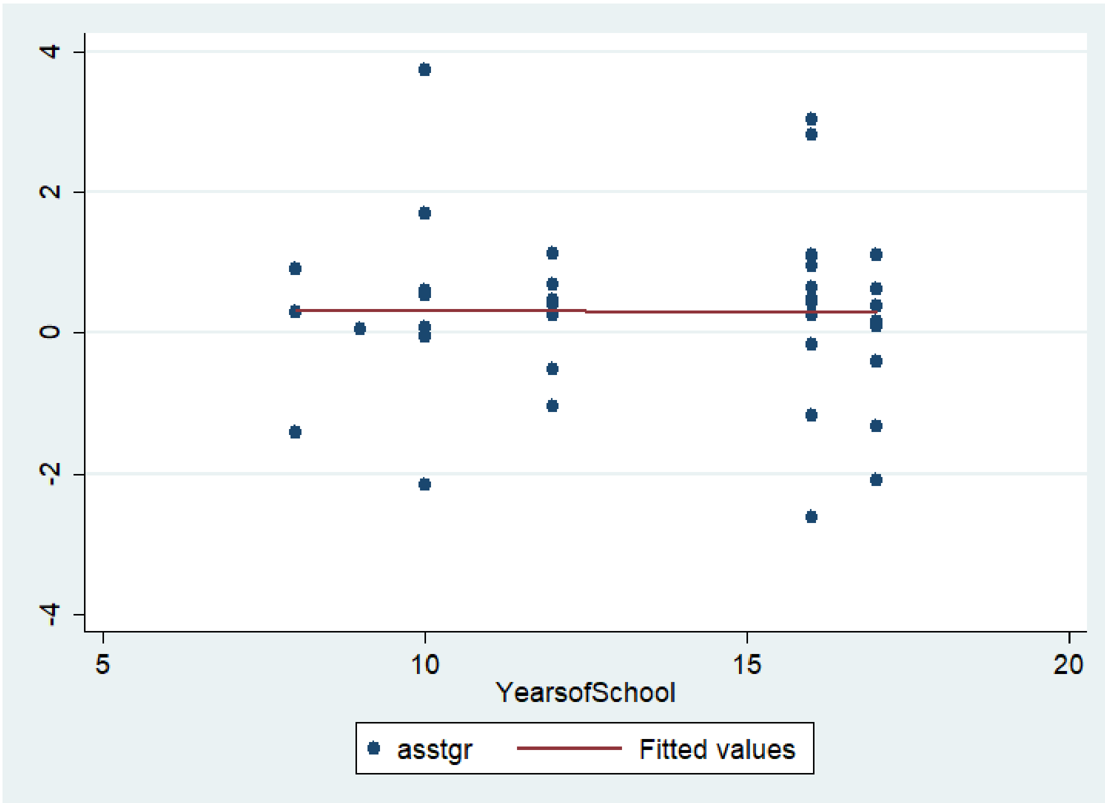
Figure 2.3: Results: no relation between asset growth and ability(education)



Note: The figure above shows correlation between asset growth and ability of the politicians. Correlation is not statistically different than 0.

More importantly, I want know whether the growth of assets of the dishonest politicians can be explained by the level of ability of the politicians. The following scatter plot and local polynomial fit show that there is no evidence that level of dishonesty measured by asset growth can be attributed to level of ability, as measured by education.

Figure 2.4: Results: no relation between asset growth (only dishonest) and ability(education)

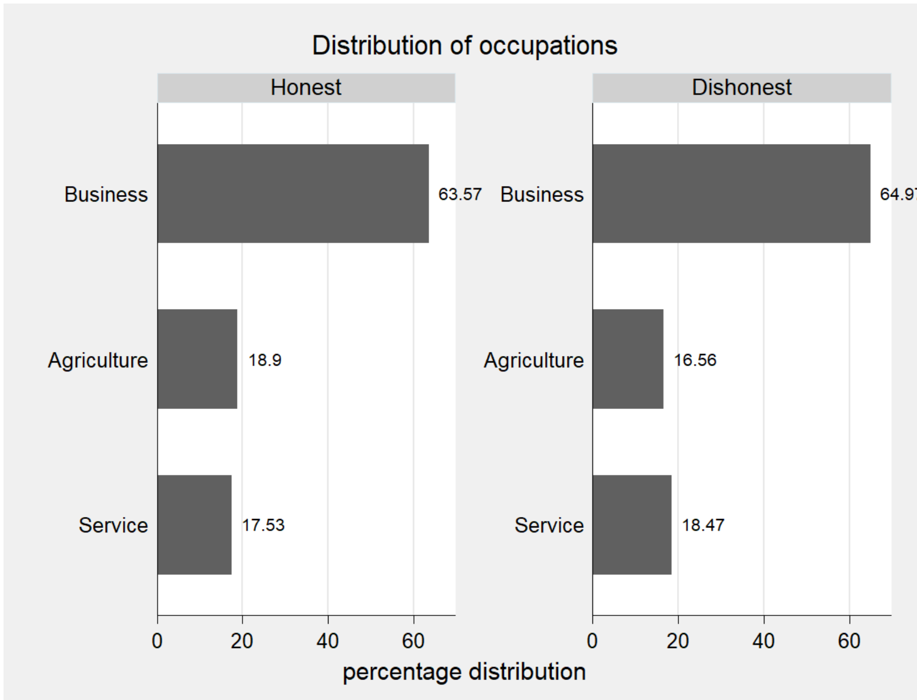


Note: The figure above shows correlation between asset growth and ability for only the dishonest politicians. Correlation is not statistically different than 0.

2.4 Occupational differences

Another important characteristic to check between dishonest and honest politicians is occupation. Is there any category of occupations that dishonest politicians are self-selecting? The following figure provides evidence that there are not much fundamental differences between dishonest versus honest winners. The majority of the politicians are involved in some sort of business activities. Dishonest chairmen are 1% point higher represented in business, and 1% point lower in Agriculture. The differences are not sadistically significant as well.

Figure 2.5: Occupations divided into three categories: Business, Agriculture and Services



Note: Left panel and right panel show distribution of occupations of honest and dishonest politicians, respectively. Occupations categories are divided into three major sectors: business, agriculture and service. There are no statistical differences between occupations of two groups.

2.5 Reelection probability

If politicians are dishonest and harmful for the development of constituents, then we need to know whether they are punished in terms of votes and winning probability in the following elections. I follow the winners and runner ups from 2009 and match them with the results of the 2014 elections. Figure-2.5 shows that there is a 23% probability that an incumbent will retain his seat, and an 18% probability that a runner up from 2009 will win a seat in the 2014 election. It shows that 59% of the time, sub-districts are getting a new chairman. Figure-2.6 shows the conditional probability from the two dimensions. There is a 25% chance that dishonest chairmen who competed in 2014 will win the election, compared to a 22% chance for honest winners from 2009. Interestingly, only 7% dishonest winners compared to 16% honest winners of 2009 are among the total number of elected politicians in 2014. As a result, if a politician is dishonest, then there is 9% point less likely that a dishonest winner will regain his seat compared to a honest politician. This shows a very minimal and low level of punishment for dishonest politicians in terms of re-election.

Figure 2.6: Probability of a candidate from 2009 winning the 2014 election

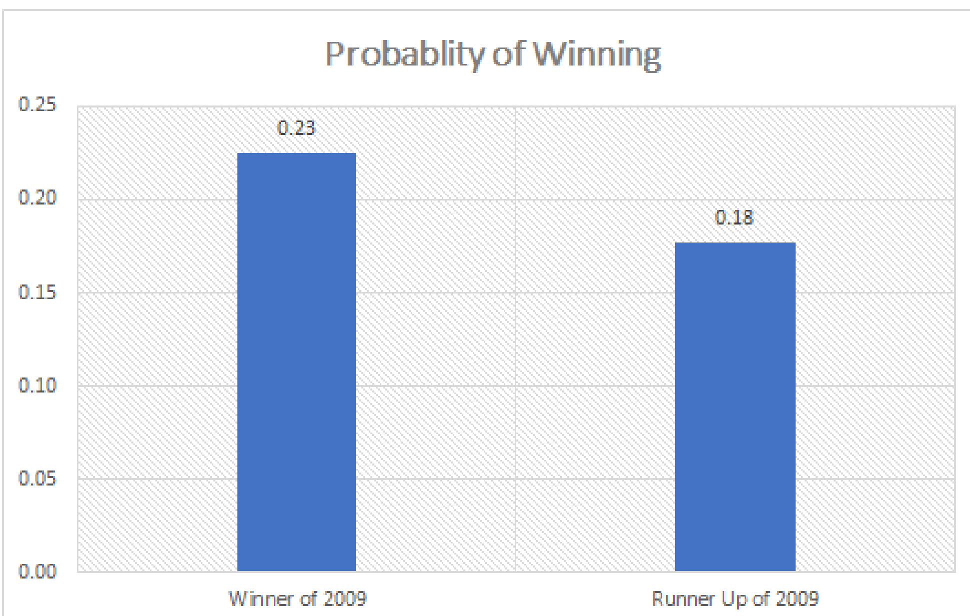
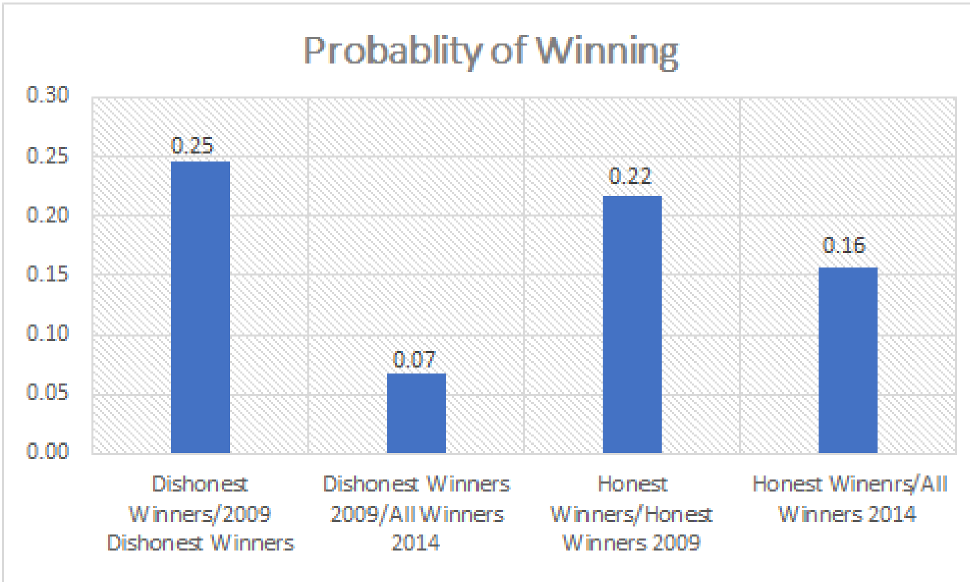


Figure 2.7: Probability decomposition of dishonest and honest winners



2.6 Mechanism: Central budget allocation

There are two more potential channels, through which the RD results can be explained. As mentioned earlier, an upazila executive officer (UNO) is the appointed civil service officer, and he is in charge of the administrative work related to government funding. If there is any exogenous difference among the quality of the UNOs and if there placement in upazilas are correlated with the honesty measure of the chairman, then the RD results could be endogenous. Secondly, if members of parliaments are disproportionally supporting any upazila chairman, then public goods provision and economic development of those upazilas can be explained by this channel as well. I do not have any direct measures of UNOs placement or their qualities, as there is no such data that exists in Bangladesh. The same could be true, if honest upazilas are getting preferential treatments by the members of parliaments (MPs) to receive higher central funds. In the case that both of the two arguments are true, then we can expect that there will be differential budget allocation and expenditure at the upazila level. From the Ministry of Finance, I have collected upazila-level budget allocation and expenditure by the central government. In 2018-19, on average, an upazila received Taka 11,34,80,000 and spent Taka 10,82,93,000. The following graphs show the distribution of budget allocation by the central government and expenditure by the upazilas, respectively.

Figure 2.8: Distribution of budget allocation at upazilas in 2018-19

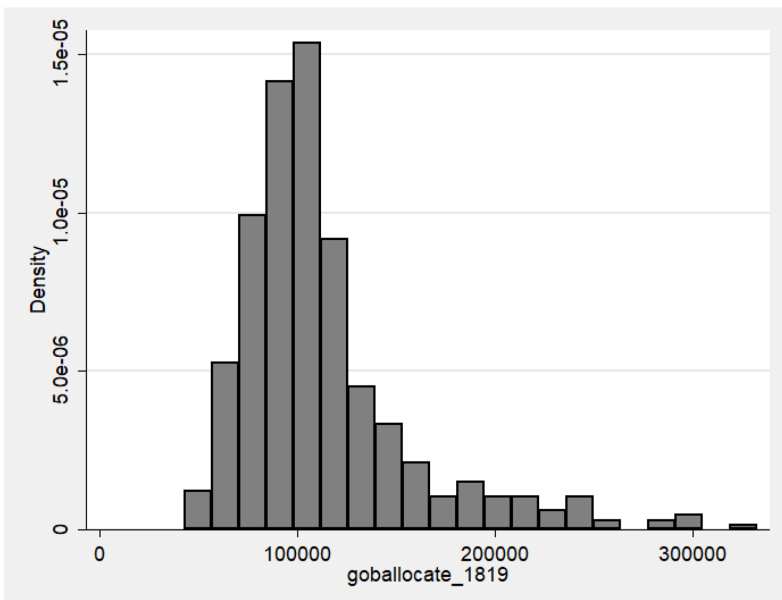
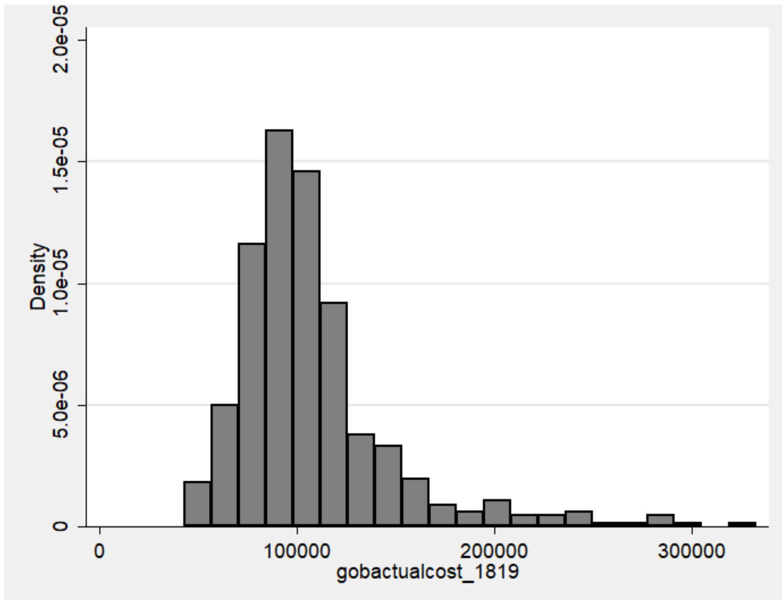
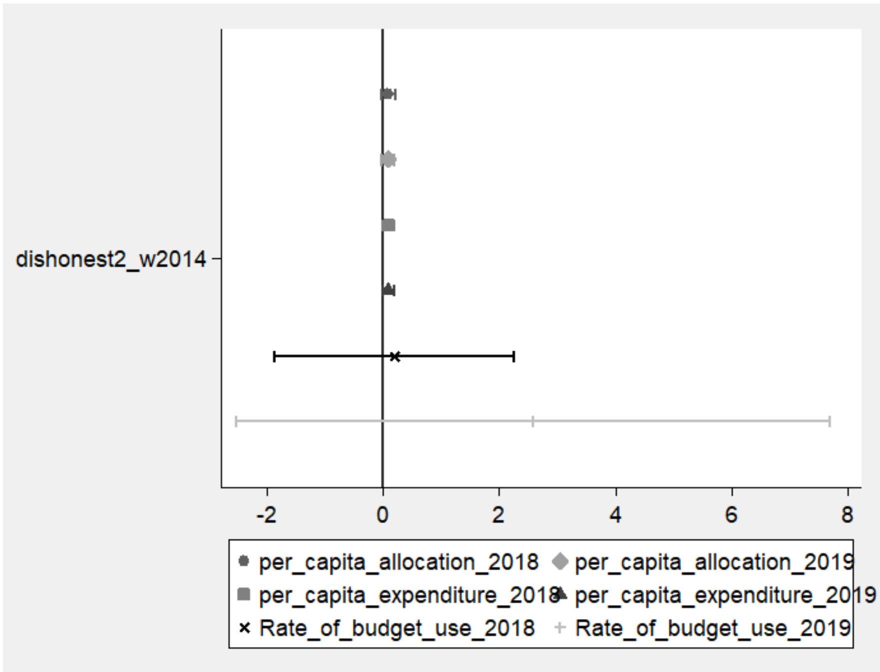


Figure 2.9: Distribution of expenditure at upazilas in 2018-19



Any analysis using the variables above might induce bias as allocation also depends on the size of the upazilas. I have used upazila-level population to calculate the per capita level of allocation and expenditure. I also calculated the percentage of expenditure in terms of the total allocation of the upazilas. One argument could be that if the ratio is lower in the upazilas with dishonest politicians, then that might explain the negative effects. The following shows the result of six regressions. Budget allocation, expenditure, and the ratio for both 2018 and 2019 are the six dependent variables that I have used to plot the coefficients.

Figure 2.10: Distribution of expenditure at upazilas in 2018-19



Note: Six coefficients are plotted in the above figure; per capita central allocation, per capita expenditure, rate of use of central funds in 2018 and 2019. Data taken from Ministry of Finance of Bangladesh.

This plot shows the six coefficients on the dummy variable of upazilas with dishonest politicians. It is clear from the results that dishonest upazilas are not receiving lower allocation from the center, nor are they spending less than the honest upazilas. If anything, both allocation and expenditure are a bit higher on average for the dishonest upazilas.

2.7 Conclusions

Using a small sample survey on upazilas, I further show that on average, upazilas with dishonest politicians are having less expenditure for development, although having similar revenues. It is a indication that embezzlement of public funds triggers the negative effects on public goods provision. I also provided evidence from the the central budget allocation that upazilas with dishonest politicians are not treated differently than the other group.

Previous literature talks about education as one of the most important attributes of politicians. Using education as a proxy of ability, I show that ability is not able to explain the causal effect on public goods provision. Moreover, ability and honesty are not correlated. Furthermore, the negative impact is not explained by a difference in the political party or occupation of the candidates. Another aspect could be a tenure-span for certain candidates of the election of 2009 and 2014. In Bangladesh, there is no limit on the number of times a politicians can run for office and govern an upazila. So the possibility of one-time tenure constraint is not explaining the results.

One could argue that dishonest politicians should not be defined with a dummy variable that takes a value of 0 or 1. Dishonesty could be defined further by its degree as well. If we believe that having more wealth and evading income taxes, is a measure of higher degree of dishonesty, then I find stronger negative effects in public goods provision.

I also conclude that dishonest politicians are not punished by the voters in terms of re-election probability. Two things can happen here. First, the model predicts that due to clientelistic behavior, dishonest politicians get some voters' support back in terms of ballots in the election. Second, voters might not have all the information needed to know whether the politician is dishonest, and as a result, voting results do not reflect the dishonesty of politicians.

Chapter 3

Balancing Lives and Livelihoods using Contagion Risk-Based COVID-19 Management for Low-Income Countries: A Study on Bangladesh

3.1 Introduction

Coronavirus Disease 2019 (COVID-19), a respiratory borne infectious disease, soon became a pandemic, infecting 213 countries and territories worldwide[1]. COVID-19 is still spreading rapidly and so far has caused more than three million global deaths. In the absence of rapid expansion of vaccination, non-pharmaceutical interventions (NPIs) are available options to the policymakers to contain the virus. NPIs are designed to reduce direct

[1]This chapter is a joint work with with Abu S. Shonchoy (Florida International University) and Towhid I. Mahmood (Texas Tech University).

human-to-human contacts, restraining the spread of the contagion, however, they come with worrying economic consequences. Researchers have observed higher rates of job loss and rising unemployment after implementing economy-wide lockdown measures. Thus it is very important to come up with a balance set of policy measures.

This scenario is dreadful in Low Middle-Income Countries (LMIC), who lack adequate safety-net measures for the vulnerable population. In the face of widespread poverty, high self-employment, and a sizeable informal economy – where a significant share of households live from hand-to-mouth – continuing strict lockdown measures for a long-time could have adverse consequences, leading to rising poverty and starvation. Moreover, weaker healthcare systems and inadequate testing capacity make it difficult for local experts to have sufficient epidemiologic data to detect contagion hotspots for targeted interventions. A recent study by Alon and co-authors supports this observation by utilizing a modeling study, demonstrating that blanket lockdowns have limited effectiveness in low-income countries. Given these harsh realities and challenges, LMICs have prematurely re-opened their economies to reduce the possibility of starvation and livelihoods interruptions – at the expense of the immediate surge in the disease caseloads.

Bangladesh is listed among the top fifteen SARS-CoV-2 (COVID-19) effected countries in the world. However, the country has one of the lowest testing capacities per million in that group and also vaccination role out is very slow. Faced with growing pressure to continue livelihoods, Bangladesh government lifted the lockdown abruptly, costing an immediate surge in the virus caseload. In April 2021, Bangladesh is facing second wave of COVID-19 cases and the numbers of infected increasing everyday. Against this backdrop, there is a dire need to derive data-driven planning for mitigation and management of COVID-19 cases in Bangladesh by prioritizing the efficient allocation of limited resources to the places with high probability of getting more cases. Utilizing publicly available and administrative data, this paper introduces a contagion risk (CR) index, which can work as a credible proxy to detect potential virus hotspots — aiding policymakers with proper planning.

In this study, we propose an efficient way of managing the virus's spread while maintaining economic activities. First, we derive a composite index of COVID-19 contagion risk (CR-index), grounded on disease spreadability vectors suggested by epidemiologists and public health experts. This CR-index was constructed with nine variables across five domains: socio-economy, demography, occupation, migration, and health infrastructure. The set of variables employed in the index is widely available for most developing countries, and the index construction is computationally straightforward. Second, we validated the proposed CR-index with sub-national (district) level confirmed COVID-19 cases in Bangladesh, demonstrating the index's reliability in the face of lacking testing capacity and absence of quality high-frequency epidemiological data. Third, based on the CR-Index distribution and percentile ranking, we identified different thresholds and clubbed districts into risky and safe zones. We recommended zone-specific mobility restriction measures as potential solutions to strike a balance between restricting disease spread while continuing economic activities for LMIC countries, such as Bangladesh.

CR-Index is highly correlated with district wise COVID-19 cases across the pandemic period (average correlation is 0.65, p-value 0.001). With our preffered specifications, we found that one percent increase in the CR-index predicts a 3.8 percent daily change in the increase of COVID-19 cases across districts.The proposed CR-Index can predict seven out of the top ten COVID-19 caseload districts of Bangladesh. The CR-Index proposed in this paper could work as the foundation to consider zone-specific mobility restriction measures in Bangladesh, which can be an effective solution to balance economic activities while limiting disease spread. Built on the CR-Index distribution and percentile ranking, we identified different thresholds and clubbed sub-districts into zones for economic activities. We propose zone-specific mobility restriction measures as potential solutions to strike a balance between disease spread and continuing economic activities. In particular, we proposed high CR-Index areas as "red-zone" to hold stricter anti-contagion policies, whereas "orange-zone" will implement moderate restrictions. On the contrary, areas identified as "green-zone" will continue regular economic activities, while maintaining appropriate public health measures. Our proposed zone-specific mobility restriction makes epidemiologic sense since the high CR-Index areas are facing an elevated COVID-19 reproduction rate (R_0). Hence imposing a strict measure in "red-zone" areas can effectively reduce the R_0 below the value of one – making the zone safer for lifting restrictions in the future[33]. Based on our proposal, only 15% districts in Bangladesh falls under the red-zone, comprising about 61% of the current COVID-19 cases. These zone-specific measures will be critical for issues such as school re-opening, which can accelerate the disease spread if the virus reproduction rate is not sufficiently reduced in the susceptible zones.

To mitigate the income-loss due to mobility restrictions, we proposed sector and age-specific compensation package for the vulnerable population in the red-zone, implemented with some conditionality. For instance, we suggested direct food-voucher or cash handouts to vulnerable populations such as the elderly, self-employed, and informal sector workers. On the other hand, government support for the sectoral employed (such as in the manufacturing or construction industry) will be distributed as partial salary support directly from the employer. Our proposed compensation package is estimated based on calorie-requirement to maintain essential nutrition. A simple back-of-an-envelop calculation shows that zone-specific lockdown for a month will cost about 0.14% of the GDP in Bangladesh. We also proposed other suggestive policies for the orange zones (such as partial lockdowns in sensitive sectors and subsidized training programs for the return migrants) and green zone (capital injection and cheap credit access to boost farm and non-farm productivity) ensuring food security and opportunity for skill enhancement.

Some scholars have proposed alternative policy suggestions, such as age-targeted restrictions [14, 6] and intermittent lockdowns[46]. We argue that zone-specific anti-contagion policy, based on CR-Index, is more suitable for developing counties like Bangladesh because of four reasons. First, most elderly in developing countries reside with their families in small homes. As a result, protecting seniors through age-specific restriction becomes challenging and could quickly increase the senior caseload and fatality rates. Second, blanket lockdown measure — forcing the whole economy to reach a standstill condition — generates a sizable economic cost. Moreover, low compliance of such countrywide lockdown in LMIC reduces the efficacy of such broad anti-contagion policies, failing to "flatten-the-curve." Third, distributing stimulus package and relief-support during the nationwide lockdown would be administratively daunting and financially challenging, which is manageable under zone-specific restrictions. Finally, the efficacy and compliance of zone-specific mobility restrictions are more achievable given limited resource and fiscal capacities these economics have.

This index gives developing country planers a viable alternative to economy-wide shutdown policy and can be replicated with available national statistics for other countries.

To the best of our knowledge, this is the first data-driven composite index of Contagion Risk, measured at the district level in Bangladesh. This aim of constructing this index is to create a viable alternative measure to predict contagion hotspots, in the absence of adequate testing capacity and reliable epidemiologic data. This index is created based on five domains of virus spreadability vectors, which is highly correlated with district-specific COVID-19 cases, evaluated at each week over the study period. This paper contributes to creating susceptibility rakings of districts in Bangladesh, based on which policy planners can plan efficient mitigation and virus management strategy as well as can prioritize the allocation of limited resources for efficiency. Although the index proposed in the paper is validated for Bangladesh, we believe this can also be replicated for other countries with available national statistics, helping the planers to derive better virus mitigation and management policy.

3.2 Methods

3.2.1 Variable Choice

We utilized various district level data of Bangladesh, sourced from the latest Bangladesh Labor Force Survey (2016-17), Bangladesh Household Income and Expenditure Survey (2016-17), Directorate General of Health Services provided health facility records and Institute of Epidemiology Disease Control And Research provided daily district-wise COVID-19 reports. The detail sources of data are given in the Appendix.

We have broadly define five domains of variables for the construction of the CR-Index which are; socio-economy, demography, occupation, migration, and health infrastructure. Under socio-economy domain we took district level poverty rate of Bangladesh, assessed by the World Bank. District level poverty rate captures the overall economic condition of a particular district — demonstrating vulnerability of the people in those districts to follow lockdown order which may trigger food insecurity. As a consequence, vulnerable population in those districts will search for livelihoods to survive from hunger, resulting continuing the spread of the virus. Poor also don't have the luxury to maintain social distancing, lack appropriate hand-washing access and limited access to hygienic face-coverings. In the demography domain, we chose the variable capturing the population belonging 21-50 years of age and who are active participants in the labor force (See Appendix B). Based on the IEDCR report, we noticed that the COVID-19 infection rate is the highest in this group compared to other age categories. We also include population density in the CR-Index, which is known to play a crucial factor for COVID -19 spread, as the virus is mainly transmitted through human-to-human contacts.

Occupational composition of the district could also play a role in COVID-19 transmission. For example, developing countries like Bangladesh has a large informal sector (both in rural and urban areas) where continuous search for new income opportunities is required for survival.[2]. As a result, we include both informal employment and rural non-farm employment variables in our index. Similarly, having large industrial cluster and related employment could play a role in the contagion threat, which has been captured by including manufacturing sector employment in our index.

Developing countries are also known to have large share of migrant population, for both domestic and international migration.[3]. Due to this pandemic and global economy shutdown, a large share of international migrants went back to their home country, which contributed to the spreading of the virus. Similarly, domestic migrants face the same consequence, lost urban sources of income due to lockdown, which forced them to go back to their origin villages — contributing to the virus diffusion as documented in a couple of recent research studies.[34, 36]. To capture this, we included both international and domestic migrant numbers among the total surveyed households in the CR-Index construction. Finally, hospital capacity, measured as number of beds available at each district in Bangladesh, for every million population, has been used — a candidate variable representing the health infras-

[2] Approximately 71% of the sectoral composition of employment in developing countries are self-employed compared to 13% in developed countries.[6, 29]

[3] Bangladesh is the sixth leading country of origin for international migrants.[28]

tructure domain. Table B.2 in appendix B presents 19 variables that we have considered to be important predictors of district-wise Covid-19 cases.Out of the 19 variables, we have used nine according to their individual statistical significance and strength of explaining the variations in Covid-19 cases.

3.2.2 Contagion Risk (CR) Index Construction

Instead of creating vulnerability index at the sub-national level as done in some recent papers, [21] our interest is to create a contagion risk index, which is collinear with the COVID-19 cases at the sub-national level and could work as a credible proxy for imposing zone-specific anti-contagion measures. Using each of the variables, mentioned above, we first created sub-indices for each using the following formula:

$$X_{index} = \frac{(X_i - min(X))}{(max(X) - min(X))} \tag{3.1}$$

There are a number of ways one can develop such an index, however for simplicity, we followed the human development index (HDI) construction method of the UNDP for wide acceptability.[52]. After generating sub-indexes for each domain, we use simple arithmetic mean to generate the composite CR-index. Formally,

$$CR_{index} = [\sum_{j=1}^{9} X_j)/n] \tag{3.2}$$

where, $j = 1, 2, ...n$

$n = 9$

Unlike HDI, which uses geometric mean, we used arithmetic mean, given some sub-indexes generated zero value (for example some districts did not have any reported international migration, resulted a score of zero for that sub-index).

3.3 Index Validation

3.3.1 Correlation method

The most crucial aspect of any index is whether it shows a strong correlation with the primary variable of interest. We validated the index using district-wise COVID-19 time-series data to test our CR-index's predicting power, starting from April 15, 2020. We conducted both week-by-week (for 23 weeks) and day-specific correlation estimations to check the CR-Index consistency.

3.3.2 Regression method

We run an Ordinary Least Squared (OLS) regression to see whether the statistical validity of the simple correlation approach remains consistent when we control for district-specific control. We run the following regression:

$$log[Cases_{id}] = \beta_i index_d + Z_d + \epsilon_i \tag{3.3}$$

where, $i = April15, April22........., July22$

$log[Casee_{id}]$ is the log of total cases in every week or every day in each district, whereas $index_i$ is the district-specific CR-index that we have generated. Z_i is the district-specific control, which is the district level population. $_it$ is time and districts specific unobservable that is uncorrelated with the dependent variable.

3.3.3 Panel regressions

In this estimation setting, we utilized the time-series pattern of the sub-national daily COVID-19 data by estimating the following set of regressions, the first two on daily reported COVID-19 cases under OLS and time fixed effect model (equation 3.4 and 3.5 below). Similarly, we estimated the daily changes in the COVID-19 cases and regressed the change against the CR- Index, day fixed effects, and district controls. Under the setting, equations 5 and 7 are the most conservative specifications, taking care of the time dimension and regional controls, while equations 3.4 and 3.6 control for the time trend. OLS Model (level):

$$Log(Cases)_{it} = \alpha + \beta CRIndex_i + \gamma(t) + \epsilon_{it} \tag{3.4}$$

Time Fixed Effects (FE) Model (level):

$$Log(Cases)_{it} = \alpha + \beta CRIndex_i + \gamma Day_t + \Omega Population_i + \epsilon_{it} \tag{3.5}$$

OLS Model (daily change)

$$Log((\Delta(Cases))_{it} = \alpha + \beta CRIndex_i + \gamma(t) + \epsilon_{it} \tag{3.6}$$

Time Fixed Effects (FE) Model (daily change)

$$Log((\Delta(Cases))_{it} = \alpha + \beta CRIndex_i + \gamma Day_t + \Omega Population_i + \epsilon_{it} \tag{3.7}$$

In equation (3.4) and (3.6), $\gamma(t)$ is the time trend controlling for the rise of district specific rise of covid-19 cases throughout the study time period. The parameter in equation (3.5) and (3.7) is the time fixed effect, which is controlling for any time related variation across each day within the study period for all the districts. $\epsilon_i t$, in each of the four above equation is the time and district specific unobservable, which is uncorrelated with the dependent variable.

One concern about our procedure to develop the CR index is the possible high level of multicolinearity among the variables that we have used. One way to get around is to use any method of dimension reduction to address the potential colinearity. Recently using machine learning algorithm, specifically with deep learning procedure, we can generate weights that can be assigned to variables. Given that our sample size is very small (only 64 districts), using deep learning algorithm, which is meant for large data, will not give us any edge to develop the index. In this regard, principal component analysis (PCA), which is also another form of synthetic learning using eigenvalues and eigenvactors can be used under this setting.[4] [5]. We use the same nine variables to construct the principle score of the districts. This principal scores work as the modified CR index (PCA). We re-run regression three, substituting the CR index by CR index (PCA).

3.4 Results

A set of nine maps are generated if Figure 3.1, using the sub-indices created for the CR-Index construction, where district-wise COVID-19 cases have been superimposed on each map. If policy makers want to focus and prioritize any of the five domains for health and livelihood

[4]Principal component analysis is appropriate here because we have nine variables and there are a degree of interdependence among them. PCA will generate a smaller number of artificial variables known as principal components. These components account for most of the variances among the observed variables. Using the principal component, we can develop scores for each sample in our data set.

[5]We follow the standard PCA calculation procedure. Please see https://academic.oup.com/heapol/article/21/6/459/612115

related risks, then following maps provide guideline to do it.

Figure 3.1: Poverty, rural non-farm employment and health index for districts in Bangladesh with confirmed COVID-19 cases till July 22, 2020

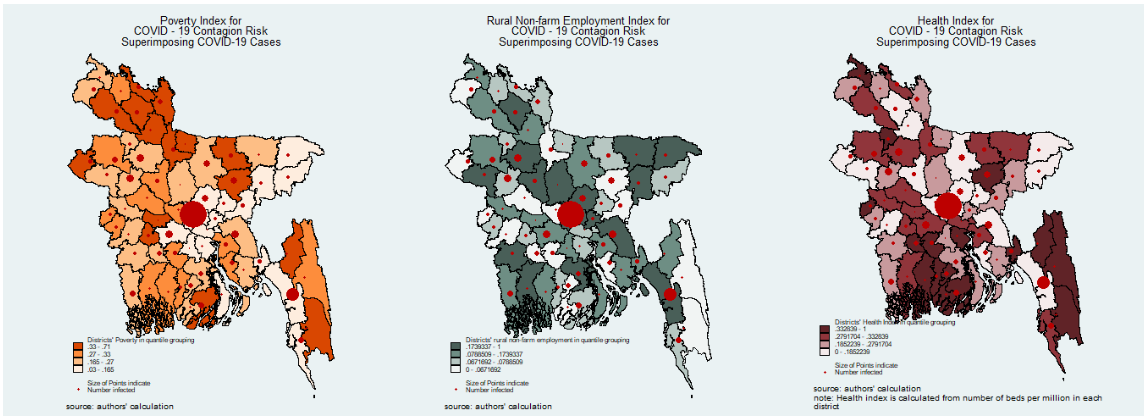


Figure 3.2: Population density, vulnerable employment and informal employment index for districts in Bangladesh with confirmed COVID-19 cases till July 22, 2020

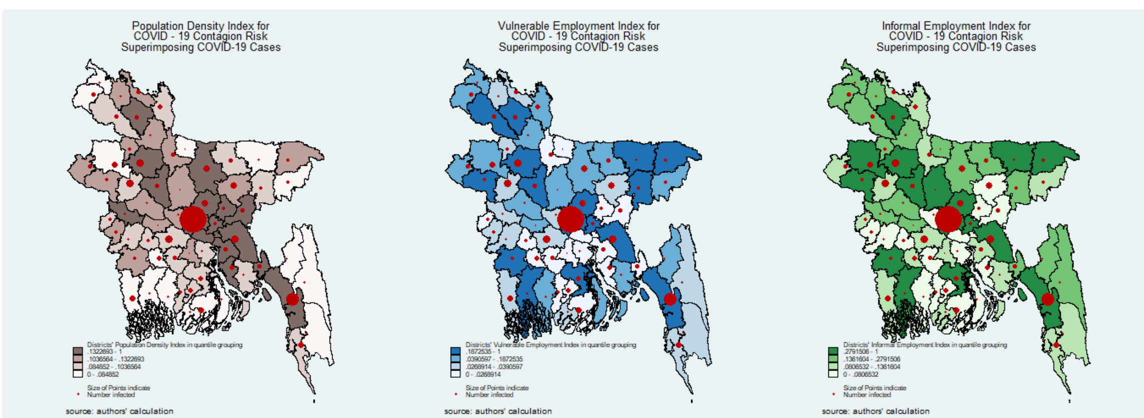
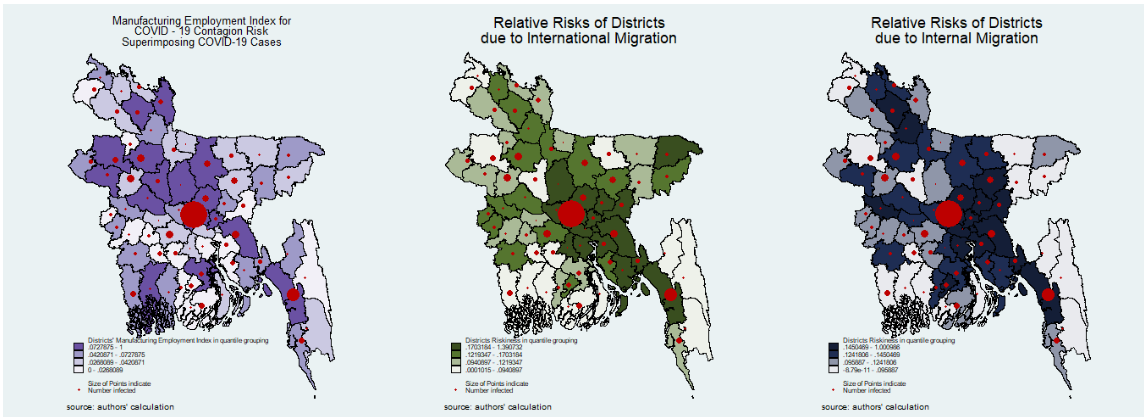


Figure 3.3: Manufacturing employment, relative risk due to international and relative risk due to internal migration for districts in Bangladesh with confirmed COVID-19 cases til July 22, 2020



3.4.1 Correlation Estimations

Correlation estimations between the CR-index and district-wise weekly and daily COVID-19 cases are presented in Figure 3.4, panel (a) and (b), respectively. The correlation coefficients between our CR-index and COVID-19 cases at the beginning is around 0·62 (based on weekly correlation, reported in panel (a)). One can easily observe a strong consistency in the correlation coefficients (average correlation is 0.61, p-value 0.001) as the week progresses, showing our index's validity and reliability. Similarly, the day-wise correlation showed comparable consistency, as reported in Panel (b) in Figure 3.4, with an average correlation coefficient being 0.57 (p-value 0.00). Our OLS based covariance estimates also showed reliable results, for both weekly and daily regressions, reported in Panel (c) and (d) of Figure 3.4. As depicted in Figure 1, panel (c), the estimated coefficients, in the beginning, were not statistically significant at the conventional level. However, starting from mid-June, the coefficients became statistically significant with lower error-bars, which remained mostly consistent and statistically precise.

Figure 3.4: Panel (a) and (b) show correlation estimations between CR-index and district-wise weekly and daily reported COVID-19 cases, respectively. Panel (c) and (d) report the OLS regression coefficients, and confidence intervals between CR-index and district-wise weekly and daily reported COVID-19 cases, respectively. A few data updating errors by the IEDCR caused a sudden drop in the estimation, which was corrected in the reported data of later weeks.

3.4.2 Time-series panel regression estimations

The OLS and FE models' estimates are reported in Table 3.1, where our parameter of interest is . Column (1) in Table 3.1 reports that is 8.487, with a p-value close to zero. This coefficient demonstrates that a one percent increase in the CR-index, relative to the district-wise mean, is associated with an 8.487 percent increase in the number of positive COVID cases, controlling for time trend. The level fixed effects model (equation 5, reported in column (2) of Table 3.1) shows that a one-unit increase of CR-index is associated with a 3.835 percent increase in the number of positive COVID cases, net of day and district controls. The reported high R-square for both these specifications demonstrate strong goodness of fit for the models. Similarly, in column (3) and (4), we reported the daily change in the COVID-19 cases under the OLS and FE specifications, which shows a strong positive association with CR-Index with p-values close to zero. The estimate reported in column (4) indicates that a one percent increase in the CR-index predicts a 3.828 percent daily change in the increase of COVID-19 cases across districts.

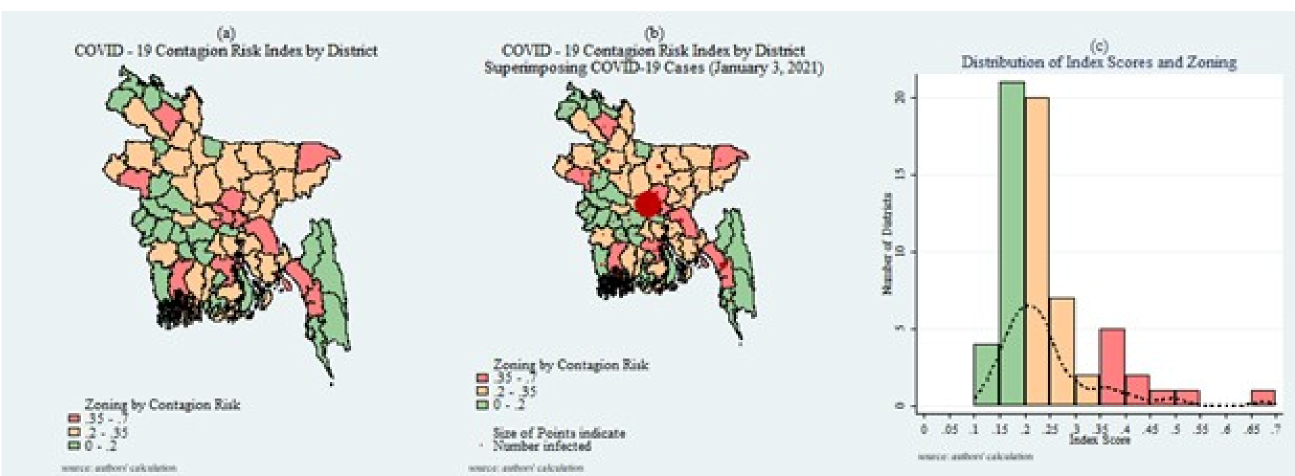
Table 3.1: Regression estimates of the OLS and Fixed effect models, using COVID-19 cases of Bangladesh from April 1,2020 to January 4, 2021

	OLS	FE	OLS	FE
VARIABLES	Log (Covid-19 Cases)	Log (Covid-19 Cases)	Log (Daily Change in Cases)	Log (Daily Change in Cases)
CR Index	8.487***	3.835***	8.571***	3.828***
	(0.203)	(0.256)	(0.347)	(0.518)
Constant	-0.614***	4.914***	-0.893***	0.573***
	(0.184)	(0.0418)	(0.212)	(0.0896)
Time Fixed Effect (Daily)	No	Yes	No	Yes
Time Trend	Yes	No	Yes	No
District Specific Control	No	Yes	No	Yes
Observations	2,299	2,299	1,063	1,063
R-squared	0.856	0.880	0.569	0.606
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1				

3.4.3 Contagion Zoning

Using the CR-index score distribution, we divided 64 districts of Bangladesh into three zones - Red, Orange, and Green. Districts that fall in the 90th percentile and above of the distribution are considered in the red zone. These districts are almost one standard deviation away from the mean CR-Index score of 0·245. Districts that fall within the 25th (mean) percentile to 90th percentile are considered in the orange zone category. All the districts below the 25th percentile are in the green zone. Figure 3.5, panel (a) shows the three zones' spatial distribution, as we can see that it does not follow any regional patterns. In Figure 3.5, Panel (b), we have superimposed district-wise latest COVID-19 positive cases on the Bangladesh map. The map is self-explanatory, and it shows that the proposed index is identifying vulnerable districts robustly. Figure 3.5, panel (c) shows the CR-Index histogram and kernel-density plot of the distribution. Table B.4 in appendix B has the list of all the districts of Bangladesh distributed among these proposed three zones, with district-specific CR-index score and COVID-19 cases (as a % of total reported cases).

Figure 3.5: Panel (a) shows zoning by contagion risk index for districts in Bangladesh. Panel (b) shows a similar map as panel (a) with superimposed COVID-19 confirmed cases on July 22. Panel (c) shows the distribution of index score and zoning with the distribution curve.



3.5 Discussion

Data-driven mitigation planning and management are crucial for resource-constrained countries – ensuring the best use of their limited resources. In the absence of adequate and regular epidemiologic data, it is difficult for the planers to derive the right policy response to contain the virus's spread and formulate a targeted resource distribution plan. Scholars have also noticed the challenge in achieving a satisfactory compliance rate from a blanket lockdown, deployed in developing countries, due to high reliance on the informal sector. Bangladesh has reported an income drop of 62-75% and a consumption drop of 28% within the first two months of the disease onset, raising concerns on prolonged lockdown measures.

This paper developed a sub-national level contagion-risk index, which can work as an alternative measure to detect potential virus hotspots in the absence of appropriate and quality daily epidemiologic data. Our proposed CR-index is positively correlated with the district level COVID-19 reported in Bangladesh, and this estimate is robustly consistent across the time period of this study. Most importantly, our index can predict seven out of the top ten COVID-19 caseload districts of Bangladesh, signifying our index's validity, as depicted in Figure 3 below. The variables employed in the CR-index construction have high reliability of 0·81, measured by Chronbach's alpha.

Built on the CR-Index, we propose zone-specific mobility restriction measures as potential solutions to the balance between disease spread and continuing economic activities, especially for the next wave and future pandemics. In particular, we proposed high CR-Index areas as "red-zone" to hold stricter anti-contagion policies when needed, whereas "orange-zone" will implement moderate restrictions. On the contrary, areas identified as "green-zone" can safely continue regular economic activities. Our proposed zone-specific mobility restriction makes epidemiologic sense, as the high CR-Index areas are incredibly susceptible to face an elevated COVID-19 reproduction rate (R0). When needed, imposing a strict measure can effectively reduce the R0 below the value of one – helping the zone become safer for lifting restrictions. Based on our recommendation, only 15% of sub-districts in Bangladesh fall under the red-zone, comprising about 60% of the current COVID-19 cases. These zone-specific measures will be critical for decisions such as school re-opening, which can accelerate the disease spread if the virus reproduction rate is not sufficiently reduced in the susceptible zones. At the end of the appendix B, we discuss in detail of the possible cost of lock-down of the ′red-zone′ districts. We present the cost and the possible stimulus packages government needs to provide for manufacturing, construction, wholesale, transportation, own production and others industry. We present the cost for each district in ′red-zone′ for one month.

Table 3.2: Distribution of Districts according to CR-Index and COVID-19 cases on January 21, 2021

Red Zone	**Index**	**% of Actual Cases**	**Orange Zone**	**Index**	**% of Actual Cases**	**Green Zone**	**Index**	**% of Actual Cases**
Dhaka	0.67	60.42	Noakhali	0.31	1.06	Patuakhali	0.21	0.32
Comilla	0.51	1.70	Gaibandha	0.3	0.27	Bagerhat	0.21	0.20
Chattogram	0.49	5.44	Sirajganj	0.3	0.48	Jamalpur	0.2	0.34
Gazipur	0.43	1.29	Manikganj	0.29	0.33	Magura	0.2	0.20
Barishal	0.4	0.88	Chandpur	0.28	0.50	Sherpur	0.2	0.10
Rangpur	0.4	0.74	Tangail	0.27	0.70	Munshigonj	0.2	0.82
Narayanganj	0.37	1.60	Kishoreganj	0.26	0.65	Pabna	0.2	0.30
Sylhet	0.35	1.71	Brahmanbaria	0.25	0.53	Chuadanga	0.2	0.31
Khulna	0.35	1.36	Feni	0.25	0.42	Faridpur	0.19	1.54
Rajshahi	0.35	1.10	Bogura	0.25	1.79	Kushtia	0.19	0.72
..					0.52	Satkhira	0.19	0.22
..	..	..	Hobiganj	0.24	0.37	Lalmonirhat	0.18	0.18
..	..	..	Jessore	0.24	0.88	Cox's bazar	0.18	1.08
..	..	..	Sunamganj	0.24	0.48	Panchagar	0.18	0.15
..	..	..	Shariatpur	0.24	0.36	Jhalokathi	0.18	0.16
..	..	..	Dinajpur	0.23	0.83	Nilphamari	0.18	0.25
..	..	..	Mymensingh	0.23	0.83	Jhenaidah	0.17	0.43
..	..	..	Kurigram	0.23	0.19	Gopalganj	0.17	0.57
..	..	..	Naogaon	0.23	0.29	Bhola	0.17	0.18
..	..	..	Laksmipur	0.23	0.44	Thakurgaon	0.17	0.28

..	..	..	Chapai-nawabganj	0.23	0.16	Natore	0.16	0.22
..	..	..	Maulvibazar	0.22	0.36	Khagrachari	0.16	0.15
..	..	..	Pirojpur	0.22	0.22	Barguna	0.15	0.19
..	..	..	Rajbari	0.22	0.65	Rangamati	0.15	0.21
..	..	..	Madaripur	0.22	0.31	Narail	0.13	0.29
..	..	..	Netrokona	0.21	0.16	Joypurhat	0.13	0.24
..	..	..	..	..	..	Bandarban	0.13	0.17
..	..	..	..	..	..	Meherpur	0.13	0.14
Total		76.25	..		13.77	..		9.98

Bibliography

[1] Acemoglu, D, V Chernozhukov, I Werning and M D Whinston (2020), “Optimal Targeted Lockdowns in a Multi-Group SIR Model”, NBER Working Paper No. 27102.

[2] Acharya, R. and Porwal, A., 2020. A vulnerability index for the management of and response to the COVID-19 epidemic in India: an ecological study. The Lancet Global Health.

[3] Ahsan R, Iqbal K, Khan M, Mobarak AM, Shonchoy A. Using Migration Patterns to Predict COVID-19 Risk Exposure in Development Countries. Yale School of Management. 2020.

[4] Anwar S, Nasrullah M, Hosen MJ. COVID-19 and Bangladesh: Challenges and how to address them. Frontiers in Public Health. 2020;8.

[5] Alon, T M, M Kim, D Lagakos and M VanVuren (2020), “How Should Policy Responses to the COVID-19 Pandemic Differ in the Developing World?”, NBER Working Paper No. 27273.

[6] Bangladesh Must Ramp Up COVID-19 Action to Protect its People, Revive Economy. The World Bank Group. 2020 April 12 [cited 2020 August 26];News. Available

from: https://www.worldbank.org/en/news/press-release/2020/04/12/bangladesh-must-act-now-to-lessen-covid-19-health-impacts

[7] Banerjee A. and Hanna, R. and Mullainathan, S. (2012) *Corruption*, Working Paper 12-09, Massachusetts Institute of Technology

[8] Banerjee, A. V. and Kumar, S. and Pande, R. and Su, F. (2014) *Do Informed Voters Make Better Choices? Experimental Evidence from Urban India*, Working paper, Harvard Kennedy School

[9] Besley, Timothy and Coate, Stephen (2003) *Centralized versus decentralized provision of local public goods: a political economy approach*, Journal of Public Economics, volume 87, pages 2611-2637

[10] Besley, T. and Pende R. and Rao V. (2004) *Political Selection and the Quality of Government: Evidence from South India*, Economics Growth Center, Yale University, Center discussion paper No. 921.

[11] Besley, T. and Persson T. and Sturm D. (2005) *Political competition and Economic performance: Theory and evidence from the United State*, Working Paper 11484, National Bureau of Economic Research

[12] Bhavnani, J. and Jenesenius, F. (2016) *Voting for Development? Ruling Coalition and Literacy in India*, R and R, Journal of Development Economics

[13] Bhavnani, R. (2012) *Using Asset Disclosures to Study Politicians' Rents: An Application to India.*, Working Paper

[14] Calculated from Bangladesh QLFS 2016-17.

[15] Callen, M., Gulzar, S., Hasanain, A., Khan, M. Y., and Razaee, A. (2018) *Personalities and public sector performance: Evidence from a health experiment in Pakistan*, Working Paper 21180, National Bureau of Economic Research

[16] Calonico, S. and Cattaneo, D. and Titiunik, R. (2014) *Robust Nonparametric Confidence Intervals For Regression-Discontinuity Designs*, Econometrica, Vol. 82, No. 6 (November 2014), pp. 2295-2326

[17] Caselli, F. and Mrelli M. (2004) *Bad Politcians*, Journal of Public Economics 88 (2004) 759 – 782

[18] Cattaneo, M. D. and Imbens G. (2011) *Optimal Bandwidth Choice for the Regression Discontinuity Estimator*, The Stata Journal

[19] Chandra, K. (2013) *Patronage, Democracy and Ethnic Politics in India.* In D. Abente, & L. Diamond (Eds.), Clientelism, Social Policy and the Quality of Democracy Johns Hopkins University Press

[20] Chowdhury, R., Heng, K., Shawon, M. S. R., Goh, G., Okonofua, D., Ochoa-Rosales, C., ... Shahzad, S. (2020). Dynamic interventions to control COVID-19 pandemic: a multivariate prediction modelling study comparing 16 worldwide countries. European journal of epidemiology, 35(5), 389-399.

[21] Covid-19 and the Ready-Made Garments Industry in Bangladesh. Asian Development Bank. 2020. Available from: https://www.adb.org/sites/default/files/linked-documents/54180-001-sd-04.pdf

[22] Ferraz, C. and Finan, F. (2008) *Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electtoral Outcomes*, Quarterly Journal of Economics

[23] Fisman, R., Schulz, F., Vig, V. (2014) *The Private Returns to Public Office,*. Journal of Political Econoour

[24] Fisman, R. and Golden M. A. (2017) *Corruption: What everyone needs to know*, Oxford University Press

[25] Golden, M. and Min, B. (2013), *Distributive Politics Around the World*, 16:1, 73-99, Annual Review of Political Science

[26] Hill R, Genoni ME. Bangladesh Poverty Assessment: Facing Old and New Frontiers in Poverty Reduction. The World Bank; 2019 Oct 31.

[27] Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Huang, L.Y., Hultgren, A., Krasovich, E. and Lau, P., 2020. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature, pp.1-9.

[28] https://www.un.org/development/desa/en/news/population/international-migrant-stock-2019.html

[29] Iqbal K, Toufique K A, Ahmed N, Pabon N F, Ibon W F. Dynamics of Rural Nonfarm Sector 2000-2016. Paper presented at; 2019; BIDS Research ALMANAC. Available from: https://bids.org.bd/uploads/events/ALMANAC2019/S1_P1.pdf

[30] Imbens G. and Lemieux, T. (2007) *Regression Discontinuity Designs: A Guide to Practice*, NBER Working Paper No. 13039

[31] Kalyanaraman, K. and Janson, M. and Ma, X. (2017) *Manipulation Testing Based on Density Discontinuity*, Volume 79, Issue 3, The Review of Economic Studies

[32] Khuda, B. (2011) *Social Safety Net Programmes in Bangladesh: A Review*, Vol. 34, No. 2 (June 2011), pp. 87-108, The Bangladesh Development Studies

[33] Lauer SA, Grantz KH, Bi Q, et al. The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application. Ann Intern Med 2020; 172(9): 577-82.

[34] Lee JN, Mahmud M, Morduch J, Ravindran S, Shonchoy A. Migration and the Diffusion of COVID-19 in South Asia.

[35] Lee D. S. and Card, D. (2008) *Regression discontinuity inference with specification error*, Journal of Econometrics

[36] Lee J. N., Mahmud M., Morduch J., Ravindran S. and Shonchoy A. Migration and the Diffusion of COVID-19 in South Asia. Financial Access Initiative. Working Paper 2/2020. weblink: https://rb.gy/qnyqoq

[37] Ludwig, J and Miller, J. (2007) *Does head start improve childrens life chances? Evidence from a regression discontinuity design*, The Quarterly Journal of Economics

[38] Michalopoulos, S. and Papaioannou, E. (2013) *Pre-Colonial Ethnic Institutions and Contemporary African Development*, Volume 81, Issue 1, Econometrica

[39] Martinez-Bravo, M. (2014) *The Role of Local Officials in New Democracies: Evidence from Indonesia*, American Economic Review

[40] Messner, M. and Polborn, M.K. (2004) *Paying Politicians*, Journal of Public Economics 88 (2004) 2423 – 2445

[41] McCrary J. (2008) *Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test*, The Stata Journal

[42] Ninno D. Carlo. (2001) *Improving the Efficiency of Tatgeted Food Programs in Bangladesh: An Investigation of the VGD and RD Programs*, International Food Policy Research Institute, Washington DC, US

[43] Paola, M. D. and Scoppa V. and Lombardo R. (2010) *Can gender quotas break down negative stereotypes? Evidence from changes in electoral rules*,Volume 94,Issues 5-6, Journal of Public Economics

[44] Prakash, N., Rockmore, M., Uppal, Y. (2015) *Do Criminally accused politicians affect economic outcomes? Evidence from India,*. Working Paper

[45] Rangarjan, L. N. (1992) *The Arthashastra by Kautilya*, Penguin Books

[46] Requests for Disbursement Under The Rapid Credit Facility and Purchase Under The Rapid Financing Instrument—Press Release. IMF 2020. IMF Country Report No. 20/187.

[47] RRentschler JE. Why resilience matters—The poverty impacts of disasters. The World Bank; 2013 Nov 1.

[48] Sukhtankar, S. and Niehaus P. (2013) *Corruption Dynamics: The Golden Goose Effect*, American Economic Journal: Economic Policy

[49] Stebbins S. Unemployment rate remains historically high: These US cities are among those with highest jobless rates. USA Today. August 8, 2020. Weblink : https://www.usatoday.com/story/money/2020/08/08/cities-with-the-worst-unemployment-since-the-pandemic-started/42

[50] Svensson J. (2005) *Eight Questions about Corruption*, Volume 19, Number 3, Journal of Economic Perspectives

[51] The Lancet. 2020. Redefining vulnerability in the era of COVID-19. [editorial] The Lancet 395(10230): P1089. https://doi.org/10.1016/S0140-6736(20)30757-1

[52] UNDP, U., 2018. Human development indices and indicators: 2018 statistical update. Briefing note for countries on the 2018 Statistical Update.

[53] Vaishnav, M. (2017) *When Crime Pays: Money and Muscle in Indian Politics*, Yale University Press and Harper Collins India.

Appendix A

Figure A.1: Administrative geography of Bangladesh

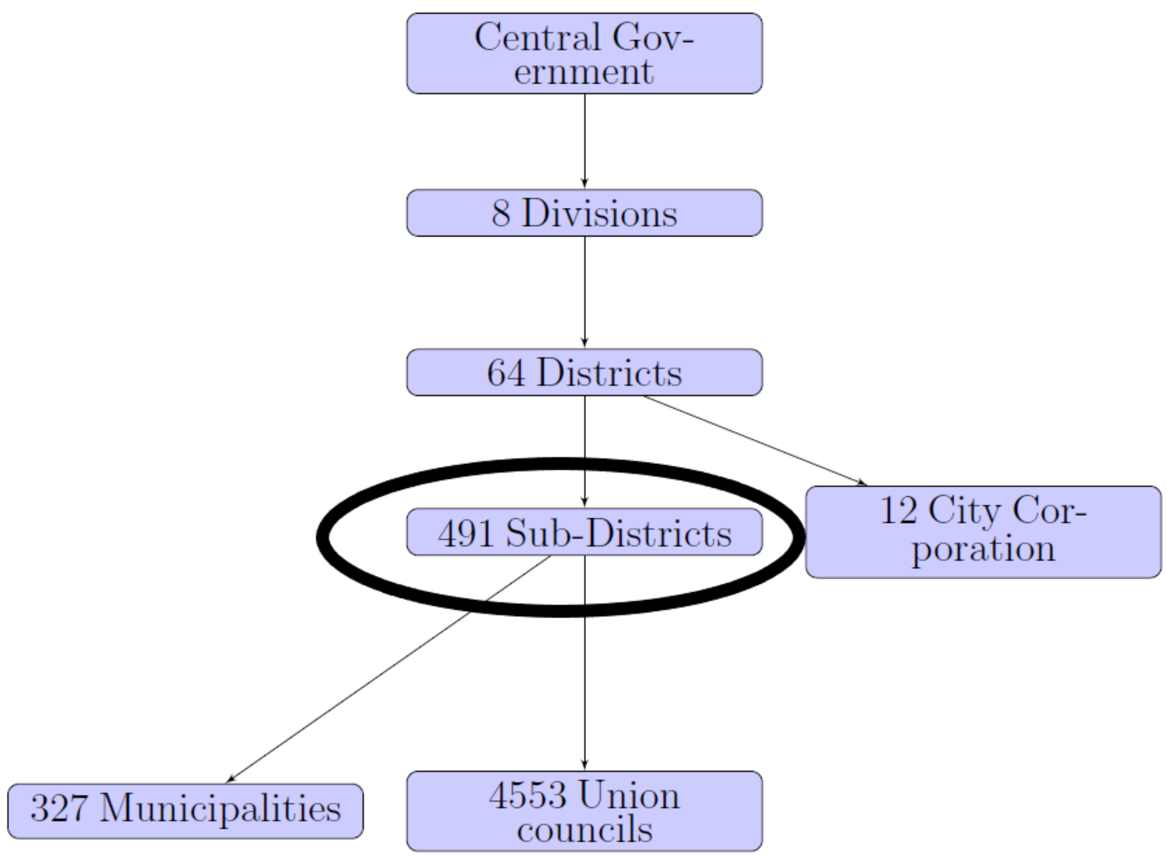


Figure A.2: Example of Affidavit form

[redacted]

২৬৭২৯৬১

Advocate Md. Abdul Majid Khan
Whole of Bangladesh
Natore
Notary Public

৬. আমার, আমার উপর নির্ভরশীল ব্যক্তি/ব্যক্তিবর্গের এবং আমার স্ত্রী/স্বামীর পরিসম্পদ এবং দায়ের বিবরণী ঃ

(ক) অস্থাবর সম্পদ

ক্রমিক নম্বর	মনোনয়নপত্র দাখিলের তারিখে সম্পদের ধরণ	নিজ নামে	স্ত্রী/স্বামীর নামে	নির্ভরশীলদের নামে
১	নগদ টাকার পরিমাণ	১,০০,০০০/=	প্রযোজ্য নয়	প্রযোজ্য নয়
২	বৈদেশিক মুদ্রার পরিমাণ (মুদ্রার নামসহ)	প্রযোজ্য নয়	প্রযোজ্য নয়	প্রযোজ্য নয়
৩	ব্যাংক ও আর্থিক প্রতিষ্ঠানে জমাকৃত অর্থের পরিমাণ	প্রযোজ্য নয়	প্রযোজ্য নয়	প্রযোজ্য নয়
৪	বন্ড, ঋণপত্র, স্টক এক্সচেঞ্জে তালিকাভুক্ত ও তালিকাভুক্ত নয় কোম্পানীর শেয়ার (পরিমান, অর্জনকালীন সময়ের মূল্যসহ)	প্রযোজ্য নয়	প্রযোজ্য নয়	প্রযোজ্য নয়
৫	পোষ্টাল, সেভিংস সার্টিফিকেটসহ বিভিন্ন ধরণের সঞ্চয়পত্রে বা স্থায়ী আমানতে বিনিয়োগের পরিমাণ	প্রযোজ্য নয়	প্রযোজ্য নয়	প্রযোজ্য নয়
৬	বাস, ট্রাক, মটরগাড়ী ও মটর সাইকেল ইত্যাদির বিবরণী (পরিমান, অর্জনকালীন সময়ের মূল্যসহ)	মটর সাইকেল ১টি মূল্য-৮৬,০০০/-	প্রযোজ্য নয়	পুত্রের মটর সাইকেল ৩টি, মূল্য- ৫,১৪,০০০/=
৭	স্বর্ণ ও অন্যান্য মূল্যমান ধাতু ও পাথর নির্মিত অলংকারাদি (পরিমান, অর্জনকালীন সময়ের মূল্যসহ)	প্রযোজ্য নয়	প্রযোজ্য নয়	প্রযোজ্য নয়
৮	ইলেকট্রিক সামগ্রীর বিবরণী (পরিমান, অর্জনকালীন সময়ের মূল্যসহ)	মোবাইল ১টি, ফ্রিজ ১টি ও ফ্যান ২টি মোট মূল্য-৪০,০০০/=	প্রযোজ্য নয়	পুত্রের মোবাইল ৪টি, ফ্যান ৮টি, ফ্রিজ ২টি মোট মূল্য-৯২,০০০/=
৯	আসবাবপত্রের বিবরণী মূল্যসহ	খাট ২টি, ড্রেসিং টেবিল ও ষ্টীল আলমারী ১টি মোট মূল্য- ৭০,০০০/=	প্রযোজ্য নয়	খাট ৪টি, ড্রেসিং টেবিল ৪টি ও আলমারী ৪টি মোট মূল্য- ১,২০,০০০/=
১০	অন্যান্য	প্রযোজ্য নয়	প্রযোজ্য নয়	প্রযোজ্য নয়

(নির্ভরশীলদের সংখ্যা অধিক হইলে অতিরিক্ত কাগজে তথ্য প্রদান করিতে হইবে)

NOTARY PUBLIC
NATORE

[redacted]

Figure A.3: Example of Tax Return Form

গণপ্রজাতন্ত্রী বাংলাদেশ সরকার
জাতীয় রাজস্ব বোর্ড
আয়কর অনুবিভাগ

আয়কর প্রত্যয়ন পত্র

করদাতার বিবরণঃ-

ক) নাম ঃ : [redacted]

খ) পিতার/স্বামীর নাম (ব্যক্তির ক্ষেত্রে) ঃ [redacted]

গ) বর্তমান ঠিকানা ঃ [redacted]

ঘ) স্থায়ী ঠিকানা ঃ ঐ

ঙ) পর্যায়ঃ ব্যক্তি/ফার্ম ঃ ব্যক্তি

চ) করদাতার সনাক্তকরণ সংখ্যা(e-TIN) ঃ [redacted]

ছ) ব্যবসা সনাক্তকরণ (BIN) ঃ প্রযোজ্য নহে

এই মর্মে প্রত্যয়ন করা যাইতেছে যে, [redacted] এর একজন নিবন্ধিত করদাতা । করদাতার ২০১৩-২০১৪ কর বৎসর পর্যন্ত কর নির্ধারণ সম্পন্ন হইয়াছে । করদাতা ২০১৩-২০১৪ কর বৎসর পর্যন্ত প্রদেয় সকল আয়কর ও অগ্রিম আয়কর পরিশোধ করিয়াছেন/~~করেন নাই~~।

তারিখঃ ০৪-১১-২০১৩ইং ।

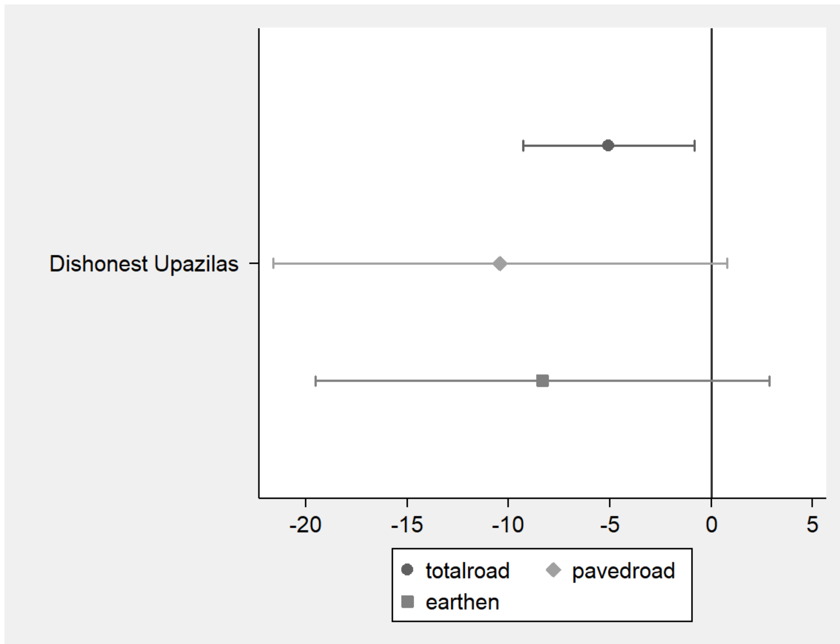
[redacted]

ফোন নং-৬২৫০১ ।

Table A.1: Ranking of Upazilas: Public Goods Index of 2015-2019

Top 20 Upazilas			Bottom 20 Upazilas		
Rank	Upazila	District	Rank	Upazila	District
1	Parbotipur	Dinajpur	461	Kalukhali	Rajbari
2	Kaliganj	Gazipur	462	Kanaighat	Sylhet
3	Gongachora	Rangpur	463	Kurigram Sador	Kurigram
4	Debhata	Shatkhira	464	Chhagalnaiya	Feni
5	Chauddagram	Comilla	465	Tetulia	Panchogor
6	Shibganj	Bogra	466	JhalokatiSadar	Jhalkathi
7	Meghna	Comilla	467	Bijoynagar	Baramonbaria
8	Babuganj	Barisal	468	Narayanganj Sador	Narayanganj
9	Sariyakandhi	Bogra	469	Bandarbon Sador	Bandarbon
10	Kaliganj	Gazipur	470	Chouhali	Shirajganj
11	Shibganj	Bogra	471	Ashuganj	Baramonbaria
12	Rupganj	Narayanganj	472	Sayedpur	Nilphamari
13	Dakup	Khulna	473	Khagrachori Sador	Khagrachori
14	Savar	Dhaka	474	MunshiganjSadar	Munshiganj
15	Pirganj	Rangpur	475	Saltha	Faridpur
16	Kaliganj	Gazipur	476	Pekuya	Cox's Bazar
17	Bondor	Narayanganj	477	Dhokkhin Surma	Sylhet
18	Nawabganj	Dhaka	478	Cox's Bazar Sador	Cox's Bazar
19	Kaliganj	Gazipur	479	RangamatiSadar	Rangamati
20	Baliadangi	Thakurgao	480	Thanci	Bandarbon

Figure A.4: Results: Coefficients values of growth of roads of upazilas with dishonest politicians



Note: All coefficients show consistent negative growth

Appendix B

Choice of Indicators

Here we explain the rationale behind choosing the indicators by domain in detail for our COVID -19 Contagion Risk Index. The detail of the units used are attached along with source of data in appendix, Table B.1.

Socioeconomic Indicator

Aims of Domain and Rationale: Densely populated communities are prone to susceptibility and contagion risk to diseases like COVID - 19 since it is hard for them to maintain social distance as well as proper hygiene.[51] It is quintessential to understand the contagion risk due to COVID - 19 to understand the impact on the labor market. In fact, the most vulnerable or susceptible to such diseases are the ones who have the ability as well as reasons to be mobilte is the highest among older age group(65+) (See Appendix B, Figure 6), such age group is not as mobile as the one who are in younger age group cohort (21-50). We also know that about 86.2 [33] of the total labor force are employed informally in Bangladesh. As figure B.1 in appendix B shows, the working age population is heavily concentrated around the age between 21-50, it will not be wrong to anticipate that, such population is employed in heavily in the informal industry. It is already established that vulnerability does not only depend on the susceptibility of the population, it is also an outcome of the policy response.[49] As mentioned above, most of the active labor have no other choice but to go out there due to a lack of unique policy response to a pandemic like COVID-19 and those who are heavy in number are between the age group of 21-50.

Indicators Used: We used the population density per kilometer for each district and vulnerable age employment data was collected for each district as well.

Source of Data: We collected data on Population density from Population Census 2011, Bangladesh Bureau of Statistics. Data on vulnerable age employment is collected from QLFS 2016-17.

Demographic Indicator

Aims of Domain and Rationale: Poverty in any situation is needlessly an impediment to find solutions to problems. At present we can see that the susceptibility to COVID-19 increases even more for households under the poverty line. It is a common understanding that there is a positive relationship between disaster and poverty.[49] This is mostly due to the lack of resources to handle such disastrous situations. Also, the type of work that people living under the poverty line has to do doesn't allow them to stay at home for a longer period of time [51]. For this, under the threat of a pandemic like COVID - 19, poorer cohorts face more contagion risk than any other class of income.

Indicators Used We used poverty rate for each district as an important element in our COVID - 19 Contagion Risk Index.

Source of Data Poverty Rate for each district is extracted from World Bank's Bangladesh Poverty Assessment report.[33]

Employment Indicator

Aims of Domain and Rationale: It is also important to understand the link between types of employment and contagion risk to pandemic like COVID-19. As mentioned in the Demographic Indicator section, most of the employment in Bangladesh is in the informal sector. It is quite obvious that such labor force does not have the luxury to stay at home to maintain social distancing. [49] This makes both the worker as well as their children and household members vulnerable to diseases like COVID - 19. We also know that, Bangladesh's export performance heavily depend on the manufacturing sector. A large share of the workers work in the manufacturing sector. From the beginning of the pandemic, due to a huge loss in export orders, such sector has been faced with a lot of challenges. Notwithstanding the worst outcome, the manufacturing sector had to continue production at the cost of high risk to support the workers. [14]. It is also prevalent that the working conditions in such industires are not ready to maintain health instructions to avoid contagion risk due to smaller spaces and density of labor in factories. Although there are commitments from aid providers like IMF [6], ADB [46] and The World Bank [14] to provide with loans to support the sector, it is not a pragmatic solution in the long run. For that, workers in the Manufacturing sector will remain vulnerable to a pandamic like COVID-19.

Rural non-farm informal employment has been a dominant sector to provide with employment to a larger portion of rural labor force [29]. Most of such employment is in the service sector as well as informal in nature. For this, such employment is prone to the contagion risk to COVID - 19.

Indicators Used: Informal employment, manufacturing employment and rural non-farm informal employment for each district is used to construct indicators.

Source of Data Data on all three indicators are collected from QLFS 2016-17.

Migration Indicator

Aims of Domain and Rationale Both internal and international migration played a significant role in spreading COVID - 19 if not the only reason in the beginning of the pandemic.[34, 36] At the brisk of COVID - 19 spread worldwide, like many other countries, a good number of Bangladeshi expatriates came back to Bangladesh from countries where the contagion risk was higher. We also have a huge number of manufacturing workers working in major cities who went back to their home districts as general holidays were announced. For that, both internal and international migration plays significant role in increasing contagion risk in Bangladesh.

Indicators Used Data on international migration and internal migration at the household level is used in constructing the COVID - 19 CR index.

Source of Data Data on international migration is collected from HIES, BBS, 2016 and data on internal migration is collected from QLFS, BBS, 2016-17.

Health Indicator

Aims of Domain and Rationale In a pandemic like COVID - 19, health facilities in any country plays a vital role in offsetting the effect of such pandemic. In a densely populated country like Bangladesh, public health facilities are scarce and can't support the influx of infected patients for a longer period of time. [28] For this, the inclusion of health facility indicator is necessary to construct a robust COVID - 19 contagion risk Index.

Indicators Used Beds per million population in each district is used for COVID - 19 contagion risk indicator. Since more beds per million population is better, the number is reversed to make it compatible with other indicators in the index. More detail is provided in the methodology section.

Source of Data Data is collected from Directorate General of Health Services(DGHS), Ministry of Family Welfare, Bangladesh.

	Variable Description	Source of Data
Demographic		
Population Density	Population per square kilometer in the district	Bangladesh Population Census 2011, Bangladesh Bureau of Statistics
Vulnerable Age Employment	Number of sample indicated as in vulnerable age (21-50) & employed in the district	Quarterly Labor Force Survey 2016-17, Bangladesh Bureau of Statistics
Socio-economic		
Poverty Rate	Upper Poverty Rate calculated from household income and expenditure	Bangladesh Poverty Assessment, World Bank 2019
Employment		
Informal employment	Number of sample indicated as informally employed in the district	Quarterly Labor Force Survey 2016-17, Bangladesh Bureau of Statistics
Manufacturing employment	Number of sample indicated as employed in manufacturing in the district	Quarterly Labor Force Survey 2016-17, Bangladesh Bureau of Statistics
Rural non-farm informal employment	Number of sample indicated as informally employed in rural and non-farm activities in the district	Quarterly Labor Force Survey 2016-17, Bangladesh Bureau of Statistics
Migration		
International migration	Number of sample indicated as international migrant in the district	Household Income and Expenditure Survey 2016-17, Bangladesh Bureau of Statistics
Internal migration	Number of sample indicated as internal migrant in the district	Household Income and Expenditure Survey 2016-17, Bangladesh Bureau of Statistics
Health		
Beds Per Million Population	Number of beds available per million population in district	Directorate General of Health Services, Ministry of Health, Bangladesh
Other Data		

COVID-19 cases	Number of COVID-19 cases in district	Institute of Epidemiology, Disease Control and Research, Bangladesh

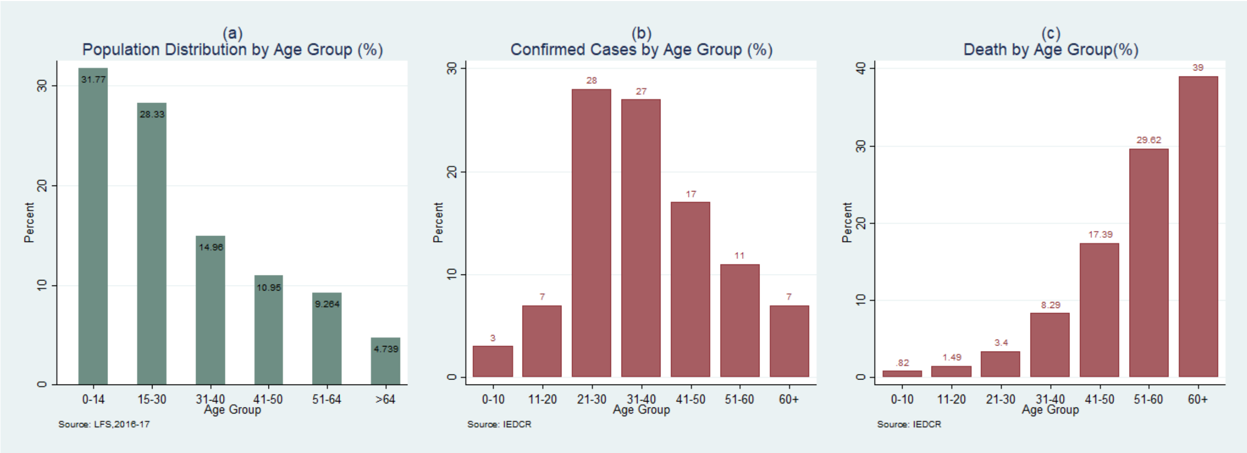
Table B.1: Domains of contagion risk, variables within and source of Data

Table B.2: Variable Choice Rationale

Variables	Coefficient	Std. Error	Constant	Std. Error - Constant	R-squared	Unit	Selection	Domain
Upper Poverty Line	-2.564*	-1.357	2.137***	-0.46	0.074	Mean percentage of Population	Yes	Demographic
Lower Poverty Line	-2.783	-1.692	1.851***	-0.359	0.049	Mean percentage of Population	No	Demographic
Manufacturing Labor	0.00125***	-0.000258	2.547***	-0.164	0.36	Sample for district	Yes	Employment
Manufacturing Labor (High-risk Aged 60>)	0.0418*	-0.0234	2.584***	-0.242	0.09	Sample for district	No	Employment
Informal Employment	0.000397***	-0.000128	0.501	-0.313	0.204	Sample for district	Yes	Employment
Total Employment	0.000310***	-0.000102	0.552*	-0.305	0.2	Sample for district	No	Employment
Formal Employment	0.00113**	-0.00048	0.872***	-0.248	0.151	Sample for district	No	Employment
Rural Non-farm Informal Employment	0.000476***	-0.000148	0.720***	-0.245	0.203	Sample for district	Yes	Employment
Rural Non-farm Informal Employment (Highrisk Aged 60>)	0.000495***	-0.000168	0.796***	-0.237	0.193	Sample for district	No	Employment
Beds/Million Population	-0.00430***	-0.00139	4.049***	-0.401	0.165	(Actual Number/Actual Population)*10ˆ6	Yes	Health
Ambulance/Million Population	0.071	-0.045	2.284***	-0.492	0.075	(Actual Number/Actual Population)*10ˆ7	No	Health
Internal Migration Risk	6.244**	-2.747	0.573	-0.388	0.08	Sample for district	Yes	Migration
International Migration Risk	1.113**	-0.522	5.008***	-0.189	0.03	Sample for district	Yes	Migration
Rural Non-farm Informal Employment (Vulnerable, Age 21-50)	0.000238***	-7.34E-05	0.586**	-0.27	0.219	Sample for district	No	Socioeconomic
Vulnerable Employment	0.000134***	-4.08E-05	0.563**	-0.273	0.221	Sample for district	Yes	Socioeconomic
Vulnearbale Employment (Formal)	0.000270***	-8.20E-05	0.565**	-0.273	0.221	Sample for district	No	Socioeconomic
Vulnearbale Employment (Informal)	0.000267***	-8.13E-05	0.561**	-0.274	0.221	Sample for district	No	Socioeconomic
Population (2011)	4.97e-07***	-5.53E-08	0.349*	-0.188	0.313	Total for district	No	Socioeconomic
Population Density /km	0.000818***	-0.000139	0.448**	-0.183	0.412	Population per square kilometer	Yes	Socioeconomic

Demographics

Figure B.1: Panel (a) shows population distribution by age group in Bangladesh. Panel (b) % share of confirmed cases by age group. Panel (c) shows % share of death from COVID-19 by age group.



Summary statistics, Indices and Index Scores

Variables	N	Mean	SD	Maximum	Minimum	Units of Measure
COVID-19 Cases (till July 22)	64	2254.391	5423.144	52083	126	Total Number
Internal Migration	64	28.766	25.988	123	1	Sample for District
International Migration	64	59.094	59.792	247	1	Sample for District
Manufacturing Labor	64	407.531	670.37	3509	40	Sample for District
Informal Employment	64	2345.734	1648.757	8696	643	Sample for District
Rural Non-farm Informal Employment	64	1496.406	1371.906	7660	298	Sample for District
Vulnerable Employment (Age 21-50)	64	6472.203	5080.601	25398	3086	Sample for District
Beds Per Million Population	64	230.8	131.642	747.88	17.893	(Number/Population)*10^6
Upper Poverty Measure	64	.275	.153	.71	.03	Mean percentage of population
Population Density	64	1201.859	1136.533	8707	92	Population per square kilometer

Table B.3: Summary statistics

District	Index1	Index2	Index3	Index4	Index5	Index6	Index7	Index8	Index9	Index10
Bagerhat	0.31	0.52	0.09	0.05	0.05	0.11	0.05	0.04	0.63	0.21
Bandarban	0.63	0.02	0.03	0.03	0.14	0.05	0.03	0.00	0.25	0.13
Barguna	0.26	0.10	0.20	0.01	0.08	0.06	0.03	0.05	0.59	0.15
Barisal	0.27	0.43	0.18	0.25	0.54	0.52	0.58	0.09	0.76	0.40
Bhola	0.15	0.20	0.08	0.03	0.08	0.11	0.05	0.05	0.75	0.17
Bogra	0.27	0.16	0.10	0.13	0.34	0.20	0.19	0.13	0.71	0.25
Brahmanbaria	0.10	0.50	0.63	0.01	0.05	0.04	0.01	0.17	0.79	0.25
Nawabganj	0.40	0.27	0.14	0.04	0.13	0.06	0.05	0.11	0.84	0.23
Chandpur	0.29	0.39	0.77	0.03	0.10	0.08	0.01	0.16	0.71	0.28
Chittagong	0.14	0.09	0.22	0.61	0.81	0.66	0.81	0.17	0.87	0.49
Chuadanga	0.32	0.16	0.16	0.04	0.08	0.08	0.04	0.11	0.77	0.20
Comilla	0.17	0.47	0.95	0.17	0.58	0.46	0.66	0.20	0.88	0.51
Cox's Bazar	0.14	0.08	0.38	0.05	0.11	0.07	0.03	0.10	0.69	0.18
Dhaka	0.10	0.00	0.06	0.91	1.00	1.00	1.00	1.00	1.00	0.67
Dinajpur	0.64	0.01	0.01	0.04	0.24	0.16	0.22	0.10	0.69	0.23
Faridpur	0.08	0.19	0.37	0.03	0.13	0.09	0.03	0.10	0.71	0.19
Feni	0.08	0.16	1.00	0.05	0.14	0.10	0.03	0.18	0.55	0.25
Gaibandah	0.47	0.57	0.05	0.06	0.27	0.15	0.16	0.12	0.85	0.30

District	Index1	Index2	Index3	Index4	Index5	Index6	Index7	Index8	Index9	Index10
Gazipur	0.07	0.00	0.05	1.00	0.70	0.36	0.57	0.22	0.91	0.43
Gopalganj	0.30	0.38	0.12	0.00	0.01	0.05	0.01	0.09	0.56	0.17
Habiganj	0.13	0.12	0.32	0.07	0.20	0.21	0.23	0.09	0.79	0.24
Jamalpur	0.53	0.12	0.10	0.04	0.12	0.06	0.03	0.13	0.72	0.20
Jessore	0.27	0.10	0.15	0.07	0.29	0.18	0.19	0.12	0.79	0.24
Jhalokati	0.22	1.00	0.26	0.00	0.00	0.03	0.00	0.10	0.00	0.18
Jhenaidah	0.27	0.07	0.11	0.02	0.08	0.05	0.03	0.10	0.84	0.17
Joypurhat	0.21	0.07	0.07	0.02	0.14	0.07	0.03	0.11	0.48	0.13
Khagrachhari	0.53	0.03	0.06	0.05	0.17	0.08	0.04	0.02	0.46	0.16
Khulna	0.31	0.07	0.07	0.29	0.54	0.56	0.58	0.05	0.71	0.35
Kishoreganj	0.54	0.58	0.24	0.03	0.07	0.05	0.03	0.12	0.66	0.26
Kurigram	0.71	0.19	0.01	0.10	0.10	0.07	0.05	0.10	0.77	0.23
Kushtia	0.18	0.16	0.21	0.05	0.16	0.10	0.04	0.14	0.69	0.19
Lakshmipur	0.33	0.12	0.49	0.02	0.06	0.06	0.01	0.14	0.83	0.23
Lalmonirhat	0.42	0.12	0.02	0.04	0.13	0.08	0.03	0.11	0.72	0.19
Madaripur	0.04	0.35	0.47	0.03	0.11	0.08	0.02	0.11	0.73	0.22
Magura	0.57	0.11	0.14	0.02	0.05	0.07	0.02	0.10	0.72	0.20
Manikganj	0.31	0.59	0.58	0.05	0.06	0.06	0.03	0.11	0.83	0.29
Maulvibazar	0.11	0.12	0.45	0.03	0.12	0.07	0.05	0.07	1.00	0.22
Meherpur	0.32	0.13	0.32	0.01	0.13	0.05	0.01	0.10	0.08	0.13
Munshiganj	0.03	0.12	0.62	0.04	0.05	0.07	0.02	0.17	0.67	0.20
Mymensingh	0.22	0.07	0.07	0.11	0.27	0.17	0.17	0.13	0.90	0.23
Naogaon	0.32	0.12	0.12	0.07	0.32	0.15	0.19	0.08	0.71	0.23
Narail	0.17	0.04	0.11	0.02	0.11	0.03	0.02	0.08	0.63	0.14
Narayanganj	0.03	0.03	0.21	0.65	0.41	0.28	0.41	0.51	0.77	0.37
Narsingdi	0.10	0.23	0.58	0.07	0.07	0.07	0.02	0.23	0.85	0.25
Natore	0.24	0.04	0.05	0.03	0.11	0.07	0.03	0.10	0.78	0.16
Netrokona	0.34	0.43	0.06	0.04	0.15	0.07	0.04	0.09	0.70	0.21
Nilphamari	0.32	0.01	0.03	0.04	0.16	0.08	0.04	0.13	0.80	0.18
Noakhali	0.23	0.64	0.72	0.06	0.11	0.11	0.05	0.09	0.77	0.31
Pabna	0.33	0.13	0.11	0.10	0.14	0.07	0.05	0.12	0.72	0.20
Panchagarh	0.26	0.27	0.01	0.06	0.17	0.11	0.06	0.08	0.61	0.18
Patuakhali	0.37	0.67	0.02	0.01	0.06	0.07	0.03	0.05	0.58	0.21
Pirojpur	0.32	0.59	0.17	0.02	0.05	0.07	0.01	0.09	0.67	0.22
Rajbari	0.34	0.29	0.19	0.03	0.17	0.09	0.05	0.10	0.72	0.22

District	Index1	Index2	Index3	Index4	Index5	Index6	Index7	Index8	Index9	Index10
Rajshahi	0.20	0.12	0.00	0.15	0.64	0.53	0.58	0.12	0.83	0.35
Rangamati	0.29	0.34	0.14	0.00	0.15	0.00	0.03	0.00	0.40	0.15
Rangpur	0.44	0.16	0.02	0.18	0.62	0.55	0.58	0.14	0.89	0.40
Sirajganj	0.30	0.08	0.09	0.28	0.31	0.21	0.23	0.31	0.89	0.30
Satkhira	0.19	0.21	0.16	0.06	0.10	0.11	0.03	0.05	0.80	0.19
Shariatpur	0.16	0.62	0.62	0.02	0.05	0.07	0.01	0.09	0.48	0.24
Sherpur	0.41	0.27	0.02	0.04	0.14	0.07	0.01	0.06	0.77	0.20
Sunamganj	0.26	0.07	0.26	0.04	0.29	0.21	0.26	0.07	0.70	0.24
Sylhet	0.13	0.03	0.56	0.05	0.32	0.50	0.59	0.11	0.89	0.35
Tangail	0.19	0.10	0.44	0.12	0.32	0.22	0.19	0.12	0.76	0.27
Thakurgaon	0.23	0.13	0.03	0.02	0.15	0.06	0.05	0.08	0.72	0.17

Table B.4: Score for CR index and sub-indices.
Here, Index1 = Poverty Index, Index2 = Internal Migration Index, Index 3 = International Migration Index, Index4 = Manufacturing Labor Index, Index5 = Informal Employment Index, Index6 = Rural Non-farm Employment Index, Index7 = Vulnerable Employment Index, Index8 = Population Density Index, Index9 = Health Index, Index10 = CR Index
Note: No specific order is followed in presenting the index scores

Cost of Lockdown for A Month

We have used the following simple method to come up with the stimulus package needed for the vulnerable industries in the red zone districts. First we need to find the total population in district $'d'$ employed in industry $'j'$. We have used the population census of 2011 for district specific total population. Using the QLFS (2016-17), we calculated the share of employment in district $'d'$ in industry $'j'$.

$$PopulationShare_{jd} = [\frac{noofemplyed_{jd}}{Totallaborforce_{jd}} * TotalPopulation_d] \tag{B.1}$$

Equation above gives us the the total population working at in district $'d'$ employed in industry $'j'$. Next we use the recent World Bank paper (please cite) to use the subsistence level cost of food and non-food expenditure per month per-capita (individual $'i'$). We adjust the costs for the inflation of the last few years. We have used both total expenditure (food and non-food) and only food expenditure as the upper and lower bound costs of the package, respectively. Assuming a scenario of complete lock-down in a red zone district, the following equation gives us the total cost government needs to bear for a one month lock-down in district $'d'$ for industry $'j'$.

$$Cost_{jd} = Cost_i * PopulationShare_{jd} \tag{B.2}$$

Using the above variable, we have given the range of total cost for the government for our proposed stimulus package.

$$Cost_{total} = \sum_{j=1}^{5}\sum_{d=1}^{10} Cost_{jd} \tag{B.3}$$

Using the three equations we have calculated the cost of shutting down the red zone districts for a month in billion Bangladeshi Taka (BDT). In appendix-B, Figures B.2-B.4 represent red zone districts' industry-wise cost of the lockdown. Figure-B.5 represents the aggregate cost of each district and figure-B.6 shows the aggregate cost by industry, respectively. A total cost of 44.28 billion is estimated as the cost of lockdown for one month from our analysis. Estimated allocation for the ADP for 2020-21 is BDT 2051.45 Billion (Resources for Annual Development Programme. Web Link: shorturl.at/rwyGT). Thus our proposed stimulus package for food and non-food items will be confined to merely 2% of total ADP allocation. And this should go even further low if we consider only the food cost in lockdown (BDT 21.31 billion) . In terms of GDP, the estimated GDP for 2020 is BDT 29534 Billion (International Monetary Fund. Web Link: shorturl.at/hyST2) and our estimated stimulus package for a month is only 0.14 % of the estimated GDP.

Figure B.2: Cost of lockdown for one month by industry in Barishal, Chittagong, Comilla and Dhaka

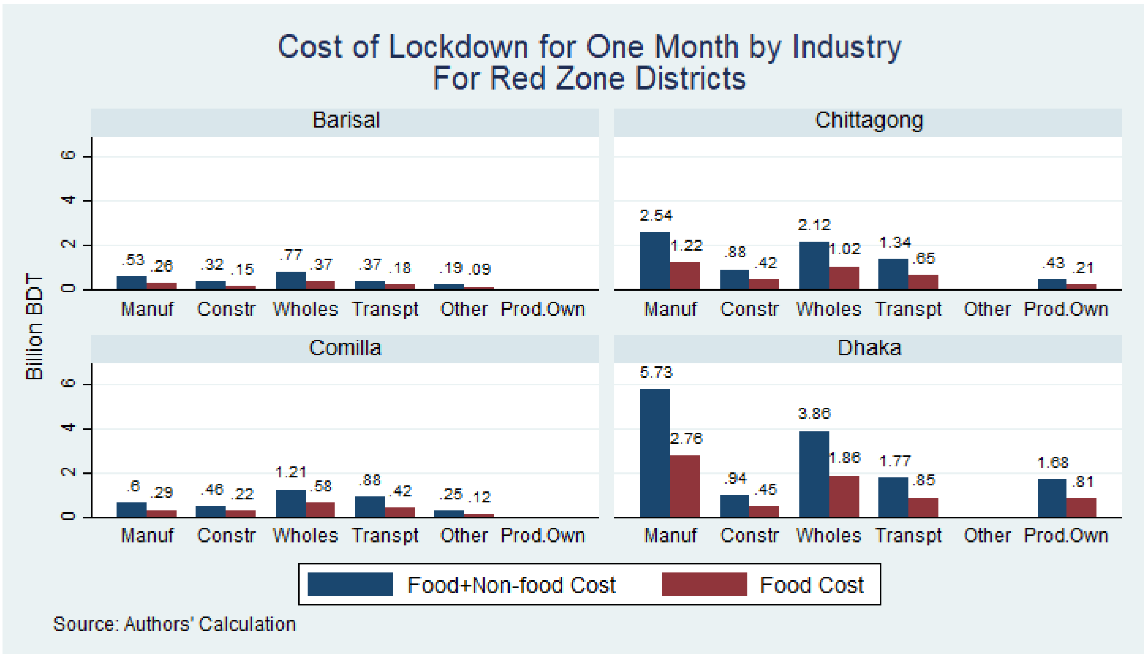


Figure B.3: Cost of lockdown for one month by industry in Khulna, Narayanganj, Rajshahi and Rangpur

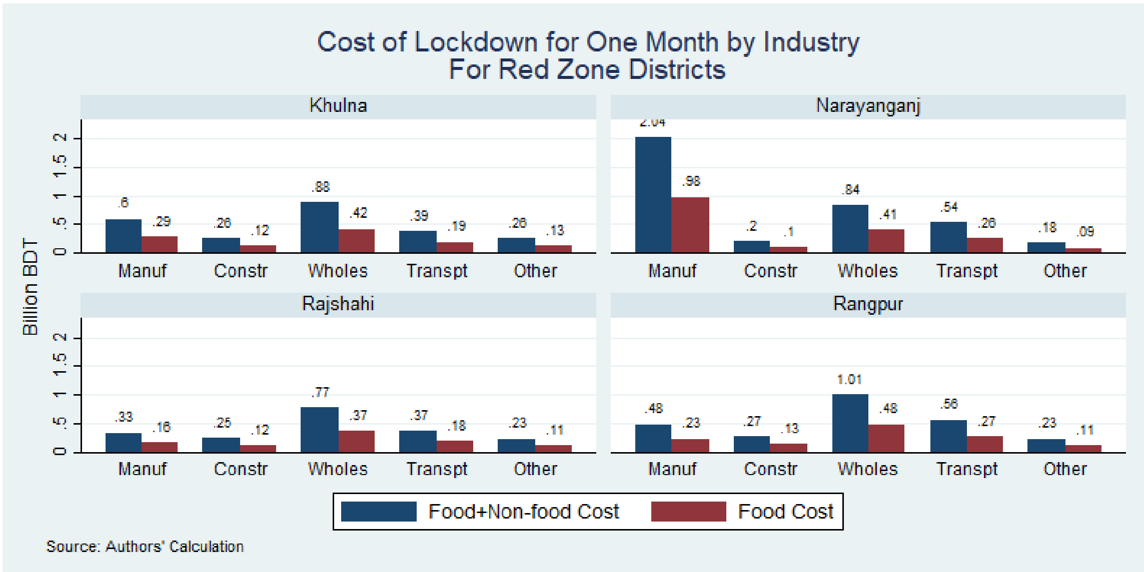


Figure B.4: Cost of lockdown for one month by industry in Gazipur and Sylhet

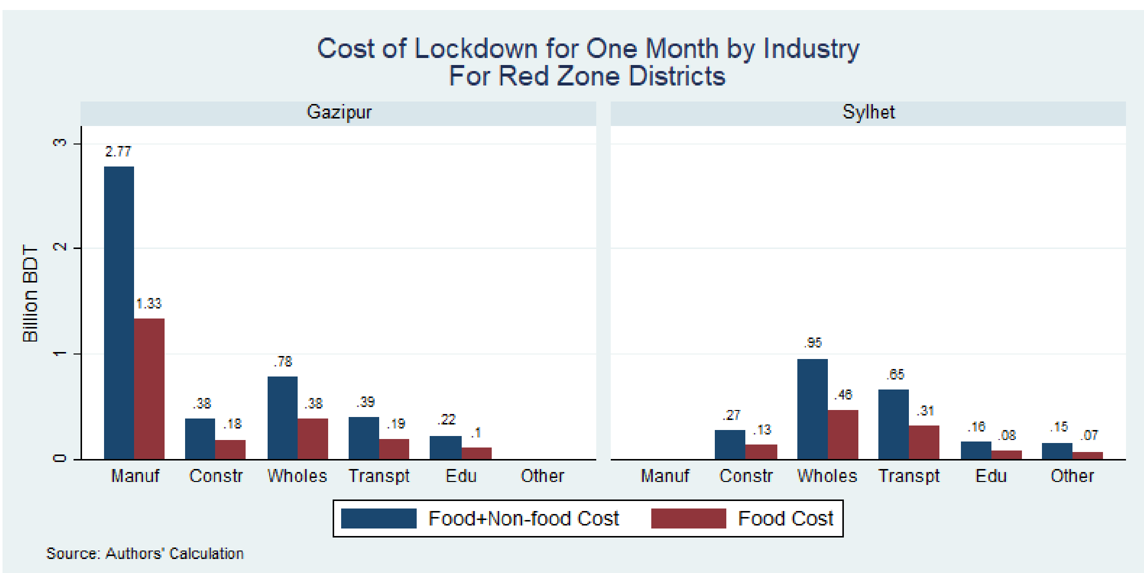


Figure B.5: Total cost of lockdown for one month for red zone districts

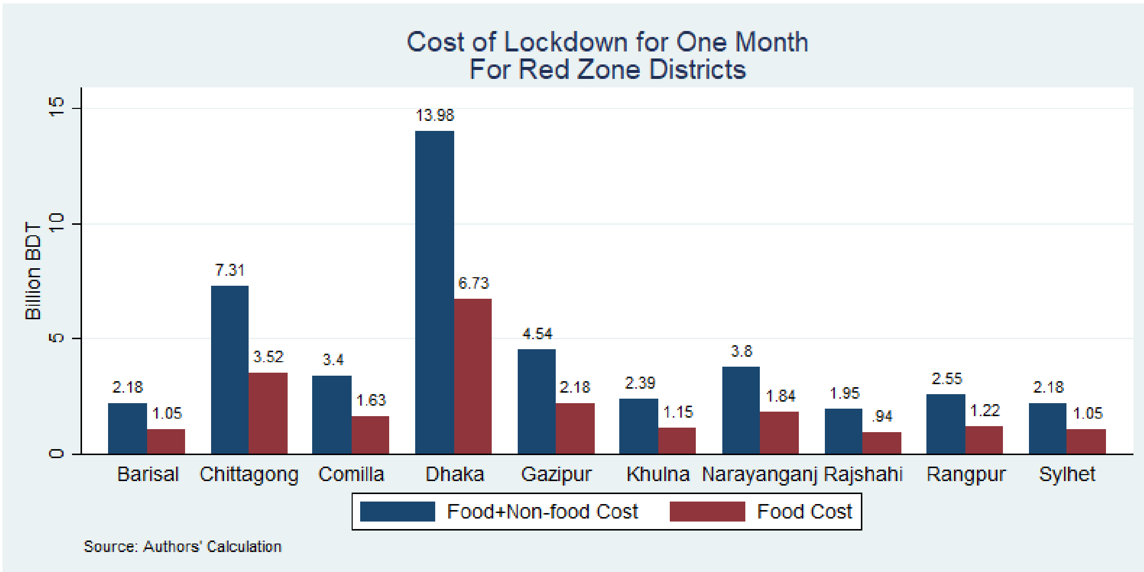


Figure B.6: Total cost of lockdown for one month for red zone industries