UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

UNDERSTANDING THE IMPACTS OF ENVIRONMENTAL, ECONOMIC, AND POLICY FACTORS ON DEVELOPING ECONOMIES

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

TEJAS GHIRNIKAR
Norman, Oklahoma
2023

UNDERSTANDING THE IMPACTS OF ENVIRONMENTAL, ECONOMIC, AND POLICY FACTORS ON DEVELOPING ECONOMIES

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF ECONOMICS

BY THE COMMITTEE CONSISTING OF

Dr. Firat Demir, Chair

Dr. Emma Colven

Dr. Jayash Paudel

Dr. Mu-Jeung Yang

DEDICATED

to:

My family back home and the family I made away from home.

Acknowledgements

I am immensely grateful for the unwavering support and encouragement of my family, especially my parents back in India, throughout my PhD journey in the US. Their sacrifices during this time and the belief they had in my aspirations have been the driving force behind my accomplishments, and I cannot thank them enough for being my pillars of strength.

I am also deeply grateful for the friends I have made, who have become my second family. Their constant support and camaraderie have made both the academic and personal challenges more manageable and enriching.

I would also like to extend my heartfelt thanks to my advisor, Dr. Firat Demir, and my esteemed committee members, Dr. Emma Colven, Dr. Jayash Paudel, and Dr. MJ Yang. Their guidance and support in my research have been invaluable, and Dr. Demir, in particular, has been instrumental in helping me navigate through personal and professional hurdles. I owe so much of my growth and success to their mentorship.

Of course, my appreciation would be incomplete without acknowledging my fiancé, Tanvi. Her belief in me and constant support have meant the world to me. Her presence in my life has brought immense joy and strength, and I am truly fortunate to have her by my side.

Finally, I would like to express my gratitude to the faculty members and colleagues at the University of Oklahoma. Their support and constructive feedback on my research have played a pivotal role in shaping my work and academic growth.

Contents

List of Tables

List of Figures

Abstracts

The first chapter of this dissertation studies the long-term effects of climate conditions during an individual's birth year on their life cycle. Drawing on data from the India Human Development Survey and monthly rainfall data from the Global Historical Climatology Network, the study focuses on adults born between 1965 and 1978. The analysis reveals that higher rainfall levels during the birth year are associated with improved socioeconomic outcomes in an individual's health, schooling, and income over time. However, the presence of birth-year rainfall volatility has a contrasting negative impact, with men experiencing a stronger effect compared to women due to pre-existing gender inequality in India. Notably, regions relying on rice farming show heightened susceptibility to the influence of rainfall on health and schooling during adulthood. These findings underscore the significance of early-life climate conditions, particularly the importance of adequate nutrition during infancy, in shaping an individual's long-term well-being.

In the second chapter, we delve into the evaluation of the IMF's Structural Adjustment Programs (SAP) and their impact on the IMF's yearly growth predictions for member countries. The analysis centers on a dataset consisting of 158 countries during the period from 1990 to 2004. The Structural Adjustment Programs were implemented by the IMF in the early 1980s and required member countries to fulfill specific conditions to receive loan tranches. We find that the IMF tends to overestimate future growth in countries subjected to a higher number of SAP conditions. This research sheds light

on the IMF's perception of SAP allocation and its implications for a country's future growth. The effectiveness of SAP remains a contentious topic, and these findings contribute valuable insights into how these programs may impact a country's economic prospects.

In the third chapter, the impact of China's Cleaner Production Law on firm behavior and long-term investment decisions is studied using a Synthetic Difference-in-Differences (SDID) framework. We focus on the role of county governments' environmental budgets in shaping firms' investment decisions, highlighting the importance of effective monitoring mechanisms. Although the implementation of environmental laws resulted in changes in firm behavior, we did not find statistically significant reductions in pollution levels after the implementation of the law. This is owing to the fact that pollution levels are affected by multiple variables apart from manufacturing activities. We also run a battery of sensitivity tests to check the validity of our results and find that the main results are consistent across various frameworks.

Chapter 1

Does Early-Years Rainfall Translate in Adulthood Success? :An Empirical Study in Rural India

1.1 Introduction

For the most part of the 20^{th} century, India has been an agrarian economy with more than half of its population relying on farming and professions related to farming. This section of the population, mostly residing in rural areas, is susceptible to illness, poor sanitation, conflicts, etc. Although some of these shocks are temporary, the effects of certain shocks can be experienced over a long time (Maccini and Yang, 2009). An illness borne by a child at a young age might have a lasting impact on their well-being in adulthood. This, in turn, can affect their education level and income. The objective of this paper is to examine whether shocks pertaining to climate have a long-lasting impact on a person's socioeconomic outcomes. With the rise in aggregate temperatures on Earth and increasingly volatile weather conditions, it is imperative to study the long-run effects of changes in weather patterns (Hoeppe, 2016).

As confirmed by the fetal origins hypothesis, the environmental conditions when a child is *in utero*, affect the epigenome which results in causing various parts of the genome to be expressed or not. Therefore, if a child does not receive adequate nourishment in the first year, the development of their intelligence quotient and motor skills can be permanently affected(Almond and Currie, 2011). As explained by Yang and Qiu (2016), income gaps among adults are mainly owed to the difference in the quality of early education and the investment towards schooling. Building on this premise, I focus on the effect of birth-year rainfall on the child's long-term health, educational attainment, and adult income. A child born during a drought in a food-insecure family may be vulnerable to such prolonged effects due to inadequate nutrition.

To establish a causal link between birth-year rainfall and the child's adult outcomes, I have selected a panel of rural Indian household-level data from the Indian Human Development Survey(IHDS) of people born between 1965-1978 and their incomes in 2008. I paired the IHDS with the data of rainfall in the district of birth in their birth year to regress it on the income levels. In my analysis, I separated the regions producing *kharif* and *rabi* crops[1], which require different levels of rainfall. The optimal level of annual rainfall for rice is 200 mm, whereas for wheat, corn, and cotton, the optimum rainfall is 70mm per year (Aggarwal, 1991). So I used the fluctuations of rainfall in the birth year from the optimal level for the crop growing to assess its effect on health and income variables.

India receives different levels of rainfall in different regions; thus, agricultural production is inherently heterogeneous in nature(Chintala et al., 2015). This, in turn leads to different sensitivity to rainfall depending on what type of crop a farmer is growing. For example, regions in south and east India are predominantly rice-intensive, which require 200mm seasonal rain for healthy production, whereas central and northern parts of India grow wheat, millet, sorghum, et cetera, which only require 50 to 100 mm rainfall

[1] *kharif* crops are grown in the summer monsoon season and need direct rainfall. *rabi* crops are grown after the monsoon season with the help of drip irrigation from the aquifers

in the monsoon season (Hutchinson, 1976). Thus, I expect to observe varying results for dry regions vs. wet regions: My empirical analysis concludes that the effect of the weather shock is stronger in the wet regions and is persistent in health, schooling, and amount of income in adulthood.

In this study, I also examine the difference in the impact of birth-year rainfall on males and females. Gender inequality in India arises through a predefined social construct that puts females in subordinate roles. In most areas in India, access to good healthcare and standard of living has been poor, especially for women (Arora, 2012). As a result of this inequality, the participation of women in the workforce has been on a constant decline (Turnbull et al., 2013). Thus, the women in rural India are only expected to do the housework, tend to the husband's and children's needs, perform religious duties, et cetera (Razvi and Roth, 2004). This divide between genders leads to the hypothesis that the effects of early childhood rainfall would be stronger for men as compared to women. Because women are not expected to go to school and enter the formal workforce, I hypothesize that the effect of birth year rainfall will be much weaker for women. This is owing to the fact that the factors behind women's education and income are more fundamental than the scope of this paper. If a family is not focused on investing in a girl child's education, favorable climate conditions at the time of birth will not have a significant impact on the schooling and income of the child. Consistent with my hypothesis, I observe that the coefficient of interest is significantly stronger in the case of a male child. With a higher harvest, a family doesn't have to worry about food shortages and the nutritional value associated with it. This also confirms that early childhood nutrition is one of the main contributors to health and economic well-being during adulthood.

An argument can be made to consider rainfall in the first few years of childhood instead of just focusing on the birth year, however, there are studies in the field of health and nutrition that conclude that if the growth of an individual is hampered in the first year of life, then it is hard to negate that effect in the subsequent years (Johnson and Schoeni, 2007). Thus, I expect to observe the strongest impact on the economic outcomes to be caused by the birth-year rainfall. As a robustness check, I include the regressions for 2 years of pre-birth and post-birth rainfall on my dependent variables and find no relationship.

This chapter is organized as follows. Section 1.2 reviews the previous literature on the socio-economic effects of rainfall. Section 1.3 discusses the data and introduces the empirical methodology. Section 1.4 presents the results, including the sensitivity analysis. Section 1.5 concludes the chapter.

1.2 Effects of Rainfall

Agriculture in India has always been heavily dependent on monsoon season (Gadgil, 1989)[2]. As we can see from Figure 1.1, the summer rainfall and crop output move together (Reserve Bank of Australia, 2018). A reduction in monsoon rains has seen agricultural production fall by as much as 15% or more (Gadgil, 1989). Majority of farmers take heavy loans from banks to buy seeds to sow and thus, volatility in the arrival of rain can create a financially unstable situation for the farmers leading, in some cases, to bankruptcy. Between 1995 to 2006, India experienced close to 16,000 cases of farmer suicides per year, a rate which is far greater than other fractions of the society. This can be attributed to problems associated with agriculture as opposed to mental health (Merriott, 2016). This is further alarming as the size of the agriculture industry has been deteriorating over the years. Despite this fact, the dependency of Indian agriculture on the monsoon and the negative impacts of the droughts have not

[2] While deciding on the types of crops to be grown in a particular season, the variability of the monsoon prediction is the most important parameter.

changed. Uncertainty in monsoon season has reduced India's agricultural production by 2% to 5% every year (Prasanna, 2014). Therefore, a volatile climate causes detrimental impacts to the rural society of India and they are further exacerbated by a reduction in investment in the agricultural and irrigation industry.

Thus, the main contribution of this paper is to assess the long-term impacts of childhood shocks. Levine and Yang (2006), while focusing on the rice fields in Indonesia, find that higher rainfall corresponds to higher productivity, likely resulting in higher income levels on a household level. They also state that these results do not hold for later years, that is, rainfall in the previous year has no impact on the production this year. In a study conducted in rural India, Flatø and Kotsadam (2014) showed that female infant mortality decreases in the presence of a positive rainfall shock relative to male infants. Thus, the literature points toward the importance of the environmental conditions present during the time of birth on child outcomes.

The phenomenon of having long run impacts due to shocks experienced during specific years of programming is characterized as critical year programming. The first year after the birth of the child is most susceptible to environmental shocks (Glewwe et al., 2001). Sharpe (2012) finds that lack of nourishment in the uterus and the first year after being born has resulted in reduced height and body mass index as compared to malnourishment in older kids. Khanam et al. (2011), using a maternal fixed-effects and IV approach finds that the kids who are malnourished in the years before school starts tend to have lower height and lower schooling in adulthood. To further bolster the argument, Johnson and Schoeni (2007) posit a fetal origins hypothesis which states that lack of nutrition during pregnancy leads to susceptibility towards coronary heart diseases, hypertension, strokes, diabetes, et cetera. Their study also provides evidence of six fatal chronic health conditions in adulthood including asthma for a national sample in the United States. Van den Berg and Modin (2013) finds a higher mortality rate during adulthood if the child is born in a recession. They also find a link between the ability of a child with the birth weight and the business cycle at birth.

How developing countries' population reacts to different types of shocks has long been a topic to study for economists. Steckel (2005) have shown that health conditions in childhood is an important determinant of adult mortality rates. The presence of droughts or floods during infancy will lead to alteration in the disease environment which will have a predictive power towards adult health as well as socio-economic outcomes.

Maccini and Yang (2009) study the impact of birth year rainfall on health outcomes, schooling, and income during adulthood in Indonesia. After linking the Indonesia Family Life Survey(IFLS) data to birth-year rainfall, they find that an increase in the rain at year of birth results in positive and significant adult health outcomes for women. The approach I have used in this paper is an extension of the one used by Maccini and Yang (2009). As Indonesia is spread across in longitudes but not in latitudes, the tropical nature of the country makes it most suitable to produce rice; which is the only crop considered in their paper. Whereas in India, becasue of its varied topography, crops like wheat, jowar which are less rain intensive are also predominantly grown. I will focus on the differentiated effects on regions requiring high volumes of rains(rice intensive) versus regions requiring lower levels of rainfall(wheat, sorghum intensive).

1.3 Empirical Analysis

1.3.1 Data

The household-level survey data was gathered by the India Human Development Survey (Desai and Vanneman, 2015). It consists of 23,629 households in 1503 villages. I consider the data pertaining to individuals in rural households as 75% of the rural population works in the agriculture sector. The sample consists of 9,130 men and 8,462 men who are born between 1965 to 1978 and the adult outcomes are observed in 2008. Since the Green Revolution took place in India in the early 1960s, this sample will not be susceptible to the heterogeneous effects on crop yields. This was a combination of higher research and technology spillover in the late 1950s and early 1960s, which resulted in a significant increase in crop yields (Ryan and Asokan, 1977). Thus, only considering the period after the Green Revolution helps us segregate that effect. The youngest person in this data set is born in 1978, and as of 2008, will be 30 years old. This will give us a comparable sample when we compute the income levels across the data set. The variation in the data is captured at the district level with 415 districts in the sample. The summary statistics of the data are presented in Table 1.1. The assets per capita variable include all monetary and physical assets owned by the household at the time of the survey. They include bank savings, houses, land, appliances, vehicles, et cetera. This variable does not have any variation at the individual level.

The rainfall data were collected from the Global Historical Climatology Network. The data includes rainfall and temperatures at every station with its latitude and longitude. In India, the monsoon season lasts from mid-June to mid-September. The timing varies for northern and southern states. In southern states, the monsoon arrives two weeks earlier than in the northern states. I have adjusted this rainfall measure on the state level. I take an average of the rainfall for four months as it will act as the main contributor to the harvest in the agricultural sector. I use the average of the rainfall at each location over 30 years of the sample as a baseline and subtract it from the observation for that particular location. This will give me a deviation from the average and will work as my main variable of interest.

The height of the respondents was measured by the surveyors in centimeters. The agricultural wage labor is a dummy variable that takes the value of 1 if the respondent has worked for more than 240 hours in agriculture-related professions in a given year. The mean of 0.93 in the case of females and 0.97 in the case of males gives us a good representation of the demographics of the population used in the analysis.

1.3.2 Level Effect of Rainfall

In the first part of empirical estimation, I focus on the level effect on birth-year rainfall on adult outcome. I use the following regression specification.

$$Y_{ijt} = \beta_1 Deviation_{ijt} + \beta_2 t + \beta_3 X_{ijt} + \gamma_j + \epsilon_{ijt} \tag{1.1}$$

Here, my dependent variable, Y_{ijt}, is the health, education, or income variable in adulthood for individual i born in district j in year t. To assess the health metrics, I look at participants' height, self reported status, and existence of a medical condition. For education, I consider years of schooling. For adult income levels, I focus on log annual earnings, log expenditures per capita, and asset index[3]. I regress it upon the log of rainfall deviation at birth, $Deviation_{ijt}$. To calculate the rainfall deviation measure, I subtract the average level of monsoon rainfall from the average for the birth location. The average for each location is calculated with respect to the average of the 30 years of data in the sample[4]. To account for the long-run changes over three decades on the national level, I include a linear time trend t. This time trend also helps in capturing the age effects for the cohorts born in different years.

X_{ijt} is a set of control variables which vary according to the dependent variable I also include the district of birth fixed effects to capture the time variant unobservables at the district level. This will also be helpful to separate out the impacts on the adult

[3] Asset index is constructed by calculating the log total value of household assets such as TV, refrigerator, toilet, vehicle.

[4] I consider the rainfall data from 1955-1985 excluding the year of birth of the individual

outcomes from the individual's birthplace. For instance, when I analyze the impact of birth-year rainfall over health, I control for parents' health condition, indicator for hospital presence in the village, and level of smoking and alcohol consumption. While analyzing level of education, I control for parents' education, money spent on books and stationary, and presence of school in the same village. Lastly, when I regress income on birth-year rainfall, I control for health conditions, years of education, and whether the person moved to the city.

The specification varies from the one used by Maccini and Yang (2009) in the following aspects. Because their study is focused on Indonesian agriculture, they have included season fixed effects alongside district fixed effects. However, since the crop yields in India are cultivated in the summer monsoon season, I have not used the variation between dry seasons and wet seasons.[5] While I compare the level of rainfall between different locations, I do not account for the flooding phenomenon where more rain will result in lower yield. As flooding is a highly localized phenomenon in the Indian subcontinent, adding a quadratic term for the rainfall does not change the results (Dhar and Nandargi, 2003). Also, the survey data I use also allows me to control for certain variables which can affect the health, education, or income in a different way.

In all specifications that follow, I have only used the portion of the sample where the weather station is located within 25 kilometers from the place of birth. The choice of stations in this subsample does not appear to be driven by specific regions and the results are consistent when compared to the full sample.

In Table 1.2, I present the results from Eq. 1.1, showing the effect of rainfall at the time of birth on the health of the people in the sample. These regressions focus on checking the validity of the fetal-origins hypothesis. The conditions present at the time of

[5] The average daily rainfall value in India ranges from 0.1mm/day to 103.1mm/day. The wet region is defined where the rainfall is more than the 90^{th} percentile (Vinnarasi and Dhanya, 2016).

birth play a significant role in determining the outcomes in a person's adult life. We see a positive effect in this framework. I find that in the regions absent of the scarcity of rain, the height of the men was higher compared to those born in drought-prone areas. This positive effect is also present in the women's subsample, albeit statistically insignificant. For men, a percent increase in rainfall deviation relates to an average increase of 0.23 cm in height. The adult health of both men and women is also positively influenced by the increased rainfall. A similar story ensues when I look at the presence of any chronic health condition in adults.

In Table 1.3 I look at the effect of rainfall deviation on schooling outcomes and find that, the effect of birth year rainfall on men is much stronger and more significant as compared to the women. For every 5% percentage increase in the rainfall, men on average attended 0.2 extra years of schooling in the rice-intensive regions. When we compare the effect across dry and wet regions, agricultural zones mainly dependent on rice are observed to be more susceptible to early-life climate shocks. This effect is more dominant in men. These results intuitively make sense as female education was not a high priority for rural households in those days, the education of female children does not observe the increase in education despite a good harvest. For dry region, the co-efficient for females is negative albeit insignificant.

In Table 1.4, I regress income on rainfall deviation at birth, and find similar results as the regressions in Table 1.3. We do not observe any significant effect on the women subsample whereas the men subsample has a more positive and significant co-efficient. As I have explained before, these coefficients are a lower bound due to the presence of a downward bias, we can safely say that the amount of rainfall at birth has a significant impact on men in rural India. Another common theme in both tables is the stronger relationship between rainfall and the dependent variable in the rice producing regions. The co-efficient is stronger and more significant in the subsample including men.

One of the major limitations of this data is the precision of the measure of rainfall deviation. Because I am matching the data at the district level, the rainfall at the place of birth will have an error associated with it. To account for this limitation, I adopt an instrumental variable(IV) approach where I instrument the rainfall at the closest station to the place of birth with data from stations in the same birth year that are second to fifth closest[6].

As we can observe from the tables 1.5, 1.6, and 1.7 for the entire sample, the results have not varied by much across both males and females. The consistency throughout different specifications bolsters the argument for exogeneity. As the instrumental variable approach accounts for the measurement error attributed to distantly spaced rainfall measuring stations, the results obtained in Tables 1.5, 1.6, and 1.7 form the benchmark of our estimation. To further elaborate on the benchmark results, a 5% increase in rainfall with respect to the average translates into a male having an increase in height by almost 0.21 cm, extra schooling of almost 0.31 year and an annual income increase of Rs 1,570. As consistent with the primary hypothesis, the effect in female children is less pronounced.

1.3.3 Effects of rainfall volatility

In our study on the impact of rainfall deviation, we observed that higher rainfall during the birth year correlated with better outcomes in adulthood, reflecting increased prosperity due to higher yields. However, solely focusing on average rainfall does not provide the whole picture. To better understand the welfare of rural society, we introduce the concept of rainfall volatility as a crucial variable of interest. Rainfall volatility measures the variation in annual rainfall from expected levels, which significantly influences

[6]This approach is adapted from Maccini and Yang (2009) and is only used to control for the inherent measurement error.

farmers' investment decisions and subsequent outcomes.

We employed a seasonal ARIMA(2,1,2) - GARCH(1,1) model to accurately capture this variability, following Yusof and Kane (2013), analyzing the inter-temporal variation in rainfall. The results revealed that higher rainfall volatility during the birth year led to adverse outcomes in adulthood, specifically lower heights for individuals across genders and regions, confirming the validity of the fetal origins hypothesis. The magnitude and significance of the effects on height, schooling, and income were even greater than those observed with average rainfall deviation, highlighting the non-linear relationship between rainfall and welfare outcomes.

To gain further insights, we compared the outcomes induced by rainfall volatility with those caused by natural disasters, specifically earthquakes. Research in South Asia, including Nepal, showed that earthquakes exacerbate disparities in human capital and labor market outcomes (Paudel and Ryu, 2018; Shakya et al., 2022). This evidence suggests that natural disasters can have lasting negative effects on human capital development and migration, deepening socioeconomic disparities in affected regions.

Moreover, temperature variation has also been studied in relation to human capital outcomes in India. Findings indicated that higher temperatures negatively impact economic productivity, underscoring the significance of environmental factors in shaping human welfare(Garg et al., 2020). Additionally, studies on the macroeconomic consequences of disasters have further emphasized their wide-ranging impact on societies (Kirchberger, 2017; Noy, 2009).

Drawing on these comparisons, it becomes evident that both rainfall volatility and natural disasters play crucial roles in shaping human welfare and economic outcomes. Understanding these complex relationships provides valuable insights into the vulnerabilities faced by rural communities. Policymakers can use this knowledge to develop climate-resilient strategies and adaptive measures to safeguard rural populations from environmental fluctuations and disasters.

In conclusion, our study demonstrates that while higher rainfall may be associated with better outcomes in rural areas on average, the volatility of rainfall is a critical factor that significantly affects welfare outcomes. Furthermore, comparing rainfall-induced outcomes with those from natural disasters and temperature variations highlights the multifaceted nature of climate impacts on human capital and economic prosperity. This comprehensive understanding is essential for designing effective policies and interventions to support and protect vulnerable communities in the face of environmental challenges. The research by Paudel and Ryu (2023) on the spillover effects of natural disasters on human capital also complements these insights, further strengthening the importance of addressing climate-related issues in development planning.

1.4 Sensitivity Analysis

One of the main arguments for the methodology used in this paper is its concentrated focus on the rainfall volatility observed in the year of birth. As analyzed by previous researchers, if nutrition received in the birth year is inadequate then it becomes almost impossible to catch up to the healthy levels in the subsequent years. Thus, to check for this hypothesis, I look at the rainfall volatility in the 2 years after birth and see its effect on health, schooling, and income. The results show that the coefficients lose their magnitude and significance across all specifications in the sample. Thus, the findings support the fetal origins hypothesis that development in the infancy year plays an important role towards improved cognitive skills and income in the future. This can be observed from the results after regressing the dependent variables on rainfall volatility 2 years before and after birth. While we look at the rainfall in consecutive years, we cannot ignore the possibility of autocorrelation between the amount of rainfall in consecutive years. A significant coefficient in Tables 1.11, 1.12, and 1.13 would point towards omitted variable bias. However, as that is not the case, we can argue that the results in the main regression are robust to the birth year rainfall volatility.

In the results stated in Tables 1.11, 1.12, 1.13, we observe that the co-efficient on rainfall volatility drops significantly when looking at later year rainfalls. Given the plausible autocorrelation between the rainfall data across years, we cannot deny the possibility that rainfall during initial school years may cause the decline in total school years and I have not totally isolated the effect of the birth-year rainfall. At the same time, the difference in the co-efficient of interest is also apparent in the regressions for income in the adulthood. If my previous hypothesis is true about the reduced effect of the rainfall volatility in the birth year, then we cannot deny the possibility that reduced education is the channel towards reduction in income and not the health during infancy itself.

Another way to check the robustness of the result is to run the regressions on men and women living in urban areas. If the rural populace is the one susceptible to monsoon, we should find no significant effect in the urban population. We see similar results in Table 1.14. Furthermore, we see an increase in rainfall causes a reduction in schooling and income. This can be explained by the fact that the disease environment in cities is different than that of in villages. Urban population may be more prone to diseases such as malaria, dengue et cetera.

Another factor which might distort the main result is the advent of technology during the four decades we have considered. For example, improvement in the seed quality would make them more weather resistant and the final yield may not be as susceptible to monsoon variations as it has been in the past. To pose an argument, in India over 66% of farmers produce seeds from their own harvest without having to deal with outside market (Sahai, 2000). This is significantly high when compared to Europe where reused seeds are used by only 10% to 50% of the farmers (Pionetti et al., 2006).

Farmers in India put heavy reliance on seed, diversity and nutrition. Also, crop diversity helps farmers diversify their risks. Another argument towards small farmers not using genetically modified seeds is the scale of their operation. Small farmers do not possess big lands, and they need very small amount of seeds if they plan to diversify (Rao et al., 2015). For example, a farmer plants approximately 100 g of sesame, 1 kg of millet, 500 g of grams et cetera. Buying seeds from the marketplace is not an option to farmers operating on such scales. To test for this hypothesis, I divide the sample into half with respect to the assets possessed by each family. The sample consisting of poorer people will predominantly include small farmers whereas the rich people will be the ones with comparatively larger farms. When we observe the results, we do not see one subsample driving the results of the whole group (See Appendix Tables 1.A7-1.A8).

With the increasing use of technology, farmer simulation models have been proven more effective in recent past to maximize the food productivity given the uncertain climate. Implementing such programs nationwide in collaboration with childhood health programs can result in an increase of social welfare in rural communities (Mall et al., 2006).

1.5 Conclusion

In this paper, I find that the income and schooling of men in rural India is significantly affected by the rainfall in their early childhood years. This factor may be mainly driven because of the unequal treatment between boys and girls in rural India in the late 20$^{\text{th}}$ century. The most likely explanation for these results is the channel of early life nutrition. Abundant rainfall increases the harvest in the farm reducing the food shortages, results in higher income and greater nutrition for children.

Due to gender discrimination and lower emphasis on girl's education, we do not observe a significant change in women's schooling even in the presence of adequate rainfall. As the women are not expected to finish schooling or join the workforce, rainfall does not have a significant effect on their education or income. However that is not the case with men. A 10% increase in rainfall results in one additional year of schooling for men.

With the increasing use of technology, farmer simulation models have been proven more effective in recent past to maximize the food productivity given the uncertain climate. Implementing such programs nationwide in collaboration with childhood health programs can result in an increase of social welfare in rural communities (Mall et al., 2006).

The integration of policy into agriculture in independent India started with the Green Revolution, where the adaptation of technology and genetically improved seeds were used nationwide which shot up the agricultural harvest in the last 3 decades of the 20$^{\text{th}}$ century. Given the severity of climate change and expectations about increased fluctuations in temperatures and rainfall, it has become of paramount importance that policymakers have to play a more active role to safeguard farmers from such volatilities which may lead to food insecurity in the household and work as a channel to cause damage in the long run to the country's human capital. As explained by Gregory et al. (2005), different countries will suffer different impacts of climate change. Since developing countries' mechanism in coping with such shocks is not as efficient compared to those in developed countries, the rural population will suffer disproportionately in countries within Africa and Asia. As a response against food insecurity, the Indian government launched National Rural Employment Guarantee Act(NREGA) which employed people for 100 days in periods of droughts. Although these policies have been received positively by the majority of the populace, we can't expect them to be enough to absorb the expected future variations in the climate. In such case, development of agriculture, fisheries, livestock resistant to climate change can work as a good solution alongside better risk management technologies(NICRA, 2019).

Thus, in light of all the short and long-term impacts of food security in rural areas, with improvements in local governance and food access, issues arising with climate change can be efficiently mitigated. Since food insecurity is the main channel through which these results are driven, future policies can be targeted towards the same. (Gurditta and Singh, 2016).

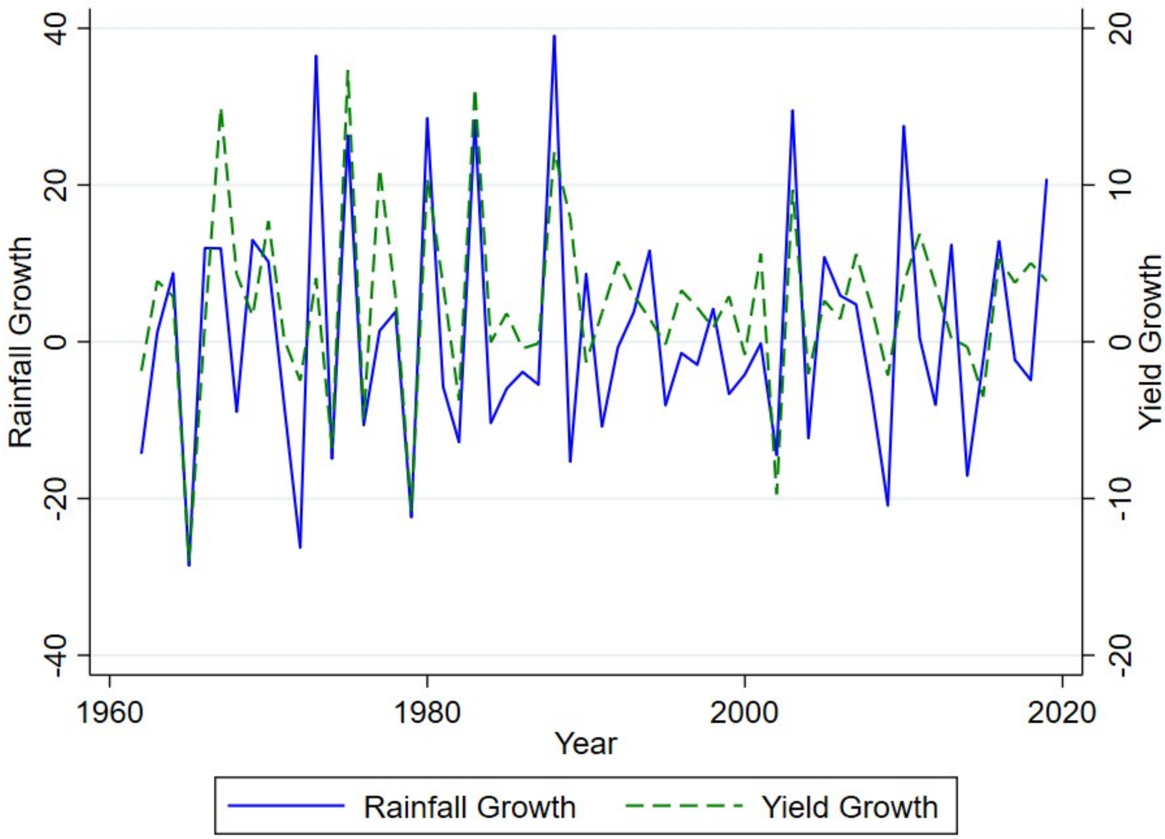
These results are important in terms of policy perspective. We observe that in villages where rice is the main source of agricultural output, early life shocks can prove to be detrimental to the population in the long run. Thus, programs assisting the health and nutrition of infants during droughts can result in high long-term societal returns in the rural areas.

While carrying out the robustness analysis, I also looked at the rainfall variation before and after 2 years of birth. Per Section 1.4, the result across all the subsamples came out to be weak and insignificant. This result has been consistent with the past literature focusing on infancy as the main channel to adult health as compared to early childhood years.

To conclude, there is adequate evidence in the results that in rural India, people are not able to smoothen out their consumption patterns, at least in case of a male child. Thus, it is imperative to focus on nationwide programs raising pre-natal as well as post-natal awareness in villages and provide subsidies to villagers in order to avoid instances of food insecurity.

Figures and Tables

Figure 1.1: Summer Monsoon and Agriculture in India



Notes: The data extends till Indian Meteorological Department's first forecast for 2020/21 monsoon.
Source: Author's calculations based on data from Indian Meteorological Department.

Table 1.1: Summary Statistics of Women and Men Born Between 1965-1978

	Women				
Variables	Observations	Mean	Standard Deviation	Min	Max
Age	8,462	36.2	7.3	30	43
Height	8,462	148.6	6.3	108.9	175.6
Reported Health Condition(ID)	8,462	0.16			
Years of Schooling	8,462	5.9	3.5	0	15
Parents' Education	8,462	12.1	3.4	0	19
Ln(Expenditure per capita)	8,460	8.6	3.4	0.2	19.4
Agricultural Wage Labor	8,460	0.93			
Ln(Assets per Capita)	8,458	17.6	2.1	0	26
Owns refrigerator	8,462	0.19			
Owns TV	8,462	0.50			
Expenditure per capita	8,462	35.8	9.4	0.3	3547.7
Ln(Annual Earnings)	8,451	16.4	1.6	13.6	18.4
Ln(Rainfall Deviation)	8,462	-0.06	0.4	-1.8	0.7

	Men				
Variables	Observations	Mean	Standard Deviation	Min	Max
Age	9,130	36.5	7.6	30	43
Height	9,130	152.9	8.7	104.9	184.6
Reported Health Condition(ID)	9,130	0.21			
Years of Schooling	9,130	9.1	2.4	0	16
Parents' Education	9,128	12.4	3.5	0	20
Ln(Expenditure per capita)	9,130	8.4	3.6	0.1	18.9
Agricultural Wage Labor	8,460	0.97			
Ln(Assets per Capita)	9,130	20.4	3.5	0	28.4
Owns refrigerator	9,130	0.19			
Owns TV	9,130	0.51			
Expenditure per capita	9,130	42.5	8.1	0.3	4,354.6
Ln(Annual Earnings)	9,130	17.2	2.0	14.1	20.2
Ln(Rainfall Deviation)	9,130	-0.06	0.5	-1.8	0.7

Notes: In this table, I present the aggregated data for women and men born all over rural India from the IHDS cross-section of 2008. A rural area is defined as a municipal area with population density of less than 400 per sq km and where 75% of the male population is working in agriculture related occupation. Assets per capita are defined as the monetary value of all the liquid and non-liquid assets owned by the household divided by population. The monetary values are adjusted to the inflation rate of 1980 and are in US dollars. Household expenses are also adjusted to inflation level of year 1980. The wage labor is a dummy variable if the person worked for more than 240 hours in a given year. Source: IHDS (2008)

Table 1.2: Effect of Rainfall Deviation on Health: OLS Estimates

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Height	0.012	0.045	0.023	0.008*	0.054**	0.021*
	(0.028)	(0.120)	(0.094)	(0.023)	(0.028)	(0.009)
Health Condition	-0.143	-0.281*	-0.205	-0.141	-0.299*	-0.276*
	(0.385)	(0.230)	(0.451)	(0.388)	(0.439)	(0.941)
Current Health Status	0.347*	0.214	0.487*	0.447**	0.588	0.813*
	(0.244)	(0.587)	(0.145)	(0.057)	(0.648)	(0.777)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	No	No	No	No	No	No

Notes: Each coefficient is a result of a separate regression. 'Height' is in cm, 'Health condition' is a dummy for chronic illness, current health status is reported as good/bad. The dependent variables in column 1 are regressed on the deviation of the rainfall in birth-year, district level fixed effects, and controls for parents' health condition, indicator for hospital presence in the village, level of smoking and alcohol consumption. The rainfall deviation measure has logarithmic form denoting a percentage change from the long-run average of 30 years. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 1.3: Effect of Rainfall Deviation on Schooling: OLS Estimates

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Years of Schooling	-0.216	0.856	0.625	0.159*	1.651*	0.985*
	(0.949)	(1.254)	(1.647)	(0.098)	(0.930)	(0.256)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	No	No	No	No	No	No

Notes: Each coefficient is a result of a separate regression. The dependent variable in column 1 is regressed on the deviation of the rainfall in birth-year, district level fixed effects, and controls for parents' education, indicator for school presence in the village, indicator for belonging to upper cast. The rainfall deviation measure has logarithmic form denoting a percentage change from the long-run average of 30 years. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.4: Effect of Rainfall Deviation on Income: OLS Estimates

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	0.351	0.062*	0.211	1.548*	2.699**	2.086*
	(0.548)	(0.165)	(0.157)	(0.847)	(1.345)	(1.984)
Ln(Expenditure per Capita)	0.015*	0.005	0.003	0.010	0.038*	0.015*
	(0.651)	(0.374)	(0.158)	(0.857)	(0.514)	(0.515)
Asset Index	0.248	0.325	0.198	0.579	0.428*	0.328**
	(0.758)	(0.354)	(0.254)	(0.259)	(0.420)	(0.217)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	No	No	No	No	No	No

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the deviation of the rainfall in birth-year, district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall deviation measure has logarithmic form denoting a percentage change from the long-run average of 30 years. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.5: Effect of Rainfall Deviation on Health: 2SLS Estimates

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Height	-0.003*	0.002*	0.003*	0.008*	0.009**	0.010*
	(0.0006)	(0.001)	(0.002)	(0.006)	(0.004)	(0.009)
Health Condition (ID)	-0.003	-0.004*	-0.017	-0.022	-0.015*	-0.019
	(0.987)	(0.752)	(1.186)	(1.247)	(1.759)	(1.377)
Current Health	0.415*	0.247	0.963	0.258*	0.855*	0.358*
	(0.368)	(0.578)	(1.415)	(0.168)	(0.503)	(0.279)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. 'Height' is in cm, 'Health condition' is a dummy for chronic illness, current health status is reported as good/bad. The dependent variables in column 1 are regressed on the deviation of the rainfall in birth-year, district level fixed effects, and controls for parents' health condition, indicator for hospital presence in the village, level of smoking and alcohol consumption. The rainfall deviation measure has logarithmic form denoting a percentage change from the long-run average of 30 years. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.6: Effect of Rainfall Deviation on Schooling: 2SLS Estimates

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Years of Schooling	-0.534	1.216	0.918	0.247*	2.408**	1.331*
	(0.718)	(1.275)	(1.718)	(0.125)	(0.730)	(0.610)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variable in column 1 is regressed on the deviation of the rainfall in birth-year(coefficient shown in the table), district level fixed effects, and controls for parents' education, indicator for school presence in the village, indicator for belonging to upper cast. The rainfall deviation measure has logarithmic form denoting a percentage change from the long-run average of 30 years. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.7: Effect of Rainfall Deviation on Income: 2SLS Estimates

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	0.281	0.062*	0.200	1.164*	1.163**	1.267*
	(0.974)	(0.051)	(0.548)	(0.641)	(1.030)	(1.054)
Ln(Expenditure per Capita)	0.015*	0.005	0.003	0.010	0.038*	0.015*
	(0.014)	(0.684)	(0.412)	(0.489)	(0.022)	(0.015)
Asset Index	0.248	0.325	0.198	0.579	0.428*	0.328**
	(0.547)	(0.748)	(0.325)	(0.352)	(0.374)	(0.113)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the deviation of the rainfall in birth-year (coefficient shown in the table), district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall deviation measure has logarithmic form denoting a percentage change from the long-run average of 30 years. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.8: Effect of Rainfall Volatility on Health

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Height	-0.003*	-0.026*	-0.019*	-0.065*	-0.095**	-0.089**
	(0.002)	(0.011)	(0.548)	(0.012)	(0.086)	(0.075)
Medical condition(ID)	0.074	0.012	0.003	0.078	0.056	0.088
	(0.526)	(1.534)	(4.255)	(1.987)	(5.967)	(4.855)
Current Health	-0.348*	-0.144	–0.549	-0.748**	-0.869**	-0.701**
	(0.320)	(0.247)	(0.483)	(0.254)	(0.448)	(0.485)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. 'Height' is in cm, 'Health condition' is a dummy for chronic illness, current health status is reported as good/bad. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' health condition, indicator for hospital presence in the village, level of smoking and alcohol consumption. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.9: Effect of Rainfall Volatility on Schooling

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Years of Schooling	-0.156*	-0.341*	-0.295*	-1.155*	-0.156**	-0.144**
	(0.101)	(0.293)	(0.199)	(0.135)	(0.094)	(0.061)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variable in column 1 is regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' education, indicator for school presence in the village, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.10: Effect of Rainfall Volatility on Income

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	-0.641*	-0.354	-0.458*	-0.849*	-0.759**	-0.809**
	(0.546)	(0.530)	(0.341)	(0.744)	(0.211)	(0.531)
Ln(Expenditure per Capita)	-0.017*	-0.085*	-0.014	-0.061	-0.005*	-0.001
	(0.153)	(0.052)	(0.844)	(0.994)	(0.004)	(0.841)
Asset Index	-0.006	-0.157	-0.984	-0.187	-0.017	-0.810
	(0.851)	(0.213)	(0.418)	(0.119)	(0.687)	(0.390)
N	4654	3808	8462	5662	3468	9130
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.11: Effect of Later Years Rainfall Volatility on Height

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Rainfall Volatility -2 Yr	0.342	0.034	0.065	0.024	0.046	0.068
	(0.744)	(0.100)	(1.324)	(0.183)	(0.439)	(0.194)
Rainfall Volatility -1 Yr	0.032	0.003	0.016	0.042	0.033	0.094
	(0.743)	(0.934)	(1.193)	(0.387)	(0.194)	(0.425)
Rainfall Volatility +1 Yr	0.004	0.006	0.006	0.002	0.003	0.001
	(0.159)	(0.418)	(1.198)	(0.961)	(0.490)	(0.402)
Rainfall Volatility +2 Yr	0.003	0.004	0.002	-0.002	-0.002	0.003
	(1.169)	(0.288)	(0.748)	(0.417)	(0.587)	(0.621)
FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. 'Height' is in cm. It is regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' health condition, indicator for hospital presence in the village, level of smoking and alcohol consumption. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.12: Effect of Later Years Rainfall Volatility on Schooling

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Rainfall Volatility -2 Yr	0.054	0.004	0.095	0.125	0.004	0.041
	(0.548)	(0.847)	(1.129)	(0.326)	(0.054)	(0.057)
Rainfall Volatility -1 Yr	0.001	0.003	0.001	0.002	0.001	0.001
	(1.124)	(0.249)	(0.699)	(0.288)	(0.517)	(0.399)
Rainfall Volatility +1 Yr	0.657	0.365	0.952	0.457	0.955	0.155
	(2.965)	(3.459)	(4.734)	(2.197)	(3.950)	(6.744)
Rainfall Volatility +2 Yr	0.456	0.783	0.847	0.834	0.193	0.493
	(3.673)	(5.294)	(4.554)	(0.390)	(1.104)	(6.473)
FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In this table, the dependent variable is years of schooling. Every number is the coefficient of interest from a separate regression. Rainfall volatility +1 Yr is the volatility measure in the year after the year of birth of an individual. Similarly, the second row is the volatility measure after 2 years of birth.The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Each coefficient is a result of a separate regression. The dependent variable is regressed on the deviation of the rainfall in birth-year, district level fixed effects, and controls for parents' education, indicator for school presence in the village, indicator for belonging to upper cast. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.13: Effect of Later Years Rainfall Volatility on Income

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Rainfall Volatility -2 Yr	0.123	0.654	0.275	0.643	0.143	0.134
	(1.367)	(2.167)	(1.974)	(1.456)	(1.439)	(1.276)
Rainfall Volatility -1 Yr	0.109	0.427	0.753	0.254	0.176	0.986
	(0.744)	(0.100)	(1.324)	(0.183)	(0.439)	(0.194)
Rainfall Volatility +1 Yr	0.104	0.013	0.112	0.129	0.214	0.158
	(1.112)	(2.312)	(1.415)	(2.410)	(1.154)	(1.847)
Rainfall Volatility +2 Yr	0.847	0.065	0.412	0.847	0.025	0.145
	(2.315)	(5.179)	(3.214)	(0.947)	(1.110)	(6.214)
FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In this table, the dependent variable is income in INR. Every number is the coefficient of interest from a separate regression. Rainfall volatility +1 Yr is the volatility measure in the year after the year of birth of an individual. Similarly, the second row is the volatility measure after 2 years of birth.The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.14: Effect of Rainfall Volatility in Urban Areas

	Women			*Men*		
	(Height)	(Schooling)	(Income)	(Height)	(Schooling)	(Income)
Rainfall Volatility	0.001	-0.015	-0.109	-0.002	-0.021	0.004
	(1.298)	(0.651)	(0.945)	(1.625)	(0.256)	(0.541)
N	3,154	3,154	3,154	3,843	3,843	3,843
FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each number is derived from a separate regression with the dependent variable being height(cm), schooling, or income. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Chapter 2

Has the IMF Overestimated the Impact of Their Own Policies?

2.1 Introduction

Every year, the International Monetary Fund (IMF) generates forecasts of major macroeconomic variables for developed and developing countries. IMF forecasts are important for the following reasons; Firstly, this information can be useful for policymakers in various countries as it helps them to identify key areas of concern and prioritize their policy initiatives. Secondly, IMF forecasts can be used to make decisions about the allocation of loans to member countries. Thirdly, IMF forecasts can be used as a reference point for assessing a country's economic performance. Finally, IMF forecasts are used as a tool to signal a country's economic policies and reforms to the world. Overall, IMF forecasts are an important source of information for policymakers, donor countries, and other stakeholders. They play a significant role in shaping the economic policies and prospects of the countries they cover (Rose, 2007; Razin and Sadka, 2005; Cerra and Saxena, 2008).

Our main objective in this chapter is to analyze the presence of a systematic bias in the IMF's growth forecasts for developed and developing countries. As growth forecasts play a major role in global politics and policy implementation, assessing their efficiency is imperative. This paper is the first to focus on the interaction between growth forecasts and Structural Adjustment Policies (SAP) also known as IMF conditionality.

The IMF, since its inception in the 1940s, provides financial assistance to countries facing economic difficulties. Since the early 1980s, if a country needs to receive assistance from the IMF, it must agree to certain terms, known as "conditionality." These conditions may include implementing certain economic policies, such as reducing budget deficits, managing external debt, adjusting the monetary policy, increasing taxes, or liberalizing trade to name a few. Conditionality is intended to help a country address the root causes of its economic problems and restore financial stability. The IMF also monitors a country's progress in meeting these conditions and provides additional assistance if needed. However, some critics argue that conditionality can be overly prescriptive and may fail to consider countries' specific circumstances and needs.

Over the last 40 years, IMF conditionality requirements have been widely debated. The country has to agree to the terms and implement the necessary adjustment to the domestic policy to receive the subsequent loan tranches. The objective behind the conditionality is to help a country move towards a path of sustainable growth and reduce its dependence on loans from other countries or the IMF itself (IMF, 2019). These conditionally approved loans are also known as Structural Adjustment Programs (SAP) which have been adopted across all the member countries. The loans approved under the SAP framework are mainly distributed over several years through small tranches. These tranches are approved by the IMF Executive Board conditional on the receiving country's successful implementation of the loan terms.

The SAP's effectiveness is the subject of heated debate, despite the fact that these programs have been implemented all over the world in the past forty years. Although the IMF has deemed these programs successful, little research has documented their positive effects. According to Dreher and Vaubel (2004), the SAPs have no effect on the countries' spending and fiscal balance. In contrast, the IMF measures the success of the SAP by a nation's participation in future lending agreements rather than the nation's fiscal stability (IMF, 2019). This is counter-intuitive because the country's need for borrowing money will decrease if the programs work. Additionally, the failure of a program is not the responsibility of the IMF; rather, it is the responsibility of the participating nation to implement the SAP. The IMF conditionality is explained in detail in section 2.2.

The objective of this paper is not to design another litmus test to test the effectiveness of the SAP but to focus on the behavior of the IMF in the context of these policies. The main hypothesis we test is if a country has participated in multiple SAP programs, do the growth forecast of the IMF for those countries will be more optimistic? Before we establish this relationship, we first need to understand how the IMF estimates growth forecasts.

A multi-region multivariate vector autoregression(VAR) econometric model calculates these forecasts by studying the propagation of economic shocks through the countries (Faruqee and Isard, 1998). These forecasts are carried out by gathering data from the member countries. However, this does not directly lead to the publication of such forecasts. There are several other factors and steps that may affect the numbers that are published. We discuss the nature of these forecasts in detail in section 2.3.

Dreher et al. (2008) posit that geopolitical characteristics play a role in the forecasts of certain countries being optimistic or pessimistic. The powerful nations who have a higher stake in the IMF will receive an optimistic GDP forecast, whereas the countries politically opposing such members may receive a lower growth projection. The political objectives of the IMF also play a key part in the forecasting process, where the optimism in the forecast can be attributed to the IMF justifying its lending behavior.

The growth forecast published by the IMF also has credibility with global financial institutions. Hence, to maintain the IMF's own reputation, some developing countries may receive a favorable projection which will also build credibility for the country leading to a higher investment flow.

Owing to the above-mentioned factors, there are multiple reasons which can create a bias in the IMF growth forecasts. For the purposes of this paper, we will focus our attention on the potential bias caused by SAP.

2.2 IMF Conditionality

The International Monetary Fund (IMF) provides financial assistance to countries in economic trouble with conditionality. In exchange for financial support, the borrowing countries agree to implement a set of policy reforms phased over one or more years. IMF funding is disbursed based on the implementation of these policies, which are assessed on a quarterly or bi-annual basis. The IMF's conditional lending practices have evolved over the years, with conditionality expanding to bring about 'structural adjustment' in the mid-1980s. This approach advanced four main types of reforms: stabilization, liberalization, deregulation, and privatization.

The effectiveness and impact of IMF conditionality have been the subject of much debate and criticism. Some authors, such as Bird et al. (2001), argue that IMF conditionality can be harmful to recipient countries, as it can lead to economic contraction, social unrest, and political instability. Others, such as Stone (2012), posit that IMF conditionality can be beneficial if it is implemented in a way that takes into account the specific needs and circumstances of recipient countries. We discuss this in detail in Section 2.2.2

In the next section, we will summarize the nature and categories of the IMF conditions in accordance with a detailed dataset compiled by Kentikelenis and Stubbs (2023)

2.2.1 Classification of IMF Conditionality

In 2016, Kentikelenis et al. published a dataset in collaboration with the IMF detailing the nature of the conditions imposed by the IMF[1]. The dataset, titled "IMF Conditionality Dataset 1980-2014," provides a comprehensive and detailed record of the conditions attached to IMF lending programs during this period. This dataset has enabled researchers to extract the underlying variation between conditions for analyzing the impact of IMF conditionality on recipient countries and to explore questions related to economic development, governance, and social outcomes. This paper also aims to use the same variation of IMF conditionality across different categories and policy areas.

The conditions are divided into two main categories: quantitative conditions and structural conditions. Quantitative conditions involve specific targets that countries must meet, such as reducing external debt, increasing net international reserves, or reducing public external arrears. These conditions are, by definition, quantifiable and allow a degree of flexibility to governments in relation to how they will be met. For instance, a government may choose to increase taxes, reduce expenditures, or a combination of both to meet the targets. On the other hand, structural conditions encompass a wider range of reforms in the economy and afford governments lesser flexibility compared to the quantitative conditions. They vary in nature from privatizing a state-owned enterprise, reforming the central bank, reducing public sector employment, and strengthening social safety nets.

These conditions are further divided into different categories such as Quantitative Performance Criteria (QPCs), Indicative Benchmarks (IBs), Structural Performance Cri-

[1] All the illustrations and calculations relating to the nature and variety of the conditions are followed and calculated from this dataset. It can be accessed at https://imfmonitor.org/conditionality/

teria (SPCs), Structural Benchmarks (SBs), and Prior Actions (PAs). QPCs are quantitative targets that the country is expected to meet, while IBs are indicative targets that allow the countries more flexibility and are seen as complementary to QPCs. SPCs are policy measures that the country needs to implement, and SBs are structural reforms that complement the SPCs. Prior Actions are policy measures that the country must take before the IMF program is considered by the Executive Board. In the early 1980s, the IMF's main focus was on implementing conditions by establishing QPCs. Over time, the IMF transformed its approach to conditionality through several key changes. Firstly, it added SPC to its quantitative performance criteria, such as limits on public sector borrowing. Secondly, it increased the number of "structural benchmarks" in its arrangements. Thirdly, it began using "prior actions," which involved policy actions that borrowing countries had to undertake before an IMF program could be considered by the Executive Board (Boughton, 2012). Finally, the scope of its program reviews expanded. These changes can be observed in Figure 2.1, which displays the annual averages of five categories of IMF conditions, including QPCs, IBs, PAs, SPCs, and SBs[2].

Apart from the nature of these conditions, the IMF formally distinguishes conditions based on their relative weights in respective programs. These categories specify the relative weight or importance the IMF attaches to the implementation of the respective conditions, and the amount of freedom countries have in implementing them. These conditions can be classified as either "hard" or "soft". Hard conditions are those that the IMF places a higher emphasis on and require implementation before a review and loan tranche disbursement can be concluded. QPCs, PAs, and SPCs are considered hard conditions because they are critical to achieving the overall objectives of the adjustment program. In the eyes of the IMF, non-implementation of these conditions could jeopardize the success of the program, and therefore, the IMF places a high degree

[2]This categorization is tabulated in Table 2.1.

of importance on their implementation. The IMF staff has limited discretion in applying these conditions, and non-implementation of any of these conditions would result in the suspension of disbursements of loan tranches. Exceptions to non-implementation of these hard conditions are granted through a waiver process, which takes place on an ad hoc basis. Thus, the IMF uses these hard conditions to ensure that countries implement critical policy measures to address their economic problems, which is the primary goal of IMF lending programs (Bird et al., 2009; Best, 2012; Beazer and Woo, 2016).

On the other hand, soft conditions are used to track program implementation but with less emphasis from the staff or the IMF executive board. The two types of soft conditions are indicative benchmarks (IBs) and structural benchmarks (SBs). Indicative benchmarks are used to track progress toward program objectives. Structural benchmarks are used to monitor progress on specific structural reforms that the IMF deems necessary for the success of the program (Kentikelenis and Stubbs, 2023).

It is important to note that the distinction between hard and soft conditions is not always clear, and staff may turn soft into hard conditions in cases where countries consistently show low implementation levels. The practical interpretation and measurement of the types of conditions are also important considerations in any discussion of conditionality. Debates surrounding the measurement of the type of conditions and their practical interpretation were summarized by Bird et al. (2009) and Kentikelenis and Stubbs (2023).

In addition to the categorization, the nature of the conditionality programs also has become more and more complex over time. The conditions now cover wide policy areas including governance, social policy, land and environment, and institutional reform to name a few (Chang, 2006; Boughton, 2012; Kentikelenis et al., 2016; Eichengreen and Woods, 2016; International Monetary Fund, 2019). Along with the growing variety, the total number of IMF conditions increased from an average of 16.6 per program in the

1980s to 26.9 per program in the 2010s. The number of conditions per program peaked in the mid-2000s at around 30 conditions per program. However, there has been a slight decrease in the total number of conditions per program in the last few years, with an average of 23.8 conditions per program in the period from 2010-2017. There was also a sharp increase in the number of conditions per program during the global financial crisis, with an average of 34 conditions per program in 2008-2009 (Kentikelenis et al., 2016). We can observe this increase from Figure 2.2, where the yearly total number of conditions imposed by the IMF has gone up from 412 to 2983.

We can observe from the dataset that the IMF conditions are not evenly distributed across countries. We find that low-income and middle-income countries are more likely to receive a higher number and more stringent conditions compared to high-income countries. For example, low-income countries receive on average 26 conditions per program, while high-income countries receive only 8 conditions per program[3]. Similarly, we see that low-income countries are more likely to receive structural adjustment programs, which are typically associated with more far-reaching reforms, compared to high-income countries.

While the IMF influences a wide variety of policies pertaining to their members, the majority of conditions fall under four policy areas from 1980 to 2014: fiscal policy (FP), external sector (EXT), financial sector (FIN), and domestic economy (DEB). Specifically, out of the 58,406 total conditions, 16,571 (28%) belonged to DEB, 9,700 (17%) to FP, 5,142 (9%) to EXT, and 15,229 (26%) to FIN. The relative importance of these policy areas has shifted over time, with a growing emphasis on financial sector reforms in the 1990s and early 2000s, and an increased focus on domestic economic policies in the post-

[3]For the period covered by the dataset (1980-2014), the income thresholds were defined as follows: Low-income countries: GNI per capita of $1,025 or less Lower-middle-income countries: GNI per capita between $1,026 and $4,035 Upper-middle-income countries: GNI per capita between $4,036 and $12,475 High-income countries: GNI per capita above $12,475. This classification follows the World Bank's Atlas method.

2008 period. Overall, the IMF's policy conditions reflect its broader mandate to promote economic stability and growth, with a particular emphasis on the areas of fiscal policy, external sector policy, financial sector policy, and domestic economic policy (Figure 2.3).

2.2.2 Effects of Conditionality

IMF arrangements and their associated conditions are designed to support economic stabilization and growth while also promoting good economic policies and reforms. However, they can also be controversial, as some argue that they can lead to austerity measures and social hardship (Przeworski and Vreeland, 2000; Casper, 2017; Dreher and Walter, 2010; Vreeland, 2003; Forster et al., 2019), while others argue that they are necessary for promoting long-term economic stability and growth (Kern et al., 2019; Crivelli and Gupta, 2016; Bird et al., 2001).

The previous literature on the effectiveness of the IMF programs has been highly critical. Vreeland (2003), Przeworski and Vreeland (2000), and Dreher (2006) find a negative relationship between the growth of the country and IMF programs. Dreher and Walter (2010) finds that the IMF programs have been a cause of currency instability. The proponents of the IMF programs point towards long-term benefits using international openness of a country, liberalization of trade and finance, balancing of fiscal accounts, etc. Multiple studies have evaluated the benefits of financial sector reforms on the skill-intensive sectors (Feenstra et al., 2013; Eta and Anabori, 2015; Mwenda and Mutoti, 2011). However, empirical estimation is absent in the presence of SAP.

The majority of literature points towards the inability of the SAP programs to improve the financial stability of the member countries(Dreher, 2006; Dreher et al., 2015; Stone, 2012). They all miss the variation within the SAP themselves. Before 2016, data was not available about the nature and intensity of the conditions. Hence all the studies before 2015 used a binary variable to control for a country's participation in the SAP. In 2016, after Kentikelenis et al. published a dataset that enumerates the number and types of conditions a country is subjected to. We intend to extract this additional level of variation to better understand the effects of the SAP across various categories.

In addition, conditionality has been linked to several detrimental economic, social, and political outcomes. On the economic side, IMF conditionality has been linked to reductions in economic growth and increases in inequality (Vreeland, 2003; Forster et al., 2019). On the social side, studies have found detrimental impacts on health systems in Africa and Europe and identified adverse effects on population health (Stubbs et al., 2017; Schrecker, 2016; Stubbs and Kentikelenis, 2018). On the political side, research has linked conditionality to decreases in unionization and greater incidence of civil war (Stroup and Zissimos, 2013; Moosa et al., 2019). Overall, the effectiveness and impact of IMF conditionality depend on a range of factors, including the design and implementation of policies, the political and economic context of recipient countries, and the involvement of local actors in the policy-making process.

Going further than the intended utility of these conditions, many have found that the IMF's intentions are not straightforward. The IMF is varied in its reputation as a lender and an advisor and will modify its behavior towards the members according to their self-image. For example, if a country fails to meet the conditions set forth by the Fund, it is unlikely to receive any punishment. Furthermore, these deviations from the criteria set forth by the IMF will lead the countries towards longer membership ties than others(Marchesi and Sabani, 2007).

2.3 IMF Forecasts

The International Monetary Fund (IMF) generates its biannual GDP forecasts through an iterative process that involves a combination of quantitative and econometric techniques, supported by subjective and expert judgment. The IMF uses a multilateral approach to forecasting, which takes into account a wide range of factors that can affect economic growth and development in each country. This includes macroeconomic variables such as inflation, employment, trade, and fiscal and monetary policies to name a few, as well as external factors such as global economic conditions and geopolitical events.

The International Monetary Fund's (IMF) GDP forecasts play an important role in the global economy as they serve as important indicators for policymakers, businesses, as well as international organizations. Policymakers rely on these forecasts to formulate and adjust their economic policies, ensuring they are aligned with the prevailing economic conditions and global trends. For investors and businesses, IMF forecasts offer vital information for making strategic decisions regarding investments, trade, and expansion into new markets. These forecasts also take into account any potential risks and opportunities in various regions, guiding businesses' allocation of resources and overall growth strategies(Dreher et al., 2008; De Resende, 2014).

The IMF does not produce these forecasts solely on the basis of the econometric models. In addition to those, the IMF also relies on expert judgment to generate its GDP forecasts (Genberg et al., 2014). This involves collecting information from a wide range of sources, including national agencies, central banks, and international organizations. The IMF uses a team of economists, also referred to as country-desk economists, who are responsible for analyzing this data and making judgments about how different economic factors will affect GDP growth in each country.

The IMF also takes into account a range of qualitative variables in the forecast-generating process. This includes political factors such as government policies, upcoming elections, the ideological inclinations of the ruling party, social factors such as population demographics, as well as environmental factors such as natural disasters and climate change. The IMF's economists also engage in extensive discussions with policymakers and central banks in each country to gather additional information about the factors that are likely to affect GDP growth.

To generate these forecasts, the IMF employs a combination of 'top-down' and 'bottom-up' approaches in its forecasting methodology. When forecasting GDP, the IMF utilizes a top-down approach that initiates with a global economic model responsible for predicting overall economic activity. This model addresses global trends, such as commodity prices, trade volumes, international treaties, etc. to estimate the growth rate of each country's economy. By adopting this top-down model, the IMF generates an initial forecast for each country. This is the first step in an iterative process.

To refine these preliminary estimates, the IMF also uses historical data and employs different econometric models. These models help to analyze the relationships among different economic variables. The IMF employs a range of econometric models for GDP growth forecasting, including time-series models, panel data models, and dynamic stochastic general equilibrium (DSGE) models(Fund, 2020; Kose et al., 2008). On the other hand, in a bottom-up approach, country-desk economists gather data from each country and use it to forecast the country's GDP growth. They use statistical methods and econometric models to forecast economic growth, taking into account factors such as consumer spending, investment, and trade. These forecasts are then aggregated to provide a global GDP forecast for all countries.

The iterative nature of the forecast process means that both the top-down and bottom-up approaches are used in tandem. Once the econometric model at the central level has been constructed, the IMF uses it to make projections about future economic growth. These projections are then reviewed by a team of country-desk economists and other experts, who may adjust the forecasts based on their own judgment and expertise. This step can add subjective bias to the final projections. A survey done by the independent evaluation office (IEO) shows that more than 75% of the country-desk economists incorporate personal judgment and a spread-sheet based macro to generate the forecasts as opposed to the more formal methods[4].

This process can cause huge discrepancies in the forecast methods and the consequent projections; Although it is valid for the desk economists to choose the method they deem fit for their country, the adaptability of the method depends on the economy's structure and more importantly the availability of data. For example, if a country's economy is largely driven by its exports to the United States. In that case, it is justified to include the variables related to the US economy while generating its forecasts. On the other hand, if we are focusing on a country dependent on oil exports, focusing on other countries is not a viable option. Furthermore, the countries with better institutions and high-quality data can afford to build complex and detailed models while predicting their forecasts; a commodity that is not available to the poorer countries.

After the country-desk economists submit their first forecasts, the above process is iterated, and the numbers are reviewed. The central board measures the discrepancies between the top-down and bottom-up approaches. If the results are inconsistent between the two approaches, the country desks are asked to revise their forecasts by focusing on removing the differences. After the two results converge, the numbers are considered to be ready for publishing. This is a very time-intensive process; each update takes more than 3 months(Genberg et al., 2014). The forecasts are published for the next five years.

[4]Less than 10% of the country-desk economists use structural multi-equation econometric model or a VAR model(Genberg and Martinez, 2014)

For example, in 1993, the IMF forecast the annual growth rate of each country for the years 1994-1998.

To understand if the bias in these forecasts can be useful to determine the link between IMF program participation and IMF conditionality, we first look at the unconditional relationship between the projected and real growth. From Figure 2.4 we can see the relationship between forecast cumulative growth rates and actual cumulative growth rates over the 5-year horizon available for all country-years. It is important to highlight that the data structure utilized in this analysis allows for forecasts to overlap. This means that the aggregate growth rate of India in a specific period, such as 1991-1995, will be closely linked to its aggregate growth rate in the subsequent period, 1992-1996. While some studies prefer non-overlapping windows to avoid this issue (e.g., using India's growth rate from 1991-1995 as one observation and 1996-2000 as the next), we follow the Blanchard and Leigh (2013) approach of using overlapping outcomes. This method preserves important variation and also eliminates the need for arbitrary choices in dividing the data into 5-year windows. The correlated errors resulting from this approach can be addressed during the identification stage.

One of the key aspects of this discrepancy is the inherently subjective nature associated with the forecasts. The country-desk economists choose the variables that they feel are relevant to the characteristics of the country they represent. This gives the economists freedom to adjust the projections concerning political variables. Also, this subjective shift is less likely to persist over 5 years, making the projection strength different over various forecast horizons (Genberg and Martinez, 2014).

Additionally, there is often uncertainty surrounding the accuracy of these forecasts, especially when it comes to the impact of fiscal policy. Fiscal multipliers, which measure the change in output resulting from a change in government spending or taxation, can vary significantly depending on the economic conditions and policy environment.

Therefore, the accuracy of GDP forecasts depends critically on the accuracy of fiscal multipliers. The IMF has made efforts to improve its estimates of fiscal multipliers, including through the use of country-specific models that capture the idiosyncrasies of each economy. However, there is still significant uncertainty surrounding the accuracy of these estimates, and the iterative nature of the forecast process means that revisions to both the GDP forecasts and the estimates of fiscal multipliers can occur at each stage of the process. As a result, the IMF's forecasts are subject to ongoing refinement and can change significantly as new information becomes available (Blanchard and Leigh, 2013).

Along with the fiscal multipliers, the forecasting process is an amalgamation of multiple simulation models which consider the movements of interest rates by each country's inflation targets. The assumptions made under these models may reduce the efficiency of the forecasts. Furthermore, the results of these models do not generate the final forecast value. After these computations, the forecasts are adjusted by consultations with the IMF staff; a process that is not made public. This has raised certain accusations of political or strategic bias on the part of the IMF.

2.4 Systemic Errors in Forecasts

A substantial body of literature has studied the interaction between IMF and the geopolitical relationship of its member countries. Dreher et al. (2008) analyze the political economy of IMF forecasts, finding that countries that hold political influence within the IMF tend to receive more favorable forecasts. Similarly, Aldenhoff (2007) provides evidence of political bias in IMF forecasts, suggesting that such bias may be driven by the political incentives of IMF staff. In another study, Artis and Marcellino (2001) assess the accuracy of fiscal forecasts made by the IMF and OECD, revealing that the IMF and

OECD tend to exhibit higher levels of accuracy compared to the European Central Bank. However, they caution that the forecasts of all three organizations are often subject to large errors. Batchelor (2001) compares the accuracy of forecasts made by the IMF and OECD to those of private sector forecasters and finds that the latter tend to be more accurate. He argues that this may be due to the fact that private-sector forecasters have stronger incentives to produce accurate forecasts than do IGOs. Edwards and Senger (2015) found that the IMF's policies towards Greece were influenced by US political and economic priorities. Similarly, a paper by Graham and Masson (2003) argues that the IMF's policies were misguided and contributed to Argentina's economic collapse which started when the country defaulted in 2001. However, other scholars, such as Frieden and Broz (2012), have suggested that the IMF operates independently of any one country's interests and that its policies are shaped by a range of factors, including economic conditions and international political dynamics.

The IMF's loans are not only aimed at promoting economic stability but also promoting political stability and supporting economic and political reforms that are aligned with the interests of powerful member countries. According to Stone (2012), the IMF is subject to influence and pressure from its major shareholders, particularly the United States, which can use its financial clout to influence the policies and conditionality attached to IMF loans. According to Easterly (2005), the IMF has a bias toward lending money to countries, even when it is unlikely to be repaid because its primary goal is to maintain its own existence as an international financial institution. The IMF's management and staff are evaluated on the basis of the number of loans that they make, not on whether those loans actually achieve their intended outcomes. This means that the IMF is more interested in lending money than in ensuring that it is repaid, which creates a moral hazard problem. As a result, the IMF continues to lend to countries that are unlikely to repay, which perpetuates a cycle of debt and underdevelopment in these countries.

Overall, these papers suggest that while Intergovernmental Organizations (IGOs) like the IMF and OECD produce important economic forecasts, their accuracy, and potential biases should be carefully scrutinized. Private sector forecasters may provide more accurate forecasts due to stronger incentives to produce accurate information.

These accusations find their basis in the differential power the members have in the IMF. The vote share between the members is divided by the size of the economy for each. This means countries like the United States and the UK will have more voting power than those in Africa. The US owns more than 15% of the vote share alone which gives them veto power in major decisions[5]. Vreeland (2005) argue that powerful members use this differential power to influence the decisions of the IMF. In such a scenario, a country's membership status and the benefits associated depend significantly on its political relationship with the US. Furthermore, countries with more political connections may be more successful at securing IMF lending, even if the lending does not have positive economic effects. Another possibility is that the IMF may be more likely to approve lending to countries with more political connections in order to maintain its political influence and credibility (Barker, 2018).

The IMF's forecasts also show a signaling effect, as they are used by other economic actors, such as rating agencies and investors, to assess the economic prospects of a country. In addition, the IMF's forecasts may influence the economic policies of the recipient country, as the IMF often requires the implementation of certain economic and financial policies (Dreher et al., 2015). At the same time, The relationship between IMF forecasts and aid is more pronounced for countries that are heavily reliant on aid, and this relationship is weaker for countries that are less reliant on aid. This suggests that

[5]The IMF requires an 85% vote for a supermajority. Thus, the United States at 17.43% of the vote share, can exercise veto power. Detailed vote shares can be accessed at `https://www.imf.org/en/About/executive-board/members-quotas`

IMF forecasts may be particularly important for countries that are heavily reliant on external financing, as these countries may be more sensitive to changes in the economic outlook.

Considering these factors, it is imperative to understand the effect of the subjective and political aspects of IMF forecasting. To determine if there is a causal link, we analyze the following regression framework.

2.5 Empirical Analysis

2.5.1 Data

The IMF conditionality data used in this study were sourced from Kentikelenis and Stubbs (2023). The data captures quantitative and structural conditions and is grouped into five types: Quantitative Performance Criteria, Indicative Benchmarks, Prior Actions, Structural Performance Criteria, and Structural Benchmarks. The conditions are also classified into 13 policy areas, including fiscal issues, revenue and tax issues, financial sector, and social policy. The total number of conditions attached to each area for each country in each year is used to create a composite indicator called the "Burden of Adjustment Indicators" (BAs), which measures the degree of "hard" and "soft" conditions imposed on countries adopting IMF programs. The study only includes hard conditions as they are considered the most important for the IMF and must be implemented for the release of loan disbursements. The data on GDP per capita and human capital are from the Penn World Table (PWT9), population, and government expenditure are from the World Bank's World Development Indicators.

The summary statistics presented in Table 2.2 yield notable observations. Notably, the mean forecasting error (ME), calculated as the average of the forecast errors across all countries and time periods, exhibits a positive value. This indicates a systematic tendency for the forecasts to be biased towards overestimation. Furthermore, the average number of hard conditions faced by countries in a given year is below 20, with a maximum of 148 conditions observed for Ukraine in 1999. These findings highlight the substantial presence of the Structural Adjustment Program (SAP) and underscore the importance of investigating the relationship between SAP implementation and forecast accuracy. Additionally, approximately 42% of the observed countries have participated in IMF programs for at least five months in a given year, indicating the relevance of studying the effectiveness of these programs. On average, countries face around 15.61 soft and hard IMF conditions, highlighting the complexity of program implementation. Important economic indicators include an average GDP per capita of 8.53 and an inflation rate of 0.43.

2.5.2 Methodology

While designing the regression framework, we start with the assumption that countries are endogenously selected into an IMF program and conditional loan disbursements. To account for this, we need to estimate the following system of equations:

We examine the effects of SAP on the bias in the IMF forecasts with the help of the following regression framework.

$$IMFProg_{it-1} = \alpha_1 X_{it-1} + \alpha_2 Z_{it-1} + \mu_i + \delta_t + u_{it-1} \tag{2.1}$$

$$SAP_{it-1} = \gamma_1 X_{it-1} + \gamma_2 Y_{it-1} + \mu_i + \delta_t + e_{it-1} \tag{2.2}$$

$$Bias_{it} = \beta_1 \widehat{IMFProg}_{it-1} + \beta_2 \widehat{SAP}_{it-1} + \beta_3 V_{it-1} + \mu_i + \delta_t + \varepsilon_{it} \tag{2.3}$$

In the above system of equations, i denotes the country, and t denotes the year (1990-

2014). $IM\widehat{F\text{Pr}og}_{it}$ are the fitted values from equation 2.1 of country i in year t which refer to the country's participation in the IMF program. $\widehat{SAP}_{it}$ are the fitted values for the number of conditions country i was exposed to in the year t. In any year t, the IMF releases GDP forecasts for each country. The variable $Bias_{it}$ is the compounded aggregated forecast for the next five years. X_{it} and V_{it} are the control variables that are discussed below; Z_{it} and Y_{it} are excludable instruments. μ_i and δ_t are country and year fixed-effects that control unobserved country-specific and time-specific factors that affect the dependent variables. ϵ_{it} denotes the error term. All control variables in equation 2.3 are lagged by one year to reduce the likelihood of simultaneous correlation and to also account for any delayed effects.

To estimate the equation of interest, we need to deal with the selection bias present in the $IM\widehat{F\text{Pr}og}_{it}$ and $\widehat{SAP}_{it}$. There is strong evidence in the literature that both these variables are endogenously determined (Beazer and Woo, 2016; Stubbs et al., 2020; Papi et al., 2015).

The dependent variable in this framework is the forecast error for country i in year t. The IMF, as part of the World Economic Outlook (WEO) database, publishes forecasts for the next 5 years every year[6]. Thus, for each time period t, forecasts are available for years $t+1, t+2, ..., t+5$. We compute the compounded aggregate of 5 forecast years for each observation. In this paper, we use the compounded forecasts for the next five years. For example, if a country is expected to grow by 5% for each year, its compounded forecast will equal 27.6%[7]. For example, in the year 2000, the IMF predicts a growth rate in 2001 through 2005. For the base specification, we subtract the realized growth rates of 2001 through 2005 from their forecasts and use it as the final dependent variable $Bias_{it}$. Furthermore, we compute a weighted average of the forecast errors as the predictive

[6] These forecasts can be accessed at https://www.imf.org/en/Publications/SPROLLs/world-economic-outlook-databases#sort=%40imfdate%20descending

[7] We get this number by calculating $1.05 \times 1.05 \times 1.05 \times 1.05 \times 1.05 = 1.276$

power for the growth 1 year in the future will be different than that of after 5 years.

The main variable of interest is SAP_{it}. It represents the total number of conditions imposed by the IMF on a given country in a specific year. This study improves on previous research that relied on binary dummy variables by accounting for policy and conditionality diversity across countries and time periods. We use a novel dataset that covers a range of conditionality requirements for all IMF members between 1990-2014. In our analysis, we use a variable that counts the number of binding conditions, which are integral to the conditionality requirements and SAPs of IMF programs. Successful implementation of these conditions is necessary for the continuation of IMF programs in any country, as future disbursements of IMF loans are contingent upon their fulfillment. Soft conditions do not have the same degree of enforcement, and their lack of implementation does not automatically lead to the suspension of an IMF loan. We include both structural and quantitative conditions in this variable.

$IMF\_Program_{it}$ equals 1 if the country i has been a part of an IMF program for at least 5 months in a given year (Dreher, 2006). This variable suffers from endogeneity on account of selection bias.

The first two equations are accounting for the endogeneity present in SAP_{it} and $IMF\_Program_{it}$. According to the previous literature, the endogeneity arises from the correlation between the IMF programs and the number of conditions imposed on the country. Also, there is some evidence where the country has requested the IMF regarding the conditions being imposed on them(Stubbs et al., 2017, 2020; Kentikelenis and Stubbs, 2023).

X_{it} specifies the number of controls which are explained as follows:

$(GDPPC)_{it}$ is the per capita GDP of country i in year t. As the power of a country's vote depends on its economic size, the GDP will in turn have an effect on the forecasting behavior of the IMF.

$UNSC_{it}$ is a binary variable that takes the value of 1 if the member country is a part of the United Nations Security Council. This variable relates to the geopolitical leverage a country has at a particular time.

$Vote\_US_{it}$ is an index specifying the behavior of a country relative to the US. The countries with political alignment with the US may be looked at favorably by the IMF. It is calculated by Lijphart's index of agreement between a country and the US. It equals 1 if a country always votes with the US, and equals 0 if the country always votes against the US(Bailey et al., 2017).

Pop is the log of the total population. We expect population size to have a positive level effect on the forecasts as it allows economies of scale within a country's production and growth.

To estimate the two equations in a simultaneous regression framework, we employ the Conditional Mixed Processing (CMP) model instead of the traditional Three-Stage Least Squares (3SLS) method. The CMP model, implemented using the 'cmp' command in Stata 17.1 as developed by Roodman (2009), offers several advantages for our analysis. First, it allows for different dependent variable formats within a multi-equation system, accommodating the binary nature of the dependent variable in Equation 1. By utilizing maximum likelihood estimation (MLE), the CMP model provides unbiased and more consistent estimates for the binary variable.

Additionally, the CMP model is built upon the principles of the Seemingly Unrelated Regression (SUR) framework, which is designed for jointly estimating multiple regression equations while considering the potential correlation between the error terms. This is particularly relevant for our analysis, as we have two equations with the same covariates but different dependent variables. The CMP model estimates the equations separately but accounts for the potential correlation between the error terms, allowing for more efficient parameter estimation by utilizing all available information across equations.

Furthermore, the 3SLS framework, commonly used in simultaneous equation modeling, is not suitable for our analysis. The recursive nature of our objective aligns better with the CMP model, making it the most appropriate estimation framework to complement our primary estimator, 3SLS. Furthermore, the CMP model offers the flexibility to break down variables such as $\widehat{IMFProg}_{it-1}$ and $\widehat{SAP}_{it-1}$ into different stages within Equation 2.3, accommodating the specific requirements of our analysis.

Overall, the CMP model provides a robust approach to address simultaneity and endogeneity concerns while accommodating different dependent variable formats, making it well-suited for our analysis compared to the traditional 3SLS framework.

Previous literature has not abundantly relied on the system Generalized Method of Moments (GMM) estimation despite its flexibility. System GMM has been used to establish a negative relationship between IMF participation and the currency crisis (Bazzi and Clemens, 2013; Dreher and Gassebner, 2012). Crivelli and Gupta (2016) have used it to establish the relationship between IMF conditionality and revenue reform. One of the biggest drawbacks of system GMM is that it assumes that lagged differences can predict contemporaneous levels. The first differences in instruments are uncorrelated with country-fixed effects. However, for the latter assumption to hold, country fixed effects and first differences of IMF participation must offset each other across the entire panel (Roodman, 2009).

Using an instrument variable in the above-mentioned framework, the biggest challenge is to meet the exclusion criterion. To tackle this issue, we use a compounded IV approach following Stubbs et al. (2020). This approach treats the number of IMF conditions differently than IMF program participation. Since both variables are susceptible to selection into the model, we must address these endogeneities one at a time. To account for the endogeneity of the IMF program participation, we use the interaction of the cross-sectional variation in the within-country average of IMF participation and

IMF's budget constraint in year t. The budget constraint of the IMF is defined by the log of liquid resources of the IMF divided by the liquid liabilities. To control for the endogeneity of the IMF conditionality, we use an interaction term between the cross-sectional variation in the within-country average number of conditionality requirements imposed on a country and IMF budget constraint in year t. Since it is an interaction between an endogenous and exogenous variable, we can treat it as exogenous to use it as an IV.

$$\widehat{SAP}_{it} = \alpha_1 \left(\overline{SAP}_i \times IMFBUDG_t\right) + \alpha_2 X_{it} + \mu_i + \delta_t$$

In the above equation, $\widehat{SAP}_{it}$ is the fitted number of IMF conditions, ($\overline{SAP}_i$ is the country-specific average and $IMFBUDG_t$ is the IMF liquidity constraint. The main argument behind using this instrument is that countries with varying exposure to IMF conditions will not be affected differently by the IMF's budget constraint. Also, the average number of conditions goes up when a country needs more IMF loans and vice versa (Chapman et al., 2017). From Figure 2.5, we can see that the average conditions imposed by the IMF in a particular year are strongly correlated with the IMF liquidity[8].

The IV we use in this analysis satisfies the relevancy condition because the number of conditions imposed by the IMF is influenced by the demand for IMF loans, which in turn is affected by the IMF's liquidity constraints. This argument is augmented by the fact that Chapman et al. (2017) has found a strong relationship between the demand for IMF loans and the number of conditions imposed on a country. Lang (2021) proves that when the IMF's liquidity ratio is high, the conditions imposed on member countries also increase. This argument is bolstered by the fact that the IMF tries to maintain its influence and power in the global geopolitical scenario (Vaubel, 1996).

[8]The co-efficient of correlation between the two variables is -0.3 and significant at $p < 0.01$.

An additional concern regarding instrument excludability is the possibility that donors may be less willing to expend funds during periods of global financial turmoil. This could cause a decline in the IMF's concessional lending budget, which is replenished through voluntary contributions from member countries rather than quota subscriptions, and lead to deteriorating socio-economic outcomes in countries that are dependent on aid. The use of year dummies in both the conditionality and outcome equations can help account for common external shocks that impact all countries, and ensure that the instrument is not related to the error term in the outcome equation. In essence, our approach to identifying this relationship depends on the homogeneity of the interaction term given the baseline controls, as per Nunn and Qian (2014).

2.6 Results

In this section, we present the results of the empirical analysis. Table 2.3 shows the results from an OLS regression. In all the specifications (columns 1-10), we fail to see a statistically significant relationship between IMF participation and the number of conditions. However, since the OLS model is susceptible to inherently endogenous decision-making by the IMF, we run the simultaneous equation system with the maximum likelihood estimator. The results of this estimation are presented in columns (1)-(6) in Table 2.4. As we add controls for the per capita GDP, current account balance, UNSC membership, voting patterns, the impact associated with the number of conditions remains robust. This further bolsters the argument that after instrumenting the effect of IMF conditionality, other covariates do not cause confounding results. While the relationship between the IMF forecasts and a country's program participation appears to be positive, it is statistically insignificant. However, we find a significantly positive association between the conditions imposed on a country and the IMF forecast bias. Column (6) demonstrates that a 10% increase in the number of hard conditions leads to an average of 2.4% overestimation in a country's growth forecast. The CMP framework also yields a strong first-stage F-statistic in all specifications.

The coefficients of $UNSC$ and $Vote_{US}$ are noteworthy in this context. We find that they continue to lack statistical significance in relation to the forecast bias. The potential interaction between a member country's voting mechanism and the involvement of the IMF offers an explanation for these estimates. As discussed earlier, if a country aligns more closely with the geopolitical interests of the United States, the IMF may view them more favorably and adjust its level of engagement accordingly. Consequently, the coefficient on the $IMF_{P}rogram$ variable may absorb some of the statistical significance. While this could affect the efficiency of the estimates, it does not introduce bias. Therefore, the consistently significant estimate on the SAP variable further reinforces the relationship between IMF conditions and the forecast error. In Table 2.4, the primary variable of interest is the number of conditions imposed on a country in a given year. Subsequent analyses will delve into the breakdown of this effect based on the type and category of conditions.

The implementation of conditionality in IMF programs is a complex process with many factors that influence compliance. Implementation depends on both government control and external factors. Compliance is not binary but rather a spectrum, and program non-completion does not necessarily equate to total failure. IMF staff have discretion over soft conditions, while hard conditions are critical to achieving the program's overall objectives. Non-implementation of hard conditions prevents the staff from concluding the review and from disbursing the loan tranche unless the staff recommends to the Executive Board (EB) to grant a waiver, which is the exception rather than the rule. Until now, we have not accounted for the implementation of conditionality. The way to adjust for this is to subtract waived conditions from the total applicable conditions[9]. This information is only available for hard conditions, which require a waiver from the Executive Board (EB) when not implemented, ensuring that there is always a record of this in the relevant EB decisions.

As the Structural Adjustment Programs (SAP) became more prevalent, the relationship between countries and the IMF exhibited increased heterogeneity. On one hand, the IMF imposed a greater number and variety of conditions on borrowing countries. Simultaneously, the extent of countries' engagement with these programs varied significantly. For instance, during the early 1990s, the average number of conditions per program was approximately 18. However, this figure rose to 32 after the year 2000. Notably, some countries had to meet over 100 hard conditions to secure a loan tranche from the IMF.

At the same time, the implementation of conditionality by the IMF is not always straightforward, and there is great variation in the patterns of the overall implementation. Compliance with IMF conditions is not a binary variable, and non-implementation of some conditions does not necessarily mean total failure of the program. IMF staff takes into account that not every condition can be implemented as laid out in the initial agreement, and there is considerable staff discretion in soft conditions. Hard conditions, on the other hand, reflect the importance that the Fund places on the implementation of certain measures and are crucial for achieving the overall objectives of the adjustment program. Non-implementation of hard conditions means that the staff cannot conclude the review, and the loan tranche is not disbursed. Exceptions to this rule are granted on an ad hoc basis, and the Executive Board may recommend granting waivers to hard conditions(Babb and Carruthers, 2008).

To account for this added variation in the dataset, we separately run the regression for total hard conditions (BA2-Total, column 1), soft conditions(BA3-Total) an

[9]The corrected implementation measure is also available in Kentikelenis and Stubbs (2023)

implementation-corrected hard condition count where waived conditions are subtracted from total hard conditions (cBATOT, column 3), implementation-discounted simple condition count (dBA1TOT, column 4). dBA1TOT equals the number of conditions in year t discounted by the number of quarters interrupted in the given year within the program. dBA2-Total and dBA3-Total are the discounted hard and soft conditions, respectively. After correcting for the discounted conditions, the positive and significant effect persists across our specifications

In Table 2.5, we separate a country's total conditions into hard and soft conditions in a given year. We also take into account the conditions that are corrected regarding their implementation. For example, a country can still receive loans if the IMF executive board waives the requirement to meet some hard conditions. In such cases, we disregard the waived conditions and only focus on the conditions fulfilled by the country. Although the effect is stronger for the hard conditions(co-efficient of BA2-Total in column (1)), we find a positive and significant relationship across all specifications between the number of conditions and optimism in the forecasts. We also account for an implementation-discounted hard condition count (dBA2TOT, column 5), and finally, implementation-discounted weighted condition count (dBA3TOT, column 6) where hard conditions are assigned a weight of 2 compared to soft conditions are assigned the weight of 1. The results of these regressions are consistent with the baseline regressions. We see a consistent and positive effect on the inherent forecast bias and the number of conditions.

The regression analysis in Table 2.6 offers a comprehensive examination of the impact of different condition categories on forecast errors. The results reveal several noteworthy patterns. Firstly, the presence of an IMF program (Column 1) is associated with larger forecast errors, indicating the inherent challenges in accurately predicting economic outcomes under these programs. Secondly, the analysis demonstrates that quantitative conditions (QCsBA2) have a consistently significant effect across other columns (2 and 3), implying that the greater the number of quantitative conditions imposed, the larger the forecast errors. This finding underscores the importance of carefully considering the design and implementation of quantitative conditions to mitigate forecast biases. Moreover, the results highlight the significance of specific types of structural conditions. Columns 4 and 7 show that a greater number of prior actions (PAs - Total) and structural performance criteria (SPCs - Total) lead to larger forecast errors, suggesting that the strict implementation of these hard conditions can contribute to forecast biases. Additionally, although indicative benchmarks (IBs - Total) and structural benchmarks (SBs - Total) are soft conditions, they also influence forecast errors, although to a lesser extent. By providing a comprehensive overview of the effects of different condition categories, these findings offer valuable insights for policymakers and analysts aiming to enhance the accuracy and reliability of economic forecasts within the context of IMF programs.

Kentikelenis and Stubbs (2023) also classify the conditions on the basis of policy areas. In Table 2.7, to check for possible conditionality heterogeneity, we run the same system of equations from before but divide the conditions based on 13 different policy areas. Among those 13, conditions focusing on External Debt Issues (DEB, column 1), Financial sector (FIN, column 4), and Fiscal Issues (FP, column 5) comprise more than 60% of the entire dataset. For those conditions, we see a positive and significant relationship between the forecast bias and the number of conditions. This effect, however, is not consistent in the remaining nine policy areas. This is partly due to fewer observations resulting in lesser degrees of freedom (There are only 173 environmental conditions compared to 16,571 in External Debt). Another potential channel through which this effect can be explained is the importance given by the IMF to each of these policy areas. One reason why we might see a higher proportion of conditions in DEB, EXT, FIN, and FP policy areas is that the IMF believes these are the means that will strongly facilitate the growth of a country. Also, until now, we have consistently found a stronger effect through hard conditions. We are not making that distinction while we focus on policy areas.

2.7 Sensitivity Analysis

In Table 2.8, we investigate whether the results observed in the previous section are driven by countries from specific geographic regions. To examine this, we apply the CMP framework separately to countries in different regions. Column (1) focuses on the Middle East, column (2) analyzes Asian countries, column (3) considers European countries, and column (4) examines countries in Latin America. By assessing the coefficients and significance levels in each region, we can determine if the baseline estimates are heavily influenced by any particular region. Interestingly, we find that the results from any single region do not substantially drive the overall findings, indicating that the observed relationships hold across different geographic contexts.

In addition to the regional differences, we also check alternate specifications of the model. In Tables 2.9 to 2.12, we run the same set of regressions but by including the lagged variable of the bias. This will inform us if the IMF learns from its previous errors. We find a strong positive coefficient on the lagged bias. From this, we can conclude that the IMF does not try to correct the previous errors. On the contrary, the IMF tries to further justify their previous estimates. It also underpins the argument made in the previous literature stating the IMF is its own entity and wants to maintain its geopolitical status (Vaubel, 1996; Easterly, 2005).

In Table 2.A2, we check the sensitivity of the soft conditions to our results. In the previous section, we only focused on the hard conditions as they posed a binding constraint on the countries' behavior. We modify the SAP variable to include hard and soft conditions in the dataset. We see that the statistical power of the coefficient of interest has gone down, but the magnitude and direction of the results remain the same. Thus, we can see that the hard conditions are the dominating factor impacting the IMF forecasts.

Furthermore, we bisect the sample based on the growth rate of the countries. First, we look at the countries that lie in the top 50 percentile with respect to growth rate compared to those at the bottom of the spectrum. We find that the countries with the lower growth rates experienced higher bias on the positive side (Appendix Table 2.A1-2.A2). We then bisect the sample based on the number of conditions imposed by the country. After running the same regression framework, we find that in the section with countries receiving more conditions, the level of bias was much higher compared to the countries without any conditions. This result points towards the fact that the IMF may want to establish higher credibility in the countries' growth where it has had the biggest presence.

2.8 Conclusion

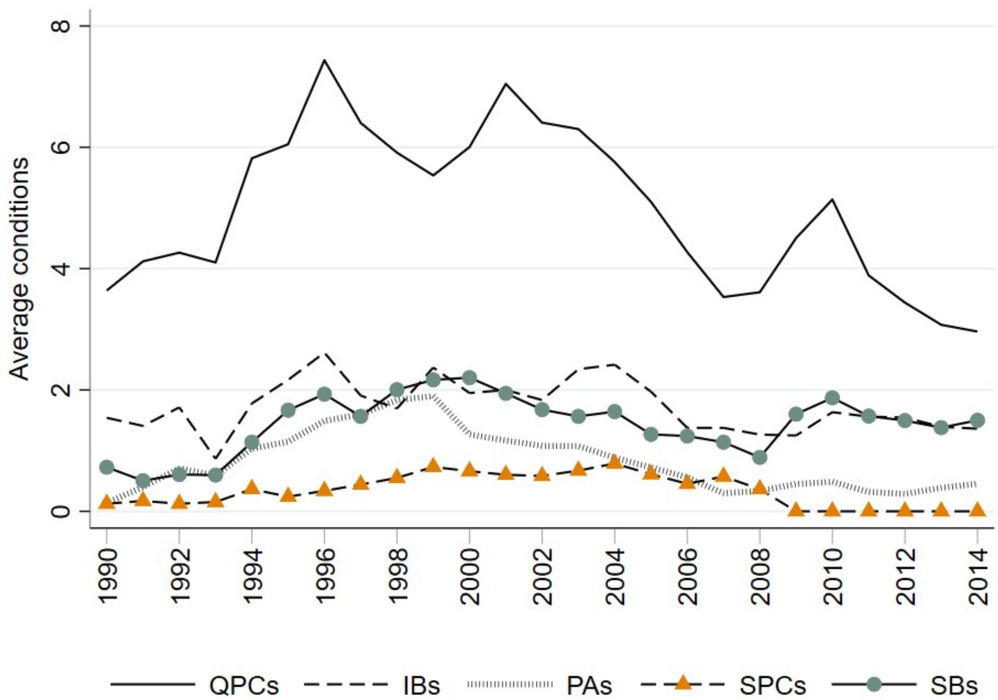
We find that the IMF forecasts are indeed influenced by the political scenario and the IMF's own vested interest as a geopolitical player. Given that these forecasts carry significant credibility across various financial institutions, they act as a catalyst for the structural changes taking place in various countries. It is not the objective of this paper to comment on the effectiveness of the IMF conditionality itself, but the results point toward the IMF being more optimistic about its effectiveness. After conducting a battery of sensitivity tests, the results are consistent and show that the IMF is overly optimistic about the countries where they have a higher level of involvement.

After dividing the conditions with respect to their respective weights, one possible channel for this bias is the use of hard conditions in IMF-supported programs. Hard conditions refer to policy measures that are considered to be more stringent or difficult to implement. We find that hard conditions have a stronger effect on forecast bias, as they may be more difficult to achieve and may require more significant policy changes. Thus, forecasts for countries facing higher amounts of hard conditions are more optimistic.

We appreciate the fact that the IMF forecasts can never be fully accurate. Data and computation constraints will always carry an inherent bias in the estimates. The objective of this paper is to check for a systematic bias present in a unilateral direction, as it is important to recognize the potential for subjectivity in the IMF's forecasts since this can also have implications for policy decisions and the effectiveness of IMF-supported programs.

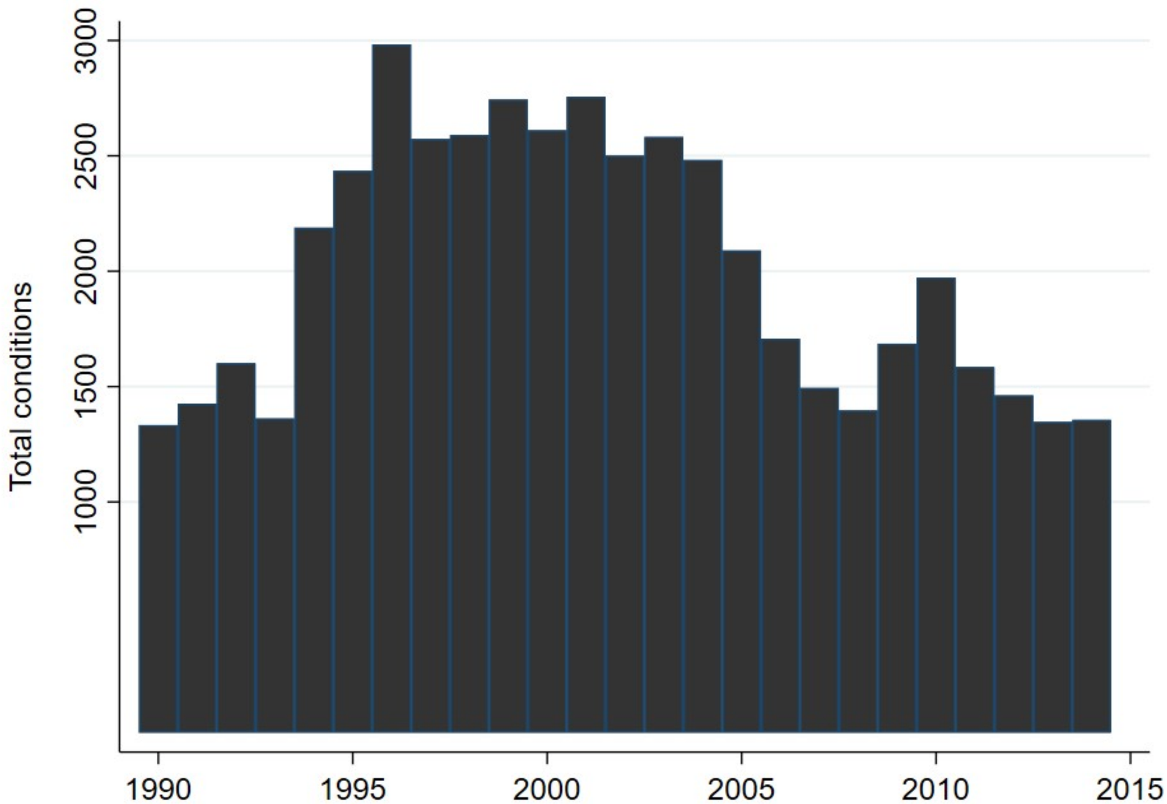
Figures and Tables

Figure 2.1: Average number of conditions in each year



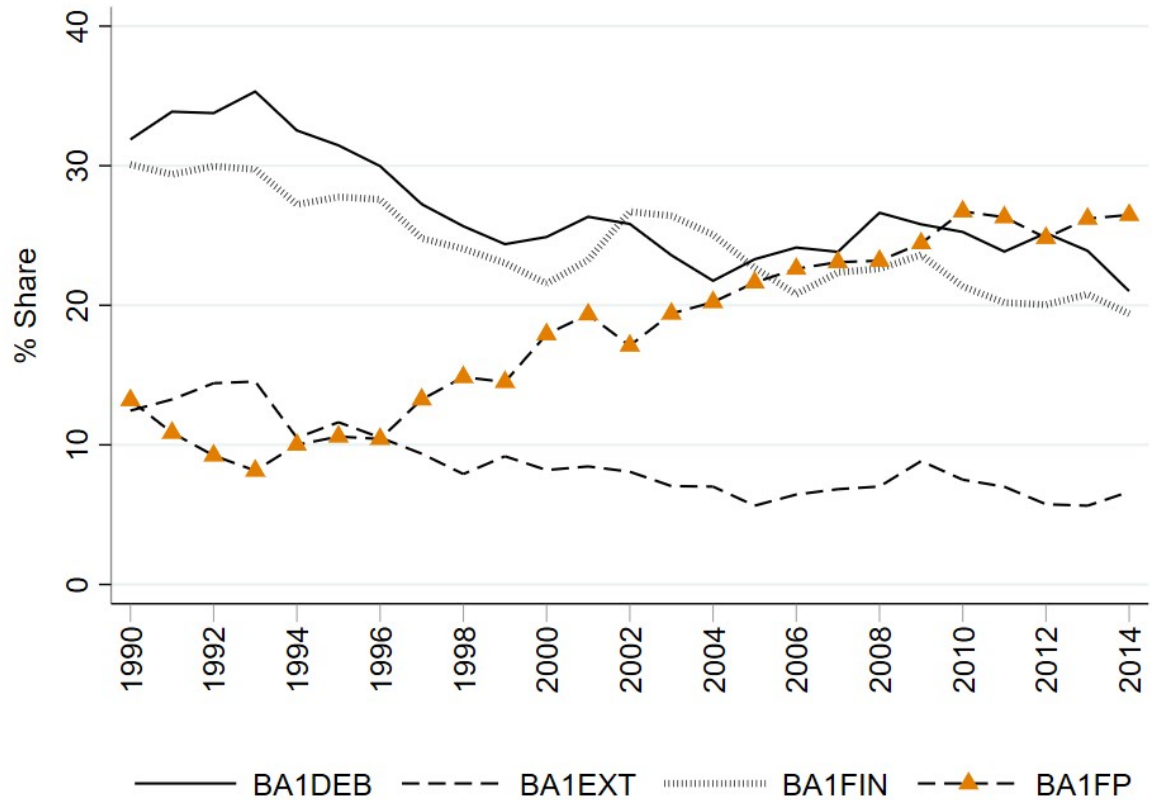
Notes: The y-axis is the average conditions imposed per country in a given year. QPCs are quantitative performance criteria, IBs is indicative benchmarks, PAs are prior actions, SPCs are structural performance criteria and SBs are structural benchmarks. Source: Author's calculations.

Figure 2.2: Amount of conditions imposed by the IMF



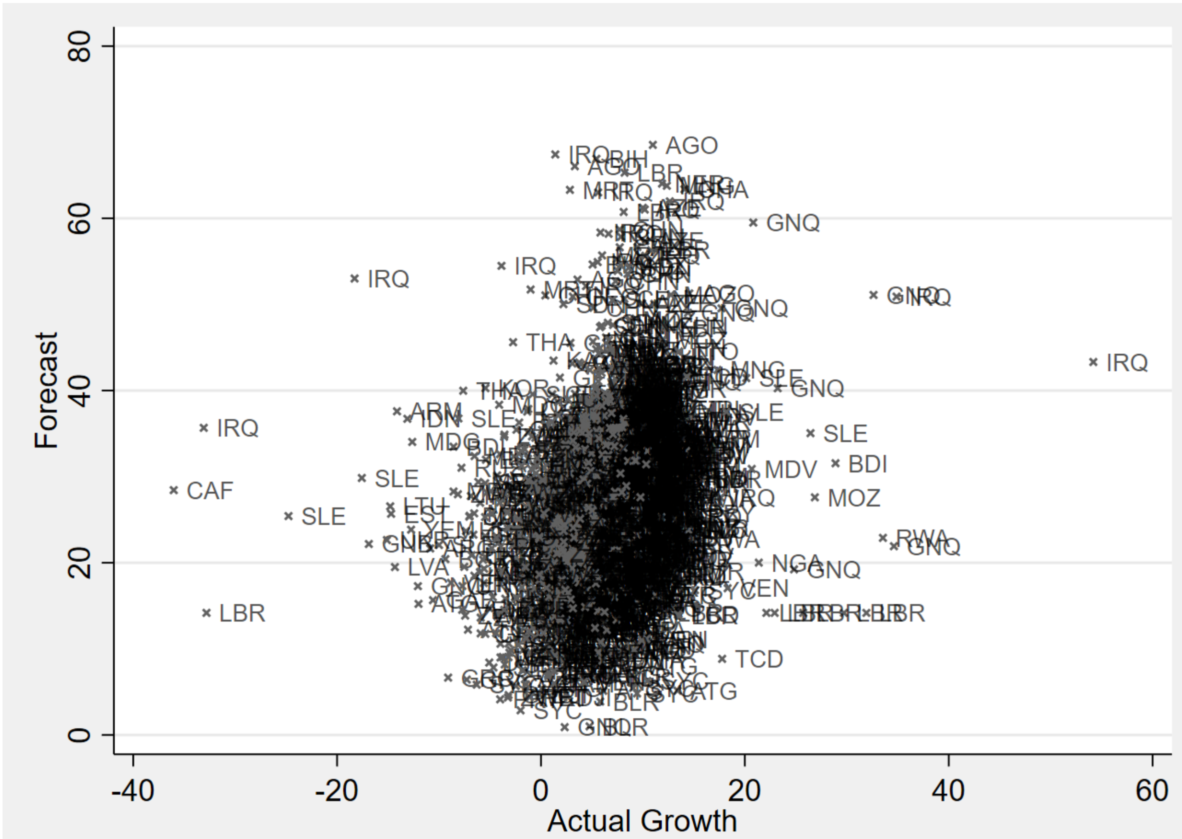
Notes: The y-axis shows total conditions imposed by the IMF across years. Source: Author's calculations.

Figure 2.3: Top 4 areas of conditionality



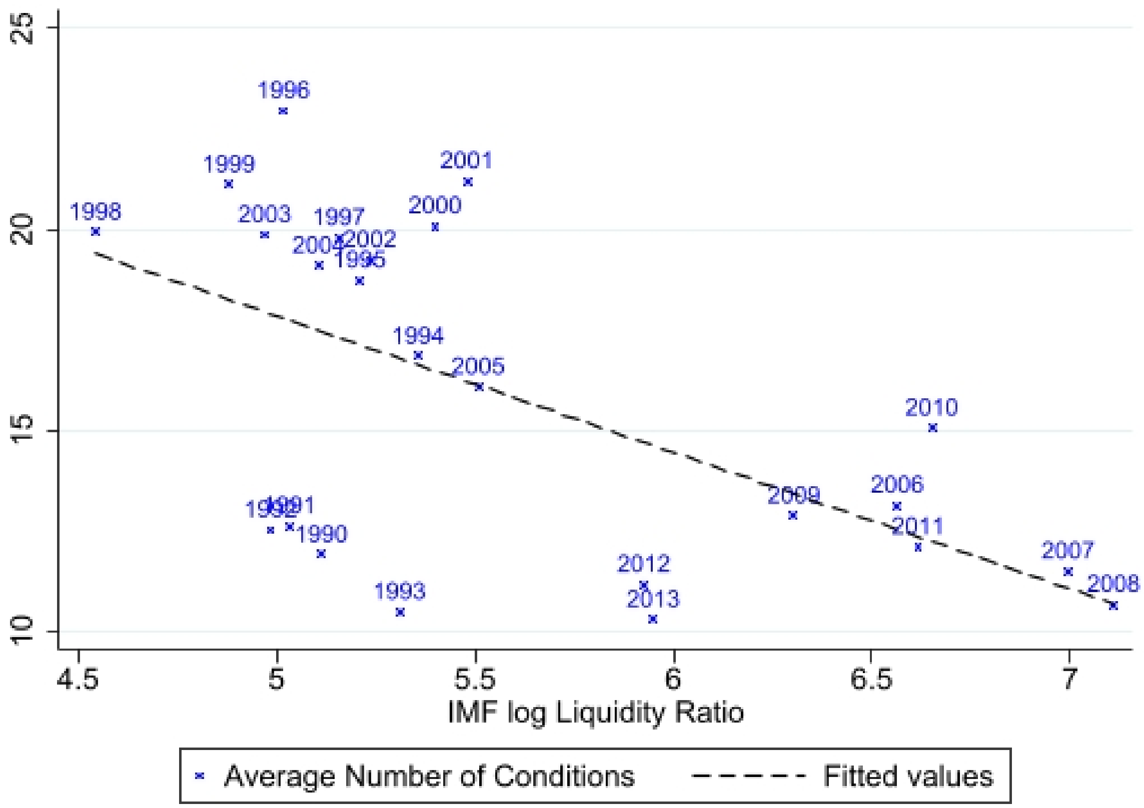
Notes: Percentage share of top four conditionality requirements. BA1DEB is external debt issues, BA1EXT is external sector, BA1FIN is financial sector, monetary policy, Central Bank issues, and BA1FP is fiscal issues. Source: Author's calculations.

Figure 2.4: Forecasts and Real Growth



Notes: Plotting the actual cumulative 5-year growth rate (y-axis) against the forecasted cumulative 5-year growth rate (x-axis) encompasses all non-advanced economy country-years, ensuring observations are less than 5 years apart with overlapping outcomes. The positive slope of the linear relationship is approximately 0.70, and a local polynomial (degree-0) regression has confirmed that linearity is an appropriate assumption for this context. We have excluded observations from the top and bottom 1% in either dimension. Source: Author's calculations.

Figure 2.5: Validity of the instrument



Notes: We can see a strong correlation between the number of conditions and the IMF liquidity constraint. The co-efficient of correlations is -0.29. Significant at 1% level. Source: Author's calculations followed by Stubbs et al. (2020).

Table 2.1: IMF Condition Categories

1. Quantitative conditions
1.1 Quantitative performance criteria (QPCs): Quantifiable conditions that need to be fulfilled for the completion of a review and are classified as hard conditions. Examples: fiscal balances, and levels of external debt.
1.2 Indicative benchmarks (IBs): Complementary targets for quantitative performance criteria and are classified as soft conditions.
2. Structural Conditions
2.1 Prior actions (PAs): Conditions that need to be met before IMF approves loans or finalizes a review. These are also used as necessary conditions if a country failed to fulfill its prior commitments. These are the strictest conditions imposed on a borrowing country and are classified as hard conditions. Examples: Labor market reforms including reducing minimum wages, increasing the retirement age, or employee hiring and firing costs.
2.2 Structural performance criteria (SPCs): Structural reforms are considered crucial for the success of an IMF program and are classified as hard conditions. Examples: Banking laws.
2.3 Structural benchmarks (SBs): Non-quantifiable reform conditions and are classified as soft conditions. Examples: Reforms for the financial sector, or management of public finances.

Table 2.2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
IMF Program	3,220	0.42	0.49	0	1
BA1TOT	3,220	15.61	22.43	0	148
BA2TOT	3,220	10.3	15.72	0	124
BA3TOT	3,220	25.91	37.64	0	272
cBATOT	2,434	10.74	15.88	0	114
dBA1TOT	2,434	13.91	21.04	0	126
dBA2TOT	2,434	9.53	15.03	0	93
dBA3TOT	2,434	23.44	35.61	0	204
QCsTOT	3,220	11.25	16.01	0	92
QPCsTOT	3,220	8.34	12.6	0	63
IBsTOT	3,220	2.91	6.27	0	56
SCsTOT	3,220	4.36	8.08	0	94
PAsTOT	3,220	1.38	4.15	0	78
SPCsTOT	3,220	0.57	1.62	0	27
SBsTOT	3,220	2.41	4.57	0	39
ln(GDP Per Capita)	3,050	8.53	1.05	5.09	10.91
5-year forecast(%)	2,438	27.44	14.19	-3.01	76.66
5-year Growth(%)	3,030	3.87	7.16	-2.45	58.25
UNSC Member	3,155	0.06	0.23	0	1
Vote with US	2,773	0.2	0.11	0	1
ln(Population)	3,050	2.04	1.88	-3.2	7.22
Employment	2,977	18.47	77.55	0.02	798.37
Current Account Balance	2,756	-4.74	9.2	-148	43.4
Bias	2,338	4.88	2.03	-0.56	34.08
Inflation	3,050	0.43	0.21	0.08	3.18
Govt. Expenditure	2,618	14.37	5.35	0.91	43.48

Notes: IMFProgram is an IMF program participation dummy that takes the value of 1 if the country has been a part of an IMF program for at least five months in the country-year. BA1TOT, BA2TOT, BA3TOT are the total number of soft and hard IMF conditions, total number of hard conditions, and weighted sum of 42 hard and soft conditions, respectively. cBATOT, dBA1TOT, dBA2TOT, dBA3TOT are implementation-corrected hard conditions, number of conditions discounted by interruptions, implementation-discounted hard conditions, and implementation-discounted weighted conditions, respectively. QCs, QPCs, IBs, SCs, PAs, SPCs, and SBs are total quantitative conditions, quantitative performance criteria, indicative benchmarks, total structural conditions, prior actions, structural performance criteria, and structural benchmarks. 5-year growth and forecasts are aggregated numbers for 5 years in percentages. UNSC is a dummy variable equaling one when a country is a temporary member in the United Nations Security Council, PctAgreeUS is Lijphart's index of agreement between a UN member state and the U.S.

Table 2.3: OLS Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IMF Program	0.182	0.311	0.415	0.349	0.349	0.101	0.085	0.067	0.022	0.022
	(0.248)	(0.316)	(0.303)	(0.296)	(0.296)	(0.305)	(0.290)	(0.292)	(0.312)	(0.312)
BA1 - Total		0.004	0.003	0.001	0.001	0.000	0.001	0.002	0.003	0.003
		(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Per Capita GDP			8.641***	6.009***	6.009***	7.644***	8.265***	8.457***	8.342***	8.342***
			(1.814)	(0.875)	(0.875)	(1.022)	(1.021)	(1.048)	(1.098)	(1.098)
Current Account Balance				0.007	0.007	-0.035	-0.049**	-0.048*	-0.051*	-0.051*
				(0.034)	(0.034)	(0.018)	(0.019)	(0.019)	(0.020)	(0.020)
Govt. Spending						0.082	0.026	0.020	0.020	0.020
						(0.045)	(0.044)	(0.044)	(0.048)	(0.048)
Employment						-0.028**	-0.027**	-0.016	-0.014	-0.014
						(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Growth							-25.170***	-25.339***	-27.328***	-27.328***
							(4.192)	(4.249)	(4.502)	(4.502)
UNSC Membership								-0.128	-0.215	-0.215
								(0.314)	(0.314)	(0.314)
Vote with US									-2.761	-2.761
									(2.419)	(2.419)
Constant	2.548*	2.554*	-70.817***	-48.380***	-48.380***	-64.177***	-66.695***	-68.092***	-65.942***	-65.942***
	(1.164)	(1.164)	(15.600)	(7.556)	(7.556)	(8.934)	(8.846)	(9.093)	(9.494)	(9.494)
Observations	2338	2338	2338	2110	2110	1823	1823	1768	1582	1582

Notes: The dependent variable is the compounded error in the 5-year forecasts. All the regressions have time and country-fixed effects. Robust standard errors in parentheses. BA1-Total variable includes a total number of hard and soft conditions imposed on country i in year t. All the independent variables lagged by one year in the regressions. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 2.4: CMP Results

	(1)	(2)	(3)	(4)	(5)	(6)
IMF Program	0.094	0.130	0.126	0.163	0.327	0.183
	(0.263)	(0.263)	(0.263)	(0.268)	(0.281)	(0.281)
BA1 - Total	0.273***	0.129***	0.134***	0.124***	0.121***	0.161***
	(0.014)	(0.018)	(0.018)	(0.019)	(0.021)	(0.021)
Per Capita GDP	12.502***	9.064***	8.798***	9.297***	3.824***	3.248***
	(0.862)	(0.835)	(0.871)	(0.924)	(0.856)	(0.921)
Current Account Balance		-0.004	-0.004	-0.002	-0.020	-0.009
		(0.014)	(0.014)	(0.014)	(0.015)	(0.016)
Population			-1.968	-0.054	0.317	1.846
			(1.522)	(1.368)	(1.390)	(1.402)
UNSC Membership				-0.026	-0.263	-0.280
				(0.389)	(0.389)	(0.425)
Vote with US					-3.096	-2.207
					(2.049)	(2.123)
Employment						-0.016
						(0.013)
Constant	0.381***	0.361***	0.364***	0.352***	0.353***	0.354***
	(0.031)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)
Observations	2690	2462	2462	2392	2353	2311
F-Stat for Program	13.34***	12.65***	16.96***	9.87***	10.65***	18.62***
F-Stat for Conditions	17.25***	20.15***	23.41***	24.29***	23.14***	15.93***
Joint F-Stat	21.26***	23.65***	27.39***	26.88***	28.15***	19.25***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. BA1 - Total defines the total number of conditions imposed by the IMF on a country in a given year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 2.5: Effect on forecasts by different conditions

	(1)	(2)	(3)	(4)	(5)	(6)
IMF Program	0.164	0.181	0.337	0.023	0.076	0.042
	(0.280)	(0.278)	(0.353)	(0.325)	(0.322)	(0.326)
BA2 - Total	0.155***					
	(0.020)					
BA3 - Total		0.089***				
		(0.012)				
cBA - Total			0.247***			
			(0.031)			
dBA1 - Total				0.190***		
				(0.023)		
dBA2 - Total					0.252***	
					(0.033)	
dBA3 - Total						0.111***
						(0.014)
Per Capita GDP	2.824**	2.947**	4.755***	4.496***	4.967***	4.608***
	(0.917)	(0.915)	(1.280)	(1.292)	(1.277)	(1.290)
Current Account Balance	-0.006	-0.007	0.015	0.020	0.015	0.019
	(0.017)	(0.016)	(0.023)	(0.023)	(0.023)	(0.023)
Employment	-0.014	-0.013	-0.017	-0.019	-0.018	-0.018
	(0.013)	(0.013)	(0.017)	(0.016)	(0.017)	(0.016)
UNSC Membership	-0.402	-0.375	-0.202	-0.387	-0.291	-0.348
	(0.429)	(0.423)	(0.548)	(0.558)	(0.551)	(0.556)
Vote with US	1.924	1.656	1.979	3.959	2.914	3.655
	(2.692)	(2.659)	(3.619)	(3.707)	(3.656)	(3.692)
Constant	-18.620*	-19.468**	-25.647*	-23.578*	-26.965*	-24.317*
	(7.334)	(7.320)	(10.514)	(10.585)	(10.488)	(10.576)
Observations	2690	2462	2462	2392	2353	2311
F-Stat for Program	13.24***	16.86***	12.65***	10.23***	9.34***	13.27***
F-Stat for Conditions	18.25***	19.38***	18.22***	23.21***	9.43***	19.44***
Joint F-Stat	20.31***	21.33***	22.54***	26.35***	13.65***	22.25***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 2.6: Effect on Forecasts by Condition Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IMF Program	0.270	0.208	0.163	0.065	0.150	0.225	0.062
	(0.283)	(0.274)	(0.214)	(0.234)	(0.205)	(0.213)	(0.238)
QCsBA2	0.234***						
	(0.027)						
QPCs - Total		0.250***					
		(0.035)					
IBs - Total			0.590***				
			(0.062)				
SCsBA2				0.319***			
				(0.052)			
PAs - Total					0.605***		
					(0.098)		
SPCs - Total						1.215***	
						(0.261)	
SBs - Total							0.343***
							(0.086)
Per Capita GDP	3.503***	3.725***	5.373***	2.974**	3.334***	6.890***	5.526***
	(0.884)	(0.873)	(0.840)	(0.927)	(0.883)	(0.750)	(0.820)
Current Account Balance	-0.011	-0.016	-0.005	-0.002	-0.007	-0.036*	-0.019
	(0.017)	(0.016)	(0.017)	(0.016)	(0.015)	(0.015)	(0.014)
Employment	-0.015	-0.014	-0.014	-0.012	-0.010	-0.018	-0.019
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
UNSC Membership	-0.374	-0.266	-0.442	-0.359	-0.353	-0.033	-0.246
	(0.438)	(0.420)	(0.447)	(0.400)	(0.398)	(0.382)	(0.352)
Vote with US	1.516	1.727	-1.631	1.508	-1.816	-3.068	0.910
	(2.741)	(2.650)	(2.770)	(2.528)	(2.490)	(2.418)	(2.406)
Constant	0.298***	0.267***	0.078**	0.250***	0.164***	0.108***	0.190***
	(0.033)	(0.032)	(0.025)	(0.027)	(0.024)	(0.025)	(0.027)
Observations	2077	2077	2077	2077	2077	2077	2064
F-Stat for Program	19.98***	10.96***	15.77***	13.42***	16.42***	18.13***	23.51***
F-Stat for Conditions	18.63***	16.95***	13.78***	16.98***	14.63***	16.74***	16.54***
Joint F-Stat	23.65***	26.31***	29.26***	29.42***	26.42***	29.16***	29.41***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 2.7: Effect on Forecasts by Condition Sub-Categories

	(1) DEB	(2) ENV	(3) EXT	(4) FIN	(5) FP	(6) INS	(7) LAB	(8) OTH	(9) POV	(10) PRI	(11) RTP	(12) SOE	(13) SP
IMF Program	0.233	0.217	0.274	0.207	0.203	0.190	0.170	0.229	0.161	0.231	0.175	0.118	0.285
	(0.264)	(0.195)	(0.243)	(0.240)	(0.231)	(0.197)	(0.212)	(0.205)	(0.197)	(0.198)	(0.206)	(0.199)	(0.198)
Condition sub-category	0.606***	16.029***	1.518***	0.673***	1.089***	8.767***	-0.343	0.535	25.017***	5.258***	-1.554***	3.500***	9.713***
	(0.068)	(1.658)	(0.199)	(0.093)	(0.127)	(0.923)	(0.383)	(1.567)	(3.108)	(0.626)	(0.274)	(0.333)	(1.119)
Per Capita GDP	3.338***	4.636***	9.897***	8.774***	9.722***	3.890***	6.142***	6.220***	7.477***	4.715***	4.852***	7.025***	4.938***
	(0.886)	(0.838)	(0.937)	(0.866)	(0.925)	(0.900)	(0.676)	(0.670)	(0.825)	(0.842)	(0.785)	(0.879)	(0.822)
Current Account Balance	-0.018	0.003	-0.012	-0.020	-0.032	-0.005	-0.013	-0.014	-0.035*	-0.016	-0.003	-0.039*	-0.005
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.018)	(0.013)	(0.013)	(0.017)	(0.017)	(0.015)	(0.018)	(0.017)
Employment	-0.014	-0.009	-0.014	-0.016	-0.014	-0.012	-0.016	-0.016	-0.014	-0.008	-0.015	-0.014	-0.010
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
UNSC Membership	-0.233	-0.275	-0.275	0.197	-0.066	-0.526	-0.173	-0.169	-0.117	-0.322	-0.214	-0.075	-0.446
	(0.435)	(0.438)	(0.429)	(0.418)	(0.436)	(0.464)	(0.340)	(0.338)	(0.430)	(0.439)	(0.389)	(0.471)	(0.432)
Vote with US	1.498	-5.753*	-5.277	-3.465	-6.776*	-1.011	-1.278	-1.436	-1.135	-0.849	-0.999	-0.196	-3.232
	(2.725)	(2.764)	(2.710)	(2.598)	(2.778)	(2.870)	(2.163)	(2.160)	(2.675)	(2.728)	(2.437)	(2.918)	(2.686)
Constant	-22.546**	-32.013***	-72.630***	-63.653***	-70.465***	-26.841***	-43.102***	-43.791***	-53.986***	-33.141***	-34.009***	-53.064***	-34.571***
	(7.122)	(6.798)	(7.576)	(7.027)	(7.440)	(7.237)	(5.669)	(5.611)	(6.725)	(6.812)	(6.378)	(7.142)	(6.680)
Observations	2077	2077	2077	2077	2077	2077	2077	2077	2077	2077	2077	2077	2077
F-Stat for Program	10.35***	9.96***	13.47***	14.63***	14.62***	13.54***	18.41***	11.12***	9.15***	14.26***	15.41***	12.44***	20.52***
F-Stat for Conditions	13.71***	14.51***	16.62***	14.26***	19.58***	9.85***	12.65***	12.85***	14.51***	13.35***	13.11***	13.47***	20.41***
Joint F-Stat	15.76***	19.31***	17.32***	24.16***	21.26***	19.43***	21.41***	16.41***	18.41***	18.31***	16.11***	15.14***	21.35***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 2.8: Effect of Conditionality Across Regions

	(1) Middle East	(2) Asia	(3) Europe	(4) Latin America
IMF Program	1.534	0.812	-0.355	0.872
	(0.926)	(0.584)	(0.589)	(0.473)
BA1 - Total	0.042	0.061	0.649*	0.681*
	(0.055)	(0.041)	(0.267)	(0.287)
Per Capita GDP	5.399	4.285**	39.436**	4.691
	(6.657)	(1.364)	(13.789)	(8.732)
Current Account Balance	-0.012	-0.118***	-0.580*	-0.078
	(0.058)	(0.035)	(0.232)	(0.143)
Population	6.126	8.438	21.135***	2.751
	(7.464)	(6.870)	(6.328)	(4.270)
UNSC Membership	-1.143	-0.293	-1.417	0.542
	(1.054)	(0.721)	(2.841)	(1.860)
Vote with US	-14.627	2.078	8.241	-1.710
	(9.040)	(5.658)	(4.318)	(4.730)
Employment	0.030	-0.004	-0.844*	0.079
	(0.129)	(0.011)	(0.345)	(0.050)
Constant	0.253**	0.690***	0.291***	0.169*
	(0.084)	(0.079)	(0.068)	(0.068)
Observations	228	289	436	408
F-Stat for Program	13.24***	12.65***	10.23***	9.34***
F-Stat for Conditions	19.38***	18.22***	9.43***	19.44***
Joint F-Stat	21.33***	22.54***	26.35***	13.65***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the ‘cmp’ command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 2.9: CMP Results: With Lagged Bias

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged bias	0.202***	0.300***	0.300***	0.305***	0.315***	0.327***
	(0.025)	(0.021)	(0.021)	(0.022)	(0.023)	(0.024)
IMF Program	0.151	0.228	0.219	0.219	0.165	0.133
	(0.265)	(0.261)	(0.262)	(0.266)	(0.281)	(0.282)
BA1 - Total	0.257***	0.040*	0.046*	0.036	0.049*	0.063*
	(0.014)	(0.020)	(0.019)	(0.022)	(0.024)	(0.025)
Per Capita GDP	14.049***	8.047***	8.059***	8.391***	8.297***	8.615***
	(0.872)	(0.773)	(0.778)	(0.848)	(0.910)	(0.941)
Current Account Balance		-0.039**	-0.039**	-0.039**	-0.033*	-0.028*
		(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Population			-0.566	-0.014	-0.338	0.059
			(1.398)	(1.369)	(1.392)	(1.418)
UNSC Membership				-0.126	-0.200	-0.168
				(0.323)	(0.336)	(0.340)
Vote with US					-3.270	-2.406
					(2.047)	(2.141)
Employment						-0.021
						(0.014)
Constant	0.458***	-1.739***	-1.113***	-1.417***	-1.839***	-1.120***
	(0.077)	(0.035)	(0.032)	(0.059)	(0.064)	(0.039)
Observations	2659	2445	2445	2375	2339	2298
F-Stat for Program	13.78***	12.32***	17.03***	9.54***	11.12***	18.99***
F-Stat for Conditions	17.89***	19.74***	22.86***	24.75***	22.98***	16.75***
Joint F-Stat	21.77***	23.95***	27.91***	26.45***	28.82***	19.89***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. BA1 - Total defines the total number of conditions imposed by the IMF on a country in a given year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 2.10: Effect on Forecasts by Conditions: With Lagged Bias

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Bias	0.319***	0.325***	0.313***	0.305***	0.359***	0.309***
	(0.023)	(0.024)	(0.031)	(0.032)	(0.032)	(0.032)
IMF Program	0.148	0.178	0.357	0.037	0.069	0.055
	(0.283)	(0.278)	(0.360)	(0.331)	(0.327)	(0.332)
BA1 - Total	0.021					
	(0.030)					
BA3 - Total		0.034*				
		(0.014)				
cBA - Total			0.137***			
			(0.036)			
dBA1 - Total				0.113***		
				(0.025)		
dBA2 - Total					0.135***	
					(0.039)	
dBA3 - Total						0.061***
						(0.016)
Per Capita GDP	7.525***	8.557***	8.635***	8.277***	13.296***	8.514***
	(0.119)	(0.909)	(1.219)	(1.219)	(1.318)	(1.221)
Current Account Balance	-0.025	-0.028*	0.001	0.005	-0.030	0.004
	(0.013)	(0.013)	(0.019)	(0.020)	(0.020)	(0.020)
Employment	-0.020	-0.021	-0.024	-0.025	-0.027	-0.025
	(0.014)	(0.014)	(0.018)	(0.018)	(0.018)	(0.018)
UNSC Membership	-0.164	-0.134	-0.230	-0.344	-0.291	-0.313
	(0.329)	(0.341)	(0.460)	(0.474)	(0.458)	(0.466)
Vote with US	-2.870	-3.695	0.097	1.820	-6.069	1.336
	(2.316)	(2.290)	(3.280)	(3.392)	(3.327)	(3.363)
Constant	-2.784	-3.723***	-3.063***	-4.864***	-1.886***	-4.896***
	(0.368)	(0.638)	(0.981)	(0.948)	(0.849)	(0.997)
Observations	2659	2445	2445	2375	2339	2298
F-Stat for Program	14.01***	12.55***	16.78***	9.72***	11.25***	19.05***
F-Stat for Conditions	17.95***	19.62***	22.94***	24.51***	22.89***	16.81***
Joint F-Stat	21.83***	24.01***	27.79***	26.56***	28.97***	19.98***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 2.11: Effect on Forecasts by Categories: With Lagged Bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged Bias	0.337***	0.331***	0.299***	0.320***	0.327***	0.318***	0.318***
	(0.025)	(0.024)	(0.025)	(0.023)	(0.024)	(0.023)	(0.024)
IMF Program	0.088	0.164	0.086	0.195	0.202	0.181	0.062
	(0.283)	(0.271)	(0.213)	(0.234)	(0.202)	(0.210)	(0.238)
QCsBA2	0.113***						
	(0.031)						
QPCs - Total		0.121***					
		(0.033)					
IBs - Total			0.369***				
			(0.061)				
SCsBA2				0.163**			
				(0.055)			
PAs - Total					0.413***		
					(0.096)		
SPCs - Total						0.481*	
						(0.236)	
SBs - Total							0.343***
							(0.086)
Per Capita GDP	8.643***	8.545***	6.688***	5.602***	5.239***	7.429***	5.526***
	(0.830)	(0.808)	(0.752)	(0.877)	(0.840)	(0.697)	(0.820)
Current Account Balance	-0.028*	-0.026	-0.016	-0.016	-0.016	-0.032*	-0.019
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Employment	-0.020	-0.021	-0.019	-0.018	-0.015	-0.022	-0.019
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
UNSC Membership	-0.121	-0.173	-0.364	-0.283	-0.313	-0.148	-0.246
	(0.352)	(0.347)	(0.375)	(0.341)	(0.351)	(0.333)	(0.352)
Vote with US	-3.907	-4.038	-2.065	-0.714	-2.586	-2.862	0.910
	(2.329)	(2.309)	(2.416)	(2.286)	(2.280)	(2.198)	(2.406)
Constant	-0.990***	-9.944***	-2.446***	-4.534***	-2.163***	-0.190***	-3.649***
	(0.978)	(0.749)	(0.172)	(0.209)	(0.815)	(0.738)	(0.757)
Observations	2064	2064	2064	2064	2064	2064	2064
F-Stat for Program	20.07***	11.02***	15.84***	13.55***	16.61***	18.27***	23.65***
F-Stat for Conditions	18.78***	17.05***	13.85***	17.04***	14.75***	16.84***	16.61***
Joint F-Stat	23.78***	26.42***	29.39***	29.53***	26.48***	29.23***	29.58***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the 'cmp' command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 2.12: Effect on forecasts by condition sub-categories

	(1) DEB	(2) ENV	(3) EXT	(4) FIN	(5) FP	(6) INS	(7) LAB	(8) OTH	(9) POV	(10) PRI	(11) RTP	(12) SOE	(13) SP
Lagged Bias	0.337***	0.295***	0.316***	0.326***	0.318***	0.332***	0.317***	0.316***	0.319***	0.345***	0.321***	0.311***	0.318***
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)	(0.023)	(0.023)	(0.024)	(0.025)	(0.023)	(0.025)	(0.024)
IMF Program	0.077	0.176	0.363	0.175	0.198	0.185	0.149	0.144	0.131	0.195	0.068	0.088	0.223
	(0.265)	(0.194)	(0.242)	(0.238)	(0.231)	(0.194)	(0.205)	(0.198)	(0.196)	(0.194)	(0.206)	(0.197)	(0.195)
Condition sub-category	0.271**	-10.117***	0.742***	0.407***	0.621***	-6.154***	-0.424	0.396	11.772***	-3.858***	0.364	2.281***	-6.318***
	(0.089)	(1.682)	(0.200)	(0.083)	(0.122)	(0.860)	(0.298)	(1.410)	(3.304)	(0.540)	(0.343)	(0.318)	(1.040)
Per Capita GDP	8.606***	6.097***	9.104***	8.710***	9.059***	5.626***	7.112***	7.196***	7.773***	6.158***	7.533***	7.705***	6.302***
	(0.864)	(0.756)	(0.860)	(0.790)	(0.831)	(0.799)	(0.679)	(0.676)	(0.731)	(0.770)	(0.761)	(0.776)	(0.748)
Current Account Balance	-0.025	-0.010	-0.021	-0.027	-0.033*	-0.016	-0.021	-0.024	-0.033*	-0.024	-0.027*	-0.039*	-0.015
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.013)	(0.013)	(0.014)	(0.015)	(0.013)	(0.015)	(0.014)
Employment	-0.021	-0.015	-0.020	-0.021	-0.020	-0.017	-0.019	-0.020	-0.020	-0.014	-0.020	-0.020	-0.016
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
UNSC Membership	-0.191	-0.259	-0.273	0.006	-0.163	-0.460	-0.180	-0.187	-0.174	-0.310	-0.178	-0.155	-0.376
	(0.347)	(0.366)	(0.354)	(0.358)	(0.361)	(0.389)	(0.325)	(0.324)	(0.348)	(0.381)	(0.326)	(0.388)	(0.368)
Vote with US	-3.737	-4.754*	-4.038	-3.279	-5.250*	-1.864	-2.140	-2.386	-1.726	-1.528	-2.364	-1.035	-3.320
	(2.311)	(2.410)	(2.337)	(2.319)	(2.408)	(2.492)	(2.148)	(2.150)	(2.274)	(2.456)	(2.156)	(2.505)	(2.378)
Constant	-70.574***	-48.028***	-74.725***	-71.413***	-73.674***	-45.640***	-57.050***	-57.581***	-62.079***	-49.371***	-60.476***	-61.698***	-50.500***
	(7.256)	(6.185)	(7.135)	(6.594)	(6.828)	(6.511)	(5.548)	(5.517)	(5.967)	(6.306)	(6.210)	(6.340)	(6.110)
Observations	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064
F-Stat for Program	10.35***	9.96***	13.47***	14.63***	14.62***	13.54***	18.41***	11.12***	9.15***	14.26***	15.41***	12.44***	20.52***
F-Stat for Conditions	13.71***	14.51***	16.62***	14.26***	19.58***	9.85***	12.65***	12.85***	14.51***	13.35***	13.11***	13.47***	20.41***
Joint F-Stat	15.76***	19.31***	17.32***	24.16***	21.26***	19.43***	21.41***	16.41***	18.41***	18.32***	16.11***	15.14***	21.35***

Notes: The dependent variable is the compounded error of the 5-year forecasts. All the independent variables are lagged by one year. The regression esimations are done by using the ‘cmp’ command by Roodman (2009). The results are based on Maximum Likelihood Estimation. Country and year fixed effects are included. F-Stat for IMF Programs and IMF conditions are p-values for Kleibergen-Paap F-statistics for the significance of compound IVs. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Chapter 3

The long-term impact of Chinese environmental laws towards cleaner production

3.1 Introduction

In this chapter, our aim is to understand how firms behave in response to environmental laws in China, specifically, the Cleaner Production Law that was passed in 2005 and which came into force in early 2006. This law is designed to encourage industries to move towards cleaner production practices, reduce environmental pollution, and promote sustainable development. Here we study how firms adjust their investment behavior before and after the implementation of this law. This also includes examining the extent to which firms allocate their resources towards environmentally friendly technologies, infrastructure, and other processes. Previous literature has explored the economic consequences of environmental laws, such as their effects on productivity, profitability, and compliance levels. However, this chapter extends the literature by specifically examining the cleaner production law and its implications for firms' investment behavior.

While our study focuses on understanding firms' investment behavior in response to the cleaner production law, it is worth noting that we do not directly assess the impact of the law on industrial pollution reduction. The complexities in the emissions data and the potential spillover effects of pollution from one sector to another make it challenging to attribute changes in pollution levels solely to the cleaner production law. We discuss these limitations and differences in detail in the results section, acknowledging the broader context in which our analysis takes place.

Although the law was passed at the national level, its implementation was left to the local government. Thus, the governments at the county level would have to spend their resources to make sure that the manufacturing firms are taking adequate measures to reduce their carbon footprint. Owing to a limited budget and manpower, the resources allocated towards environmental management will vary across jurisdictions. This chapter aims to extract this variation within the country for a law that is passed on a national level.

Our empirical analysis, based on a synthetic difference-in-differences(SDID) model, shows that the implementation of environmental laws in China had distinct effects on firm behavior and investment decisions. We find that within counties with higher levels of law enforcement, firms exhibited a cautious response by decreasing their long-term investment-to-market capitalization ratio. This indicates that firms were more sensitive to increased compliance costs associated with stricter environmental regulations. Conversely, in counties with lower levels of monitoring and enforcement, a slight increase in the investment ratio was observed, suggesting that firms took advantage of lenient enforcement to increase their investments. However, despite these changes in firm behavior, the study did not find statistically significant reductions in pollution levels. This indicates that pollution levels are influenced by a range of factors beyond the actions of manufacturing firms alone. These findings emphasize the intricate dynamics of firm behavior in response to regulatory stringency and monitoring, underscoring the importance of effective monitoring mechanisms and the need for a comprehensive approach to address pollution challenges.

The rest of the chapter is organized as follows: Section 3.2 focuses on the evolution of Chinese environmental laws, section 3.3 lays out the industrial landscape in China, section 3.4 explains the 2005 law on cleaner production in detail, 3.5 illustrates the data and empirical methodology followed by Results (Section 3.6), Sensitivity Analysis (Section 3.7); Section 3.8 concludes the chapter.

3.2 Environmental Laws in China

While focusing on industrial growth, China began implementing environmental regulation in the last quarter of the twentieth century with the first environmental protection law passed in 1979. However, it was not until the late 1990s that China began to take environmental protection more seriously. Since the late 1990s, the laws passed by China had hard quantitative measures to control the pollution levels. The government acknowledged that environmental degradation posed a threat to both economic growth and social stability, leading to the implementation of more stringent environmental laws and regulations.

One of the first pivotal law that emerged during this period was the Environmental Protection Law of 1989. It mandated that firms acquire environmental permits and adhere to government-set environmental standards. Furthermore, the law also granted the government the authority to impose penalties on companies found to be violating environmental regulations (Bao, 2004; Mu et al., 2014; Mushkat, 2008).

Despite these efforts, the implementation of environmental regulations in China has encountered various challenges, particularly regarding non-compliance. Although the regulations became stricter over time, the companies have continued to operate outside their scope. Lo et al. (2012) conducted a study highlighting the weak enforcement of environmental regulations in China, often due to limited resources and capacity at the local government level. Furthermore, scholars such as Wang et al. (2003), Lindhjem et al. (2007), and Xu et al. (2013) shed light on the Environmental Impact Assessment (EIA) process in China, revealing issues such as inadequate public participation, insufficient consideration of cumulative impacts, inconsistent enforcement, data availability challenges, and the need for enhanced expertise and valuation methods to name a few. They also highlighted the importance of transparency, stakeholder engagement, capacity building, and comprehensive approaches to address these challenges and enhance the effectiveness of environmental impact assessments.

In addition to the Environmental Protection Law, the Law on the Prevention and Control of Air Pollution, which has been revised multiple times, addresses air quality issues through emission standards and clean technologies. The Water Pollution Prevention and Control Law addresses wastewater discharge and aims to improve water quality in residential areas. China has also enacted laws targeting soil pollution and promoting renewable energy, such as the Law on the Prevention and Control of Soil Pollution and the Renewable Energy Law. These laws underscore the government's commitment to environmental protection and can be explored further through official government resources (Beyer, 2006; Shen et al., 2019; Li and Taeihagh, 2020).

The evolution of environmental laws in China has also been influenced by various factors, most importantly the focus on economic development, international pressures, and notably, social unrest and civic protests. Research by Steinhardt and Wu (2016), Lang and Xu (2013), and Deng and Yang (2013) highlights the significant role played by environmental protests in shaping China's environmental policies. Their studies conclude that protests against environmental degradation have prompted the introduction of new environmental laws and regulations, as well as stricter enforcement of existing regulations. This underscores the effectiveness of public pressure in advocating for stronger environmental regulations and fostering sustainable development.

3.3 Industrial Development in China

China's industrial landscape has changed significantly over the past four decades as the country moved away from a centrally planned economy to a market-oriented one. The economic reforms of the late 1970s were the beginning of rapid industrialization and urbanization in China. According to World Bank, the share of industry in China's GDP rose from below 40% in 1980 to over 50% in 2019. This growth in the GDP has been driven by investments in heavy industry, infrastructure, and export-oriented manufacturing(Zhang, 2019).

The industrial growth in China has resulted in both positive and negative consequences for their economy. On the positive side, it has generated millions of jobs and contributed to overall economic growth. Fisher-Vanden et al. (2006) highlights the role of industrial growth in driving productivity improvements and technological advancements, which have resulted in higher wages and higher living standards for the workers.

On the other hand, rapid industrialization has also resulted in adverse effects on the environment and public health at large. The expansion of heavy industry has caused significant air and water pollution, with dire implications for public health. For example, Li et al. (2018) studied the impact of industrialization and environmental protection on pollution levels in China's Taihu Lake region. They find that industrialization had a significant influence on pollution levels, but the implementation of environmental protection measures has helped mitigate its extent. Similarly, Liu and Bae (2018) studied the relationship between industrialization and CO_2 emissions in China, they posit that industrialization did contribute to the overall increase in emissions. Moreover, Bradbury et al. (1996) examined the dynamics between rural industrialization, small-town growth, and environmental factors, emphasizing the need for sustainable approaches to strike a balance between economic progress and environmental preservation.

As discussed in the previous section, the Chinese government has taken steps to address environmental degradation and promote sustainable development in recent years. Stricter environmental regulations, such as the amendments added to Air Pollution Prevention and Control Law in 2015 and the Water Pollution Prevention and Control Law in 2018, have been introduced which have built upon the regulatory framework in the earlier decades. In addition, research by Zhu et al. (2016) indicates that state-owned enterprises (SOEs) in China exhibit higher levels of corporate social responsibility (CSR) compared to privately-owned firms. This variation is attributed to the incentives provided by the Chinese government to promote social responsibility and the monitoring and control mechanisms it possesses over SOEs.

These government efforts have yielded some positive outcomes. Data from the NBSC (2006) posits that China's overall energy consumption per unit of GDP has decreased by over 45% from 2005 to 2019. Additionally, the adoption of renewable energy sources has significantly increased, with renewable energy accounting for over 16% of total energy consumption in 2019, compared to less than 1% in 2000.

This evolution of China's industrial landscape has been facing rapid growth along with significant environmental challenges. While industrial growth plays a huge role in economic development and improved living standards, it has also resulted in environmental degradation and public health concerns. Thus, as the country moves forward, the government needs to maintain its focus on the negative aspects of industrialization. In addition, corruption and bureaucratic inefficiencies have long been prevalent issues in China, greatly influencing firm behavior in the country. Yang et al. (2021) suggests that corruption negatively affects firm performance by increasing transaction costs and creating an uneven business playing field. Similarly, Duvanova (2014) found that bureaucratic inefficiencies and excessive regulations discourage firms from investing in research and development activities.

3.4 Laws on Cleaner Production

Similar to the earlier environmental regulations, the government's implementation of the law on cleaner production in 2006 in China also highlights the trade-off between environmental regulation and economic development, as evidenced by several studies (Shittu et al., 2021; Koval et al., 2021; Usman et al., 2022). According to the aforementioned literature, such a policy is expected to have positive effects on economic performance as it encourages firms to adopt more efficient and environmentally sustainable production processes. On the other hand, implementing environmental regulations can come with its own challenges, especially for industries with higher environmental impacts such as industries related to the metallurgical or mining sector. These industries may also face higher compliance costs and they may be reluctant to make adjustments to their operations. To address these issues, the Chinese government has implemented a range of policies by providing incentives to firms to improve energy efficiency, renewable energy investments, as well as low-carbon development. These policies include measures such as subsidies, emissions trading schemes, and energy efficiency standards for buildings and appliances(Ren et al., 2018).

The transition to a low-carbon or low-emission economy also requires significant investments in new technologies and infrastructure, particularly in the renewable energy and energy efficiency sectors (Lin and Jia, 2020). However, traditional industries which rely on coal, steel, and cement industries may face challenges during this transition, with them experiencing declining demand as the country adopts cleaner forms of energy production (Yuan et al., 2018). As a result, significant restructuring may be required with significant social and economic implications.

China's law concerning cleaner production primarily focuses on reducing emissions of gases and particulate matter to enhance air quality and towards reducing environmental pollution. The Chinese government has implemented various regulations and standards to address this issue. For example, the Law on the Prevention and Control of Air Pollution requires industries to control emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), volatile organic compounds (VOCs), and particulate matter (PM). By applying hard quantitative limits, this law promotes the adoption of cleaner technologies and practices(Mol and Liu, 2005). Furthermore, amendments have been introduced to this law for different sectors. In the energy sector, the Air Pollution Prevention and Control Action Plan added in 2015 requires coal-operated power plants to install newer and advanced emission control technologies to reduce emissions of sulfur dioxide, nitrogen oxide, and particulate matter (Fang and Côté, 2005). Similarly, the plan for the Prevention and Control of Solid Waste Pollution promotes amended 2017 sets emission standards for industries to reduce the release of harmful gases and particulate matter(Guo et al., 2021; Zhou et al., 2019).

3.5 Empirical Analysis

3.5.1 Data Sources

We use the firm-specific data obtained from the Chinese National Bureau of Statistics (NBSC). The dataset includes the balance sheets for all industrial firms with annual revenues exceeding 5 million RMB and covers more than 88% of the total industrial output from 1998 to 2013. The final sample used in the study consists of 684,125 firms belonging to 421 four-digit CIC (Chinese Industry Classification) manufacturing industries.

The county-level data used in this study is also obtained from NBSC and is accessible through Open China Data Online (2021). The summary statistics for the variables associated with the firms' behavior are provided in Table 3.1. Our analysis reveals that all county-level variables are statistically correlated with long-run investment, although their economic significance is relatively low. This issue is further explored in the estimation section.

The pollution and industrial emission data is sourced from the CHAP (China High Air Pollutants) dataset, which is maintained by Wei et al. (2021). The CHAP dataset is a comprehensive and high-quality collection of ground-level air pollutant data in China. It is generated using a combination of various data sources, including ground-based measurements, satellite remote sensing products, atmospheric reanalysis, and model simulations. The dataset takes into account the spatiotemporal heterogeneity of air pollution and provides information on seven major air pollutants, $PM_{2.5}$ chemical composition, and ambient polycyclic aromatic hydrocarbons (PAHs), including seven carcinogenic PAHs.

In our sensitivity analysis, we utilize the industrial pollution index, as explained in Qian et al. (2022). This index allows us to examine the relationship between industrial emissions and environmental regulations, providing additional insights into the effectiveness of the law on cleaner production in mitigating pollution and promoting sustainable development. By incorporating this data into our analysis, we are able to strengthen the robustness of our findings and further validate the implications of the law on cleaner production in China.

3.5.2 Methodology

Before we design the regression framework, there are some key aspects that we need to keep in mind. While analyzing the impact of this law, some firms may need more time to adjust their operation owing to their size and their nature. Thus, the effect of the law may not be visible right after the implementation. In such cases where the implementation of a law or a policy change lacks a clear pre- and post-treatment period, the synthetic DID approach can be a valuable methodological tool. Although the law came into effect at the beginning of 2006, the impact will be different within different industries. We use synthetic difference-in-differneces(DID) following Arkhangelsky et al. (2021) which allows us to create a counterfactual scenario by constructing a comparison group that closely resembles the treated group in terms of observable characteristics.

Building a synthetic control group allows us to simulate a counterfactual that approximates what would have happened to the treatment group before the law is passed. This method also takes into account the lack of a clear pre and post-treatment period by using data from similar counties where the implementation of the law was not stringent. The stringency of the law can be approximated by the county's budget proportion allocated towards environmental management and control. When counties allocate a larger budget proportion towards environmental management, they provide a higher level of commitment and emphasis on enforcing environmental regulations. This increased budget allocation then allows the counties to increase their monitoring capabilities, such as conducting regular inspections, implementing stricter enforcement measures etc. As a result, counties with higher budget allocations towards environmental regulation are likely to exhibit higher levels of monitoring stringency. This relationship between budget allocation and monitoring stringency underscores the importance of financial resources in enabling effective enforcement and compliance with environmental laws (Qi and Zhang, 2014). Thus, our treatment group comprises of the counties in the top 50 percentile with respect to the budget spent towards environmental management, whereas the control group comprises of the counties in the lower 50 percentile.

We construct the synthetic control group by selecting a weighted combination of control units that best matches the treated unit's pre-treatment characteristics and trends(Arkhangelsky et al., 2021). In constructing the synthetic control group, we assign the weights based on county-specific variables. We standardize the outcome variable and covariates, including GDP, employment rate, fiscal balance, and distance from the coast. We estimate pre-treatment trends and calculate weights by comparing the kernel density of the control variables, after ensuring that control units closely match the treatment unit's characteristics. We run balance tests to address any imbalances between the covariates. Following Arkhangelsky et al. (2021), these steps allowed us to construct a synthetic control group that closely resembled the treated unit, which allows a robust comparison of the treatment effect on firm behavior across counties. However, it is important to acknowledge the limitations and potential disadvantages of this approach. Constructing a synthetic control group relies on the assumption that the selected control units are comparable to the treatment units in all relevant aspects except for the treatment itself. Additionally, the synthetic control group may not perfectly capture unobserved factors or characteristics of the treatment unit, which can introduce bias in the estimation results. To account for this, we conduct a balance test on the relevant covariates to examine any underlying differences between the treatment and control groups. As we can see in Figure 3.2, the density plot of the treatment and control variables follows a similar distribution[1].

[1] All covariates display a statistically insignificant difference at $\alpha = 0.1$.

$$Y_{ct} = \alpha + \beta \text{Treatment}_c \text{Post}_t + \gamma_{\text{X}ct} + \ldots + \delta_c + \lambda_t + \sum_{k=1}^{K} \omega_k X_{ckt} + \epsilon_{ct} \qquad (3.1)$$

In the above equation, the dependent variable is the ratio of the long-term investments and the total market valuation of all the publicly listed firms in county c. The term Treatment_c indicates whether county c belongs to the treatment group, and Post_t indicates whether the time period t is before or after 2005 (the passing of the law). The counties in the treatment group belong to the top 50 percentile in the amount of budget allocated towards environmental management.

In the regression analysis, we incorporate several control variables to account for factors that may influence the average long-term investment by firms in a given county. These control variables are listed as follows:

The county's gross domestic product (GDP), serves as a measure of the region's economic activity. A higher GDP implies a potentially more conducive business environment, which could encourage greater long-term investment. Employment rate, which captures the within-county labor market. A higher employment rate can potentially attract firms to invest in the county for access to skilled workers. The fiscal balance of the county reflects its financial stability. A favorable fiscal balance may indicate a lower tax burden or higher public investment, which can positively affect long-term investment decisions. We also consider the distance of the county from the coastline. Coastal proximity can influence investment due to varying accessibility to international markets.

Furthermore, the equation incorporates county-specific (δ_c) and time-specific weights (λ_t) to control for unobserved heterogeneity across counties and time periods. The error term ϵ_{ct} represents the residual, accounting for the unexplained variation in the outcome variable.

3.6 Results

In Table 3.2, we see that both the treatment and control groups experienced a decrease in investments after the implementation of the law started in 2006. Our findings in column (4) demonstrate that the long-term firm investment in the treatment group decreased by 0.42% (from an average of 15.23% to 14.89%), while that in matched control group counties increased by 1.9% (from 15.91% to 16.85%). The decrease in investment was higher in magnitude as well as statistical significance in the treatment group. Regarding the economic effect, counties with stricter law enforcement(treatment group) witnessed an increase in investments of 41.63 million yuan after the policy, accounting for 32% of the average investment amount of 94.11 million yuan in the treatment group during the sample period[2]. As for the matched private firms, the change in investment amount was 20.24 million yuan, representing 21.51% of the group mean. Additionally, there was no statistically significant difference in investments between the treated and control groups prior to the policy, supporting the assumption of parallel trends as seen in Figure 3.1. Specifically, in counties with higher levels of implementation, a significant decrease in the investment ratio is observed. This indicates that firms in these counties adjusted their investment levels, potentially due to the increased compliance costs associated with environmental regulations. This decline in the investment ratio points toward a cautious approach taken by firms as they prefer to balance their assets and liabilities while at the same time adapt to the new regulatory environment.

For counties with lower levels of environmental monitoring(control group), we observe an increase in the long-term investment-to-market capitalization ratio. This suggests that firms in these counties may have capitalized on the comparatively lenient enforcement and lower compliance costs to invest more in their long-term capital projects.

[2] The LCU values are adjusted to the base price level of 2005 using a GDP deflator

Because these counties have not allocated a higher budget towards environmental management, it provides the firms an avenue to circumvent the implementation of the law. It also provides evidence of firms strategically relocating their operations within the country to optimize their investment decisions in response to varying regulatory environments.

Furthermore, we examine the impact of the law on cleaner production on pollution levels by using the industrial pollution index as the dependent variable. Tables 3.4 and 3.5 show that the implementation of the environmental law did not lead to statistically significant reductions in pollution. It is important to acknowledge that pollution is a multifaceted variable influenced by a variety of factors beyond the emissions of manufacturing firms alone. Other contributors to pollution levels, such as transportation emissions, agricultural operations, and energy production may also play significant roles. Therefore, we are not focusing on the absence of a statistically significant change in pollution, as it may be due to the influence of these additional factors rather than solely the operations of the manufacturing firms.

To sum up, our results show a decrease in the long-term investment-to-market capitalization ratio for counties with higher levels of environmental law implementation, pointing towards the firms' cautious response to increased compliance costs, or, potential costs in research and development. The increase in the investment ratio for counties with lower monitoring levels also suggests the firms' ability to adapt their investment strategies within the country. The decrease in investment in high-monitored counties and the increase in low-monitored counties after the implementation of the law can be associated, in part, to the dynamics of firm behavior. In the treatment group, stricter enforcement and monitoring lead to a higher likelihood of identifying and penalizing non-compliant firms. In addition, some firms may opt to reduce their investments or exit the market to avoid potential penalties or compliance burdens. This hypothesis cannot be fully tested as we lack the data on a firm level across our entire panel. On the other hand, in low-monitored counties, the relatively weaker enforcement may have attracted new firms or encouraged existing ones to expand their operations, leading to an increase in investment.

3.7 Sensitivity Analysis

To assess the validity and reliability of our results, we conduct a series of sensitivity tests. First, in addition to the weights assigned in the SDID framework, we use the Propensity Score Matching(PSM) model to match the treatment and control groups. We also vary the bandwidth selection in the PSM model. The results consistently showed a significant and negative treatment effect on the long-term investment-to-market capitalization ratio, supporting the results of our main findings. These results are provided in Appendix Table 3.A3.

Furthermore, we conduct alternative specifications in the Synthetic DID approach. First, we carry a falsification test by changing the treatment cutoff to 2004, one year before the law's implementation. Since the law hasn't been passed yet, we should not see any significance in our results. As can be seen in 3.6, we observe no significant change in firms' investment behavior. Also, we explore different control groups consisting of counties with similar characteristics but no exposure to environmental law. The consistent findings across these specifications provide additional support for the robustness of our results. When we shift the treatment year to 2006 and 2007, we observed statistical significance one year after the law's implementation, but the effect diminished after two years. This suggests that some firms required additional time to adjust their behavior in response to the law. Detailed results can be found in Tables 3.7 and 3.8.

In order to further test the sensitivity of our findings, we ran industry-level regressions to check for any unobserved variation within the counties using the 4-digit CIC code. This approach allowed us to explore whether specific industries are driving the observed effects. The results of these analyses are presented in Table 3.10. Importantly, we find consistent effects across industries when controlling for industry-fixed effects. This indicates that the implementation of the law has a significant impact on investment behavior within various sectors, further supporting our earlier findings. Specifically, we also do not observe a specific group of industries that consistently drives the results in a particular direction.

Our robustness tests support the consistency and reliability of our findings regarding the impact of the law on the long-term investment-to-market capitalization ratio. These results provide strong evidence for the validity of our main findings.

3.8 Conclusion

In this chapter, we study the impact of the law passed in 2005 by the Chinese government on the firms' behavior. After carrying out a regression analysis on the county level with the SDID framework, we find significant evidence that the firms adjust their investment behavior after the law is implemented.

In our baseline regression framework, we find that after the law was implemented, counties with higher levels of implementation and monitoring, i.e. the counties with a higher budget allocation towards environmental control experienced an overall reduction in the long-term investment to market cap ratio. On the other hand, the counties with lower levels of environmental monitoring saw a slight increase in the investment to market cap ratio in the firms. These results point directly towards the overall effectiveness of the law. If the firms reduce their long-term investment in jurisdictions with higher environmental monitoring, then they have found some alternative avenues to circumvent their liabilities. One of the potential channels that can explain this behavior is the movement of the firms across jurisdictions. We also find evidence that highly monitored areas see a reduction in the number of firms after the law is passed.

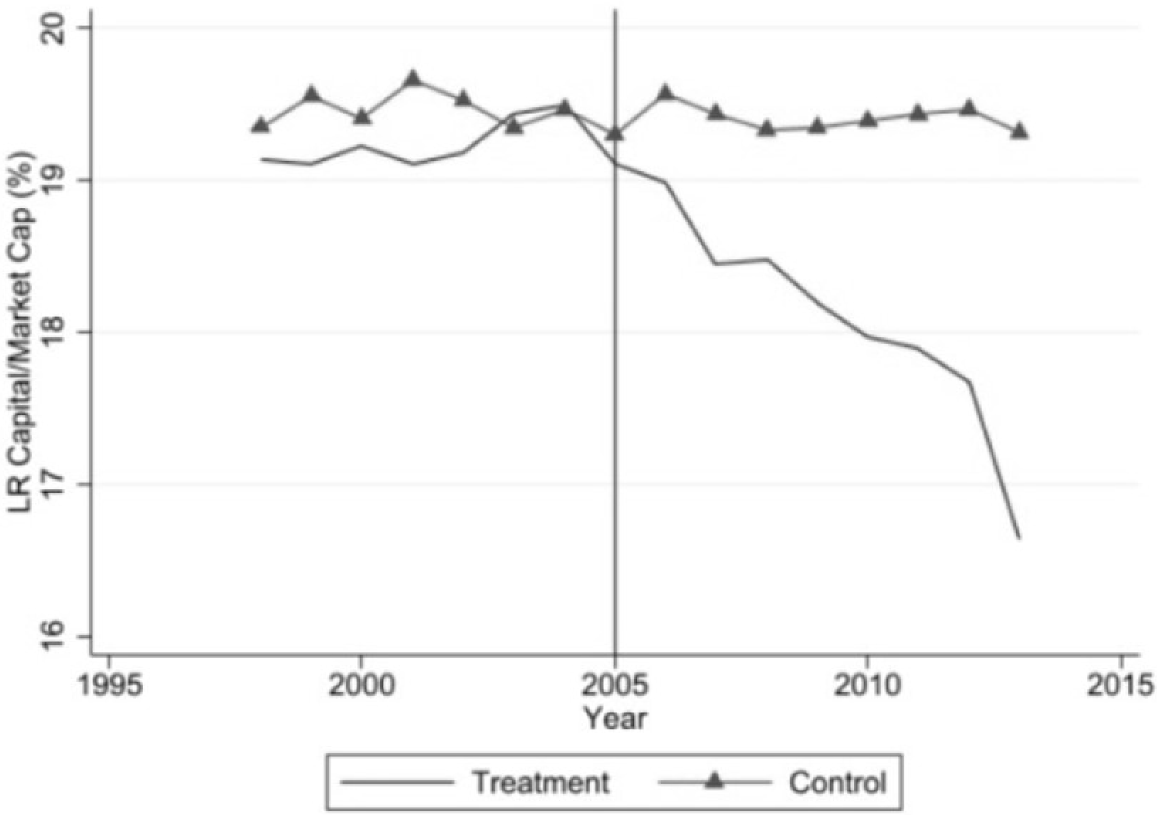
We do not find sufficient evidence regarding the impact of the law on the level of pollution. Since pollution is also caused by the transportation, residential, and agricultural sectors, it is difficult to separate the effect of manufacturing industries owing to data limitations.

These findings have significant policy implications for environmental regulation in China and also for other countries. Policymakers need to be wary of the potential trade-offs between environmental protection and economic development when designing and implementing environmental laws. Additionally, further research is warranted to explore additional factors that may mediate the relationship between environmental regulations and firm behavior, the next step is to study variables such as corruption and see its effect on the firms' behavior to understand the complete picture.

Overall, these findings point toward key policy variables. After a law is passed aiming to protect the environment, the unintended consequence of the law is the adverse trade-off between economic growth and financial profits.

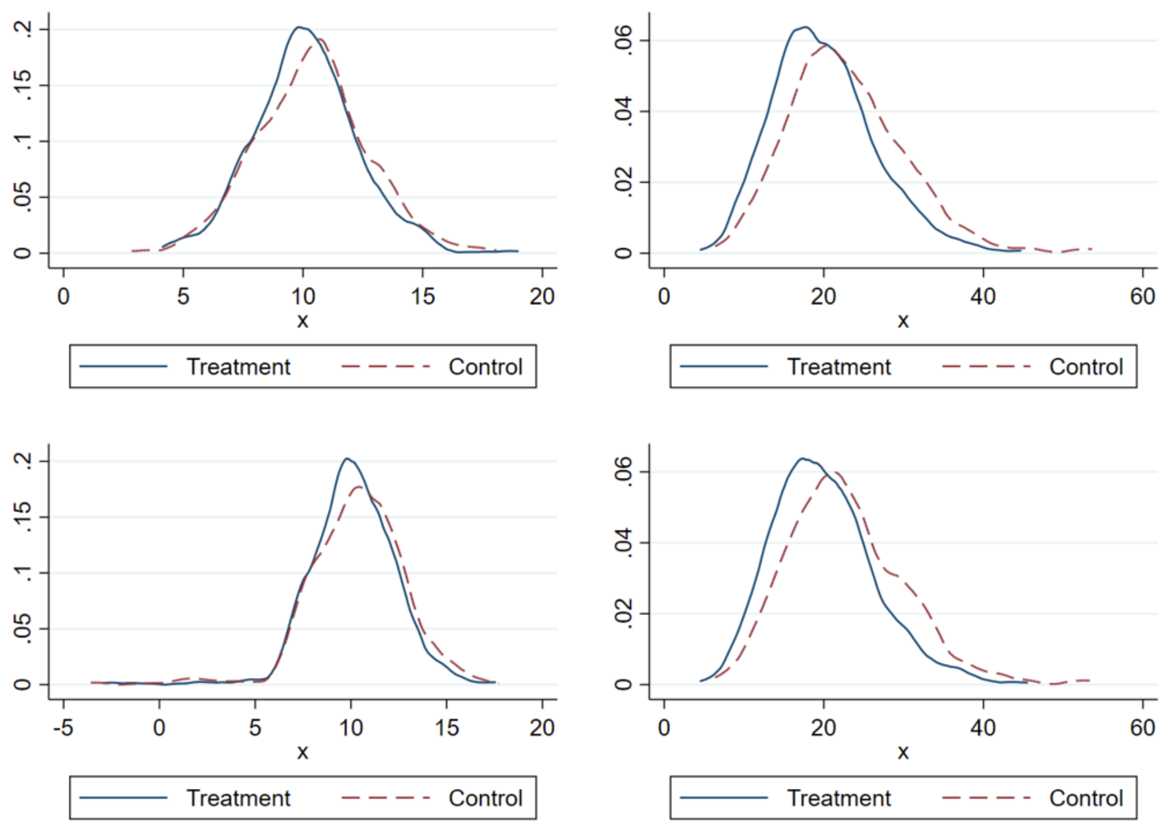
Figures and Tables

Figure 3.1: Evolution of the long-term capital investment in China



Notes: The y-axis denotes the ratio of long-term investments as a percentage of company's market cap. The data are aggregated for each year over the whole country. The data only focuses on manufacturing firms. Source: Author's calculations.

Figure 3.2: Comparison of the treatment and control groups



Notes: The figures compare the Kernel densities of the variables (starting from top-left) fiscal balance, distance from coast, log(GDP), and employment rate for treated and untreated counties. Source: Author's calculations.

Table 3.1: Summary Statistics: Firms

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(Firm Age)	2,315,904	2.344	0.968	0	4.985
ln(Output)	2,315,904	10.612	1.524	0	20.365
ln(Capital per worker)	2,315,904	3.919	1.368	-8.154	11.985
Share of State-Owned-Equity	2,315,904	0.214	0.257	0	1
Real Investment Growth Rate	2,315,904	0.061	0.241	-0.124	1
Liability to Asset Ratio	2,315,904	0.514	0.269	0.009	1.894
Output growth	2,315,904	0.07	0.296	-1.325	1.698
Employment Growth	2,315,904	0.008	0.259	-0.998	0.996
Fixed Investment to GDP Ratio	2,315,904	0.496	0.298	0	2.296
FDI to GDP Ratio	2,315,904	0.947	0.846	0.005	39.154
Fiscal	2,315,904	0.16	0.169	0.002	1
Share of govt expenditure	2,315,904	0.098	0.046	0	0.996
Profits	2,315,904	0.147	0.136	-0.326	0.467

Notes: ln(Output) is measured as log firm total output; ln(Age) is (log) years in operation since the built-up date. ln(Wage) is the log of firms' total wage payment per worker; ln(Capital per worker) is the log of the firm's real capital stock per employee; Investment: real investment growth computed as real capital stock this year minus real capital stock from last year and divided by the mean of real capital stock from both years; Leverage: total liability divided by total assets; Employment: growth of total employment; Output: output growth; Profit is sales profit divided by sales revenue; Finance: a city's financial sales revenue to GDP ratio; Investment: a city's investment in fixed asset to GDP ratio; FDI: a city's foreign direct investment to GDP ratio; Fiscal: county's fiscal balance.

Table 3.2: Baseline SDID Results

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2005	1.734*	1.121	1.877**	1.991**
	(1.389)	(1.925)	(1.057)	(1.297)
Treatment	1.543	1.015*	1.687*	1.813
	(1.781)	(0.932)	(1.249)	(1.902)
Treatment*Post	-2.481**	-3.398*	-2.284**	-2.212**
	(1.567)	(3.079)	(2.016)	(2.569)
Unemployment		-0.047		-0.071*
		(1.178)		(0.034)
ln(GDP)		0.289*		0.353**
		(0.196)		(0.279)
Fiscal Balance		0.179*		0.116**
		(0.213)		(0.096)
Distance to coast		-0.012		0.008*
		(1.309)		(0.003)
FDI Share		0.238*		0.312**
		(0.208)		(0.256)
Constant	2.895*	3.286**	4.372***	3.721***
	(2.048)	(3.023)	(1.389)	(0.598)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,423	18,422	18,321	18,321
R-squared	0.14	0.15	0.19	0.21

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. The estimated coefficients provide insights into the treatment effect, representing changes in the investment ratio associated with the law. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 3.3: Baseline SDID Results: Excluding outliers

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2005	1.813*	1.032	2.009**	1.912**
	(1.319)	(1.876)	(1.095)	(1.318)
Treatment	1.620	1.041*	1.673*	1.817
	(1.836)	(0.904)	(1.245)	(1.986)
Treatment*Post	-2.551**	-3.278*	-2.136**	-2.095**
	(1.529)	(3.043)	(1.964)	(2.491)
Unemployment		-0.053		-0.079*
		(1.215)		(0.040)
ln(GDP)		0.272*		0.331**
		(0.189)		(0.274)
Fiscal Balance		0.167*		0.125**
		(0.225)		(0.108)
Distance to coast		-0.009		0.010*
		(1.279)		(0.005)
FDI Share		0.249*		0.301**
		(0.195)		(0.236)
Constant	2.762*	3.309**	4.247***	3.681***
	(2.112)	(3.013)	(1.387)	(0.609)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,417	18,403	18,210	18,204
R-squared	0.15	0.16	0.20	0.22

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. The estimated coefficients provide insights into the treatment effect, representing changes in the investment ratio associated with the law. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 3.4: DID Results: Industrial Pollution Index

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2005	0.659	0.186	0.329	0.184
	(0.538)	(0.268)	(0.298)	(0.138)
Treatment	0.423	0.886*	0.417*	0.736
	(1.665)	(0.184)	(1.487)	(1.259)
Treatment*Post	0.416	0.365	0.487	0.416
	(1.369)	(2.958)	(2.758)	(2.539)
ln(GDP)		0.418		0.628*
		(1.396)		(0.529)
Distance to coast		-0.419		0.958*
		(1.428)		(0.857)
FDI Share		0.429*		0.598**
		(0.358)		(0.284)
Constant	2.444*	3.325**	4.418***	3.325***
	(2.311)	(2.477)	(1.344)	(0.328)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,420	18,418	18,254	18,254
R-squared	0.12	0.17	0.16	0.19

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the industrial pollution index at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. The estimated coefficients provide insights into the treatment effect, representing changes in the investment ratio associated with the law. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 3.5: DID Results: Industrial Pollution Index (No outliers)

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2005	0.569*	0.198	0.269	0.146
	(0.536)	(0.476)	(0.193)	(0.142)
Treatment	0.268	0.264	0.358	0.688
	(1.298)	(0.209)	(1.239)	(1.118)
Treatment*Post	0.322	0.268	0.623	0.422
	(1.299)	(2.487)	(2.539)	(2.847)
ln(GDP)		0.263		0.887
		(1.009)		(0.711)
Distance to coast		-0.039		0.429*
		(1.589)		(0.478)
FDI Share		0.287		0.477
		(0.398)		(0.487)
Constant	2.258	3.547	4.638	3.428
	(2.425)	(2.298)	(1.851)	(0.389)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,314	18,314	18,178	18,177
R-squared	0.13	0.14	0.14	0.17

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the industrial pollution index at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. The estimated coefficients provide insights into the treatment effect, representing changes in the investment ratio associated with the law. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 3.6: Falsification Tests

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2003	1.498	1.312	2.013	1.830
	(1.147)	(1.698)	(1.057)	(1.297)
Treatment	1.768	1.057	1.596	1.735
	(1.925)	(0.798)	(1.249)	(1.002)
Treatment*Post	-2.730	-3.147	-3.107	-3.140
	(1.698)	(2.968)	(2.016)	(2.569)
Unemployment		0.032		-0.047
		(1.235)		(0.034)
Distance to coast		0.078		-0.040
		(1.254)		(0.004)
FDI Share		0.169		0.364
		(0.200)		(0.241)
Constant	2.689*	3.165**	4.187***	3.698***
	(2.157)	(2.977)	(1.421)	(0.627)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,423	18,422	18,321	18,321
R-squared	0.12	0.14	0.18	0.20

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. The estimated coefficients provide insights into the treatment effect, representing changes in the investment ratio associated with the law. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 3.7: SDID Results: Treatment cutoff after 1 year

	OLS (1)	OLS (2)	FE (3)	FE (4)
Post2006	1.921*	1.156	1.942**	1.853**
	(1.421)	(1.875)	(1.074)	(1.321)
Treatment	1.598	1.042*	1.732*	1.899
	(1.801)	(0.922)	(1.215)	(1.961)
Treatment*Post	-2.459**	-3.426*	-2.319**	-2.171**
	(1.502)	(3.045)	(1.939)	(2.516)
Unemployment		-0.051		-0.077*
		(1.195)		(0.037)
ln(GDP)		0.311*		0.337**
		(0.189)		(0.267)
Fiscal Balance		0.187*		0.129**
		(0.221)		(0.103)
Distance to coast		-0.011		0.009*
		(1.273)		(0.005)
FDI Share		0.254*		0.295**
		(0.205)		(0.249)
Constant	2.942*	3.271**	4.409***	3.712***
	(2.082)	(3.027)	(1.377)	(0.581)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,423	18,422	18,321	18,321
R-squared	0.16	0.17	0.21	0.23

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. The treatment cut-off does not start until one year after the implementation of the law. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 3.8: SDID Results: Treatment cutoff after 2 years

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2007	1.789*	1.189	1.823**	1.936**
	(1.421)	(1.989)	(1.096)	(1.315)
Treatment	1.512	1.065*	1.678*	1.842
	(1.791)	(0.945)	(1.271)	(1.972)
Treatment*Post	-2.604**	-3.349*	-2.224**	-2.133**
	(1.536)	(2.994)	(2.009)	(2.485)
Unemployment		-0.059		-0.083*
		(1.163)		(0.039)
ln(GDP)		0.295*		0.327**
		(0.205)		(0.283)
Fiscal Balance		0.201*		0.119**
		(0.209)		(0.095)
Distance to coast		-0.014		0.007*
		(1.293)		(0.006)
FDI Share		0.228*		0.301**
		(0.198)		(0.242)
Constant	2.743*	3.288**	4.331***	3.705***
	(2.108)	(2.987)	(1.374)	(0.596)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,423	18,422	18,321	18,321
R-squared	0.17	0.18	0.22	0.24

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the county level. The treatment group consists of counties with high levels of law implementation, while the control group comprises counties with low levels. The treatment cut-off does not start until two years after the implementation of the law. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the county level. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 3.9: SDID Results: Industry level regressions

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2005	2.102*	1.032	1.745**	1.901**
	(1.568)	(2.098)	(1.149)	(1.421)
Treatment	1.679	0.982*	1.738*	1.864
	(1.902)	(0.874)	(1.193)	(1.852)
Treatment*Post	-2.875**	-3.457*	-2.457**	-2.216**
	(1.714)	(3.202)	(2.093)	(2.589)
Unemployment		-0.065		-0.087*
		(1.146)		(0.042)
ln(GDP)		0.342*		0.389**
		(0.215)		(0.305)
Fiscal Balance		0.214*		0.126**
		(0.239)		(0.112)
Distance to coast		-0.019		0.006*
		(1.298)		(0.007)
FDI Share		0.185*		0.284**
		(0.192)		(0.228)
Constant	2.589*	3.311**	4.453***	3.694***
	(2.267)	(2.978)	(1.412)	(0.621)
Year weights			Yes	Yes
Industry weights			Yes	Yes
Observations	231,459	231,458	230,356	230,356
R-squared	0.18	0.19	0.23	0.25

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the industry level. The treatment group consists of industries in areas with high levels of law implementation, while the control group comprises industries with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the industry level. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 3.10: SDID Results: Number of Industries

	OLS (1)	OLS (2)	FE (3)	FE (4)
Post2005	3.250*	1.575	2.890**	2.450**
	(2.413)	(3.217)	(1.767)	(2.183)
Treatment	2.310	1.350*	2.400*	2.630
	(2.733)	(1.256)	(1.710)	(2.652)
Treatment*Post	-3.620**	-4.360*	-3.910**	-3.520**
	(2.570)	(4.803)	(2.485)	(3.079)
Unemployment		-0.090		-0.120*
		(1.586)		(0.058)
ln(GDP)		0.480*		0.550**
		(0.301)		(0.427)
Fiscal Balance		0.400*		0.250**
		(0.447)		(0.210)
Distance to coast		-0.038		0.012*
		(2.097)		(0.009)
FDI Share		0.320*		0.480**
		(0.336)		(0.399)
Constant	3.800*	4.500**	5.900***	4.800***
	(3.350)	(4.400)	(2.100)	(0.930)
Year weights			Yes	Yes
Industry weights			Yes	Yes
Observations	231,459	231,458	230,356	230,356
R-squared	0.18	0.19	0.23	0.25

Notes: The regression table employs a synthetic Difference-in-Differences (DID) approach to examine the impact of the environmental law on the average long-term investment to market capitalization ratio at the industry level. The treatment group consists of industries in areas with high levels of law implementation, while the control group comprises industries with low levels. Control variables, including GDP, employment rate, fiscal balance, and distance from the coast, are included to mitigate confounding effects. Robust standard errors are clustered at the industry level. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Bibliography

Aggarwal, P. (1991), 'Estimation of the optimal duration of wheat crops in rice-wheat cropping systems by crop growth simulation', *Simulation and systems analysis for rice production (SARP), PUDOC, Wageningen, The Netherlands* pp. 3–10.

Aldenhoff, F.-O. (2007), 'Are economic forecasts of the international monetary fund politically biased? a public choice analysis', *The Review of International Organizations* **2**(3), 239–260.

Almond, D. and Currie, J. (2011), 'Killing me softly: The fetal origins hypothesis', *Journal of economic perspectives* **25**(3), 153–72.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S. (2021), 'Synthetic difference-in-differences', *American Economic Review* **111**(12), 4088–4118.

Arora, R. U. (2012), 'Gender inequality, economic development, and globalization: A state level analysis of india', *The Journal of Developing Areas* pp. 147–164.

Artis, M. and Marcellino, M. (2001), 'Fiscal forecasting: The track record of the imf, oecd and ec', *The Econometrics Journal* **4**(1), 20–36.

Babb, S. L. and Carruthers, B. G. (2008), 'Conditionality: forms, function, and history', *Annual Review of Law and Social Science* **4**, 13–29.

Bailey, M., Strezhnev, A. and Voeten, E. (2017), 'Estimating dynamic state preferences from un voting data', *Journal of Conflict Resolution* **61**(2), 430–456.

Bao, M. (2004), 'Environmental history in china', *Environment and History* **10**(4), 475–499.
URL: *http://www.jstor.org/stable/20723506*

Barker, D. K. (2018), 'The real wolves of wall street: Examining debt, austerity, and accountability through the lens of primitive accumulation', *International Critical Thought* **8**(4), 535–552.

Batchelor, R. (2001), 'How useful are the forecasts of intergovernmental agencies? the imf and oecd versus the consensus', *Applied Economics* **33**(2), 225–235.

Bazzi, S. and Clemens, M. A. (2013), 'Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth', *American Economic Journal: Macroeconomics* **5**(2), 152–186.

Beazer, Q. H. and Woo, B. (2016), 'Imf conditionality, government partisanship, and the progress of economic reforms', *American Journal of Political Science* **60**(2), 304–321.

Best, J. (2012), 'Ambiguity and uncertainty in international organizations: A history of debating imf conditionality', *International Studies Quarterly* **56**(4), 674–688.

Beyer, S. (2006), 'Environmental law and policy in the people's republic of china', *Chinese journal of international law* **5**(1), 185–211.

Bird, G. et al. (2001), 'Imf programmes: Is there a conditionality laffer curve?', *World Economics* **2**(2), 29–49.

Bird, G. et al. (2009), 'Reforming imf conditionality', *World Economics* **10**(3), 81–104.

Blanchard, O. J. and Leigh, D. (2013), 'Growth forecast errors and fiscal multipliers', *American Economic Review* **103**(3), 117–120.

Boughton, M. J. M. (2012), *Tearing down walls: the international monetary fund 1990-1999*, International monetary fund.

Bradbury, I., Kirkby, R. and Guanbao, S. (1996), 'Development and environment: the case of rural industrialization and small-town growth in china', *Ambio* pp. 204–209.

Casper, B. A. (2017), 'Imf programs and the risk of a coup d'état', *Journal of Conflict Resolution* **61**(5), 964–996.

Cerra, V. and Saxena, S. C. (2008), 'Growth dynamics: the myth of economic recovery', *American Economic Review* **98**(1), 439–457.

Chang, H.-J. (2006), 'Policy space in historical perspective with special reference to trade and industrial policies', *Economic and Political Weekly* **41**(7), 627–633.

Chapman, T., Pickford, S., Tonks, I. and Yun, K.-Y. (2017), 'Mixed signals: Imf lending and capital markets', *British Journal of Political Science* **47**(2), 329–349.

Chintala, S. R., Jha, C., Diwakar, P. and Dadhwal, V. (2015), 'Nationwide classification of forest types of india using remote sensing and gis', *Environmental Monitoring and Assessment* **187**.

Crivelli, E. and Gupta, S. (2016), 'Does conditionality in imf-supported programs promote revenue reform?', *International Tax and Public Finance* **23**, 550–579.

De Resende, C. (2014), ‘An assessment of imf medium-term forecasts of gdp growth’, *IEO Background Paper No. BP/14/01 (Washington: Independent Evaluation Office of the IMF)* .

Deng, Y. and Yang, G. (2013), ‘Pollution and protest in china: Environmental mobilization in context’, *The China Quarterly* **214**, 321–336.

Desai, S. and Vanneman, R. (2015), ‘India human development survey-ii (ihds-ii), 2011-12’, *ICPSR36151-v2. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]* **31**.

Dhar, O. and Nandargi, S. (2003), ‘Hydrometeorological aspects of floods in india’, *Natural Hazards* **28**(1), 1–33.

Dreher, A. (2006), ‘Imf and economic growth: The effects of programs, loans, and compliance with conditionality’, *World Development* **34**(5), 769–788.

Dreher, A. and Gassebner, M. (2012), ‘Do imf and world bank programs induce government crises? an empirical analysis’, *International Organization* **66**(2), 329–358.

Dreher, A., Marchesi, S. and Vreeland, J. R. (2008), ‘The political economy of imf forecasts’, *Public Choice* **137**, 145–171.

Dreher, A., Sturm, J.-E. and Vreeland, J. R. (2015), ‘Politics and imf conditionality’, *Journal of Conflict Resolution* **59**(1), 120–148.

Dreher, A. and Vaubel, R. (2004), ‘The causes and consequences of imf conditionality’, *Emerging Markets Finance and Trade* **40**(3), 26–54.

Dreher, A. and Walter, S. (2010), ‘Does the imf help or hurt? the effect of imf programs on the likelihood and outcome of currency crises’, *World Development* **38**, 1–18.

Duvanova, D. (2014), ‘Economic regulations, red tape, and bureaucratic corruption in post-communist economies’, *World Development* **59**, 298–312.

Easterly, W. (2005), ‘What did structural adjustment adjust? the association of policies and growth with repeated imf and world bank adjustment loans’, *Journal of Development Economics* **76**(1), 1–22.

Edwards, M. S. and Senger, S. (2015), ‘Listening to advice: Assessing the external impact of imf article iv consultations of the united states, 2010–2011’, *International Studies Perspectives* **16**(3), 312–326.

Eichengreen, B. and Woods, N. (2016), ‘The imf’s unmet challenges’, *Journal of Economic Perspectives* **30**(1), 29–52.

Eta, A. E. and Anabori, M. B. (2015), 'Financial sector reforms and economic growth in nigeria', *International Journal of Economics, Commerce and Management* **3**(9), 150–171.

Fang, Y. and Côté, R. P. (2005), 'Towards sustainability: Objectives, strategies and barriers for cleaner production in china', *The International Journal of Sustainable Development & World Ecology* **12**(4), 443–460.

Faruqee, M. H. and Isard, M. P. (1998), *Exchange rate assessment: extension of the macroeconomic balance approach*, International monetary fund.

Feenstra, R., Hong, C., Ma, H. and Spencer, B. (2013), 'Contractual versus non-contractual trade: The role of institutions in china', *Journal of Economic Behavior & Organization* **94**, 281–294.

Fisher-Vanden, K., Jefferson, G. H., Jingkui, M. and Jianyi, X. (2006), 'Technology development and energy productivity in china', *Energy Economics* **28**(5-6), 690–705.

Flatø, M. and Kotsadam, A. (2014), Droughts and gender bias in infant mortality in sub-saharan africa, Technical report, Memorandum.

Forster, T., Kentikelenis, A. E., Reinsberg, B., Stubbs, T. H. and King, L. P. (2019), 'How structural adjustment programs affect inequality: A disaggregated analysis of imf conditionality, 1980-2014', *Social Science Research* **80**, 83–113.

Frieden, J. and Broz, J. L. (2012), 'The political economy of international monetary policy coordination', *The Encyclopedia of Financial Globalization, Gerard Caprio, ed., Elsevier Publishing Inc* .

Fund, I. M. (2020), *World Economic Outlook, April 2020: The Great Lockdown*, International Monetary Fund.

Gadgil, S. (1989), Monsoon variability and its relationship to agricultural strategies, *in* 'International symposium on climate variability and food security in developing countries', pp. 249–267.

Garg, T., Jagnani, M. and Taraz, V. (2020), 'Temperature and human capital in india', *Journal of the Association of Environmental and Resource Economists* **7**(6), 1113–1150.

Genberg, H. and Martinez, A. (2014), 'On the accuracy and efficiency of imf forecasts: A survey and some extensions', *IEO Background Paper No. BP/14/04 (Washington: Independent Evaluation Office of the IMF)* .

Genberg, H., Martinez, A. and Salemi, M. (2014), 'The imf/weo forecast process', *IEO Background Paper No. BP/14/03 (Washington: Independent Evaluation Office of the IMF)* .

Glewwe, P., Jacoby, H. G. and King, E. M. (2001), 'Early childhood nutrition and academic achievement: a longitudinal analysis', *Journal of public economics* **81**(3), 345–368.

Graham, C. and Masson, P. (2003), 'Between politics and economics: The imf and argentina', *Current History* **102**(661), 72–76.

Gregory, P. J., Ingram, J. S. and Brklacich, M. (2005), 'Climate change and food security', *Philosophical Transactions of the Royal Society B: Biological Sciences* **360**(1463), 2139–2148.

Guo, W., Xi, B., Huang, C., Li, J., Tang, Z., Li, W., Ma, C. and Wu, W. (2021), 'Solid waste management in china: Policy and driving factors in 2004–2019', *Resources, Conservation and Recycling* **173**, 105727.

Gurditta, H. and Singh, G. (2016), 'Climate change, food and nutritional security: Issues and concerns in india', *Journal of Climate Change* **2**(1), 79–89.

Hoeppe, P. (2016), 'Trends in weather related disasters–consequences for insurers and society', *Weather and climate extremes* **11**, 70–79.

Hutchinson, J. B. (1976), 'India: local and introduced crops', *Philosophical Transactions of the Royal Society of London. B, Biological Sciences* **275**(936), 129–141.

IMF (2019), 'Imf annual report 2019 - international monetary fund'.
URL: *https://www.imf.org/external/pubs/ft/ar/2019/eng/assets/pdf/imf-annual-report-2019.pdf*

International Monetary Fund (2019), 'Imf conditionality'. Accessed on February 5, 2019. https://www.imf.org/en/About/Factsheets/Sheets/2016/08/02/21/28/IMFConditionality.

Johnson, R. C. and Schoeni, R. F. (2007), 'Early-life origins of adult disease: the significance of poor infant health and childhood poverty', *UC Berkeley Unpublished Manuscript* pp. 1–42.

Kentikelenis, A. and Stubbs, T. (2023), *A thousand cuts: Social protection in the age of austerity*, Oxford University Press. downloaded in March 2019.

Kentikelenis, A., Stubbs, T. and King, L. (2016), 'Imf conditionality and development policy space, 1985-2014', *Review of International Political Economy* **23**(3), 543–582.

Kern, A., Reinsberg, B. and Rau-Göhring, M. (2019), 'Imf conditionality and central bank independence', *European Journal of Political Economy* **59**, 212–229.

Khanam, R., Nghiem, H. S. and Rahman, M. M. (2011), 'The impact of childhood malnutrition on schooling: evidence from bangladesh', *Journal of biosocial science* **43**(4), 437–451.

Kirchberger, M. (2017), 'Natural disasters and labor markets', *Journal of Development Economics* **125**, 40–58.

Kose, M. A., Otrok, C. and Whiteman, C. H. (2008), 'Understanding the evolution of world business cycles', *Journal of international Economics* **75**(1), 110–130.

Koval, V., Mikhno, I., Udovychenko, I., Gordiichuk, Y. and Kalina, I. (2021), 'Sustainable natural resource management to ensure strategic environmental development', *TEM Journal* **10**(3), 1022.

Lang, G. and Xu, Y. (2013), 'Anti-incinerator campaigns and the evolution of protest politics in china', *Environmental Politics* **22**(5), 832–848.

Lang, V. (2021), 'The economics of the democratic deficit: The effect of imf programs on inequality', *The Review of International Organizations* **16**(3), 599–623.

Levine, D. I. and Yang, D. (2006), 'A note on the impact of local rainfall on rice output in indonesian districts'.

Li, L. and Taeihagh, A. (2020), 'An in-depth analysis of the evolution of the policy mix for the sustainable energy transition in china from 1981 to 2020', *Applied Energy* **263**, 114611.

Li, Y., Zhou, S., Jia, Z., Ge, L., Mei, L., Sui, X., Wang, X., Li, B., Wang, J. and Wu, S. (2018), 'Influence of industrialization and environmental protection on environmental pollution: a case study of taihu lake, china', *International journal of environmental research and public health* **15**(12), 2628.

Lin, B. and Jia, Z. (2020), 'Is emission trading scheme an opportunity for renewable energy in china? a perspective of ets revenue redistributions', *Applied Energy* **263**, 114605.

Lindhjem, H., Hu, T., Ma, Z., Skjelvik, J. M., Song, G., Vennemo, H., Wu, J. and Zhang, S. (2007), 'Environmental economic impact assessment in china: Problems and prospects', *Environmental Impact Assessment Review* **27**(1), 1–25.

Liu, X. and Bae, J. (2018), 'Urbanization and industrialization impact of co2 emissions in china', *Journal of cleaner production* **172**, 178–186.

Lo, C. W.-H., Fryxell, G. E., van Rooij, B., Wang, W. and Li, P. H. (2012), 'Explaining the enforcement gap in china: Local government support and internal agency obstacles as predictors of enforcement actions in guangzhou', *Journal of environmental management* **111**, 227–235.

Maccini, S. and Yang, D. (2009), ‘Under the weather: Health, schooling, and economic consequences of early-life rainfall’, *American Economic Review* **99**(3), 1006–26.

Mall, R., Singh, R., Gupta, A., Srinivasan, G. and Rathore, L. (2006), ‘Impact of climate change on indian agriculture: a review’, *Climatic Change* **78**(2-4), 445–478.

Marchesi, S. and Sabani, L. (2007), ‘Imf concern for reputation and conditional lending failure: theory and empirics’, *Journal of development economics* **84**(2), 640–666.

Merriott, D. (2016), ‘Factors associated with the farmer suicide crisis in india’, *Journal of epidemiology and global health* **6**(4), 217–227.

Mol, A. P. and Liu, Y. (2005), ‘Institutionalising cleaner production in china: the cleaner production promotion law’, *International Journal of Environment and Sustainable Development* **4**(3), 227–245.

Moosa, I. A., Moosa, N., Moosa, I. A. and Moosa, N. (2019), ‘The imf as an instigator of riots and civil unrest’, *Eliminating the IMF: An Analysis of the Debate to Keep, Reform or Abolish the Fund* pp. 89–110.

Mu, Z., Bu, S. and Xue, B. (2014), ‘Environmental legislation in china: Achievements, challenges and trends’, *Sustainability* **6**(12), 8967–8979.

Mushkat, R. (2008), ‘Implementing environmental law in transitional settings: the chinese experience’, *S. Cal. Interdisc. LJ* **18**, 45.

Mwenda, A. and Mutoti, N. (2011), ‘Financial sector reforms, bank performance and economic growth: Evidence from zambia’, *African Development Review* **23**(1), 60–74.

NBSC (2006), ‘National bureau of statistics of china — stats.gov.cn’, http://www.stats.gov.cn/english/. [Accessed 07-Apr-2022].

NICRA, S. (2019), ‘Nicra:’.
URL: *http://www.nicra-icar.in/nicrarevised/index.php/home1*

Noy, I. (2009), ‘The macroeconomic consequences of disasters’, *Journal of Development economics* **88**(2), 221–231.

Nunn, N. and Qian, N. (2014), ‘Us food aid and civil conflict’, *American Economic Review* **104**(6), 1630–1666.

Papi, L., Presbitero, A. F. and Zazzaro, A. (2015), ‘Imf lending and banking crises’, *IMF Economic Review* **63**, 644–691.

Paudel, J. and Ryu, H. (2018), ‘Natural disasters and human capital: The case of nepal’s earthquake’, *World Development* **111**, 1–12.

Paudel, J. and Ryu, H. (2023), '16 spillover effects of natural disasters on human capital', *Behavioural Economics and the Environment: A Research Companion* p. 329.

Pionetti, C. et al. (2006), *Seed diversity in the drylands: Women and farming in south India*, International Institute for Environment and Development.

Prasanna, V. (2014), 'Impact of monsoon rainfall on the total foodgrain yield over india', *Journal of earth system science* **123**(5), 1129–1145.

Przeworski, A. and Vreeland, J. (2000), 'The effect of imf programs on economic growth', *Journal of Development Economics* **62**(2), 385–421.

Qi, Y. and Zhang, L. (2014), 'Local environmental enforcement constrained by central–local relations in china', *Environmental Policy and Governance* **24**(3), 216–232.

Qian, H., Ren, F., Gong, Y., Ma, R., Wei, W. and Wu, L. (2022), 'China industrial environmental database 1998–2015', *Scientific Data* **9**(1), 259.

Rao, C. S., Lal, R., Prasad, J. V., Gopinath, K. A., Singh, R., Jakkula, V. S., Sahrawat, K. L., Venkateswarlu, B., Sikka, A. K. and Virmani, S. M. (2015), 'Potential and challenges of rainfed farming in india', *Advances in agronomy* **133**, 113–181.

Razin, A. and Sadka, E. (2005), *The decline of the welfare state: demography and globalization*, MIT press.

Razvi, M. and Roth, G. L. (2004), 'Socio-economic development and gender inequality in india.', *Online Submission* .

Ren, S., Li, X., Yuan, B., Li, D. and Chen, X. (2018), 'The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in china', *Journal of cleaner production* **173**, 245–255.

Reserve Bank of Australia, c. a. (2018), 'Economic development and agriculture in india: Bulletin – june quarter 2011'.
URL: *https://www.rba.gov.au/publications/bulletin/2011/jun/3.html*

Roodman, D. (2009), Estimating fully observed recursive mixed-process models with cmp, Working Paper 168, Center for Global Development.

Rose, A. K. (2007), 'The foreign service and foreign trade: embassies as export promotion', *World Economy* **30**(1), 22–38.

Ryan, J. G. and Asokan, M. (1977), 'Effect of green revolution in wheat on production of pulses and nutrients in india', *Indian Journal of Agricultural Economics* **32**(3), 8–15.

Sahai, S. (2000), 'Farmers' rights and food security', *Economic and Political Weekly* pp. 878–880.

Schrecker, T. (2016), 'Neoliberalism and health: the linkages and the dangers', *Sociology Compass* **10**(10), 952–971.

Shakya, S., Basnet, S. and Paudel, J. (2022), 'Natural disasters and labor migration: Evidence from nepal's earthquake', *World Development* **151**, 105748.

Sharpe, P. (2012), 'Explaining the short stature of the poor: chronic childhood disease and growth in nineteenth-century england 1', *The Economic History Review* **65**(4), 1475–1494.

Shen, N., Liao, H., Deng, R. and Wang, Q. (2019), 'Different types of environmental regulations and the heterogeneous influence on the environmental total factor productivity: empirical analysis of china's industry', *Journal of Cleaner Production* **211**, 171–184.

Shittu, W., Adedoyin, F. F., Shah, M. I. and Musibau, H. O. (2021), 'An investigation of the nexus between natural resources, environmental performance, energy security and environmental degradation: Evidence from asia', *Resources Policy* **73**, 102227.

Steckel, R. H. (2005), 'Young adult mortality following severe physiological stress in childhood: Skeletal evidence', *Economics & Human Biology* **3**(2), 314–328.

Steinhardt, H. C. and Wu, F. (2016), 'In the name of the public: Environmental protest and the changing landscape of popular contention in china', *The China Journal* **75**(1), 61–82.

Stone, R. W. (2012), *Lending credibility: The International Monetary Fund and the post-communist transition*, Princeton University Press.

Stroup, C. and Zissimos, B. (2013), Social unrest in the wake of imf structural adjustment programs, MIT Press.

Stubbs, T. and Kentikelenis, A. (2018), 'Targeted social safeguards in the age of universal social protection: the imf and health systems of low-income countries', *Critical Public Health* **28**(2), 132–139.

Stubbs, T., Kentikelenis, A., Stuckler, D., McKee, M. and King, L. (2017), 'The impact of imf conditionality on government health expenditure: A cross-national analysis of 16 west african nations', *Social Science & Medicine* **174**, 220–227.

Stubbs, T., Reinsberg, B., Kentikelenis, A. and King, L. (2020), 'How to evaluate the effects of imf conditionality. an extension of quantitative approaches and an empirical application to public education spending', *The Review of International Organizations* **15**, 29–73.

Turnbull, P. et al. (2013), *Promoting the employment of women in the transport sector: Obstacles and policy options*, International Labour Organization (ILO).

Usman, M., Jahanger, A., Makhdum, M. S. A., Balsalobre-Lorente, D. and Bashir, A. (2022), 'How do financial development, energy consumption, natural resources, and globalization affect arctic countries' economic growth and environmental quality? an advanced panel data simulation', *Energy* **241**, 122515.

Van den Berg, G. J. and Modin, B. (2013), 'Economic conditions at birth, birth weight, ability, and the causal path to cardiovascular mortality'.

Vaubel, R. (1996), 'Bureaucracy at the imf and the world bank: A comparison of the evidence', *World Economy* **19**(2), 195–210.

Vinnarasi, R. and Dhanya, C. (2016), 'Changing characteristics of extreme wet and dry spells of indian monsoon rainfall', *Journal of Geophysical Research: Atmospheres* **121**(5), 2146–2160.

Vreeland, J. R. (2003), *The IMF and economic development*, Cambridge University Press.

Vreeland, J. R. (2005), The international and domestic politics of imf programs, Technical report, Yale University, mimeo.

Wang, Y., Morgan, R. K. and Cashmore, M. (2003), 'Environmental impact assessment of projects in the people's republic of china: new law, old problems', *Environmental impact assessment review* **23**(5), 543–579.

Wei, J., Li, Z., Lyapustin, A., Sun, L., Peng, Y., Xue, W., Su, T. and Cribb, M. (2021), 'Reconstructing 1-km-resolution high-quality pm2. 5 data records from 2000 to 2018 in china: spatiotemporal variations and policy implications', *Remote Sensing of Environment* **252**, 112136.

Xu, X., Tan, Y. and Yang, G. (2013), 'Environmental impact assessments of the three gorges project in china: Issues and interventions', *Earth-Science Reviews* **124**, 115–125.

Yang, J. and Qiu, M. (2016), 'The impact of education on income inequality and intergenerational mobility', *China Economic Review* **37**, 110–125.

Yang, K., Ma, P. and Cui, L. (2021), 'Subnational corruption and foreign firms' performance: Evidence from china', *Journal of Business Research* **123**, 106–116.

Yuan, J., Na, C., Lei, Q., Xiong, M., Guo, J. and Hu, Z. (2018), 'Coal use for power generation in china', *Resources, Conservation and Recycling* **129**, 443–453.

Yusof, F. and Kane, I. L. (2013), 'Volatility modeling of rainfall time series', *Theoretical and applied climatology* **113**(1-2), 247–258.

Zhang, C. (2019), 'How much do state-owned enterprises contribute to china's gdp and employment?'.

Zhou, M.-H., Shen, S.-L., Xu, Y.-S. and Zhou, A.-N. (2019), 'New policy and implementation of municipal solid waste classification in shanghai, china', *International journal of environmental research and public health* **16**(17), 3099.

Zhu, Q., Liu, J. and Lai, K.-h. (2016), 'Corporate social responsibility practices and performance improvement among chinese national state-owned enterprises', *International Journal of production economics* **171**, 417–426.

Appendix

CHAPTER 1

1.A Construction of the rainfall volatility measure

The main objective to study the volatility measure is to extract the variation in the rainfall which is not expected by the farmers. That is, if the rainfall in the monsoon is growing at a constant rate of 2% per year, the farmers will learn to incorporate this change into their expectation and plan the season accordingly. Thus, now I will try to remove the explanatory part of the change in rainfall at a particular location and construct a volatility measure capturing the uncertainity in the weather across the time period. The methodology used below is derived from the method described by Yusof and Kane (2013).

The ARIMA-GARCH model is combined with the use of two models where the ARIMA part takes into account the mean variable of the rainfall at a particular location, whereas the GARCH model accounts for the variability. The GARCH model is built by extracting the residuals of the ARIMA which is the part not explained by the common trend.

ARIMA Model

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots\dots\dots - \phi_p B^p$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots\dots\dots - \theta_g B^q$$

Here, ϕ_i are the AR coefficients whereas θ_i are the MA coefficients. The ARIMA(p,d,q) model is defined as

$$\phi(B)\Delta^d y_t = \theta(B)\varepsilon_t$$

In the scope of this paper, I estimate ARIMA(2,1,2). The rainfall series obtained is stationary at the first degree of differencing. The locations where the series is non-stationary for the same ARIMA model, those observations are discarded from the estimation procedure.

GARCH Modeling

Since the ARIMA model cannot capture the variable effects, we apply the GARCH model to the residuals obtained from the ARIMA model, ϵ_i.

The variance of GARCH model is defined as follows:

$$\begin{aligned}\sigma_t^2 &= \omega + \sum_{i=1}^{P} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \\ &= \omega + a(B)\varepsilon_{t-i}^2 + \beta(B)\sigma_{t-1}^2\end{aligned}$$

where,

$$\begin{aligned}&\varepsilon_t = z_i \sigma_i \\ &Z_1 \sim \psi_t(0,1)\end{aligned}$$

Tables

Table 1.A1: Effect of Negative Rainfall Volatility on Health

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Height	-0.005*	-0.018*	-0.014*	-0.124*	-0.158**	-0.125**
	(0.004)	(0.015)	(0.006)	(0.025)	(0.097)	(0.130)
Health Condition	0.035	0.005	0.021	0.053	0.054	0.057
	(0.398)	(0.758)	(3.968)	(0.498)	(3.487)	(6.214)
Health Status	-0.548*	-0.547	-0.525	-0.648*	-0.268	-0.381
	(0.387)	(0.920)	(0.256)	(0.611)	(0.778)	(0.975)
N	1247	1036	2283	2148	2086	4234
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. 'Height' is in cm, 'Health condition' is a dummy for chronic illness, current health status is reported as good/bad. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' health condition, indicator for hospital presence in the village, level of smoking and alcohol consumption. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A2: Effect of Positive Rainfall Volatility on Health

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Height	-0.004*	-0.025*	-0.020*	-0.168*	-0.204**	-0.197**
	(0.003)	(0.019)	(0.018)	(0.031)	(0.124)	(0.144)
Health Condition	0.026	0.012	0.053	0.014	0.033	0.042
	(0.466)	(0.889)	(0.154)	(0.758)	(0.633)	(0.256)
Health Status	-0.648	-0.315	-0.879	-0.218*	-0.488	-0.214
	(1.547)	(1.648)	(1.874)	(0.154)	(1.858)	(1.695)
N	1247	1036	2283	2148	2086	4234
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. 'Height' is in cm, 'Health condition' is a dummy for chronic illness, current health status is reported as good/bad. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' health condition, indicator for hospital presence in the village, level of smoking and alcohol consumption. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A3: Effect of Negative Rainfall Volatility on Education

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Years of Schooling	-0.010*	-0.034*	-0.029*	-0.206*	-0.214**	-0.206**
	(0.008)	(0.025)	(0.021)	(0.196)	(0.184)	(0.155)
N	1247	1036	2283	2148	2086	4234
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variable in column 1 is regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' education, indicator for school presence in the village, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A4: Effect of Positive Rainfall Volatility on Education

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Rainfall Volatility	-0.011*	-0.098*	-0.074*	-0.206*	-0.168**	-0.196**
	(0.008)	(0.068)	(0.058)	(0.133)	(0.158)	(0.196)
N	1247	1036	2283	2148	2086	4234
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variable in column 1 is regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for parents' education, indicator for school presence in the village, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A5: Effect of Negative Rainfall Volatility on Income

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	-0.002*	-0.031*	-0.028*	-0.102*	-0.115**	-0.108**
	(0.004)	(0.009)	(0.018)	(0.014)	(0.105)	(0.130)
Ln(Expenditure Per Capita)	-.006	-0.002	-0.001	-0.015	-0.002	-0.012
	(0.154)	(0.658)	(0.965)	(2.054)	(2.448)	(3.962)
Asset Index	-0.587	-0.488	-0.598	-0.340**	-0.502*	-0.441*
	(0.684)	(0.621)	(0.668)	(0.047)	(0.402)	(0.315)
N	1247	1036	2283	2148	2086	4234
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A6: Effect of Positive Rainfall Volatility on Income

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	-0.003*	-0.002*	-0.002*	-0.007*	-0.053**	-0.036**
	(0.009)	(0.007)	(0.016)	(0.098)	(0.074)	(0.231)
Ln(Expenditure Per Capita)	-0.003	-0.003	-0.003	-0.015	-0.006	-0.008
	(0.687)	(0.174)	(0.144)	(0.413)	(0.277)	(0.114)
Asset Index	-0.541	-0.388	-0.514	-0.668	-0.771	-0.1954
	(0.378)	(0.187)	(0.005)	(0.034)	(0.687)	(0.478)
N	1247	1036	2283	2148	2086	4234
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A7: Effect of Rainfall Volatility on Income- Low Asset subsample

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	-0.009	-0.003*	-0.005**	-0.012*	-0.008**	-0.010*
	(0.010)	(0.005)	(0.019)	(0.068)	(0.074)	(0.003)
Ln(Expenditure per Capita)	-0.005	-0.001	-0.003	-0.004	-0.004	-0.005
	(0.074)	(1.480)	(2.322)	(3.111)	(2.359)	(5.149)
Asset Index	-0.235	-0.648	-0.144	-0.115	-0.615	-0.611
	(0.331)	(0.378)	(0.847)	(0.378)	(0.411)	(0.514)
N	2598	1633	4231	2978	1587	4565
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

Table 1.A8: Effect of Rainfall Volatility on Income-High Asset subsample

	Women			*Men*		
	(Dry)	(Wet)	(Full)	(Dry)	(Wet)	(Full)
Ln(Annual Earnings)	-0.001	-0.001	-0.001	-0.003*	-0.009	-0.006
	(0.010)	(0.003)	(0.005)	(0.002)	(0.015)	(0.012)
Ln(Expenditure per Capita)	-0.002	-0.004	-0.003	-0.008	-0.001	-0.005
	(0.165)	(2.149)	(2.412)	(4.165)	(3.998)	(4.135)
Asset Index	-0.031	-0.598	-0.910	-0.625	-0.879	-0.698
	(0.654)	(0.633)	(0.103)	(0.479)	(0.352)	(0.992)
N	1533	2698	4231	1550	3015	4565
FE	Yes	Yes	Yes	Yes	Yes	Yes
$2SLS$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is a result of a separate regression. The dependent variables in column 1 are regressed on the rainfall volatility in birth-year, district level fixed effects, and controls for education, indicator for school presence in the village, indicator for a person moving to a city, indicator for belonging to upper cast. The rainfall volatility measure is measured in standard deviations derived from an ARIMA-GARCH model. Time trend is linear throughout the sample. Fixed effects are at the district level. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

CHAPTER 2

Table 2.A1: CMP Results (Upper 50 Percentiles)

	(1)	(2)	(3)	(4)	(5)	(6)
IMF Program	0.210	0.198	0.146	0.138	0.268*	0.421
	(0.362)	(0.421)	(0.324)	(0.195)	(0.196)	(0.201)
BA1 - Total	0.148***	0.026	0.039	0.035	0.071*	0.102***
	(0.163)	(0.063)	(0.063)	(0.041)	(0.032)	(0.041)
Per Capita GDP	1.526**	3.422***	5.154***	5.269***	4.105**	5.184**
	(0.439)	(0.488)	(0.689)	(0.529)	(0.571)	(0.413)
Current Account Balance		-0.200***	-0.050***	-0.073**	-0.062**	-0.031
		(0.147)	(0.465)	(0.844)	(0.046)	(0.084)
Population			-1.325	-0.432	-0.164	1.477
			(1.320)	(1.036)	(1.324)	(1.008)
UNSC Membership				-0.625	-0.329	-0.412
				(0.309)	(0.405)	(0.347)
Vote with US					-3.416	-2.3326
					(2.154)	(2.635)
Employment						-0.416
						(0.377)
Constant	-31.456***	-74.821***	-15.987***	-92.365***	-57.124***	-40.729***
	(1.345)	(8.632)	(3.987)	(5.124)	(9.365)	(2.729)
Observations	1173	1073	1229	1151	1205	1148
F-Stat for Program	18.13***	14.43***	17.12***	16.7***	19.96***	11.26***
F-Stat for Conditions	17.41***	11.25***	10.04***	14.66***	17.13***	19.54***
Joint F-Stat	15.48***	17.16***	14.47***	10.67***	10.53***	16.27***

Notes: The dependent variable is the 5-year compounded error of the forecasts. The forecast for 1 year in the future has a higher weight than the subsequent years. The SAP variable only contains hard conditions. Country-level fixed effects are present in all specifications. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 2.A2: Effect on forecasts by conditions (Lower 50 Percentiles)

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Bias	0.756***	0.89***	0.967***	0.115***	0.652***	0.225***
	(0.895)	(0.998)	(0.369)	(0.91)	(0.657)	(0.029)
IMF Program	0.21	0.255	0.628	0.829	0.795	0.520
	(0.245)	(0.483)	(0.617)	(0.64)	(0.003)	(0.056)
BA1 - Total	0.032					
	(0.062)					
BA3 - Total		0.039*				
		(0.029)				
cBA - Total			0.120***			
			(0.041)			
dBA1 - Total				0.133***		
				(0.059)		
dBA2 - Total					0.128***	
					(0.084)	
dBA3 - Total						0.057***
						(0.041)
Per Capita GDP	8.666***	7.92***	1.206***	5.222***	1.457***	9.326
	(0.411)	(0.667)	(0.331)	(0.885)	(0.849)	(0.964)
Current Account Balance	0.568	0.122	0.85	0.405	0.936	0.938
	(0.781)	(0.134)	(0.464)	(0.716)	(0.052)	(0.255)
Employment	-0.584	-0.843	-0.835	-0.06	-0.487	-0.844
	(0.943)	(0.628)	(0.634)	(0.583)	(0.623)	(0.012)
UNSC Membership	-0.399	-0.662	-0.987	-0.745	-0.052	-0.966
	(0.418)	(0.508)	(0.916)	(0.344)	(0.351)	(0.518)
Vote with US	4.97	0.225	1.897	3.598	1.345	3.518
	(1.954)	(2.722)	(2.241)	(1.761)	(1.75)	(3.909)
Constant	-26.411***	-29.009***	-22.93***	-22.704***	-25.311***	-23.307
	(4.462)	(2.065)	(2.567)	(6.431)	(1.255)	(2.565)
Observations	1191	1133	1203	1247	1226	1091
F-Stat for Program	10.27***	17.04***	17.11***	12.97***	14.12***	17.55***
F-Stat for Conditions	17.11***	13.59***	11.25***	12.87***	12.49***	17.07***
Joint F-Stat	12.67***	16.99***	17.27***	19.0***	12.37***	13.59***

Notes: The dependent variable is the 5-year compounded error of the forecasts. The forecast for 1 year in the future has a higher weight than the subsequent years. The SAP variable only contains hard conditions. Country-level fixed effects are present in all specifications. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent $p<0.01$, $p<0.05$, $p<0.1$, respectively.

Table 2.A3: Effect on forecasts by categories (Upper 50 Percentiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged Bias	0.278***	0.238***	0.297***	0.283***	0.299***	0.241***	0.382
	(0.056)	(0.021)	(0.061)	(0.006)	(0.053)	(0.016)	(0.054)
IMF Program	0.204	0.116	0.025	0.038	0.195	0.111	0.034
	(0.215)	(0.641)	(0.654)	(0.436)	(0.666)	(0.525)	(0.254)
QCsBA2	0.139***						
	(0.038)						
QPCs - Total		0.214***					
		(0.098)					
IBs - Total			0.318***				
			(0.097)				
SCsBA2				0.188**			
				(0.049)			
PAs - Total					0.499***		
					(0.094)		
SPCs - Total						0.410*	
						(0.329)	
SBs - Total							0.427***
							(0.098)
Per Capita GDP	3.846***	4.880***	2.964***	6.688***	2.328***	2.394***	3.487
	(0.299)	(0.34)	(0.212)	(0.633)	(0.605)	(0.639)	(0.565)
Current Account Balance	-0.028	-0.024	-0.024	-0.007	-0.017	-0.019	-0.003
	(0.033)	(0.046)	(0.032)	(0.044)	(0.045)	(0.033)	(0.037)
Employment	-0.029	-0.028	-0.008	-0.011	-0.028	-0.014	-0.012
	(0.047)	(0.039)	(0.043)	(0.039)	(0.033)	(0.034)	(0.032)
UNSC Membership	-0.016	-0.270	-0.149	-0.126	-0.142	-0.111	-0.191
	(0.043)	(0.044)	(0.033)	(0.043)	(0.04)	(0.043)	(0.034)
Vote with US	-1.588	-2.855	-2.044	-1.729	-2.777	-3.242	-0.844
	(1.625)	(1.202)	(1.099)	(1.357)	(1.199)	(1.084)	(1.478)
Constant	-41.459***	-49.503***	-40.27***	-40.84***	-41.038***	-48.688***	-57.835***
	(5.294)	(10.661)	(9.141)	(10.621)	(2.752)	(2.513)	(4.792)
Observations	1039	1033	1035	1008	1013	1023	1022
F-Stat for Program	15.04***	14.74***	17.3***	19.06***	12.76***	12.33***	17.48***
F-Stat for Conditions	11.04***	11.0***	19.78***	13.01***	16.2***	14.27***	13.22***
Joint F-Stat	14.02***	16.52***	14.69***	14.69***	16.82***	16.08***	14.39***

Notes: The dependent variable is the 5-year compounded error of the forecasts. The forecast for 1 year in the future has a higher weight than the subsequent years. The SAP variable only contains hard conditions. Country-level fixed effects are present in all specifications. Robust standard errors in parentheses. Two-tailed t-test. ***, **, and * represent p<0.01, p<0.05, p<0.1, respectively.

CHAPTER 3

Table 3.A1: Propensity Score Matching: Diagnostic Tests

	Pre-match	Post-match
ln(Fiscal Deficit)	0.254***	0.213**
	(0.035)	(0.165)
ln(GDP)	0.165**	0.117*
	(0.111)	(0.112)
Fiscal	-0.157	-0.229
	(0.654)	(0.749)
Unemployment	26.315**	23.154
	(6.154)	(26.178)
Distance to port	0.015	0.036
	(0.079)	(0.196)
ROA	-0.025	0.003
	(0.298)	(0.358)
Leverage	0.065	-0.014
	(0.265)	(0.638)
Constant	-4.326**	-6.215***
	(3.615)	(3.487)
County weights	Yes	Yes
Year weights	Yes	Yes
Pseudo-R-squared	0.26	0.19
Chi-square	26.41	8.34
N	3,965,154	3,568,190

Notes: This table reports the diagnostic tests of our propensity score matching. The dependent variable is the level of environmental budget for each county. The first column contains the parameter estimates of the logit model estimated using the sample before matching. These estimates are then used to generate the propensity scores for matching treatment and control counties. The second column contains the parameter estimates of the logit model estimated using the subsamples. We report t-statistics in parentheses. Our standard errors are robust and clustered. *, **, *** indicate that the coefficients are significant at 10%, 5% and 1%, respectively.

Table 3.A2: Propensity Score Matching: Diagnostic Tests

	Pre-match	Post-match
ln(Fiscal Deficit)	0.534**	0.329**
	(0.035)	(0.165)
ln(GDP)	0.129**	0.195*
	(0.111)	(0.112)
Fiscal	-0.153	-0.153
	(0.654)	(0.749)
Unemployment	24.122**	20.864
	(6.154)	(26.178)
Distance to port	0.002	0.004
	(0.079)	(0.196)
ROA	-0.175	0.045
	(0.298)	(0.358)
Leverage	0.295	-0.174
	(0.265)	(0.638)
Constant	-4.492**	-6.198***
	(3.615)	(3.487)
County weights	Yes	Yes
Year weights	Yes	Yes
Pseudo-R-squared	0.19	0.23
Chi-square	26.41	8.34
N	3,965,892	3,568,190

Notes: This table reports the diagnostic tests of our propensity score matching. The dependent variable is the level of environmental budget for each county. The first column contains the parameter estimates of the logit model estimated using the sample before matching. These estimates are then used to generate the propensity scores for matching treatment and control counties. The second column contains the parameter estimates of the logit model estimated using the subsamples. We report t-statistics in parentheses. Our standard errors are robust and clustered. *, **, *** indicate that the coefficients are significant at 10%, 5% and 1%, respectively.

Table 3.A3: DID Results with PSM Matching

	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)
Post2005	1.879*	1.245	1.912**	1.987**
	(1.452)	(1.978)	(1.087)	(1.307)
Treatment	1.632	1.021*	1.743*	1.816
	(1.751)	(0.895)	(1.230)	(1.892)
Treatment*Post	-2.531**	-3.389*	-2.208**	-2.195**
	(1.526)	(3.022)	(1.972)	(2.529)
Unemployment		-0.053		-0.079*
		(1.178)		(0.034)
ln(GDP)		0.302*		0.346**
		(0.195)		(0.273)
Fiscal Balance		0.191*		0.126**
		(0.206)		(0.101)
Distance to coast		-0.009		0.010*
		(1.286)		(0.004)
FDI Share		0.226*		0.309**
		(0.201)		(0.261)
Constant	2.762*	3.309**	4.247***	3.681***
	(2.112)	(3.013)	(1.387)	(0.609)
Year weights			Yes	Yes
County weights			Yes	Yes
Observations	18,423	18,422	18,321	18,321
R-squared	0.15	0.16	0.20	0.22

Notes: This table reports the DID results after our propensity score matching. The dependent variable is the level of environmental budget for each county. The first column contains the parameter estimates of the logit model estimated using the sample before matching. These estimates are then used to generate the propensity scores for matching treatment and control counties. The second column contains the parameter estimates of the logit model estimated using the subsamples. We report t-statistics in parentheses. Our standard errors are robust and clustered. *, **, *** indicate that the coefficients are significant at 10%, 5% and 1%, respectively.