Document de Recherche du Laboratoire d'Économie d'Orléans
Working Paper Series, Economic Research Department of the University of Orléans (LEO), France
DR LEO 2023-05

The Effects of Climate Change on Public Investment Efficiency in Resource-rich Countries : Evidence from Stochastic Frontier Analysis.

Yacouba COULIBALY

Mise en ligne / *Online* **: 11/04/2023**

Remplace une version précédente du même numéro / *Replaces a previous version of the same DR LEO number*
Cette version remplace celle du / ***This replaces the previous version dated*** **: XX/XX/XXXX**
Titre précédent / *A previous version was titled* **:** "Remplacer par l'ancien titre"
A paraitre dans / *Forthcoming in* **: Nom du journal, vol, numéro, pages**
Paru dans / *Published in* **: Nom du journal, vol, numéro, pages**

Laboratoire d'Économie d'Orléans
Collegium DEG
Rue de Blois - BP 26739
45067 Orléans Cedex 2
Tél. : (33) (0)2 38 41 70 37
e-mail : leo@univ-orleans.fr
www.leo-univ-orleans.fr/

The Effects of Climate Change on Public Investment Efficiency in Resource-rich Countries : Evidence from Stochastic Frontier Analysis.

Yacouba COULIBALY

U. of Orléans and U. Clermont Auvergne, France, LÉO

Research Consultant at UNU-WIDER

Helsinki 00160, Finland

Abstract

Developing countries suffer disproportionately from the negative impacts of climate change and environmental degradation on economic development in terms of financial costs and loss of potential revenues. In this paper, we examine the impact of climate change on the efficiency of public investment in 34 developing countries, with a particular focus on resource-rich countries, over the period 2000-2013. Using stochastic frontier analysis (SFA) to determine efficiency scores, we find that developing countries could increase the capital stock by 29% on average without changing their public investment spending. In particular, resource-rich countries could increase the capital stock by 26% without changing their spending. In the second step, we then use the fractional regression model (FRM) to capture the impact of climate change on the investment efficiency values obtained in the first step. Our results show that climate change has a negative impact on public investment efficiency. However, when the climate change index is disaggregated for the regressions, we find that only precipitation has a negative effect, while a 1°C temperature increase in resource-rich countries leads to a 16.32% improvement in public investment efficiency of GDP. These results are also statistically and economically robust to different controls and specifications. The main findings of this paper suggest that policies to address climate change in general and heavy rainfall shocks in particular should include strong provisions for financing more resilient public investments to adapt to climatic conditions and modernise public infrastructures to mitigate the negative environmental impacts for developing countries, especially resource-rich countries.

Keywords : • Climate change • Public investment • Technical efficiency • Weather shocks • Environment • Stochastic frontier analysis.

JEL Codes : O13, H81, C12, Q54, Q01.

Acknowledgments : We are grateful to Patrick Villieu, Yannick Lucotte, and the seminar participants at the Laboratoire d'Économie d'Orléans and 9th Public Policy Analysis Day of Université le Havre Normandie for their comments and suggestions.

1 Introduction

Public investment has played a catalytic role in strengthening resilience to shocks and economic crises in emerging economies. Historically, the economic crisis of 1929, which was ended by the implementation of Keynesian-inspired economic policies that public investment can raise a nation's wealth level (Naoussi et al., 2020). Indeed, to achieve sustainable growth, it is important to significantly increase investment in physical and social infrastructure based on the high returns on investment (Dabla-Norris et al., 2012). However, the literature identifies several reasons for the weakness of public investment in developing countries. For example, the authors of Dabla-Norris et al. (2012) have shown that low returns on public investment due to poor project selection and implementation due to limited information, waste and displacement of resources, and weak technical expertise have led to inadequate returns on public and private investments in many low-income countries. In addition, the authors believe that returns on private investment are in turn diminished by the lack of complementary public input.

In addition to these weaknesses, there is another phenomenon that affects the profitability of investments in developing countries : climate change. For decades, all of humanity has faced the harmful effects of climate change, making it one of the most important problems of the 21st century (Diallo, 2021). Basically, climate change is defined as the persistent increase in the average temperature on Earth (Diallo, 2021). The impact that climate change could have on public investment may differ from the weaknesses listed by Dabla-Norris et al. (2012) due to the disasters, natural catastrophes, etc. that it could cause. The literature presents results on the impact of climate change on the economy in general, but on infrastructure in particular. Raddatz (2009) has shown that natural disasters have had quite significant macroeconomic costs in recent decades. He estimates that GDP per capita has declined by at least 0.6% due to the occurrence of climate disasters.

According to Cavallo et al. (2013), very large disasters have a negative impact on the economic growth of countries in both the short and long term. However, some analyses conclude that natural disasters have a positive impact. For example, Caballero and Hammour (1996) show that extreme climate shocks could be considered as an exogenous and catalytisor factor for the incentive to reinvest and thus increase the productivity of capital. In the same vein, Skidmore and Toya (2002) show that in the period following a natural disaster, the capital stock is updated and the adoption of new technologies is encouraged. This improves the growth performance of economic activity. In addition, it has been shown that countries that are used to experiencing natural disasters are less and less affected economically as they learn to better prepare for future disasters (Cavallo et al., 2010; Escaleras et al., 2007). Since we know from previous studies that climate change is likely to have an impact on the economy, it is detrimental to assess the impact of natural disasters on infrastructure.

The literature identifies two measures to reduce the impact of natural disasters, namely prevention and mitigation (McDaniels et al., 2015; Havko et al., 2017). While risk prevention aims to reduce the likelihood of the risk occurring, mitigation measures focus on reducing the damage associated with the disaster after it has occurred (Taghizadeh-Hesary et al., 2021). In this context, many recent studies have examined the role of high-quality infrastructure in mitigating the impact of natural disasters (Rahman, 2018; Hosoya, 2019; Rehak, 2020; Hosoya, 2016; Marto et al., 2018). All of these studies focused on how better infrastructure can reduce disaster risk (Taghizadeh-Hesary et al., 2021), the multisectoral impacts of climate change, particularly on agriculture (Dell et al., 2014; Adams, 1989; Siwar et al., 2013), and economic growth (Caballero and Hammour, 1996; Nakamura et al., 2013; Cavallo et al., 2013).

However, the literature has so far been silent on the impact of natural disasters caused by climate change on the efficiency of public investment in all its dimensions and sectors. This is surprising, because climate change can not only impose enormous economic costs, but also trigger very high social costs and increase the vulnerability of countries (Leichenko and Silva, 2014; Wiley et al., 2010). Despite the efforts made in recent years by the different actors such as the World Bank, the International Monetary Fund, the French Development Agency, the African Development Bank, non-governmental organizations, governments, etc., there are still many challenges in the fight against climate change and in the realization of a modern, more adequate infrastructure. Our study is part of this dual objective. The focus of our study is clearly on measuring the climate impact on the efficiency of investments made during these decades. Public investment efficiency can be defined as the relationship between the value of the public capital stock and the measured coverage and quality of infrastructure assets (IMF, 2015).

Farrell (1957) has identified two types of efficiency : technical efficiency [1] and allocate or price efficiency [2]. In addition, climate change can have direct and indirect effects on investment efficiency. One of the direct effects of climate change on investment efficiency is related to heavy rainfall. Namely, heavy rains can trigger a flood shock that could accelerate infrastructure deterioration and increase the cost of mitigation and adaptation investments. Indirectly, the environmental consequences of climate change may force governments to take on more debt to finance a sustainable energy transition and green policies, leading to over-indebtedness. Unsustainable public debt would hinder economic growth (Reinhart and Rogoff, 2010; Eberhardt and Presbitero, 2015), limit the ability to mobilize domestic resources, and thus discourage investment in climate change adaptation infrastructure (Van den Bergh, 2013). Fundamentally, unsustainable public debt

1. The unit of production that achieves maximum output with a given set of factors or, conversely, uses as few factors of production as possible for a given level of output.

2. The ability of a unit of production to use factors of production in optimal proportions given their price.

limits fiscal space and weakens the ability to build effective infrastructure to address climate change and environmental challenges. Combes et al. (2015) believes that repaying the debt burden may force heavily indebted governments to increase pressure on natural capital to increase government revenues. This could accelerate the depletion of natural resources, increase the loss of forest lands (Culas, 2003; Combes et al., 2018) that sequester CO2, and increase greenhouse gas emissions in the country, as fossil fuels are responsible for 73% of global greenhouse gas emissions (Nations, 2021). These factors would result in the negative impacts of climate change affecting the state's ability to provide quality infrastructure.

Most studies on public investment efficiency focus on the relationship with economic growth (Chakraborty and Dabla-Norris, 2009 ; Gupta et al., 2014 ; Abiad et al., 2014 ; Calderon and Servén, 2004 ; 2008), the calculation of efficiency evaluation indicators such as the PIMI [3] (Dabla-Norris et al., 2012), assessment of public investment management (IMF, 2015), and stronger institutions conjugated with low dependence on natural resource revenues (Albino-War et al., 2014). To date, no study has examined climate change as an exogenous determinant of investment efficiency in developing countries. This is surprising, as climate change is responsible for many infrastructure losses. In 2013, for example, Mexico was hit simultaneously by two tropical storms that caused significant economic losses to the country (Pedrozo-Acuña et al., 2014). These extreme flows resulted in 134 bridges being destroyed and 1035 roads damaged, leading to estimated reconstruction costs of about $1.1 billion (Bizikova et al., 2008). Thus, further research is needed to improve the understanding of current risks and to accurately model impacts at a scale relevant to policy makers in order to take climatic conditions into account in the design of infrastructure systems and to reduce associated economic losses. To our knowledge, we are the first to demonstrate the impact of climate change on public investment efficiency using a stochastic frontier analysis model. Albino-War et al. (2014) their study shows how good intentional quality and a diversification context can improve public investment efficiency in resource-rich countries [4]. In addition, the authors show that higher efficiency is associated with lower natural resource dependence. However, the authors do not control for the role of climate change in the investments made. With this in mind, the goal of this study is to fill this gap. In contrast to Albino-War et al. (2014), we extend our sample to countries that produce resources other than oil and to countries that do not produce minerals. This allows us to account for cross-country heterogeneity in our

3. The Public Investment Management Index, which was developed as a composite index of the efficiency of the public investment process for 71 EM and LIDC in four successive phases : Project Appraisal, Selection, Implementation, and Evaluation

4. In the remainder of this study, we use the IMF classification of resource-rich countries from the Fiscal Rules Dataset, 1985-2021. See this link : http://ec.europa.eu/economy_finance/db_indicators/fiscal_governance/index_en.htm.

results. Our study makes two important contributions to the literature. First, we provide additional evidence that weather shocks affect economic performance through their impact on agricultural production, economic growth, infrastructure, etc. A few previous studies have found evidence of an infrastructure mechanism (e.g., Ali et al., 2020; Alirezaei et al., 2017), and we add to this literature by providing evidence from a new context with a novel empirical approach. Second, we provide the first evidence that high-quality infrastructure can mitigate the effects of rainfall and temperature shocks. Finally, while previous studies focused on the impact of climate change on agriculture (See for instance Leppänen et al., 2017 and Calzadilla et al., 2014) and financial stability (e.g., Dafermos et al., 2018 and Trinh, 2018), this study focuses instead on the impact of climate change on the public investment efficiency in order to provide relevant and updated policy recommendations, taking into account current the fiscal policy context in these countries. Basically, its focus is motivated by the fact that climatic instability and climate shocks at the global level over the past decade call for a fundamental revision of the adaptation and mitigation strategy through the implementation and strengthening of environmental policies focused on green and resilient investments to reduce macroeconomic vulnerabilities in developing countries. The choice of countries rich in natural resources is justified by two main arguments. First, it is recognized that resource-rich countries have a significant lack of fiscal resources to finance development (See for instance Kolstad and Søreide, 2009 and Sachs and Warner, 1995). This leads to a very disappointing economic outcome, i.e., lower average growth rates, lower levels of human development associated with high inequality and poverty (Bulte et al., 2005; Gylfason, 2001; Kolstad and Søreide, 2009, etc.). Second, the economics literature finds that climate change and natural disasters have quite significant implications for fiscal sustainability in developing countries with limited financial resources and underdeveloped institutions (Catalano et al., 2020). This could be the case for resource-rich countries already suffering from the resource curse (Sachs and Warner, 1995). In this context, it seems appropriate to focus on the proper management of public expenditures in particular, and fiscal policy in general, in order to increase the capacity of governments to finance policies to combat climate change, poverty, and income inequality in these resource-rich countries.

Our results show that climate change has a negative impact on the efficiency of public investment in developing countries using a stochastic frontier model and a fractional regression model. These results support the argument that policies to protect the environment from climate shocks can have the added benefit of reducing investment costs and inducing governments to build high-quality infrastructure to mitigate and adapt to climate change. The remainder of the paper is organised as follows. The following section presents a relevant theoretical framework that illustrates the impact of climate change on the economy. Section 3 reports some stylized facts. Then, Section 4 describes the empirical methodology, while Section 5 presents the data and descriptive statistics. The main results are presented in Section 6, while in Section 7 we examine the sensitivity of these results. Section 8 analyses the possible heterogeneity of our results. Finally, Section 9 concludes the study and presents the main policy recommendations from the results.

2 Theoretical background

The damage caused by climate change may lead to a reallocation of the government's portfolio in the provision of goods and services that may result in a gradual decline in the public investment efficiency in several sectors of economy. In this section, we provide an appropriate theoretical framework to identify the main channels through which the climate change may affect public investment efficiency. To do so, we briefly review the literature on the effect of climate change on the economy and then discuss how it may affect the public investment efficiency more specifically.

2.1 Effects of Climate Change on the Economy

We begin the discussion by looking at how climate change is affecting key sectors of the economy. Indeed, climate change has negative consequences for manufacturing and service sector output. Deteriorating weather conditions negatively affect the labor productivity of factory and manufacturing workers, as well as white-collar workers. Hsiang (2010) showed that a 1°C increase in temperature due to climate change leads to a 2.4% decline in nonagricultural sector output in a sample of 28 Caribbean countries over the period 1970-2006. This result was confirmed by Dell et al. (2014) for the value added of the industrial sector in poor countries, which would decrease by 2% for a marginal 1°C temperature increase. Herweijer et al. (2009) analyzed the functioning of the private insurance market in the face of climate change threats. The authors focused on both the risks posed by inadequate adaptation to the impacts of climate change and the opportunities presented by global adaptation efforts. They conclude that climate change will affect underwriting practices in the short term by requiring approaches to quantify risk, and that in the long term, inadequate adaptation in areas of increasing risk would threaten the very concept of insurability by limiting the availability and accessibility of private insurance coverage.

The analysis of the consequences of climate change for the agricultural sector is the subject of a large number of studies. A synthesis of these studies shows that the agricultural sector is the most affected by climate change. Indeed, agricultural productivity, agricultural income, and agricultural value added of agricultural production in an economy are strongly correlated with weather conditions. For example, Sanchez (2000) and Siwar et al. (2013) show that food security is threatened by climate change because it leads to instability in production and prices and consequently affects the entire agricultural production chain. Mano and Nhemachena (2007) uses a Ricardian approach to examine the economic impact of climate change on agriculture in Zimbabwe. The author finds that net agricultural income is negatively affected by the increase in temperature and positively affected by the increase in rainfall. Furthermore, his results from the sensitivity analysis show that agricultural production in smallholder agriculture in Zimbabwe is constrained by climatic factors, namely higher temperatures and lower rainfall. Moreover, higher rainfall reduces the yield differential between rain-fed and irrigated agriculture in African economies (Falloon and Betts, 2010), thereby increasing their vulnerability. Since agriculture in Africa accounts for about 32% of the continent's GDP and more than two-thirds of the population depends on agricultural activities for their livelihoods (Chauvin et al., 2012; Tongwane and Moeletsi, 2018; Ba, 2016), about 65% of Africa's total population is employed in the agricultural sector (Tongwane and Moeletsi, 2018).

The relationship between climate change and financial stability has also been analyzed in the literature (e.g., Battiston et al., 2017; Stolbova et al., 2018; Trinh, 2018). Although the results of these studies are mixed, it is clear that many studies conclude that climate change is likely to trigger instability in the financial system. For instance, Dafermos et al. (2018) analyzed the relationship between climate change, financial stability, and monetary policy using an ecological macroeconomic stock-flow model. First, he finds that climate change gradually worsens corporate liquidity by leading to higher default rates that harm both the financial and non financial sectors of firms. Second, climate change leads to a gradual decline in corporate bond prices. Third, climate-induced financial instability penalizes credit expansion, which negatively affects economic activity. However, Dietz et al. (2016)'s study, using a standard integrated assessment model (IAM) and climate value at risk (VAR), finds that climate change has a business-as-usual issuance path on corporate bond returns. In other words, no impact of climate change on individual financial assets. Heipertz and Nickel (2008), found a direct and indirect effect of weather shocks on public finances in the case of European Union countries and the United States. However, some studies find a positive effect of natural disasters due to climate change on economic growth (e.g., Skidmore and Toya, 2002 and Albala-Bertrand, 1993). In Loayza et al. (2012) and Loayza et al. (2012), on the other hand, the effects of natural disasters on economic growth differ by economic sector and type of natural disaster.

2.2 Implications of Climate Change on Public Investment

Climate change is likely to alter the structure of public investment through public spending, public infrastructure, and fiscal sustainability in developing countries. Indeed, the cost of adapting or mitigating climate shocks is very high in most developing countries that already have very limited financial resources, forcing them to Catalano et al. (2020), which forces them either change the reallocation of their budgets or resort to international aid (Caballero and Hammour, 1996; Catalano et al., 2020). Faced with the increase in temperature and reduced rainfall due to climate change, countries need to improve the profitability of their public investments in order to respond to the impact and magnitude of such a natural phenomenon. This idea is defended by Calzadilla et al. (2014), estimating that South Africa should improve the return of more than 20% of these investments compared to what existed.

Climate change can affect public investment by driving up current spending. The mechanism of public spending through which climate change affects investment is found, for example, in energy consumption in government buildings, road maintenance, forest firefighting strategy, and subsidies to agricultural producers (Leppänen et al., 2017). In addition, according to Korppoo (2008) and Turkowski et al. (2012), the increase in forest and peat fires due to climate change can lead to flooding and public health problems. This leads to adaptation and mitigation costs in the form of public investment in these sectors. Auffret (2003) finds, based on a sample of Latin American and Caribbean countries, that natural disasters cause a moderate decline in public spending. Noy and Nualsri (2011) breaks down this data and finds that public spending increases in developed countries while it decreases in developing countries following a natural disaster due to climate change.

3 Stylized facts

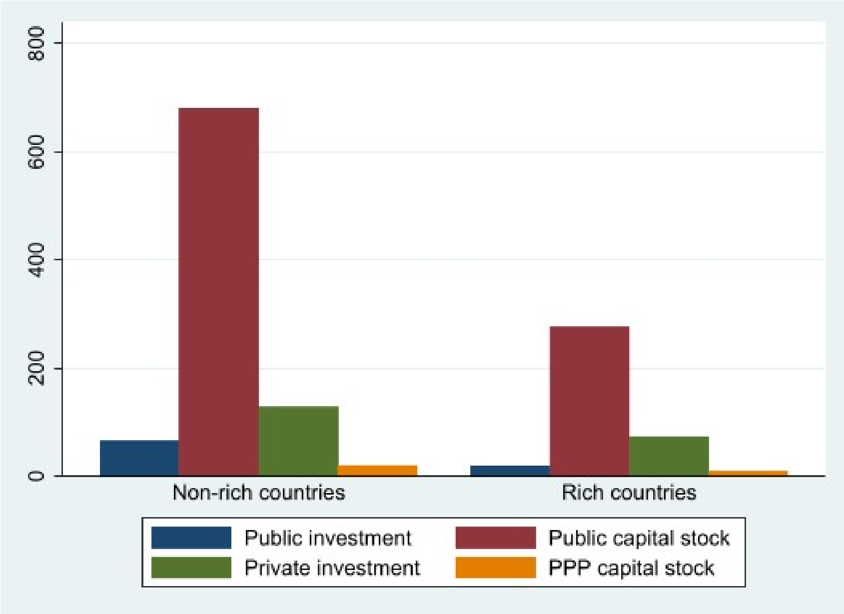
In this section, we present some stylized facts that characterize public investment and climate change in developing countries between 2000 and 2013.

3.1 Status Public Investment

The concept of efficiency relates the results achieved to the resources used. In other words, it is an analysis from the point of view of maximization or from the point of view of minimization depending on the objectives of economic policy (Naoussi et al., 2020; Farrell, 1957). The maximization approach refers to an optimal outcome for a given level of inputs or resources, while the minimization approach refers to a minimum level of inputs for an unchanged level of outcomes. Public investment is efficient when the best outcome is achieved at a given level of public capital stock or when the minimum level of public capital stock is used at an unchanged level of outcome. Indeed, in their investment impulses, governments choose to produce the same outcomes with at least a smaller amount of one input or to use the same inputs to produce more of at least one outcome. The underlying intuition of the paper is that governments' investment policies may be disoriented. As shown in Figure 1, there has been substantial investment in these countries over the period 2000 to 2013.

On average, countries accumulated 40.50 and 92.8 percentage points of GDP in pu-

Figure 1 – **Average investment and capital stock, 2000-2013 (% of GDP).**

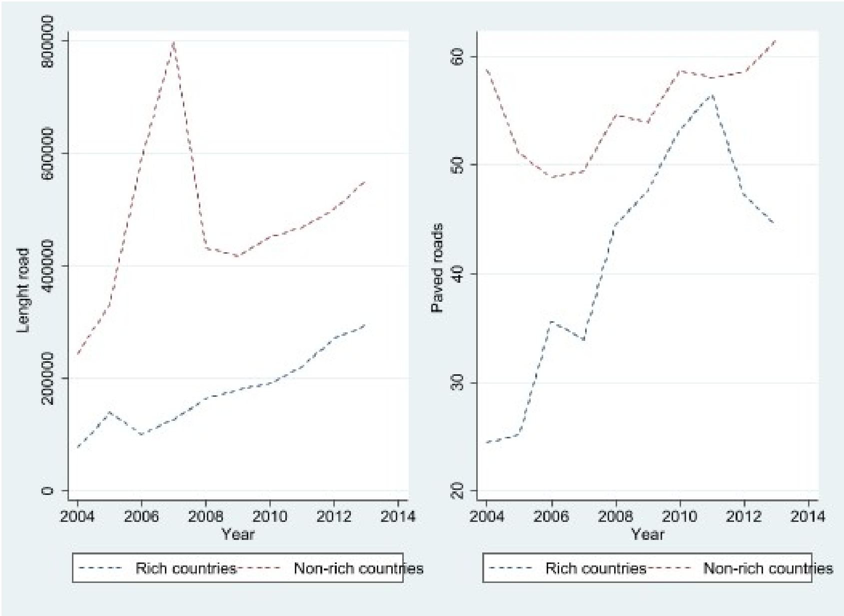


Source : Author's construction

blic and private investment, respectively. At the public capital stock level, countries have invested on average 13.55% and 93.80% of GDP. However, Figure 1 shows a strong disparity between countries. Indeed, countries rich in natural resources find it difficult to make sound investments to support their economies. All investment variables are low in resource-rich countries, in contrast to countries that do not have a rich subsoil. This observation suggests that resource-rich countries have a wide margin in the provision of goods and services and that careful analysis of the problems associated with investment in these countries will be necessary. Since the work of Aschauer (1989), many studies have emphasized that an adequate supply of infrastructure services is considered a key element of economic development. The idea is that the provision of adequate infrastructure, such as rural roads, could improve farm workers' incomes by reducing the transportation and logistical costs that farm workers face in accessing markets. If this is the case, it is very important to evaluate the variables that may contribute to the deterioration or expansion of these infrastructures.

Indeed, a sharp rise in temperature is recognized as a determinant of extreme weather. Thus, higher temperature would cause various problems, such as damage to tires, overheating of motor vehicles, thermal expansion of pavement joints, and softening of asphalt (Ali et al., 2020). In addition, Alirezaei et al. (2017) showed that the deterioration of road infrastructure was observed due to unpredictable weather changes, which were also responsible for shortening the life of roads. Figure 9 clearly shows that the road network in non-rich countries is better than in rich countries. Rich countries have an average road length of 176723 km^2, while non-rich countries have an average of 479095 km^2. The same is true for paved roads. Non-rich countries have had greater investment than rich countries.

FIGURE 2 – **Length of road network and paved roads in kilometers.**



Source : Author's construction

Many studies have attempted to identify the determinants that would explain this low level of infrastructure in developing countries. Institutional problems (Dabla-Norris et al., 2012), large-scale corruption [5] (Albino-War et al., 2014; IMF, 2015), poor project selection and implementation (Dabla-Norris et al., 2012). It is clear that all of these studies have overlooked the impacts of climate change. To be sure, material, human, and economic damages due to climate change have been demonstrated throughout the world. We suspect that climate variables will cause significant infrastructure damage in developing countries, especially resource-rich countries.

3.2 Climate change

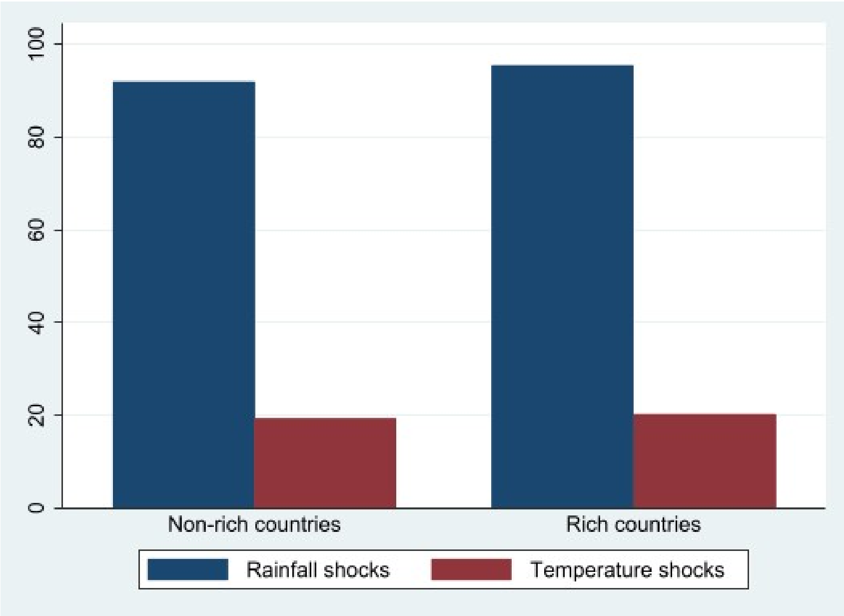
The literature has revealed that climate change is a real and global fact with enormous consequences for individual and economic well-being (Diallo, 2021). Following recent studies (Hsiang, 2010; Ali et al., 2020; Alirezaei et al., 2017; Trinh, 2018; Diallo, 2021; Burke et al., 2015), we use temperature and precipitation variables to measure the impact of climate variability on the public investment efficiency. In 2018 [6], the GIF released a report that indicated that the observed global average surface temperature for the decade 2006 to 2015 was 0.87°C. According to this report, global warming is expected to reach the critical threshold of 1.5°C between 2030 and 2052 if temperatures continue to rise at their

5. Tanzi and Davoodi (1998) show that higher levels of corruption are associated with higher levels of public investment, lower levels of operation and maintenance spending, and lower levels of infrastructure quality. Grigoli and Mills (2014) also finds that lower levels of corruption and rent-seeking are the main reasons for lower levels of investment in mature economies.

6. See :https://www.ipcc.ch/sr15/chapter/spm/

current rate. However, the distribution of the impact of climate change is not uniform between developed and developing countries (Diallo, 2021). This can be clearly seen in Figure 3 below.

FIGURE 3 – **Average Rainfall shocks (mm) and Temperature shochs (°C).**

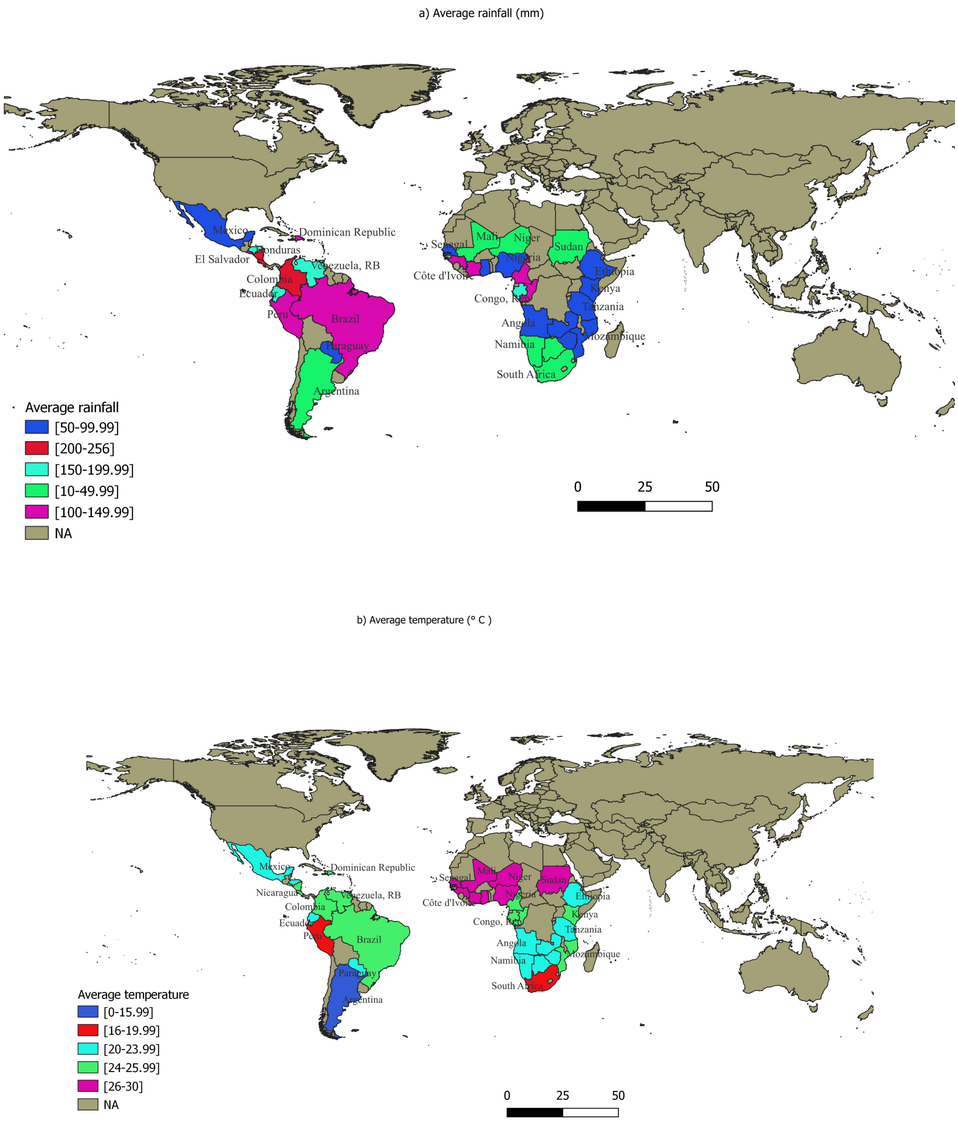


Source : Author's construction

Rainfall shocks are more important in rich countries than in non-rich countries. Moreover, rich countries have an average of 95.54 mm of rainfall during period 2000 to 2013. Non-rich countries received an average of 92.07 mm of rainfall (see Figure 3). This observation suggests that resource-rich countries experience severe flooding, storms, and intense rainfall that can damage public infrastructure. As for temperature, it is not very similar in the two geographical areas. In the resource-rich countries, the average temperature during the study period is 20.26°C, while in the non-rich countries it is 19.28°C. Overall, the average temperature is 19.65°C and precipitation is very high, averaging 93.38 mm during 2000-2013. Since we have illustrative evidence that resource-rich countries are highly affected by climate variability and have low capital accumulation, we empirically investigate whether investment efficiency in these countries is dampened by climate change.

Figure 4 shows the average temperature and rainfall trends during 2000-2013 at the continental scale. We observe a strong spatial heterogeneity in the variability of climatic conditions. The Latin American and Caribbean region recorded high rainfall averages of around 149 mm during 2000-2013. Countries such as Brazil and Peru are the most affected by this strong rainfall trend. In contrast, sub-Saharan African countries received relatively low rainfall of about 76 mm, compared to the sample average of 104 mm during the study period. In terms of temperature, global warming was almost more pronounced in both regions, with about 25 °C during 2000-2013.

FIGURE 4 – **Geographical representation of average annual trend of climate variables over the period 2000-2013.**



Source : Author's construction

4 Empirical methodology

The relationship between investment efficiency and weather conditions (shocks) is analyzed in a two-stage approach. Efficiency is first defined in terms of technical efficiency (scores), which is calculated based on a stochastic frontier model[7]. In a second step, the estimated technical efficiency is explained by extreme weather events (shocks). Before

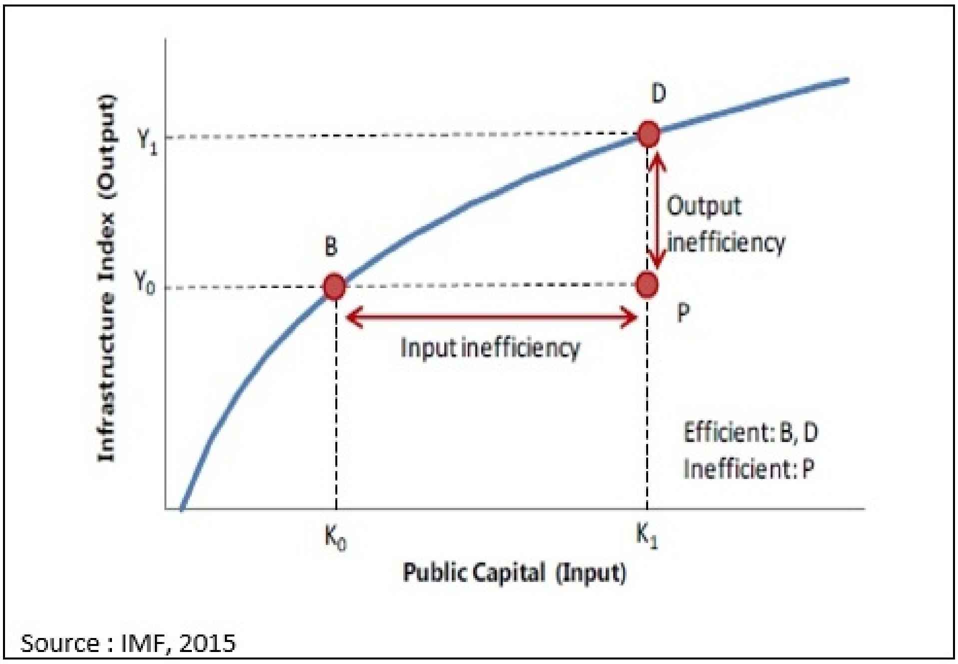
7. In where disturbances associated with the weather trend are also used to explain inefficiency

presenting the econometric model, the conceptual framework on which the econometric analysis is based is presented.

4.1 Conceptual framework

According to Farrell (1957), efficiency is defined as the productive effectiveness of producers in efficiently using available resources (inputs) to produce maximum output at minimum cost (output).

FIGURE 5 – **The Public Investment Efficiency Frontier.**



By Farrell (1957) definition, all points on the blue curve are points corresponding to efficient production (the efficiency frontier). This is the case for points B and D (see Figure 5). Point P, on the other hand, corresponds to inefficient production, as it illustrates the use of an excessive amount of inputs. The distance to the production frontier corresponds to technical inefficiency, i.e. BP (Figure 5). Moreover, the point D of the tangent between the isoquant and the isocosts corresponds to the optimal production at given factor prices. At this point, the factor price ratio is equal to the marginal rate of technical substitution.

4.2 Estimation of technical efficiency

There is a lot of work on estimating efficiency scores. These efficiency scores are obtained by estimating an efficiency frontier using two different methods. Some studies (Herrera and Pang, 2005 ; Honjo et al., 1997 ; IMF, 2015 ; Afonso and Aubyn, 2005 ; Albino-War et al., 2014 ; Kumbhakar et al., 2015) use nonparametric «DEA» or semiparametric «FDH» methods. These methods rely on mathematical programming, i.e., linear optimization, to estimate an efficiency frontier for production units. In these methods, the relationship between inputs and outputs is not subject to any constraints in estimating the efficiency frontier or production frontier. In other words, these methods do not require that a functional form be specified to estimate the efficiency frontier. Nevertheless, they are very sensitive to measurement errors and existing exogenous shocks. As for the estimated inefficiencies, they are very sensitive to the presence of outliers, to variations in the sample, and to heterogeneity across individuals or production units (Odeck, 2007; Hjalmarsson et al., 1996).

In contrast to non-parametric models, parametric models, mainly , require a functional form to the production technology. They have the particularity of being able to explain why we have a deviation of the observations from the deterministic frontier due to the existence of measurement errors and stochastic variations of the data. The idea here is to say that no economic agent can exceed this ideal frontier. Stochastic frontier models decompose the error into two terms : an error term that represents country-specific inefficiency and an idiosyncratic error component that combines both measurement errors and noise. Different methods are used to estimate stochastic frontier models. Among them we have the method of Tsionas and Kumbhakar (2014) which proposes a three-step approach, Colombi et al. (2014) which use a maximum likelihood estimator, while Filippini and Greene (2016) instead use a simulated maximum likelihood approach and to finish, Tsionas and Kumbhakar (2014) which use a Bayesian approach. In this study, we use the stochastic frontier method in panel data.

Unlike non parametric models, parametric models, especially «Stochastic Frontier Analysis [8]», require a functional form of production technology. They have the distinction of being able to explain why observations deviate from the deterministic limit because of measurement error and stochastic variation in the data. The idea is that no economic agent can exceed this ideal frontier. Stochastic frontier models decompose the error into two terms : an error term representing the country-specific inefficiency, and an idiosyncratic error component combining both measurement error and noise. Several methods are used to estimate stochastic frontier models. These include the method of Tsionas and Kumbhakar (2014), which proposes a three-step approach, Colombi et al. (2014), which uses a maximum likelihood estimator, while Filippini and Greene (2016) uses a simulated maximum likelihood approach instead, and finally Tsionas and Kumbhakar (2014), which uses a Bayesian approach. In this study, we use the stochastic frontier method with panel data.

8. Introduced by Aigner et al. (1977), Stochastic frontier Analysis (SFA) estimation has been used extensively to estimate technical efficiency in the literature for both cross-section and panel data.

4.3 Econometric strategy

We now apply the conceptual framework explained above to an econometric model, first, to determine the efficiency scores of public investments and, second, to estimate the impact of climate shocks on TE through an FRM model in second step.

4.3.1 First step : Estimation of Technical Efficiency

We can consider a country i at time t that uses x inputs to build infrastructure defined by y :

$$y_{i_t}=f(x_{i_t};\beta)+\varepsilon_{i_t}, \tag{1}$$

$$\varepsilon_{i_t}=\nu_{i_t}-u_i,$$
$$\nu_{i_t}\sim N(0,\sigma_\nu^2),$$
$$u_i\sim N^+(\mu,\sigma_u^2)$$

With f the function that defines the production technology. The rational government will try to maximize its total investment output while minimizing its total input consumption. On the production frontier, the country produces the maximum output for a given set of inputs or uses the minimum set of inputs to produce a given level of output. Moreover, the definition of the production frontier and the estimation of technical efficiency depend on the type of orientation : input-oriented or output-oriented (Coelli, 1996). In this paper, we use the output-oriented measure of technical efficiency (more output with the same set of inputs), which gives the technical efficiency of a country i as follows :

$$TE_{i_t}=[max\Psi\ \textbf{:}\psi y\leq f(x_{i_t})]^{-1}, \tag{2}$$

where Ψ is the maximum output expansion with the set of inputs x_{i_t}. We rewrite Equation 1 so that the three auxiliary assumptions of the output-oriented measure of technical efficiency.

$$y_{i_t}=f(x_{i_t},\beta).e^{-U_{i_t}} \tag{3}$$

where y_{i_t} is a scalar of output, x_i is a vector of inputs used by country i=1,2,3...,N ; t=1,2,...T ; $f(x_i;\beta)$ is the production frontier and β is a vector of technology parameters to be estimated. U_{i_t} are non-negative unobservables random variables associated with technical inefficiency that follow an arbitrary half-sided distribution law. Re-estimating Equation 3, we obtain :

$$y_{i_t}=f(x_{i_t},\beta).e^{-U_{i_t}}.eV_{i_t} \tag{4}$$

where V_{i_t} represent random shocks assumed to be independent and identically distributed random errors with a normal distribution with zero mean and unknown variance. Thus, we obtain our model to be estimated, written in the following form :

$$TE_{i_t}{=}\frac{f(x_{i_t},\beta).e^{-U_{i_t}}.eV_{i_t}}{f(x_{i_t},\beta).e^{-U_{i_t}}} \tag{5}$$

Finally, since we are trying to determine the optimal level of production for a given unit of output, the literature recommends using a Cobb-Douglas type production function. We switch to a Translog specification to model this function and simplify it. After transforming the translog function, we obtain the following equation :

$$lnY_{i_t}{=}\beta_0+\sum\beta_k lnX_i+\varepsilon_{i_t} \tag{6}$$

$$lnY_{i_t}{=}\beta_0+\sum_{j=1}^{3}\beta_j lnX_{i_{j,t}}+\frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{j_k} lnX_{i_{j,t}} lnX_{i_{k,t}}-U_{i_t}+V_{i_t} \tag{7}$$

Where lnY_{i_t} is the logarithm of the output indicator of total investment for country i at time t ; i=1, N indicates the number of countries ; j,k=1,...,3 are the three inputs used (see Table 1) ; lnX_{i_j} is the logarithm of the jth input used from the ith country ; and β_j,β_{j_k} are coefficients to be estimated. We follow the method of Aigner et al. (1977) and Kumbhakar et al., (1990 ; 2015) in which the maximum likelihood estimator is used to estimate the technical efficiency under a half-sided normal law.

4.3.2 Second step : estimation of the effects of climate shocks on TE

In the second step, we regress the production efficiency score on a set of exogenous variables using a fractional regression model (FRM) proposed by Papke and Wooldridge (1996). The reason for using this type of model is the limited value of the efficiency scores and, in some cases, the possibility of a nontrivial probability mass accumulating on one or both boundaries. The literature highlights the limitations of linear regressions for estimating the second stage after the efficiency score. For example, it is considered that the standard linear regression model is not appropriate because it does not guarantee that the predicted values of the dependent variable are restricted to the unit interval (Ramalho et al., 2010). Moreover, since the dependent variable is strictly limited to the interval ($]0;1]$), it is generally unreasonable to assume that the effect of any explanatory variable is constant over its entire range (Ramalho et al., 2011).

Similarly, the Tobit approach has traditionally been used to estimate the efficiency score. However, there are some problems with this approach. First, the predicted values of the dependent variable are restricted to the unit interval only in the two-tailed Tobit model. However, this approach can only be used if the observations are within the two bounds, which is often not the case. Second, the Tobit model is appropriate for data on the interval ($[0;1]$), but its application to data defined on only one interval ($]0;1]$) seems inadequate and inappropriate. Finally, it should be noted that the Tobit model contains very stringent assumptions that require normality and homoscedasticity of the dependent variable variables (Ramalho et al., 2011). Therefore, the estimation of the FRM model must be done with a QML estimator as described by Papke and Wooldridge (1996). In fact, the application of the FRM requires only the assumption of a functional form that constrains the conditional mean of the dependent variable as follows :

$$E(y|x)=G(x\omega) \tag{8}$$

where G(·) is some nonlinear function satisfying 0 ≤G(·)≤ 1.

It is important to note that Equation 8 can be estimated using nonlinear least squares or maximum likelihood estimation. But beware : not only is the former less efficient than QML estimation, the latter also requires the specification of the conditional distribution of y at x. For these reasons, Papke and Wooldridge (1996) has proposed to estimate the FRM using QML with reference to the Bernoulli model (log-likelihood function). The log-likelihood function is written as follows :

$$LL_i(\omega)=y_i log[G(x_i\omega)] + (1-y_i)log[1-G(x_i\omega)] \tag{9}$$

with QML estimator of ω defined by :

$$\hat{\omega} \equiv arg\max_{\omega} \sum_{i=1}^{N} LL_i(\omega) \tag{10}$$

If Equation 8 is well specified, $\hat{\omega}$ will be consistently and asymptotically normal, regardless of the true distribution of y on x (Gourieroux et al., 1984).

4.3.3 Construction of Outputs

In this section, we present the different methods used to calculate our various indicators, which are divided into two outputs to calculate the efficiency score of countries using a frontier model. In addition, the two indicators we calculate capture the activities in which governments direct their investments. To calculate these two indicators, we follow the same approach as IMF (2015). Based on the literature, we selected a set of variables related to infrastructure investment. Albino-War et al. (2014) uses the infrastructure part of the Global Competitiveness Indicator [9] as an output to measure the efficiency of public investment. However, this index does not fully reflect the performance of public investment because it is not possible to separate public infrastructure from private infrastructure (Bamba, 2020).

For the first index, we use the number of hospital beds per 1000 population, the ratio of students to primary school teachers, the total length of roads in kilometers, the number of people using at least a basic portable water supply as a percentage of the population, and electricity generation from oil, gas, and coal (% of the total). For the

9. This indicator was developed by the World Economic Forum

second index, we use paved roads as a percentage of total roads, the number of fixed-line telephone subscriptions, the length of the road network normalized by population density [10], electricity consumption in kilowatt-hours per capita, electricity generation from oil, gas, and coal sources (% of total), and the number of fixed-line telephone subscriptions per 100 people. These variables are selected by IMF (2015) because the authors calculate an index that includes pure infrastructure indicators (electricity generation, access to an improved water source, and length of the road network) and social service indicators (number of teachers in secondary schools and number of hospital beds).

Furthermore, we perform a standardization of all our variables to bring them to the same scale level and avoid bias in the calculation of the output. Then, we take the arithmetic mean or weight of all variables to obtain each indicator.

(a) First Output

$$Y_{i_1} = \sum_{j=1}^{5} \left(\frac{x_{i_j} - \bar{x_j}}{\sigma_{xj}}\right) \tag{11}$$

where Y_{i_1} represents the first output for the country i, $\bar{x_j}$, σ_{xj} denotes the mean and the standard error of sub-index j respectively; $x_{i_j}=$ the number of hospital beds per 1000 people, the ratio of students to primary school teachers, the total length of roads in kilometers, the number of people using at least basic portable water services as a % of the population, and the generation of electricity from oil, gas, and coal sources (% of total).

Indeed, this formula can lead to negative values of our outputs, that is, production. However, we intend to implement these outputs in a stochastic frontier model that does not consider negative values of an output obtained. Indeed, output cannot be negative in a rational way. Therefore, we standardize [11] the value of the outputs to get positive values.

(b) Second Output

$$Y_{i_2} = \sum_{j=1}^{6} \left(\frac{x_{i_j} - \bar{x_j}}{\sigma_{xj}}\right) \tag{12}$$

10. Normalization is done using the total length of roads in kilometers divided by the population density.

11. The formula is as follows : $\phi_i = \frac{Y_{i_1} - Min(Y_{i_1})}{Max(Y_{i_1}) - Min(Y_{i_1})}$, where ϕ_i is the standardized value of Y_{i_1} given by the Equation 11. This gives us the output 1.

where Y_{i_1} is the first output for country i, $\bar{x_j}$, σ_{xj} is the mean and denotes the standard error of sub-index j respectively ; x_{i_j}= paved roads as a percentage of all roads, number of landline telephone subscriptions, length of road network normalized by population density, electricity consumption in kilowatt-hours per capita, electricity generation from oil, gas, and coal (% of total), and number of landline telephone subscriptions per 100 people. Finally, as with Output 1, standardization is performed using we standardize [12].

5 Data and descriptive statistics

5.1 Data

The second group of variables is used to analyze the determinants of the investment efficiency score. These variables determine heterogeneity across countries and affect performance and efficiency. These variables include : Rainfall shocks, temperature shocks, natural resource depletion, resource rents, Oils reserve horizon, GDP per capita, corruption, government stability, ODA, trade openness.

(i) Rainfall shocks : We use this variable to measure climate change as in Burke and Emerick (2016). It measures the deviation from the annual average of rainfall levels (mm). The impact of rainfall shocks on infrastructures, especially road infrastructures, is assessed, for example, by extreme flooding, which poses a major threat to highways by challenging their construction, operation, efficiency, and safety (Pedrozo-Acuña et al., 2017). Flooding can also significantly affect the performance and life of highway infrastructure by influencing the number of incidents such as landslides, washed out roads, flooded and inundated bridge girders, and road closures (Bizikova et al., 2008).

(ii) Temperature shocks : We use this variable to measure climate change as in Diallo (2021). The higher temperature causes several problems such as thermal expansion of pavement joints and softening of asphalt (Ali et al., 2020).

(iii) Natural resources depletion :Measures the sum of net forest depletion, energy depletion and mineral depletion. The more resources are extracted, the more the environment is damaged by air pollution, greenhouse gas emissions, CO2 emissions, and ozone layer depletion, leading to extreme weather events. This can affect the quality of public investment.

(iv) Natural resources rents : This variable measures the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents as a percentage of GDP. Maximizing commodity rents could accelerate fossil fuel production, which exacerbates the effects of climate change. As a result, heavy rains, floods, and storms could occur, threatening the quality of infrastructure. Literature suggests that there is a ne-

12. We apply the following formula $\phi_i = \frac{Y_{i_2}\text{-}Min(Y_{i_2})}{Max(Y_{i_2})\text{-}Min(Y_{i_2})}$, where ϕ_i is the standardized value of Y_{i_2} obtained from the Equation 12. This results in the output 2.

gative relationship between natural resource dependence and the effectiveness of public investment. This is the case with Albino-War et al. (2014), who finds that a one standard deviation increase in natural resource revenues of 17 percent could reduce the efficiency of public investment by 0.02 percent of the average value in his sample.

(v) Oils reserve horizon : The oil reserves dummy variable equals 1 if a country's reserve horizon is greater than the median of all oil-exporting countries. The time horizon of oil reserves explains the degree of dependence of producing countries on natural resources. The longer the horizon, the greater the dependence, and the country is often vulnerable to the high volatility of natural resource revenues. This contributes to the poor quality of public spending in general and capital spending in particular (Gelb, 2010).

(vi) GDP per capita : GDP per capita, constant 2017 USD, captures the stock of physical capital that enables efficient production of public goods and services, but can also facilitate monitoring by policymakers (Afonso et al., 2010). Higher efficiency of public investment is associated with higher GDP per capita.

(vii) Corruption : Corruption control captures perceptions of the extent to which public power is exercised for private gain, including small and large forms of corruption and the "capture" of the state by elites and private interests. High levels of corruption are associated with lower efficiency of public investment (Dabla-Norris et al., 2012; IMF, 2015).

(viii) Government Stability : Government effectiveness captures perceptions of the quality of public services, the quality of public service and the degree to which it is independent of political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to those policies.

(ix) Net Official development assistance (ODA) : This variable represents disbursement flows (net of repayment of principal) that meet the Development Assistance Committee (DAC) definition ODA. One channel through which aid financing can affect investment effectiveness is through the volatility and unpredictability of cash flows.

(x) Trade openness : This variable measures the sum of exports and imports of goods and services, % of GDP. Trade openness could increase the efficiency of public investment by increasing competitive pressures on the domestic economy, including the government, and by increasing exposure to the outside world (Rayp and Van De Sijpe, 2007).

5.2 Descriptive statistics

Table 1 – Summary Statistics of key variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Sources
First stage regression						
PPP capital stock	476	9.33	32.762	0	269.859	IMF databases
Public capital stock	472	158.835	395.476	1.909	2418.607	IMF databases
Gdp per capita	462	7029.798	5413.643	630.702	24647.629	IMF databases
Investment efficiency						
Efficiency 1	476	0.835	0.184	0.363	0.966	Authors computing
Efficiency 2	476	0.695	0.223	0.14	0.944	Authors computing
Second stage regression						
ODA	340	4.067	4.824	-0.219	28.275	World Bank WDI
Rainfall shocks	340	104.304	61.47	13.023	309.619	Climatic Research Unit, University of East Anglia and CERDI https://data.cerdi.org/
Temperature shocks	340	24.139	3.031	14.196	29.376	Climatic Research Unit, University of East Anglia and CERDI https://data.cerdi.org/
Natural resource depletion	451	6.27	9.457	0	58.643	World Bank WDI
Oil reserve horizon	462	0.152	0.359	0	1	Computing with BT dataset
Government effectiveness	429	-0.537	0.523	-1.546	0.729	International Country Risk Guide (ICRG)
Natural resources rents	462	10.631	11.627	0.023	58.65	World Bank WDI
Government Stability	462	8.432	1.537	4.458	11.583	International Country Risk Guide (ICRG)
Trade openness	465	65.917	26.853	21.641	156.862	World Bank WDI
Investment volatility	476	0.059	0.235	0	1	Authors computing based on BP dataset
Corruption	462	2.091	0.777	0	5	International Country Risk Guide (ICRG)

Source : Authors' calculation

6 Econometric results

6.1 Estimation of SFA model

Before presenting the results, we need to perform a validity test of the SFA model, which consists in verifying the theoretical basis of the inputs used. This test, of course, refers to the validity of the model, the hypotheses and the significance of the error term representing the inefficiency.

First, the SFA model is based on the determination of efficiency scores and assumes that the error term of inefficiency follows a half-normal distribution (Aigner et al., 1977) so as to account for all hazards that may interfere with the achievement of optimal production. However, this half-normal distribution of the inefficiency term seems to be difficult to determine. Therefore, some authors have proposed distributions that are even easier to determine. Meeusen and van Den Broeck (1977) propose an exponential distribution of the inefficiency term in their study. Stevenson (1980), on the other hand, proposes a truncated normal distribution. Finally, Greene (2003) proposes a gamma distribution for the inefficiency term. Knowing the literature on the distribution of inefficiency, we proceed to the preliminary tests of hypothesis and theory validation presented in Table 2 for our two outputs.

TABLE 2 – Model validity test

VARIABLES	[1] Efficiency 1	[2] Efficiency 2	[3] Efficiency 1	[4] Efficiency 2
	Model Kumbhakar	Model Kumbhakar	Model Battese and Coelli	Model Battese and Coelli
Log (public capital stock)	0.1962	0.0150	0.3431***	0.3923***
	(0.1596)	(0.2214)	(0.0864)	(0.0639)
Log (Gdp per capita)	0.2415**	0.4539***	0.3670***	0.4307***
	(0.0973)	(0.1606)	(0.0566)	(0.0525)
Log (ppp capital stock)		-0.0167		-0.1179***
		(0.0622)		(0.0257)
Constant	-3.9745***	-4.8714***	-5.7557***	-6.4468***
	(1.3677)	(1.8115)	(0.7487)	(0.6724)
σ_u	3.4585*	1.0116**	3.9263	4.2629
	(2.0588)	(0.4514)	(2.9261)	(3.4871)
σ_v	0.0772***	0.0825***	-3.2520***	-4.2772***
	(0.0143)	(0.0156)	(0.3168)	(0.3373)
Observations	77	76	77	76
Number of countries	19	18	19	18

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. **Notes :** Efficiency 1 obtained with output 1 as dependent variable in the model and efficiency 2 obtained with output 2 as dependent variable in the model (see Kumbhakar (1990) and Battese and Coelli (1995)).

A review of the signs of the coefficients of the inputs confirms the specification of the model. In Table 2, we estimate two stochastic frontier models. The results are given in columns ([1] - [4]). Columns [1] and [2] present the results of the Kumbhakar model, and columns [3] and [4] present the results of Battese and Coelli. In column [1] and [2], we applied the model (Kumbhakar, 1990), which is based on a flexible efficiency model with random effects and time variation, and specifies output 1 in column [1] and output 2 in column [2] as the dependent variable. Then, in columns [3] and [4], we apply the model (Battese and Coelli, 1995) based on a random effects model with time-varying inefficiency effects by introducing output 1 as the dependent variable in column [3] and output 2 in column [4]. Then, we can easily see in Table 2 that the inputs used for the estimates are all positive than for Indicator 1 (see columns [1] and [3]). We recall that the objective of estimating these two models (Kumbhakar (1990) and Battese and Coelli (1995)) is to compare and select the efficiency scores that maximise the state's objective function. In other words, the score that brings government investment closest to the technically best efficiency frontier curve. The assumption of positive monotonicity of inputs remains in these two cases. Consequently, we retain these two models and efficiency 1 in the rest of our study, i.e., for the second stage estimates. This is consistent with the economics literature, which states that an increase in inputs should lead to an additional increase in output.

TABLE 3 – Average country efficiency scores for different specifications, 2000-2013.

Rich Countries	Efficiency scores			Non-rich Countries	Efficiency scores		
	I	**II**	**III**		**I**	**II**	**III**
Angola	0.96	0.84	0.96	Argentina	0.94	0.79	0.81
Botswana	0.95	0.78	0.96	Brazil	0.57	0.85	0.85
Cameroon	0.90	0.50	0.50	Colombia	0.58	0.88	0.90
Congo, Rep	0.96	0.94	0.96	Costa Rica	0.37	0.38	0.41
Cote d'Ivoire	0.96	0.73	0.73	Dominican Republic	0.96	0.85	0.86
Ecuador	0.46	0.60	0.60	El Salvador	0.74	0.70	0.69
Gabon	0.96	0.73	0.72	Ethiopia	0.96	0.14	0.96
Ghana	0.66	0.68	0.68	Honduras	0.88	0.56	0.56
Guinea	0.96	0.94	0.96	Kenya	0.81	0.39	0.40
Mali	0.96	0.94	0.96	Mexico	0.45	0.36	0.37
Namibia	0.95	0.71	0.67	Mozambique	0.96	0.65	0.65
Niger	0.85	0.91	0.91	Nicaragua	0.80	0.43	0.42
Nigeria	0.82	0.87	0.86	Paraguay	0.96	0.40	0.39
Peru	0.42	0.23	0.24	Senegal	0.93	0.61	0.61
Sudan	0.96	0.94	0.96	South Africa	0.96	0.92	0.93
Tanzania	0.89	0.64	0.64	Zimbabwe	0.96	0.93	0.95
Venezuela, RB	0.96	0.94	0.96				
Zambia	0.96	0.79	0.96				

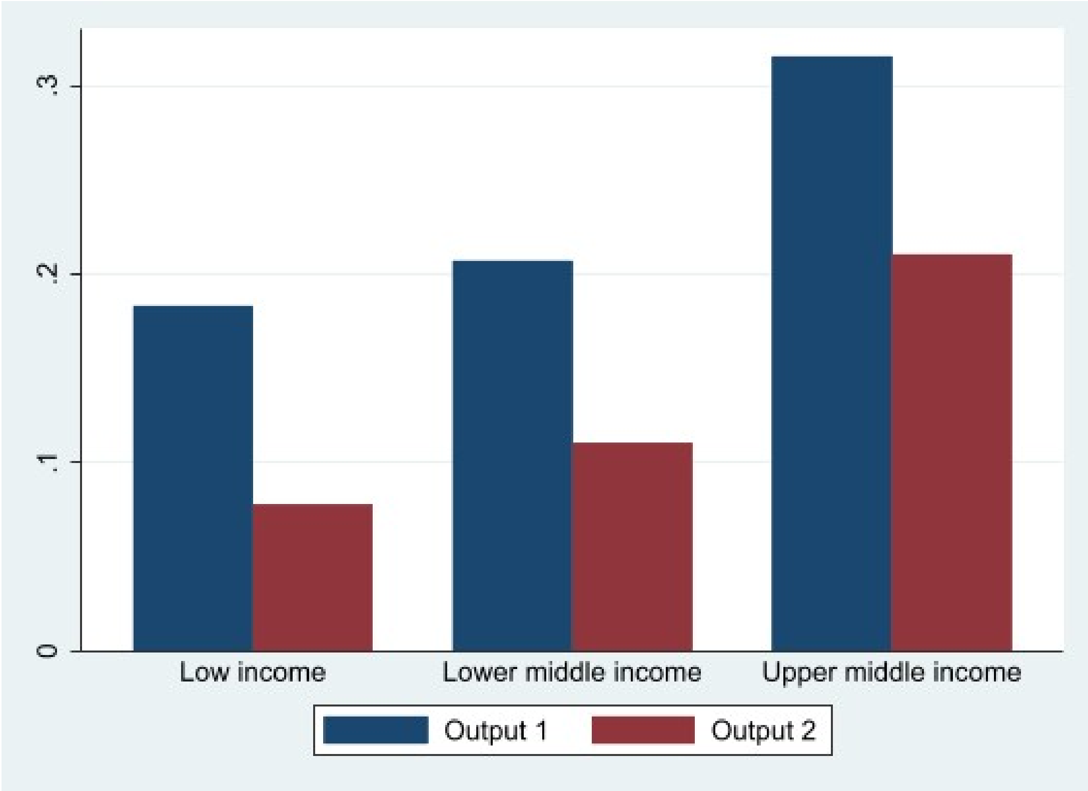
Note : **I** : Output : Output 1 ; Inputs : public capital stock (% GDP), GDP per capita.
II : Output : Output 2 ; Inputs : Public capital stock (% GDP), GDP per capita.
III : Output : Output 2 ; Inputs : public capital stock (% GDP), GDP per capita, PPP capital stock.

Source : Autors' calculations

Table 3 above shows the results of the investment efficiency scores for both resource-rich and non-resource-rich countries. For ease of comparison, we include the non-rich countries in our analysis. To begin the analysis of these scores, note that an efficiency score of (α) indicates that (1-α) percent of public investment is allocated inefficiently, i.e., the share of total investment that would be foregone by the government. This is the case in Peru, where Output 1 has an efficiency score of 0.42 for a given level of public investment (% of GDP) during the period under consideration. This means that Peru could increase this public investment by 58%, given the distance to the efficiency frontier on average and compared to other countries (1-0.42).

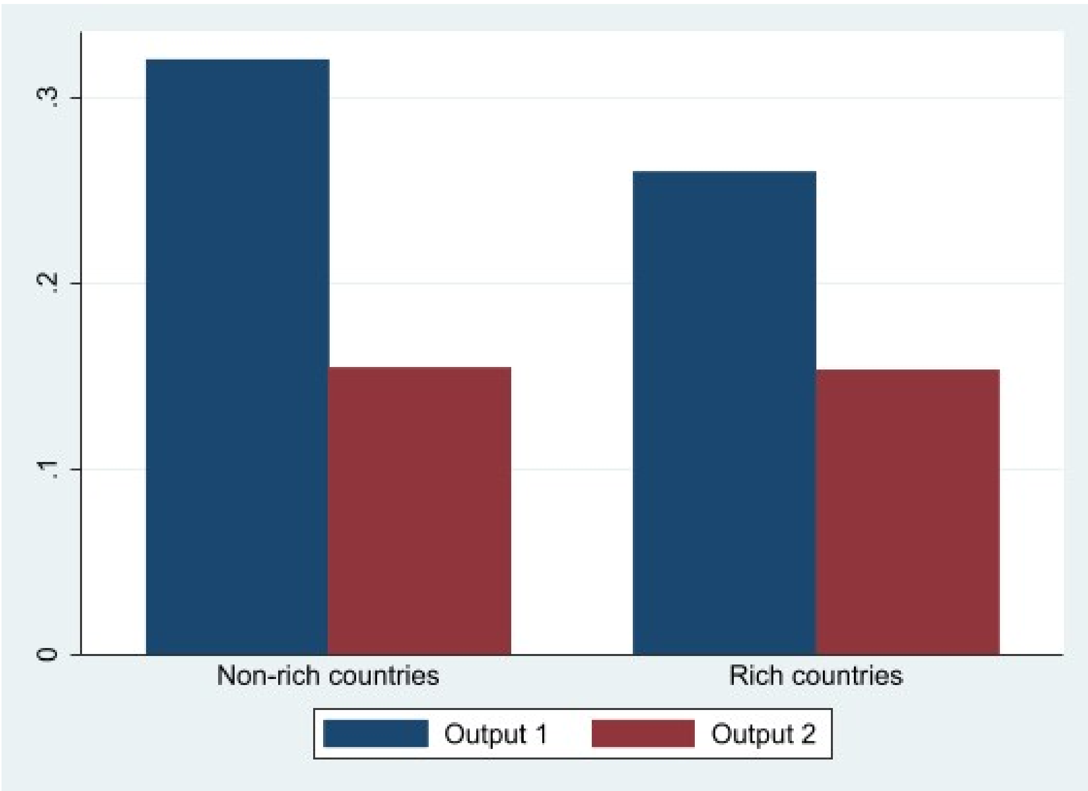
We observe a significant heterogeneity in the estimation of efficiency scores, even between rich and non-rich countries. These differences in efficiency scores could be due to the different estimation techniques and methods used to calculate the output indicators of public investment (output 1 and output 2). For one country selected in the sample, we have different efficiency scores for each output indicator. For example, Angola has an efficiency score of 0.96, 0.84, and 0.96 for Output 1 and 2, respectively (see columns I, II and III, Table 3). These results could be explained by the choice of variables used to calculate the outputs. Indeed, the first output indicator alone would not be able to capture the quantity and quality of infrastructure. This result is notable in Kenya, with scores of 0.81, 0.39, and 0.40, respectively, for the first and second output indicators of public investment. However, not all of these differences should be attributed to the calculation methods or techniques used. An analysis of efficiency scores by income level, as shown in Figure 6, indicates that low-income countries have the lowest efficiency scores in the two periods from 2000 to 2013. This result confirms by Dabla-Norris et al. (2012)'s finding, that efficiency increases with the level of income. In Figure 7, we also see heterogeneity in investment efficiency scores between resource-rich and non-rich countries. Non-resource-rich countries have a better public investment efficiency than resource-rich countries during the study period. These facts confirm the arguments of resource curse theorists that the discovery of a huge deposit of oil, gold, diamonds, bauxite, etc., slows down the economic recovery plan through public investment There is also a clear difference between countries in terms of outcome indicators. Overall, Output 1 seems to be better than Output 2 for all countries in our sample, which is why we keep Output 1 in the second estimation phase of our study.

FIGURE 6 – **Efficiency scores of outputs by income level.**



Source : Author's construction

FIGURE 7 – **Efficiency scores of outputs by resource endowment.**



Source : Author's construction

6.2 Effects of climate change events on technical efficiency.

To estimate the impact of climate shocks on the efficiency of public investment, we construct a climate shock index based on a normalized weighting of several indicator variables [13]. We could have also used the principal component analysis (PCA) method, which is widely used in the literature. However, this method has many limitations, as pointed out by the authors. One of the limitations that led us to abandon this technique and use normalized weighting is that PCA has difficulty dealing with missing data and outliers (Libório et al., 2020; Najar et al., 2002). Since the correlations between variables are used to calculate the eigenvalues and eigenvectors of the indicator, the weight of the variable or the variable itself may be different if the correlation coefficients change (Nardo et al., 2005).

The results of the estimations are presented in Table 4 and Table 5. Table 4, reports the results for our total sample, while Table 5 reports the results for the rich countries. In both tables, column [1] reports the results of the regression of our reference model, and columns [2] and [3] report the results obtained by adding the temperature shocks squared and rainfall shocks squared. It should be noted that the rationale for using or specifying squared precipitation and temperature shocks will be explained in more detail a little later. The results of column [1] in both tables show that climate change has a negative and statistically significant impact on the efficiency of public investment in all countries studied. However, the magnitude seems to be much larger in resource-rich countries. More specifically, when we control for the effects of other variables, we find that an increase in a climate event leads to a 0.83 percentage point decrease in public investment efficiency in our sample overall and a 0.52 percentage point decrease in resource-rich countries. Mechanically, climate change causes heavy rainfall, floods, storms, and droughts that negatively affect public infrastructure. These results are consistent and corroborate with those of other authors (Pedrozo-Acuña et al., 2017; Bizikova et al., 2008). We acknowledge that the climate change index we calculate, based on a normalized weighting of multiple variable indicators, is unlikely to be a credible representation of the intensity of the climate shock in the countries in our sample, which somewhat undermines the analysis. Therefore, we use the temperature and rainfall data in a disaggregated form. Nevertheless, when we disaggregate the climate change index, we find that rainfall shocks have a negative impact, while temperature shocks have a positive impact on public investment efficiency only in resource-rich countries (see Table 6). This result is not surprising, as it is well documented in the literature. For example, Caballero and Hammour (1996) shows that extreme climate shocks can be viewed as exogenous and catalytic to the incentive to reinvest and thus increase capital productivity. Moreover, most of the signs of our control variables are consistent with our original hypothesis. The results suggest that the depletion

13. See Anderson (2008) for instructions and Stata commands and more details on the index

of natural resources, the range of oil reserves, and corruption negatively affect the efficiency of public investment. These results suggest that countries that are highly dependent on natural resource depletion are vulnerable because a large portion of their tax revenues come from natural resource exploitation. Similarly, as corruption increases, rent-seeking, bureaucracy, and poor project selection by managers increase. As a result, the efficiency of public investment declines significantly (Dabla-Norris et al., 2012). However, resource rents, government stability, and trade openness have a statistically significant impact on public investment efficiency The positive sign of resource rents found here is opposite to that found by Albino-War et al. (2014). Those authors found that a one standard deviation increase in resource revenue reduces the efficiency of public investment by 0.02, or about 3 percent of the average score in the sample. Unlike these authors, whose study is based only on a sample of oil-producing countries, our sample includes countries rich in other minerals (oil, gold, diamonds, bauxite, cobalt, nickel, etc.) in addition to oil. In addition, our sample includes countriessuch as [14] that have signed resource-backed loans, the amount of which is intended for the construction of public infrastructure (Mihalyi et al., 2020, 2022).

Trade openness increases the efficiency of public investment by increasing competitive pressure on the domestic economy, including the government, and by increasing contact with the outside world. This allows governments to free up tax revenues to finance further public investment. In addition, trade openness has been shown to potentially improve economic growth in the long run by providing access to goods and services (Keho, 2017). This could have a positive impact on the efficiency of public investment.

14. Angola, Congo, Rep., Ecuador, Ghana, Guinea, Niger, Sudan, Venezuela, Brazil, and Zimbabwe (see Coulibaly et al. (2022); Mihalyi et al. (2022))

Table 4 – Impact of climate shocks on TE of full data

VARIABLES	[1]	[2]	[3]
	Baseline		
Climate change index	-0.8303***	-1.0366***	-0.9286***
	(0.0703)	(0.0806)	(0.2944)
Natural resources depletion	-0.1080***	-0.0946***	-0.0934***
	(0.0219)	(0.0212)	(0.0214)
Oil reserve horizon	-0.8808***	-0.8821***	-0.8904***
	(0.1780)	(0.1670)	(0.1727)
Natural resources rents	0.0997***	0.0922***	0.0909***
	(0.0172)	(0.0166)	(0.0167)
Government stability	0.3700***	0.3023***	0.3024***
	(0.0418)	(0.0388)	(0.0388)
Corruption	-0.6151***	-0.4424***	-0.4459***
	(0.0857)	(0.0944)	(0.0952)
Trade openness	0.0078***	0.0086***	0.0085***
	(0.0021)	(0.0021)	(0.0022)
Temperature shocks square		0.0021***	0.0019**
		(0.0006)	(0.0008)
Rainfall shocks square			-0.0000
			(0.0000)
Constant	-0.3356	-1.3297**	-1.1919*
	(0.3676)	(0.5331)	(0.6871)
Pseudo R2	0.1379	0.1434	0.1434
Observations	316	316	316

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. **Notes :** Estimation method : fractional logistic regression. The dependent variable is the score of technical efficiency estimated in Table 16. In column [2] and [3], rainfall shocks square and temperature shocks square are controlled.

Table 5 – Impact of climate shocks on TE in Resource-rich countries

VARIABLES	[1]	[2]	[3]
	Baseline		
Climate change index	-0.5185**	-0.8674***	-0.5034
	(0.2331)	(0.1921)	(0.6430)
Natural resources depletion	-0.1301***	-0.1203***	-0.1187***
	(0.0289)	(0.0259)	(0.0254)
Oil reserve horizon	-0.8628***	-0.5226***	-0.5375***
	(0.1845)	(0.1457)	(0.1548)
Natural resources rents	0.1252***	0.1329***	0.1314***
	(0.0241)	(0.0208)	(0.0206)
Government stability	0.4028***	0.2715***	0.2670***
	(0.0483)	(0.0441)	(0.0458)
Corruption	-0.6644***	-0.0044	-0.0082
	(0.1387)	(0.1547)	(0.1553)
Trade openness	0.0128**	0.0107*	0.0108*
	(0.0065)	(0.0063)	(0.0064)
Temperature shocks square		0.0046***	0.0041***
		(0.0008)	(0.0009)
Rainfall shocks square			-0.0000
			(0.0000)
Constant	-1.2803***	-4.4032***	-3.9737***
	(0.4722)	(0.7345)	(0.8315)
Pseudo R2	0.1253	0.1528	0.1530
Observations	183	183	183

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. **Notes :** Estimation method : fractional logistic regression. The dependent variable is the score of technical efficiency estimated in Table 16. In column [2] and [3], rainfall shocks square and temperature shocks square are controlled.

Table 6 – Results using temperature and rainfall shock variable

VARIABLES	[1] Full data	[2] Rich-countries
Rainfall shocks	-0.0093***	-0.0081***
	(0.0007)	(0.0017)
Temperature shocks	0.0082	0.1632***
	(0.0236)	(0.0366)
Natural resources depletion	-0.0951***	-0.1169***
	(0.0214)	(0.0256)
Oil reserve horizon	-0.8949***	-0.5247***
	(0.1694)	(0.1439)
Natural resources rents	0.0926***	0.1314***
	(0.0167)	(0.0205)
Government stability	0.3038***	0.2556***
	(0.0393)	(0.0448)
Corruption	-0.4522***	0.0174
	(0.0941)	(0.1526)
Trade openness	0.0082***	0.0101
	(0.0021)	(0.0062)
Constant	0.2874	-4.9987***
	(0.6987)	(1.1202)
Pseudo R2	0.1430	0.1555
Observations	316	183

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. Estimation method : fractional logistic regression. The dependent variable is the score of technical efficiency estimated in Table 16.

7 Robustess Check

7.1 Alternative climate change index definition

To check the robustness of our results, we redefine the measure of the climate variable used in our original regressions. This climate measure consists of calculating the optimal daily temperature and rainfall shocks that are expected to increase in frequency and magnitude as climate change progresses. Clearly, for temperature, we want to measure the standardized deviations of interannual temperature estimates from the panel mean for each country in the sample. The same is true for precipitation, which should measure the standardized deviations of precipitation at the country level. In doing so, we take inspiration from Eastin (2018). Namely, the author uses a measure of climate shocks based on the following formula :

$$\Omega_{i_t}=(\frac{x_{i_t}\text{-}\bar{x_i}}{\sigma_i}) \tag{13}$$

where is $\bar{x_i}$ the panel mean for country i, x_{i_t} is the estimated temperature for country i at time t , and σ_i is the standard deviation for country i. Once these scores are calculated from the above formula, they are used as dependent variables as follows :

$$TE_{i_t}=\alpha_0 + \alpha_1.\Omega_{i_t} + \alpha_2.W_{i_t} + \varepsilon_{i_t} \tag{14}$$

Ω_{i_t} represents the newly calculated weather shock scores, TE is the Technical efficiency and W_{i_t} is the set of control variables.

The results are shown in Table 7 below (column [1] and [2]). We find a positive and a negative effect for the rainfall and temperature shocks, respectively. Basically, rising temperatures and temperature shocks are the most consistent environmental impacts of climate change and can have a number of negative effects on the economy as a whole. Therefore, affected governments that are aware of these damages could preempt these temperature shocks, which could be a boon to public investment. In some countries located in geographic areas such as the Sahara, the Sahel, and some sub-Saharan African countries, the intensity of high temperatures could encourage policymakers to put in place infrastructure to adapt to climate shocks. This could have a positive impact on the efficiency of public investment. This result could be explained by the fact that limited access to electricity in some localities due to lower hydropower production during droughts leads to a deterioration in health status, prompting the government to invest heavily in high-quality infrastructure to protect people's lives in the face of shocks.

The negative impacts of rainfall shocks may be due to the fact that engagement, early awareness, and consideration of climate risks are not yet central to the planning and implementation of public investments, particularly in infrastructure, in developing countries.

Table 7 – Robustness of results with change in the climate change.

VARIABLES	[1] Full data	[2] Rich-countries
Rainfall shocks (Z)	-0.5710***	-0.4955***
	(0.0443)	(0.1048)
Temperature shocks (Z)	0.0250	0.4948***
	(0.0716)	(0.1108)
Natural resources depletion	-0.0951***	-0.1169***
	(0.0214)	(0.0256)
Oil reserve horizon	-0.8949***	-0.5247***
	(0.1694)	(0.1439)
Natural resources rents	0.0926***	0.1314***
	(0.0167)	(0.0205)
Government stability	0.3038***	0.2556***
	(0.0393)	(0.0448)
Corruption	-0.4522***	0.0174
	(0.0941)	(0.1526)
Trade openness	0.0082***	0.0101
	(0.0021)	(0.0062)
Constant	-0.4825	-1.8996***
	(0.3530)	(0.4075)
Pseudo R2	0.1430	0.1555
Observations	316	183

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. **Notes :** rainfall shocks (Z) and temperature shocks (Z) are obtained by applying the method of Eastin (2018), see Equation 13. Estimation method : fractional logistic regression. The dependent variable is the score of technical efficiency estimated in Table 16.

7.2 Alternative estimation method

To estimate the impact of climate change on the efficiency of public investment, we use a series of fractional regressions on a country-specific panel data set covering the period 2000-2013. Fractional regression is a preferred method for modeling independent variables that contain values between 0 and 1, i.e., for a dependent variable that is greater than or equal to 0 and less than or equal to 1. It uses a probit, logit, or heteroscedastic probit model for the conditional mean (Ramalho et al., 2010). All fractional regressions were performed with a logit regression. To assess the robustness of these results, we also estimate each model with a fractional regression that includes a probit regression that captures fractional heteroscedasticity. The results are presented in the Table 8 and Table 9.

TABLE 8 – Robustness results impact of climate shocks on TE

VARIABLES	[1]	[2]	[3]
Climate change index	-0.4801***	-0.5873***	-0.4364***
	(0.0394)	(0.0446)	(0.1561)
Natural resources depletion	-0.0563***	-0.0507***	-0.0487***
	(0.0116)	(0.0117)	(0.0118)
Oil reserve horizon	-0.4795***	-0.4680***	-0.4801***
	(0.0984)	(0.0934)	(0.0967)
Natural resources rents	0.0530***	0.0500***	0.0480***
	(0.0091)	(0.0091)	(0.0092)
Government stability	0.1890***	0.1560***	0.1559***
	(0.0231)	(0.0215)	(0.0216)
Corruption	-0.3204***	-0.2334***	-0.2375***
	(0.0461)	(0.0502)	(0.0505)
Trade openness	0.0042***	0.0048***	0.0047***
	(0.0012)	(0.0012)	(0.0012)
Temperature shocks square		0.0010***	0.0008*
		(0.0003)	(0.0004)
Rainfall shocks square			-0.0000
			(0.0000)
Constant	-0.0449	-0.5645*	-0.3745
	(0.1990)	(0.2917)	(0.3730)
Pseudo R2	0.1345	0.1395	0.1398
Observations	316	316	316

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. Estimation method : fractional probit regression. The dependent variable is the score of technical efficiency estimated in Table 16.

Table 9 – Robustness results for Rich-countries

VARIABLES	[2]	[3]	[4]
Climate change index	-0.3118**	-0.4979***	-0.4128
	(0.1340)	(0.1156)	(0.3649)
Natural resources depletion	-0.0667***	-0.0631***	-0.0627***
	(0.0152)	(0.0142)	(0.0141)
Oil reserve horizon	-0.4489***	-0.2651***	-0.2693***
	(0.1059)	(0.0867)	(0.0922)
Natural resources rents	0.0660***	0.0717***	0.0713***
	(0.0135)	(0.0121)	(0.0121)
Government stability	0.2119***	0.1512***	0.1500***
	(0.0280)	(0.0265)	(0.0276)
Corruption	-0.3281***	0.0156	0.0145
	(0.0759)	(0.0877)	(0.0880)
Trade openness	0.0051	0.0039	0.0039
	(0.0035)	(0.0034)	(0.0034)
Temperature shocks square		0.0025***	0.0023***
		(0.0004)	(0.0005)
Rainfall shocks square			-0.0000
			(0.0000)
Constant	-0.5298*	-2.2601***	-2.1534***
	(0.2704)	(0.4299)	(0.5279)
Pseudo R2	0.1183	0.1445	0.1445
Observations	183	183	183

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. Estimation method : fractional probit regression. The dependent variable is the score of technical efficiency estimated in Table 16

7.3 Additional control variable

We examine the robustness of the article's main result when various considerations enter the analysis. Donor countries and development partners actively assist developing countries with public investments that meet environmental standards. Some countries also receive aid in the event of natural disasters to rebuild destroyed infrastructure. We take this into account by including official development assistance (ODA) in the baseline specification. We then control for the volatility of official investment over time in our reference model. Indeed, many countries experience large swings in their investment dynamics when an exogenous shock follows. This can have a significant impact on the efficiency of public investment. We account for this by including public investment volatility in the baseline specification. This the public investment volatility [15]. In addition, we observe the economic costs incurred by countries in the event of a natural disaster caused by climate change. This cost measures the monetary value of the total or partial destruction of existing physical assets in a country affected by a natural disaster as GDP [16]. The idea is to test whether the higher absolute economic cost in a given natural disaster affects the efficiency of public investment by the government of the affected country. Therefore, we include in our reference specification the economic costs of disasters from the EM-DAT international disaster database and Our world in data. Finally, we control for the level of public debt service. Unsustainable public debt may affect the government's ability to mobilize more tax revenues to finance more profitable public investments in the future.

The main result of the paper remains unchanged when ODA is included in the reference equation. Climate shocks reduce the efficiency of public investment. The estimation results suggest that ODA increases the efficiency of public investment only in resource-rich countries, but the coefficient of the climate change index remains negative and not significant (Panel B, column [2]). This result could be explained by the strong presence and intensification of ODA from some countries like China in developing countries, especially in resource-rich countries. From a strategic point of view, China is very interested in strategic minerals for the energy transition and directs its FDI and ODA to countries whose mineral resources are rich in these minerals. This not only increases the stock of public capital, but also increases the efficiency of government investment, as public-private partnerships exist between governments and private investors. The volatility of public investment has a negative impact on the efficiency of public investment not only in non-rich countries but also in rich countries. This result could be due to the fact that, for example, after elections, the ruling party tends to reward the voters who brought it to power. An increase in a ruling party's election results in a region is traditionally followed by higher per capita public investment in that region. This leads to systematic underinvestment in infrastructure and excessive spending on certain goods, which negatively affects the efficiency of public investment (Panel A and B, column [3]).

The main results of the study remain qualitatively unchanged when these variables are added to the baseline model. All coefficients on the climate change index variables remain negative (significant at 1% in panel A and significant at 5% in panel B for the most part).

15. It is a dummy variable that takes the value of 1 if the standard deviation of the annual percentage change in real public investment in year t in country i is greater than the 95th percentile. To generate this variable, we followed Dabla-Norris et al. (2012) and Albino-War et al. (2014).

16. We assume that the direct economic loss or economic cost is nearly equivalent to the physical damage.

Table 10 – Robustness with addition of relevant controls

Panel A : Full data	[1]	[2]	[3]	[4]
Climate change index	-0.8613***	-0.8132***	-0.8690***	-0.8466***
	(0.1024)	(0.0758)	(0.0668)	(0.0783)
Oda		0.0131		
		(0.0177)		
Public investment volatility			-0.9538***	
			(0.2161)	
Log(Economic costs of disasters)				-1.60e-07***
				(5.77e-08)
Constant	2.0456***	-0.3318	-0.1857	-0.6630*
	(0.1002)	(0.3680)	(0.3774)	(0.3653)
Pseudo R2	0.0437	0.1381	0.1440	0.1465
Observations	340	316	316	250
Main controls	**No**	**Yes**	**Yes**	**Yes**
Panel B : Resource-rich countries	[1]	[2]	[3]	[4]
Climate change index	-0.5185**	-0.2309	-0.6949***	-0.6667**
	(0.2331)	(0.2692)	(0.2199)	(0.2640)
Oda		0.0695**		
		(0.0300)		
Public investment volatility			-2.1091***	
			(0.2336)	
Log(Economic costs of disasters)				-7.34e-08
				(6.39e-08)
Constant	-1.2803***	-1.5362***	-1.0749**	2.7157***
	(0.4722)	(0.5161)	(0.4903)	(0.6984)
Pseudo R2	0.1253	0.1311	0.1459	0.1589
Observations	183	183	183	133
Main controls	**No**	**Yes**	**Yes**	**Yes**

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. Estimation method : fractional logit regression. The dependent variable is the score of technical efficiency estimated in Table 16. Main controls are those in Table 4, column [1].

8 Heterogeneity effects

8.1 Size of economy and climate shocks

In this section, we explore the implications of a possible source of heterogeneity that might be included in our conclusion. Indeed, the empirical literature has found heterogeneity in the macroeconomic structure and political situation in developing countries

(Acemoglu et al., 2019; Minea and Tapsoba, 2014). We evaluate the sensitivity of our results by considering these factors. The main idea, of course, is to find out whether structural factors can amplify or mitigate the effects of climate change on the efficiency of public investment. In doing so, we will examine whether the effects of climate shocks on the efficiency of public investment differ across countries depending on their income levels. To this end, we first replicate the baseline regressions specified by country income level. Second, we generate a variable that captures the business cycle and takes the value 1 if GDP growth is above its average value and 0 otherwise by following Sawadogo (2020).

TABLE 11 – Heterogeneity in income level.

	Panel A : Full data		
VARIABLES	[1]	[2]	[3]
	Low Income	Lower middle income	Upper middle income
Climate change index	0.9869***	-0.7759***	-0.7605***
	(0.2604)	(0.0957)	(0.1008)
Constant	2.6231***	2.3528***	1.4782***
	(0.1119)	(0.0909)	(0.1373)
Pseudo R2	0.0102	0.0170	0.0607
Observations	60	140	140
Main controls	**No**	**No**	**No**
	Panel B : Resource-rich countries		
VARIABLES	[1]	[2]	[3]
	Low Income	Lower middle income	Upper middle income
Climate change index	1.1129***	-1.0440***	0.5347*
	(0.2609)	(0.2655)	(0.2848)
Constant	2.5142***	2.5814***	0.6287***
	(0.1199)	(0.1063)	(0.1993)
Pseudo R2	0.0148	0.0129	0.0161
Observations	50	80	60
Main controls	**No**	**No**	**No**

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. Estimation method : fractional logit regression. The dependent variable is the score of technical efficiency estimated in Table 16.

Table 12 – Heterogeneity by business cycle

	Full data		Resource-rich countries	
	Good business cycle	Poor business cycle	Good business cycle	Poor business cycle
VARIABLES	[1]	[2]	[1]	[2]
Climate Change index	-0.7937***	-0.6355***	0.3786	-0.4338*
	(0.1021)	(0.0988)	(0.2741)	(0.2239)
Constant	1.5517***	2.4494***	0.8355***	2.4222***
	(0.1340)	(0.0768)	(0.1893)	(0.0922)
Pseudo R2	0.0608	0.0113	0.0075	0.0031
Observations	155	185	67	123
Main controls	**No**	**No**	**No**	**No**

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1. Estimation method : fractional logit regression. The dependent variable is the score of technical efficiency estimated in Table 16.

The results of the estimates are presented in Table 11 and 12. Table 11 reports the results of the potential heterogeneity bias by country income level. The results for panel A are for the overall sample and panel B specifically for the resource-rich countries. The results confirm heterogeneity in climate shocks across countries at their income level. Climate change improves the efficiency of public investment in low-income countries. However, it negatively affects the efficiency of public investment in low- and upper-middle-income countries (panel A , column [1]). Our results show a much larger magnitude in resource-rich, low-income countries (panel B, column [1]).

The positive impact of climate shocks on the efficiency of public investment in developing countries, especially in resource-rich, low-income countries, could be explained by the fact that these countries are generally the largest recipients of funding for green infrastructure projects to accelerate climate change adaptation at the infrastructure planning level. In addition, some creditors or even multilateral institutions offer financial benefits (debt service forgiveness, debt-for-nature swaps, green project funds, etc.) for environmental public investments (Essers et al., 2021). The role of green financing conjugated with the fact that creditors forgive part of the debt service in favour of the environmental impact of the funds they disburse, could also be considered as an explanation for this result. Countries that perform well on investment efficiency are rewarded with funds and/or debt service forgiveness. As a result, countries face an obligation to make their investments more effective or efficient in order to continue receiving these benefits.

Table 12 shows that there is no heterogeneous impact of climate change on the efficiency of public investment at the business cycle level. This result suggests that regardless of the type of business cycle [17], the effect is not attenuated : Climate change negatively affects investment efficiency even in resource-rich countries.

8.2 Effects non-linearity of weather

In this section, we examine the non-linear effects of climate change and public investment. The empirical literature on climate frequently highlights problems of nonlinearity in weather conditions, especially temperature (Leppänen et al., 2017; Deschênes and Greenstone, 2011). Given the heterogeneity across countries, it is quite possible that nonlinearity exists in our sample with respect to the impact of temperature on public investment. Indeed, the literature suggests that the effect of nonlinearity in climate-related studies, if it exists, is captured by focusing on temperature (e.g., Deschênes and Greenstone, 2011).

We then test for nonlinearity between climate variables and public investment using both a linear and a quadratic specification. The results for the quadratic specification are reported in Tables 4 and 5, column ([2]- [3]). Not surprisingly, only the quadratic of temperature is statistically significant and positive. This result suggests that a quadratic relationship seems appropriate for the temperature effect on public investment.

For the linear specification, we could have used a fixed effects model. However, we face two limitations. First, the fact that our dependent variable is bounded between 0 and 1 can potentially bias our estimation results. Second, the effects model in a climate study only captures short-term adaptation, and its ability to estimate the long-term effects of climate change is weak (Leppänen et al., 2017). For these reasons, we use a long-difference model (LD) to capture the short- and long-term nonlinear effects of climate change on public investment. However, we should be cautious in interpreting the results of the long-difference model because our baseline regression results may be subject to long-term fluctuations due to the sample size, as recommended by Leppänen et al. (2017).

The results of the estimates are shown in Table 13. Overall, the results suggest that temperature has a cumulative effect on public investment. The estimation suggests that a 1°C increase in temperature leads to a decrease in public investment as a percentage of GDP of about 15.34%. The regression also suggests that precipitation has a nonlinear effect on public investment in our overall sample. In contrast, none of these variables has a nonlinear effect on public investment in resource-rich countries. This could be due to the small number of observations for resource-rich countries and the relatively short duration of weather averages in our data.

17. we characterize the good business cycle as the recovery and expansion phase and the poor economic cycle as the overheating and recession phase.

Table 13 – Long-difference (LD) estimations with full and resource-rich countries data.

	[1]	[2]
VARIABLES	Full data	Resource-rich countries
Rainfall shocks	0.0009	0.0010
	(0.0011)	(0.0021)
Temperature shocks	-0.1534***	-0.1101
	(0.0578)	(0.0852)
	(0.0028)	(0.0040)
Constant	0.0846***	0.1233***
	(0.0195)	(0.0295)
Main controls	**Yes**	**Yes**
Observations	247	146
R-squared	0.0527	0.0443

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1

9 Concluding and remarks

Developing countries face a lack of adequate infrastructure because they have limited resources to finance it, while the needs of their populations are growing significantly. In particular, those rich in natural resources are victims of the phenomenon known as the **"natural resource curse"** which summarises the macroeconomic imbalances caused by exploitation and heavy dependence on natural resources. In addition, many of these countries have faced a series of economic crises conjugated with climate change in recent decades, requiring fiscal space for adaptation and mitigation measures in the event of shocks. Therefore, assessing the efficiency of public investment in these countries is critical.

In this paper, we examine the efficiency of public investment and the important factors that influence the design and future performance of public investment in developing countries, with a particular focus on resource-rich countries. To this end, we used a two-stage approach for a sample of 34 developing countries over the period 2000 to 2013.

First, we calculate an efficiency score that captures the performance of governments with respect to the optimal production of goods and services in the economy. This compares not only inputs but also countries to find the best allocation that maximizes the total level of output given the same level of inputs. Second, it identifies the factors that determine the efficiency of public investment in the context of climate change. For this second step, the paper uses unbalanced panel data.

We used stochastic frontier analysis (SFA) to estimate the efficiency values of public investments. This technique accounts for factors that are not under the control of the government, such as exogenous shocks. In addition, this model considers two types of errors that can affect public investment. The first is technical, and the second is stochastic. Since our final objective is to determine the impact of climate shocks on public investment efficiency associated with exogenous disturbances, the SFA model is more appropriate than the more deterministic approach DEA. To analyze the determinants of public investment effectiveness, this paper uses a fractional regression model (FRM).

Our results show that, on average, developing countries could increase the provision of public goods and services by 29% through excellent investment programs without changing the level of public investment spending. The efficiency of investment returns is low in resource-rich, low- and middle-income countries.

The FRM results show that the efficiency of public investment in developing countries is affected by climate change (rainfall and temperature) as well as economic and institutional factors. This study shows that climate change not only has a direct impact on agriculture in general, but also affects the returns to public investment. As a result, it leads to a deterioration of the fiscal balance through a reduction in tax revenues and a pro-cyclical orientation of fiscal policy.

These findings inform policymakers about the macroeconomic realities of climate change, which should prompt them to increase their efforts and actions to address climate damage by building more resilient infrastructure. Clearly, they need to consider climate shocks when planning new infrastructure to adapt to climate change and mitigate its impacts. This is the right time to remind the international public, businesses and multinational corporations of their social responsibility to the environment. We also call on international institutions and donors to step up their action on climate change funds, clean development financing and budget relief for developing countries, because climate change has proven to be a global phenomenon for which everyone is responsible.

Références

Abiad, A., Almansour, A., Furceri, D., Granados, C. M., and Topalova, P. (2014). Is it time for an infrastructure push ? the macroeconomic effects of public investment. *World Economic Outlook*, pages 75–114.

Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2019). Democracy does cause growth. *Journal of political economy*, 127(1) :47–100.

Adams, R. M. (1989). Global climate change and agriculture : an economic perspective. *American journal of agricultural economics*, 71(5) :1272–1279.

Afonso, A. and Aubyn, M. S. (2005). Non-parametric approaches to education and health efficiency in oecd countries. *Journal of applied economics*, 8(2) :227–246.

Afonso, A., Schuknecht, L., and Tanzi, V. (2010). Public sector efficiency : evidence for new eu member states and emerging markets. *Applied Economics*, 42(17) :2147–2164.

Aigner, D., Lovell, C. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, 6(1) :21–37.

Albala-Bertrand, J.-M. (1993). Natural disaster situations and growth : A macroeconomic model for sudden disaster impacts. *World Development*, 21(9) :1417–1434.

Albino-War, M. M. A., Cerovic, M. S., Grigoli, F., Flores, M. J., Kapsoli, M. J., Qu, M. H., Said, M. Y., Shukurov, M. B., Sommer, M. M., and Yoon, M. S. (2014). *Making the most of public investment in MENA and CCA oil-exporting countries*. International Monetary Fund.

Ali, Q., Yaseen, M. R., and Khan, M. T. I. (2020). The impact of temperature, rainfall, and health worker density index on road traffic fatalities in pakistan. *Environmental Science and Pollution Research*, 27(16) :19510–19529.

Alirezaei, M., Onat, N. C., Tatari, O., and Abdel-Aty, M. (2017). The climate change-road safety-economy nexus : a system dynamics approach to understanding complex interdependencies. *Systems*, 5(1) :6.

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention : A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American statistical Association*, 103(484) :1481–1495.

Aschauer, D. A. (1989). Is public expenditure productive ? *Journal of monetary economics*, 23(2) :177–200.

Auffret, P. (2003). *High consumption volatility*. Number 2962. World Bank Publications.

Ba, M. N. (2016). Analysis of agricultural commodities value chains and greenhouse gas emission in rice and maize in west africa : Impact on food security. *Agricultural Sciences*, 7(7) :457–468.

Bamba, M. (2020). *Four essays on fiscal policy and public spending management*. PhD thesis, Université Clermont Auvergne.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical economics*, 20(2) :325–332.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., and Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, 7(4) :283–288.

Bizikova, L., Neale, T. L., and Burton, I. (2008). *Canadian communities' guidebook for adaptation to climate change : Including an approach to generate mitigation co-benefits in the context of sustainable development*. Adaptation and Impacts Research Division, Environment Canada.

Bulte, E. H., Damania, R., and Deacon, R. T. (2005). Resource intensity, institutions, and development. *World development*, 33(7) :1029–1044.

Burke, M. and Emerick, K. (2016). Adaptation to climate change : Evidence from us agriculture. *American Economic Journal : Economic Policy*, 8(3) :106–40.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577) :235–239.

Caballero, R. J. and Hammour, M. L. (1996). On the timing and efficiency of creative destruction. *The Quarterly Journal of Economics*, 111(3) :805–852.

Calderon, C. (2008). Infrastructure and growth in africa. africa infrastructure country diagnostic. *World Bank, Washington, DC*.

Calderon, C. A. and Servén, L. (2004). The effects of infrastructure development on growth and income distribution. *Available at SSRN 625277*.

Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R. S., and Ringler, C. (2014). Climate change and agriculture : Impacts and adaptation options in south africa. *Water Resources and Economics*, 5 :24–48.

Catalano, M., Forni, L., and Pezzolla, E. (2020). Climate-change adaptation : The role of fiscal policy. *Resource and Energy Economics*, 59 :101111.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5) :1549–1561.

Cavallo, E., Powell, A., and Becerra, O. (2010). Estimating the direct economic damages of the earthquake in haiti. *The Economic Journal*, 120(546) :F298–F312.

Chakraborty, S. and Dabla-Norris, E. (2009). The quality of public investment.

Chauvin, N. D., Mulangu, F., Porto, G., et al. (2012). Food production and consumption trends in sub-saharan africa : Prospects for the transformation of the agricultural sector. *UNDP Regional Bureau for Africa : New York, NY, USA*, 2(2) :74.

Coelli, T. J. (1996). A guide to frontier version 4.1 : a computer program for stochastic frontier production and cost function estimation. Technical report, CEPA Working papers.

Colombi, R., Kumbhakar, S. C., Martini, G., and Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis*, 42(2) :123–136.

Combes, J.-L., Delacote, P., Motel, P. C., and Yogo, T. U. (2018). Public spending, credit and natural capital : Does access to capital foster deforestation ? *Economic Modelling*, 73 :306–316.

Combes, J.-L., Motel, P. C., Minea, A., and Villieu, P. (2015). Deforestation and seigniorage in developing countries : A tradeoff ? *Ecological Economics*, 116 :220–230.

Coulibaly, Y., Minea, A., and Villieu, P. (2022). How do natural resource-backed loans affect the public debt sustainability in developing countries ? empirical evidence.

Culas, R. J. (2003). Impact of credit policy on agricultural expansion and deforestation.

Dabla-Norris, E., Brumby, J., Kyobe, A., Mills, Z., and Papageorgiou, C. (2012). Investing in public investment : an index of public investment efficiency. *Journal of Economic Growth*, 17(3) :235–266.

Dafermos, Y., Nikolaidi, M., and Galanis, G. (2018). Climate change, financial stability and monetary policy. *Ecological Economics*, 152 :219–234.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather ? the new climate-economy literature. *Journal of Economic Literature*, 52(3) :740–98.

Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation : Evidence from annual fluctuations in weather in the us. *American Economic Journal : Applied Economics*, 3(4) :152–85.

Diallo, Y. (2021). *Socio-economic impacts of climate change in developing countries*. PhD thesis, Université Clermont Auvergne (2021-...).

Dietz, S., Bowen, A., Dixon, C., and Gradwell, P. (2016). ‘climate value at risk’of global financial assets. *Nature Climate Change*, 6(7) :676–679.

Eastin, J. (2018). Climate change and gender equality in developing states. *World Development*, 107 :289–305.

Eberhardt, M. and Presbitero, A. F. (2015). Public debt and growth : Heterogeneity and non-linearity. *Journal of international Economics*, 97(1) :45–58.

Escaleras, M., Anbarci, N., and Register, C. A. (2007). Public sector corruption and major earthquakes : A potentially deadly interaction. *Public Choice*, 132(1) :209–230.

Essers, D., Cassimon, D., and Prowse, M. (2021). Debt-for-climate swaps : Killing two birds with one stone ? *Global Environmental Change*, 71 :102407.

Falloon, P. and Betts, R. (2010). Climate impacts on european agriculture and water management in the context of adaptation and mitigation—the importance of an integrated approach. *Science of the total environment*, 408(23) :5667–5687.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society : Series A (General)*, 120(3) :253–281.

Filippini, M. and Greene, W. (2016). Persistent and transient productive inefficiency : a maximum simulated likelihood approach. *Journal of Productivity Analysis*, 45(2) :187–196.

Gelb, A. (2010). How should oil exporters spend their rents ? *Center for Global Development Working Paper*, (221).

Gourieroux, C., Monfort, A., and Trognon, A. (1984). Pseudo maximum likelihood methods : Theory. *Econometrica : journal of the Econometric Society*, pages 681–700.

Greene, W. H. (2003). Simulated likelihood estimation of the normal-gamma stochastic frontier function. *Journal of Productivity Analysis*, 19(2) :179–190.

Grigoli, F. and Mills, Z. (2014). Institutions and public investment : an empirical analysis. *Economics of Governance*, 15(2) :131–153.

Gupta, S., Kangur, A., Papageorgiou, C., and Wane, A. (2014). Efficiency-adjusted public capital and growth. *World Development*, 57 :164–178.

Gylfason, T. (2001). Nature, power and growth. *Scottish Journal of Political Economy*, 48(5) :558–588.

Havko, J., Mitašová, V., Pavlenko, T., Titko, M., and Kováčová, J. (2017). Financing the disaster resilient city in the slovak republic. *Procedia engineering*, 192 :301–306.

Heipertz, M. and Nickel, C. (2008). Climate change brings stormy days : case studies on the impact of extreme weather events on public finances. *Available at SSRN 1997256.*

Herrera, S. and Pang, G. (2005). *Efficiency of public spending in developing countries : an efficiency frontier approach*, volume 3645. World Bank Publications.

Herweijer, C., Ranger, N., and Ward, R. E. (2009). Adaptation to climate change : threats and opportunities for the insurance industry. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 34(3) :360–380.

Hjalmarsson, L., Kumbhakar, S. C., and Heshmati, A. (1996). Dea, dfa and sfa : a comparison. *Journal of Productivity Analysis*, 7(2) :303–327.

Honjo, M. K., Gupta, M. S., and Verhoeven, M. (1997). *The efficiency of government expenditure : Experiences from Africa.* International Monetary Fund.

Hosoya, K. (2016). Recovery from natural disaster : A numerical investigation based on the convergence approach. *Economic Modelling*, 55 :410–420.

Hosoya, K. (2019). Importance of a victim-oriented recovery policy after major disasters. *Economic Modelling*, 78 :1–10.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of sciences*, 107(35) :15367–15372.

IMF (2015). Making public investment more efficient. page 8.

Keho, Y. (2017). The impact of trade openness on economic growth : The case of cote d'ivoire. *Cogent Economics & Finance*, 5(1) :1332820.

Kolstad, I. and Søreide, T. (2009). Corruption in natural resource management : Implications for policy makers. *Resources Policy*, 34(4) :214–226.

Korppoo, A. (2008). Russia and the post-2012 climate regime : Foreign rather than environmental policy. *The Finnish Institute of International Affairs Briefing Paper*, 23.

Kumbhakar, S. C. (1990). Production frontiers, panel data, and time-varying technical inefficiency. *Journal of econometrics*, 46(1-2) :201–211.

Kumbhakar, S. C., Wang, H., and Horncastle, A. P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata.* Cambridge University Press.

Leichenko, R. and Silva, J. A. (2014). Climate change and poverty : vulnerability, impacts, and alleviation strategies. *Wiley Interdisciplinary Reviews : Climate Change*, 5(4) :539–556.

Leppänen, S., Solanko, L., and Kosonen, R. (2017). The impact of climate change on regional government expenditures : evidence from russia. *Environmental and Resource Economics*, 67(1) :67–92.

Libório, M. P., da Silva Martinuci, O., Machado, A. M. C., Machado-Coelho, T. M., Laudares, S., and Bernardes, P. (2020). Principal component analysis applied to multidimensional social indicators longitudinal studies : Limitations and possibilities. *GeoJournal*, pages 1–16.

Loayza, N. V., Olaberria, E., Rigolini, J., and Christiaensen, L. (2012). Natural disasters and growth : Going beyond the averages. *World Development*, 40(7) :1317–1336.

Mano, R. and Nhemachena, C. (2007). Assessment of the economic impacts of climate change on agriculture in zimbabwe : A ricardian approach. *World Bank Policy Research Working Paper*, (4292).

Marto, R., Papageorgiou, C., and Klyuev, V. (2018). Building resilience to natural disasters : An application to small developing states. *Journal of Development Economics*, 135 :574–586.

McDaniels, T. L., Chang, S. E., Hawkins, D., Chew, G., and Longstaff, H. (2015). Towards disaster-resilient cities : an approach for setting priorities in infrastructure mitigation efforts. *Environment systems and decisions*, 35(2) :252–263.

Meeusen, W. and van Den Broeck, J. (1977). Efficiency estimation from cobb-douglas production functions with composed error. *International economic review*, pages 435–444.

Mihalyi, D., Adam, A., and Hwang, J. (2020). Resource-backed loans : pitfalls and potential. *New York, NY : Natural Resource Governance Institute.*

Mihalyi, D., Hwang, J., Rivetti, D., and Cust, J. (2022). Resource-backed loans in sub-saharan africa.

Minea, A. and Tapsoba, R. (2014). Does inflation targeting improve fiscal discipline ? *Journal of International Money and Finance*, 40 :185–203.

Najar, A. L., Farias, L. O., Marques, E. C., and Zackiewicz, C. (2002). Desigualdades sociais no município do rio de janeiro : uma comparação entre os censos 1991 e 1996. *Cadernos de Saúde Pública*, 18 :S89–S102.

Nakamura, E., Steinsson, J., Barro, R., and Ursúa, J. (2013). Crises and recoveries in an empirical model of consumption disasters. *American Economic Journal : Macroeconomics*, 5(3) :35–74.

Naoussi, C., Ndambendia, H., and Dimai, L. B. (2020). Efficience des investissements publics au cameroun : Une analyse multi-output, orientée output sur données de panel.

Nardo, M., Saisana, M., Saltelli, A., and Tarantola, S. (2005). Tools for composite indicators building. *European Comission, Ispra*, 15(1) :19–20.

Nations, U. (2021). Transforming extractive industries for sustainable development.

Noy, I. and Nualsri, A. (2011). Fiscal storms : public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics*, 16(1) :113–128.

Odeck, J. (2007). Measuring technical efficiency and productivity growth : a comparison of sfa and dea on norwegian grain production data. *Applied Economics*, 39(20) :2617–2630.

Papke, L. E. and Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, 11(6) :619–632.

Pedrozo-Acuña, A., Breña-Naranjo, J. A., Domínguez-Mora, R., et al. (2014). The hydrological setting of the 2013 floods in mexico. *Weather*, 69(11) :295–302.

Pedrozo-Acuña, A., Moreno, G., Mejía-Estrada, P., Paredes-Victoria, P., Breña-Naranjo, J., and Meza, C. (2017). Integrated approach to determine highway flooding and critical points of drainage. *Transportation research part D : transport and environment*, 50 :182–191.

Raddatz, C. E. (2009). The wrath of god : macroeconomic costs of natural disasters. *World Bank policy research working paper*, (5039).

Rahman, M. H. (2018). Earthquakes don't kill, built environment does : Evidence from cross-country data. *Economic modelling*, 70 :458–468.

Ramalho, E. A., Ramalho, J. J., and Henriques, P. D. (2010). Fractional regression models for second stage dea efficiency analyses. *Journal of Productivity Analysis*, 34(3) :239–255.

Ramalho, E. A., Ramalho, J. J., and Murteira, J. M. (2011). Alternative estimating and testing empirical strategies for fractional regression models. *Journal of Economic Surveys*, 25(1) :19–68.

Rayp, G. and Van De Sijpe, N. (2007). Measuring and explaining government efficiency in developing countries. *The Journal of Development Studies*, 43(2) :360–381.

Rehak, D. (2020). Assessing and strengthening organisational resilience in a critical infrastructure system : Case study of the slovak republic. *Safety Science*, 123 :104573.

Reinhart, C. M. and Rogoff, K. S. (2010). Growth in a time of debt. *American economic review*, 100(2) :573–78.

Sachs, J. D. and Warner, A. (1995). Natural resource abundance and economic growth.

Sanchez, P. A. (2000). Linking climate change research with food security and poverty reduction in the tropics. *Agriculture, Ecosystems & Environment*, 82(1-3) :371–383.

Sawadogo, P. N. (2020). Can fiscal rules improve financial market access for developing countries ? *Journal of Macroeconomics*, 65 :103214.

Siwar, C., Ahmed, F., and Begum, R. A. (2013). Climate change, agriculture and food security issues : Malaysian perspective. *J. Food Agric. Environ*, 11(2) :1118–1123.

Skidmore, M. and Toya, H. (2002). Do natural disasters promote long-run growth ? *Economic inquiry*, 40(4) :664–687.

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of econometrics*, 13(1) :57–66.

Stolbova, V., Monasterolo, I., and Battiston, S. (2018). A financial macro-network approach to climate policy evaluation. *Ecological Economics*, 149 :239–253.

Taghizadeh-Hesary, F., Sarker, T., Yoshino, N., Mortha, A., and Vo, X. V. (2021). Quality infrastructure and natural disaster resiliency : A panel analysis of asia and the pacific. *Economic Analysis and Policy*, 69 :394–406.

Tanzi, V. and Davoodi, H. (1998). Corruption, public investment, and growth. In *The welfare state, public investment, and growth*, pages 41–60. Springer.

Tongwane, M. I. and Moeletsi, M. E. (2018). A review of greenhouse gas emissions from the agriculture sector in africa. *Agricultural Systems*, 166 :124–134.

Trinh, T. A. (2018). The impact of climate change on agriculture : findings from households in vietnam. *Environmental and resource economics*, 71(4) :897–921.

Tsionas, E. G. and Kumbhakar, S. C. (2014). Firm heterogeneity, persistent and transient technical inefficiency : A generalized true random-effects model. *Journal of Applied Econometrics*, 29(1) :110–132.

Turkowski, A. et al. (2012). № 027 : Russia's international climate policy.

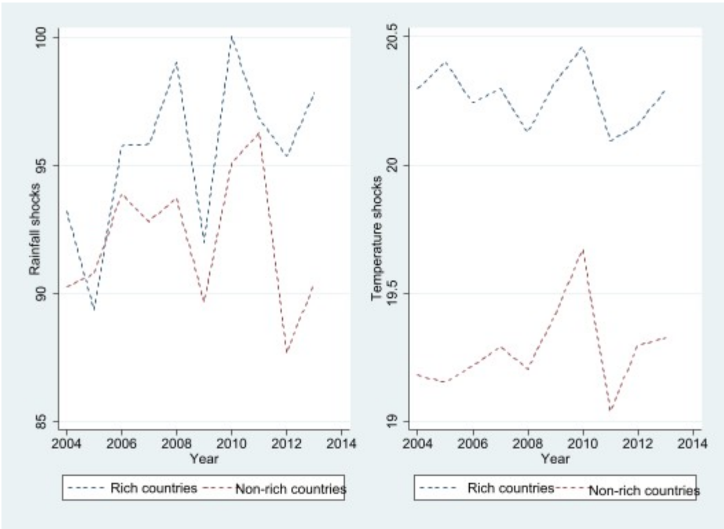
Van den Bergh, J. C. (2013). Policies to enhance economic feasibility of a sustainable energy transition. *Proceedings of the National Academy of Sciences*, 110(7) :2436–2437.

Wiley, J., Association, A. . A. E., et al. (2010). Applied economic perspectives and policy.

Appendix

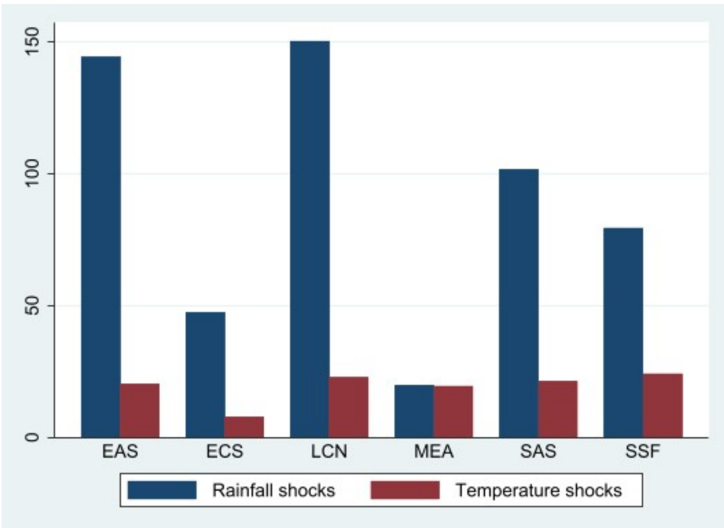
Appendix A Graphs

FIGURE 8 – **Temperature and Rainfall trends from 2000-2013.**



Source : Author's construction

FIGURE 9 – **Temperature and Rainfall trends by region.**



Source : Author's construction

Appendix B Sample

TABLE 14 – List of developing countries included in the dataset

Rich countries(*)	Non-rich countries
Angola	Argentina
Botswana	Brazil
Cameroon	Colombia
Congo, Rep	Costa Rica
Cote d'Ivoire	Dominican Republic
Ecuador	El Salvador
Gabon	Ethiopia
Ghana	Honduras
Guinea	Kenya
Mali	Mexico
Namibia	Mozambique
Niger	Nicaragua
Nigeria	Paraguay
Peru	Senegal
Sudan	South Africa
Tanzania	Zimbabwe
Venezuela, RB	
Zambia	

(*) IMF classification available in fiscal rules dataset, 1985-2021

TABLE 15 – Descriptive statistics of output variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Hospital beds	187	1.462	0.976	0.1	6.3
Pupil teacher ratio	341	37.088	12.87	13.342	82.795
Lenght road	235	4.282	4.793	0.003	37.038
People using water	476	71.326	20.429	18.085	98.904
Electricity total	448	42.008	32.618	0	100
Paved roads	255	20.038	10.896	5	54.9
Fixed telephone sub	476	2890681.3	7443687.6	0	45038117
Lenght road dnst	235	6054.411	14906.12	0.719	82482.805
Electricity power consumption	448	952.528	1014.269	22.756	4851.692

Appendix C Summary statistics of output efficiency and Robustness results

Table 16 – Average country efficiency scores, 2000-2013

Country	Output efficency 1	Output efficency 2
Angola	0.96	0.84
Argentina	0.94	0.8
Botswana	0.96	0.78
Brazil	0.57	0.85
Cameroon	0.9	0.5
Colombia	0.59	0.88
Congo. Rep	0.96	0.94
Costa Rica	0.37	0.38
Cote d'Ivoire	0.96	0.73
Dominican Republic	0.96	0.85
Ecuador	0.46	0.6
El Salvador	0.74	0.7
Ethiopia	0.96	0.14
Gabon	0.96	0.73
Ghana	0.66	0.68
Guinea	0.96	0.94
Honduras	0.88	0.56
Kenya	0.81	0.4
Mali	0.96	0.94
Mexico	0.44	0.36
Mozambique	0.96	0.65
Namibia	0.95	0.71
Nicaragua	0.79	0.43
Niger	0.84	0.91
Nigeria	0.83	0.88
Paraguay	0.96	0.4
Peru	0.42	0.24
Senegal	0.93	0.61
South Africa	0.96	0.92
Sudan	0.96	0.94
Tanzania	0.89	0.64
Venezuela. RB	0.96	0.94
Zambia	0.96	0.79
Zimbabwe	0.96	0.93

Source : Author's calculation

Table 17 – Robustness results with fractional probit regression

	[1]	[2]
VARIABLES	Full data	Rich-resource
Rainfall shocks	-0.0053***	-0.0046***
	(0.0004)	(0.0010)
Temperature shocks	-0.0001	0.0856***
	(0.0122)	(0.0209)
Natural resource depletion	-0.0508***	-0.0616***
	(0.0117)	(0.0140)
Oil reserve horizon	-0.4750***	-0.2621***
	(0.0944)	(0.0854)
Natural resources rents	0.0501***	0.0710***
	(0.0091)	(0.0119)
Government stability	0.1563***	0.1427***
	(0.0217)	(0.0268)
Corruption	-0.2359***	0.0309
	(0.0500)	(0.0864)
Trade openness	0.0046***	0.0036
	(0.0012)	(0.0034)
Constant	0.3868	-2.5428***
	(0.3813)	(0.6523)
Pseudo R2	0.1393	0.1475
Observations	316	183

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1

Table 18 – Robustness results with addition controls : Fractional probit regression

VARIABLES	[1]	[2]	[3]	[4]
Climate change index	-0.4735***	-0.4756***	-0.5029***	-0.4902***
	(0.0563)	(0.0417)	(0.0376)	(0.0437)
Natural resource depletion		-0.0551***	-0.0464***	-0.0643***
		(0.0113)	(0.0113)	(0.0106)
Oil reserve horizon		-0.4667***	-0.1327	-0.3907***
		(0.1073)	(0.0898)	(0.1161)
Natural resources rents		0.0521***	0.0404***	0.0577***
		(0.0090)	(0.0090)	(0.0092)
Government stability		0.1861***	0.1828***	0.2038***
		(0.0226)	(0.0229)	(0.0251)
Corruption		-0.3166***	-0.3038***	-0.3096***
		(0.0477)	(0.0466)	(0.0535)
Trade opennes		0.0042***	0.0042***	0.0053***
		(0.0012)	(0.0011)	(0.0010)
Oda		0.0032		
		(0.0089)		
Public investment volatility			-0.5847***	
			(0.1256)	
Log(Economic costs of disasters)				-0.0000***
				(0.0000)
Constant	1.1963***	-0.0432	0.0504	-0.2374
	(0.0514)	(0.1979)	(0.2028)	(0.1957)
Pseudo R2	0.0429	0.1346	0.1414	0.1451
Observations	340	316	316	250

Standard errors in parentheses *** p <0.01, ** p <0.05, * p <0.1