Chinese Foreign Direct Investment and local development in Africa

Final Thesis

by:

Xianning Chu

MASTER OF ARTS IN DEVELOPMENT STUDIES

Major **ECD**

Supervisor:

John Cruzatti

Second Reader:

Elissaios Papyrakis

The Hague, The Netherlands
March 2024

0. Introduction

China experienced by far one of the most impressive growth in the past decades. The strong economy, coupled with dominant political power, unsurprisingly pushed forward the “Beijing Consensus” as its guiding principle. While China was not among the first to embrace globalisation, it has become a crucial and exemplary manifestation of the concept. Since 2009, China has been the world's largest exporter and known as the “world factory”. It is deeply embedded in global supply chains, capital transformation, and has become an indispensable initiator of outward investment. Chinese investment has experienced rapid expansion, with the total outward FDI doubling to 200 billion US dollars between 2012 and 2016. Presently, measured in FDI stock, China ranks as the 5th largest investor in Africa, and while investments from France, Netherlands, and the US are shrinking, China continues to witness growth (UNCTAD, 2022).

Much has been written on the economic consequences of FDI since the end of cold war and following reopen economies and liberalisation in the 1980s. The total amount of FDI that goes to developing countries catches up later, starting from 2000 and reaching its first peak in 2008. As of 2021, inward FDI stock accounted for nearly 40% of the gross domestic product, while inward FDI flows doubled from 2020 and reached 15% of gross capital formation in Africa (UNCTAD, 2022). FDI is expected to bring capital stock, know-how, and technology to the host country, addressing its needs. Therefore, it is viewed as a necessary means for developing countries, directly contributing to economic growth. Indirectly, the horizontal spillover effect through market competition may both benefit local firms and create obstacles. Finally, vertical spillovers are expected to enhance backward and forward linkage with the domestic market (Colen et al., 2012).

This research is an attempt to provide new insights into the impact of Chinese FDI, particularly studies of the local development impact in 109 subnational regions of African countries between 2003 to 2018. Employing recently available subnational level data, this study delves into the causal relationship between Chinese FDI inflows and subnational human development indicators.

This paper is structured as follows: Chapter 1 provides a comprehensive overview of existing literature on FDI and human development. This paper identifies a notable gap in empirical analyses concerning FDI at the subnational level. Section 1.3 articulates the specific objectives of this research. Chapter 2 establishes the methodological framework for its main models and estimation strategies. Chapter 3 introduces the two primary datasets utilised in the research and offers summary statistics pertaining to the main dependent and independent variables of interest. Chapter 4 reports on the results and our main finding and we perform robustness tests Chapter 5 conducts robustness tests aimed at enhancing the validity and reliability of the estimated results. The final Chapter 6 concludes our study and discusses further on the implication for theory and practice. Additionally, this section reflects on the limitations of the research and suggests avenues for future inquiry.

1. Literature Review

1.1 literature review of FDI impact

1.1.a. Theoretical and empirical literature of FDI impact on economic growth

Theoretical inquiries into the effects of FDI on economic growth depend on the development of analytical models. Within the neoclassical growth framework, FDI is considered as a factor that promotes technological progress and positively affects economic growth of the recipient country in the short run. In the endogenous growth model, FDI is associated with factors such as human capital accumulation and technological spillovers that directly contribute to endogenous growth of the recipient country in the long run. Studies following neoclassical trade theory explores indirect channels such as employment and capital flows. In the more elaborated models, scholars included factors, such as absorptive capability and trade openness of the recipient countries, and contending that the impact of FDI on recipient economies is contingent upon specific conditions (Iamsiraroj, 2016).

The policy relevance of FDI has attracted significant academic attention, leading to numerous empirical studies. Generally the literature observed a clear correlation of higher economic growth associated with higher FDI inflow, but with many empirical studies attempting to establish the causation of FDI impact on economic growth, the mechanism remains rather ambiguous (Acquach & Ibwrahim, 2019). Dinh (et al., 2019) reviewed research from recent decades, noting inconsistent results across both single-country and cross-country analyses. The mixed empirical evidence can be attributed to various factors, including the heterogeneity of FDI types and investment sectors, regional differences among recipients, and variations in the measurement and composition of economic growth functions across different studies.

The total amount of FDI that goes to developing countries only started from 2000 and reached its first peak in 2008. As of 2021, inward FDI stock accounted for nearly 40% of the gross domestic product, while inward FDI flows doubled from 2020 and reached 15% of gross capital formation in Africa (UNCTAD, 2022). FDI is expected to bring capital stock, know-how, and technology to the host country, addressing its needs. Therefore, it is viewed as a necessary means for developing countries, directly contributing to economic growth. Indirectly, the horizontal spillover effect through market competition may both benefit local firms and create obstacles. Finally, vertical spillovers are expected to enhance backward and forward linkage with the domestic market (Colen et al., 2009). Theoretical studies of FDI impact in developing countries also addressed concerns on the crowding-out effect and the efficiency of skill transfer and spillover effect (Titiloye Ademola et al., 2009). In the case of Africa, FDI is strongly driven by natural resources. Angola, for example, received US$ 20.7 billion worth of FDI investment in gas and oil sectors in the 2010s (Kimiagari et al., 2023). The over-concentration of investment in the extractive sector also raises concern in weakening manufacturing development in Africa.

Literature of Chinese FDI in African countries primarily focuses on political implications (Wang et al., 2021) and on determinants of investment allocations. The empirical study is limited when looking at Chinese FDI in African countries. Donou-Adonsou & Lim (2018) is one of the first studies that provides econometric analysis on this topic. They analysed FDI from China, US, and Germany separately, using data from 36 African countries over the period of 2003-2012, found that increase in Chinese FDI, both flows and stocks, significantly improves income measure by GDP per capita.

1.1.b. Theoretical and empirical literature of FDI impact on welfare

However, economic factors alone do not provide a complete picture of development. Currently there is a literature gap in understanding the FDI impact on actual living conditions and welfare of a country.

It is important to note that FDI, in most of the cases, does not benefit local residents in a straightforward manner. However, it can indirectly contribute to their well-being through various channels, primarily by stimulating increased economic activity. Theories regarding FDI and human development thus largely follow the same direction as through the channel of potential spillover effect. Early literature is divided into two sides. The 'race to the bottom' hypothesis emphasizes that FDI is attracted by weak institutions and poor working conditions due to its low cost. On the other hand, the 'climb to the top' hypothesis explains that profit-driven foreign investors are also motivated to improve labor quality and the business environment, thereby benefiting local development in the long run (Colen et al., 2009).

In some studies, GDP per capita has been treated as a measurement of income and thus studied as a representation of the welfare factor (Donou-Adonsou & Lim, 2018). A few empirical studies have explored HDI and found unanimously insignificant results. Kosack and Tobin (2006) shows the FDI effect is contingent to the level of human capital in a country. They found an insignificant effect on HDI for countries with a human capital higher than 55, and a negative effect for countries with lower human capital level. De Groot (2014) explored household consumption and HDI index and found no effect of FDI on welfare but instead enlarged the inequality distribution of the investigated 214 countries.

The first empirical study that linked Chinese FDI in 52 African countries and using HDI index as welfare measurement was by Atitianti and Dai (2021), and their findings suggest that FDI significantly improves HDI at country level, and their results holds true in robustness tests using SSA sample countries. However, their study did not provide more insight on the compositions of HDI, and although their finding suggests FDI is positively correlated to HDI, it is lacking explanatory context.

The relationship between Chinese FDI and human development is still a topic understudied, and empirical literature often focuses on the comparison across countries or within a single region. There is a clear literature gap in investigating FDI and HDI, particularly in the context of developing countries. To the best knowledge of the author, this research provides the first econometric analysis to the literature of Chinese FDI and local development in African countries. The next section will briefly introduce HDI index, the strength and weakness of its analytical value, and solution of using SHDI to overcome these limitations.

1.2 HDI and local development index

The United Nations Human Development Index (HDI) is a quantified measurement of well-being of a society, of which three dimensions are represented: access to education, health and income. Education is measured as years of schooling, health as life expectancy at birth, and income by gross national income(GNI) per capita. HDI is informative for economic analysis, and this requires awareness of the subjective biases and limitations in both the interpretive level and methodological level.

The construction of HDI is out of good intention: an alternative approach to measure the well-being of a society, instead of GDP per capita, where the latter is not only exclusively monetary based, but also neglects the capability approach. But just like any other indices, the computing process inevitably takes

multiple averages, and in the end the score provides a new perspective from a different scale, rather than direct messages or information with clear meanings.

The interpretation of HDI involves understanding the relative context in each country. HDI ranges from 0 to 1. According to the chart from the Human Development Report, in 2021, the world average is 0.732, a drop of 0.003 from the previous year. Switzerland has the highest score of 0.962, where Sudan at the bottom scores 0.508. How do we interpret the gap inbetween? In 2021 the gap between Switzerland and Sudan is 0.454, while in 1990 the gap was 0.606 (Sudan: 0.336; Switzerland: 0.942). How do we interpret the change in vertical distances between Switzerland and Sudan, from 0.606 to 0.454? One must refrain themselves from drawing simple conclusions, such as, while the well-being in Switzerland out-performed Sudan in all periods, the gap was narrowed and thus indicates convergence between the rich and the poor. On the other hand, GDP per capita of the same two countries, after adjusted for inflation and cost of living, shows an expanded disparity with 54225$ in 1990 and 67323$ in 2021. (Sudan:2757$(1990), 3710$(2021); Switzerland: 56982$(1990), 71033$(2021)) [Source: Our World in Data]

It is evident from the above example that there is a limit to reading the composite HDI index at its face value. The challenge is, however, both on the interpretive level as well as on the methodological level. Since its creation in 1990, the calculation system of HDI has undergone several major changes. The reconstruction in 2010 changed its aggregation formula from calculating arithmetic mean into geometric mean. Many more specifications and variations, such as augmented HDI proposed by Prados de la Escosura (2021) which include political freedom as fourth dimension, were inspired soon after. But none of these computation updates can resolve the subjectivity concerns of the produced rankings. In fact, each one of the formulas reflect a preference of which an ethical system is embedded. This results in inconsistency in the ranking depending on which aggregation formula is used. HDI thus should be restricted from nominal interpretation. The numeral nature more importantly puts a challenge in using HDI as a means to compare welfare across countries and over time. (Amendola & Vecchi, 2023)

Additionally, when analysing countries from the same development tier, HDI index has even more limited statistical value for the lack of variation in the data sample. The HDI index developed by the UN contains information only at the national level. When comparing countries with different levels of development, there is often a significant gap between the wealthier and the poorer, as illustrated in the previous example of Switzerland and Sudan. In the context of developing countries, however, the variation is rather limited. For example, the HDI index of 52 African countries studied by Atitianti and Dai (2021) are where, population-wise, about two-thirds of the world's poorest people lives (Schoch & Lakner, 2020). Amongst the 253 countries, geographically the bottom 24 countries concentrate on the land of Africa, and at country level they have the lowest HDI mean (The 2021 UNDP HDI index mean: World 0.732, SSA 0.547, South Asia 0.632, Latin America and the Caribbean 0.745, Europe and central Asia 0.796).

Using HDI country level data to analyse past trends amongst countries from the same tier not only suffer from lower variation in the observation, it also ignores the important fact that within-country inequality of development is significantly larger in developing countries than in developed countries. Looking at all four subdimensions of human development, Permanyer & Smits (2019) using mean log deviation shows an interesting comparison of within-country inequality in high, medium and low development countries. In low and medium human development countries, which are defined as countries with HDI<0.7 and of which classification all African countries studied in this paper falls into, the subnational

inequality contributes to half of the total inequality. Their findings suggest an overlooked subnational human development variation in developing countries.

This paper will use the subnational level human development index, the SHDI dataset, constructed by Smits, J. and Permanyer, I. (2019). To the best of the author's knowledge, this is also the first paper that links Chinese FDI and African local development using SHDI as local welfare measurement. We believe using SHDI in this topic has three major advantages. Firstly, it contributes to the existing HDI literature in African countries by addressing regional variation. Secondly, SHDI dataset is constructed to be compatible with UNDP HDI. This means any results and conclusions drawn from analysis using this data complements the HDI literature, thus eliminating concerns for compatibility of data with different structures. And lastly, the SHDI dataset also includes data of all three subdimensions, namely life expectancy at birth, log of gross national income per capita, mean years of schooling of adults aged 25 and above. This provides transparency in the construction of SHDI index, and also facilitates meaningful interpretations of the regression results.

1.3 Research objective

The previous two sections show a distinct literature gap in the current study of Chinese FDI and its local impact in the developing country context. Leveraging the recently available data, this research contributes to both FDI and HDI literatures. In the broader sense, this is the first empirical study that looks into subnational level FDI impact in the context of the developing world. Furthermore, the findings of this paper augment the HDI literature, which has predominantly focused on the country level, by providing insights at the subnational level.

Two primary datasets serve as the foundation for this research. Firstly, the Chinese FDI inflow data sourced from fDi market, which is manually labelled with geographical information by Wang et al., (2021), and the access to a replication dataset facilitated by the university website enhances the robustness of the analysis. The second is the recently published dataset SDHI by Smits and Permanyer in 2019. Using panel data of 109 subnational regions from 2003-2018, this paper aims to answer the following questions:

1) Correlation and causality: Does Chinese FDI inflow exhibit significant correlations with changes in SHDI variations, and can causal relationships be inferred from these associations?
2) Sectoral impact on HDI subdimensions: How does Chinese FDI inflow impact the different subdimensions of SHDI, particularly concerning health, education, and income indices? Are there differences when comparing the effects on income-related indices versus non-income-related indices?
3) Alignment with existing theories and empirical evidence: To what extent do the findings of this study corroborate or diverge from existing theoretical frameworks and empirical studies in the field?

This paper is structured with the following section delves into the detailed descriptions of the original datasets and provides a summary overview of the panel data utilised in the study. Section 3 first introduces methodology and identification strategy employed to establish causality. This paper uses instrumental variable IV regression, where the Chinese's reserve of foreign of foreign currency is used to construct the instrument that addresses the endogeneity concern. The second part outlines the specific estimation models to address the research questions articulated earlier. Section 4 discusses and

interprets the results. The robustness tests in section 5 provides insights in the internal and external validity of the study results. Through this structured approach, the paper contributes to the existing literature on Chinese FDI and its impact on local development in developing countries.

2. Estimation Strategy

2.1 Main model

The baseline model looks at annual FDI inflow at subnational admin, and we estimate its impact on local SHDI as:

$$(1) \qquad Y_{i,t} = \beta_1 FDI\_total_{i,t-n} + \beta_2 Pop_{i,t-1} + \beta_3 M + \beta_4 N + \delta$$

Where $Y_{i,t}$ is the group of outcome variable of subnational admin i in the year t. The main dependent variable of interest is SHDI and its sub dimensions, namely health, education and income. We also include night-time light emission as a proxy of GDP per capita to examine the impact on local economic activities. On many occasions multiple FDI projects were allocated to the same subnational admin in the same year. For analytical purpose, rather than conducting regressions at the project level we regress Y on the FDI_total inflow amount (US dollar) in the subnational admin i, in the announcement of operation year t with lag n years. Pop controls for population of subnational admin i in year $t-1$. M denotes subnational-fixed effects that control for time-invariant differences between the subnational regions. N controls for country-year fixed effect. Including country-year fixed effect as control variable enhances the regression results at subnational, because this eliminates differential effect on the local development condition in subnational regions caused by any country-wide economic or political shock at a given year. δ denotes error. Elaboration on the data see section 3 for summary statistics of dependent variables.

Due to the limitation on existing empirical literature, we do not have a reference for the number of lags n should take. On the one hand, we expect the take off of FDI projects locally to have immediate impact, even before the investment is received. This is because the announcement of FDI projects has premature influences on the future expectation of local business and employees, under such influences individuals and businesses may take different economic decisions. On the other hand, the measurement SHDI is a composite of long term warfare dimensions that do not change dramatically in the short run. Which means there is a necessity to test different lags in the following model specifications.

As it is emphasised in literature focusing on the determinants of Chinese FDI in Africa, the allocation of investment is not random but influenced by both economic and political conditions of the local recipient. Early observational evidence shows Chinese FDI is concentrated in developing countries. In the case of Africa, big projects initiated by state owned enterprises (SOE) are mostly resource seeking and invest heavily in natural resources and infrastructure. Medium and small private owned companies (POE) in contrast are market seeking and invest in manufacturing, telecommunications and wholesale sectors (Sanfilippo 2010). Political risks also affect the allocation of SOE and POE investment but in different ways. Biglaiser & Lu (2022) compared the investment pattern of Chinese SOE and POE in 118 developing countries and observed consistent risk-seeking behaviour of SOE.

Empirical literature study firm-level and investment-level behaviour shows natural resource reserve, quality of the institutions and infrastructures attract Chinese FDI in different ways (Utesch-Xiong & Kambhampati, 2021). However, FDI not only is an economic means for China to reach out to a broader market, it is also a political means and the operation is often beyond firm-level. The deep penetration of the Chinese government involved in both SOE and PE projects implies political interests and opens back doors to the allocation and execution of the FDI projects. The Chinese government provides

monetary assistance, such as issuing conditional loans, and guides future investment through bundled contracts, and facilitates negotiation with local high-level institutions (Benfratello et al., 2023).

Sectoral preference, political environment as well as resource-seeking and market-seeking motivation are major determinants for Chinese FDI inflow. As economically well-off and infrastructure-developed regions attract FDI inflow, these factors are also closely related to local development conditions. This puts concerns for other time-variate factors that account for simultaneous determinants between FDI and outcome variables. To address the endogeneity concern of FDI, in the next section I will introduce the solution: instrumental variable (IV) two-stage least square (2sls) regression, and the instrument of choice.

2.2 Identification strategy

The instrument used in this paper is a combination of two sources of variations: an exogenous time-variate instrument with a time-invariant probability variable. This combined instrument was widely employed in Aid literatures, first proposed in Nunn & Qian (2014) on the study of US food Aid effect on civil conflict, and further developed in Dreher (et al., 2021) and Cruzatti (et al., 2023). Following a similar concept, in this paper we construct the instrument with Chinese international reserve (the time-variate exogenous instrument in our case) and probability of a subnational region receiving FDI (time-invariant variable).

The amount of foreign exchange reserves in China has seen a significant rise since 80s, and until today China is the largest foreign exchange reserve holder. China's foreign exchange reserves reached USD 3.1277 trillion, according to China's State Administration of Foreign Exchange (SAFE) 2022 report. The main drive of variations in Chinese foreign exchange reserve is economic stability and GDP growth, other factors including financial openness and reserve policies (Obstfeld et al., 2010). The foreign exchange reserve thus satisfies the excludability restriction and it is arguably exogenous to the dependent variables of interest in this paper.

This paper uses the Chinese international reserve dataset directly obtained from Cruzatti (et al., 2023). FDI projects initiated by private and state owned enterprises require finance through the China Development Bank, the China Ex-IM Bank, State Owned Investment Fund, and private banks (Eshete, 2020). This means the holding of Chinese international reserves in the previous year is correlated to the operation decision of FDI projects in the following years. Therefor in any given year t of which a FDI project is announced to be allocated to subnational region i, we argue this investment amount is correlated to the holding of Chinese international reserve in the lagged year $t-m$, where m > n.

The structural model is the same as main model (1):

$$(2) \qquad Y_{i,t} = \beta_1 FDI\_total_{i,t-n} + \beta_2 Pop_{i,t-1} + \beta_3 M + \beta_4 N + \delta$$

The first stage equation is:

$$(3) \qquad FDI\_total_{i,t-n} = \beta_1 Reserves_{t-m} * p_i + \beta_2 Pop_{i,t} + \beta_3 M + \beta_4 N + \delta$$

p_i indicates probability for investment amount to be allocated to subnational admin i. It is calculated as the total times a subnational region receives FDI in the range of 16 years from 2003 to 2018, as $p_i =$

$\frac{1}{16}\sum_{t=2003}^{2018} p_{it}$. p_{it} is a binary variable that takes value of 1 when a positive value of $FDI_total_{i,t}$is observed in year t and 0 otherwise. p_i is therefore a time-invariant variable and it is being controlled for in subnational-fixed effect M.

Although using instruments to address endogeneity, the regression model, however, follows a difference-in-difference (DID) approach. In the structural equation (2) and first stage equation (3), subnational-fixed effect controls for the time-invariant probability, and country-year-fixed effect controls for the time-variate exogenous instrument Chinese international reserve. The estimator of our interest $\beta_1$estimate the effect of FDI inflow on local development, by comparing subnational regions that have high probabilities receiving FDI to those with low probabilities, and in year Chinese foreign reserve compared with higher net changes to the years with lower net changes.

The identifying assumption of this combined instrument is that the changes in Chinese international reserve in the 2 years ahead of the announcement of FDI projects would only have an impact on local development of the subnational regions in Africa through the investment inflow. Additionally, because the parameters are estimated in a DID regression, it is also important to make sure the parallel trend assumption holds for the variables of interest. Country-year-fixed effects although controls for the time trend, but it is also necessary to make sure there is no significant time trend that could be a confounder account for the variation in the instrument and in the main variable.

Following Cruzatti (et al., 2023), the following Figure 1 plots the time trend of Chinese international reserve. Based on the probability each region receives FDI, recipient regions are grouped into above- and below- medium frequency. Figure 2 shows the mean FDI inflow per year by the two groups and figure 3 shows the mean SHDI index per year by groups. In figure 2 and 3, it is clear that the time trends are parallel across low- and high- frequency groups. Also the plots show no obvious non-linear trend amongst the three graphs, it is unlikely that parallel trend assumption is violated in this context. The validity of the parallel assumption enhances the excludability restriction and gives validity to the instrument for causal inference.

Figure 1

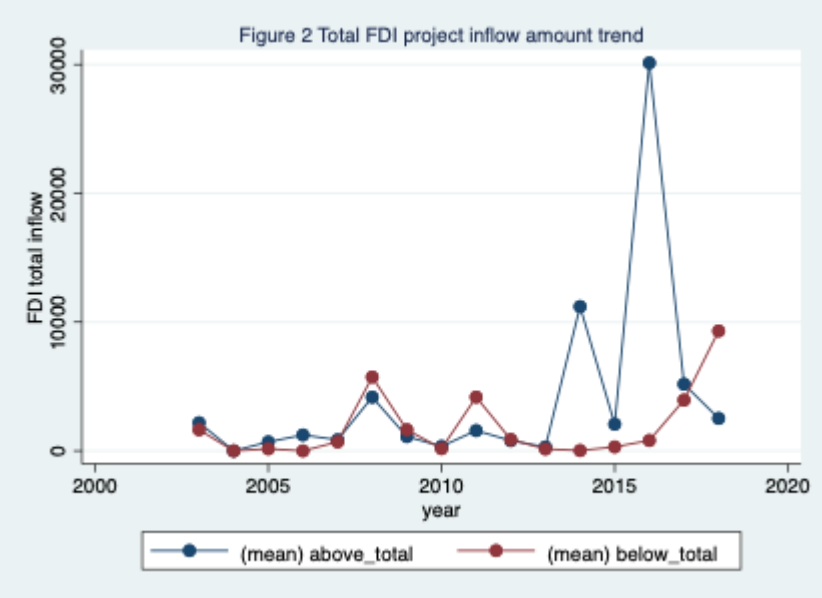


Figure 2

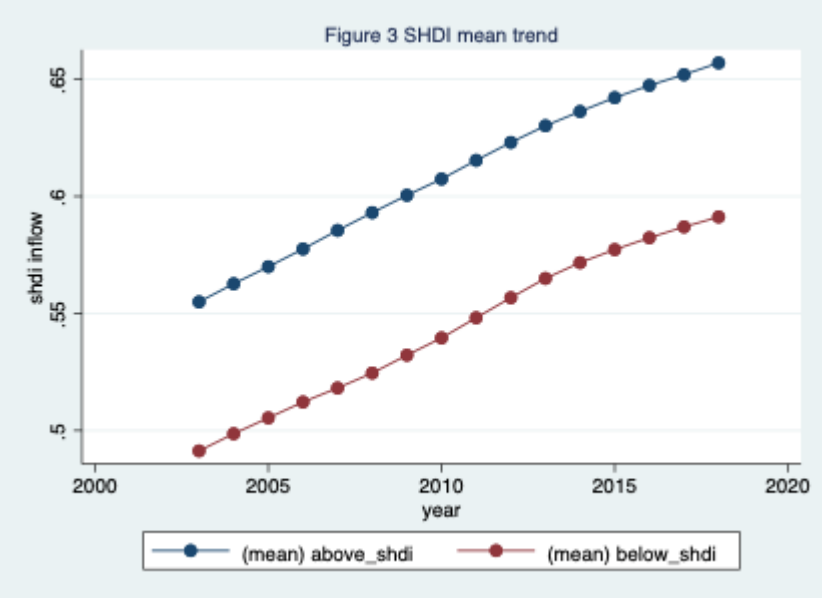


Figure 3

Our instrument is inspired by Cruzatti (et al., 2023). In their research on the Chinese aid effect, Chinese international reserve and steel production was used as instruments for the endogenous variable aid projects. One concern should be addressed here is that any valid instruments that are used for other variables introduce potential confounders to our study. If reserve is correlated to aid projects in Africa, this would open other backdoor pathways through which aid projects indirectly affect the dependent

variables and introduce bias in our estimates, and we would fail to identify causal effects of FDI. In chapter 5 I control for aid in the robustness test.

3. Description of the data

3.1 Dependent variables: NTL data and SHDI data

In this paper, we use Night-time light (NTL) to measure subnational level economic activity. The NTL dataset[1] contains mean and medium value of admin 1 level night time light emission.

NLT is developed by the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). Using remote sensing satellites to collect information of light emission, it is widely accepted amongst researchers as a proxy measurement of local economic activity (Li et al., 2020). Compared to GDP, NTL has two main advantages, particularly in the context of the developing world. First, The institutional capacity in developing countries undermines the quality of official reports and statistics of key economic indexes such as GDP. NTL on the other hand has more data integrity. With the development in recent years, the improvement in resolution at 1 km * 1 km cell allows consistent and reliable analysis at subnational regions. Second, NTL measures human activity not only at a monetary level, it captures population, employment and consumption at very local levels which are beyond what can be reflected on GDP.

Although NTL has high statistical precision, it is important to note the limitations when applying NTL in empirical studies. Asher (et al., 2021) shows when using NTL as proxy for different economic factors, the elasticity of NTL is inconsistent across places and time. This makes NTL a less ideal measurement when studying development changes over time across regions that are highly heterogeneous.

The second database we use for the main dependent variable of interest obtained from the original Subnational Human Development Index (SHDI) Database, developed by Smits and Permanyer (2019) contains 1625 regions in 161 countries, subnational HDI and composite indicators covering the period from 1990 to 2017. The Area Database from Global Data Lab (GDL-AD) provides a major source for the African profile at the sub-national level. Years of schooling is directly obtained, while life expectancy is derived from child mortality (under-5 mortality, U5M), and income is derived from household wealth possession measured by International Wealth Index (IWI).

One of the major advantages of this SHDI is that the constructed subnational indices show consistency in the population-weighted average with HDI. This was done by adjusting the four indicators with different scaling coefficients. In some cases due to lack of information, the subnational indicators variation was compromised, national value was taken from UN HDI and applied to each regions [2].

3.2 Independent variables: FDI data

The raw data of 531 Chinese FDI projects in Africa from 2003 to 2018 with geocode are downloaded from Harvard Dataverse, where replication data for Wang (et al., 2022) are open licence for reuse. Wang (et al., 2022) labelled the geographical references by matching location informations obtained from news and articles with project description obtained from fDi market[3]. According to their precision

[1] NTL data and Chinese international reserve data are directly obtained from my supervisor John Cruzatti, whom I am deeply in debt to. Without his help I would not be able to finish this research.
[2] The three countries Cape Verde, Libya and Mauritius, are missing regional variations in both education and health dimension.
[3] fDi market is an FDI project monitor created by Financial Times.

coding scheme[4], 280 of the FDI projects could be allocated precisely[5]. 152 projects can be located to second-order administrative division (ADM2), another 3 projects at first-order administrative division (ADM1), and 98 projects with only country-wide information and cannot be located at subnational level.

However, the raw data does not include information on subnational administrative divisions. Projects were labelled at the national level. This could have two reasons. First, Wang (et al., 2022) was at national level and regarding respondents' attitude towards their regime leader. Second, the actual geographical distance between the location of the FDI projects to the interviewed respondents was one of the explanatory variables of interest, regional differences in the local impact of FDI was overlooked.

This paper is interested in the local impact of FDI, and based on the raw data, it was easy to map the projects at a lower administrative level. The high resolution geo-reference of each FDI project enabled this research to specify subnational administrative information, by incorporating with administrative division polygon from GADM[6], using the geographic information system QGIS.

In the merging process of FDI (mapped in Admin 1) with SHDI dataset, a few adjustments and compromises were made to solve the administrative division inconsistency. In the case of Algeria, for example, admin 1 divisions from the FDI dataset are grouped into east, west, south and north in SHDI. I defined a new subnational division variable ADM1 which aligns with SHDI.

The FDI data used in this research includes 449 FDI projects that 1) could be located at subnational level (Admin 1), and 2) has information on project investment amount. 117 projects are Chinese central and local state-owned, and the remaining 204 projects are owned by the private sectors. We further aggregated the investment amount of projects from the same years at ADM1 level, to obtain 260 observations of yearly FDI inflow in 109 subnational units in 37 African countries. Investment type was further labelled according to a three-sector industrial classification system as primary sector (Extraction and Agriculture), secondary sector (Manufacturing) and Tertiary Sector (Services).

3.3 Summary statistics

3.3.1 Summary statistics of FDI

Table 3.1 lists summary statistics of FDI. Amongst the 260 observations of FDI inflow, the highest value 20 million USD, was committed to Cairo, Egypt in 2016. The lowest single inflow was 200 thousand US dollars to Eastern Cape, South Africa in 2012. The magnitude of the investments shows significant variation across time and investment sections as well as by investment ownership types. Around 52% of the projects are from secondary industries including manufacturing materials, automotive components, pharmaceuticals, transportation and warehousing. Business and services contribute to another 38% of the projects. The sectoral preference shows in both POE and SOE projects.

[4] See Wang (et al., 2022) Appendix Table 5
[5] This refers to projects with exact locations, those in the area of or within 25 km of an exact location, and those in an industrial zone(Wang et al., 2022)
[6] Spatial database of global administrative areas, version 4.1 was used in this paper and can be accessed via https://gadm.org/download_world.html

It is also worth to note that PE projects take a higher share in terms of number, SOE projects value higher on average, this is especially the case for resource targeted projects.

Table 3.2 lists the top 5 recipient countries of Algeria, Egypt, Ghana, Nigeria and South Africa, which gives more insight on country-wide differences. Similar to the trend we see earlier, POE accounts for the bigger share of investment in all countries except for Algeria. Although as reflected in table 1 when looking at numbers, the majority of the projects are invested into manufacturing, here in the case of top 5 recipients this sectoral trend is reversed with services and business topped for the majority share. This twist is caused by the single largest inflow to Cairo in 2016, specifically into the real estate sector by POE. In Algeria, almost 98% of the FDI is SOE. Here we see different countries show different investment preferences in sector and ownership. This is caused by the huge variation in each project, which can be better seen at the subnational level.

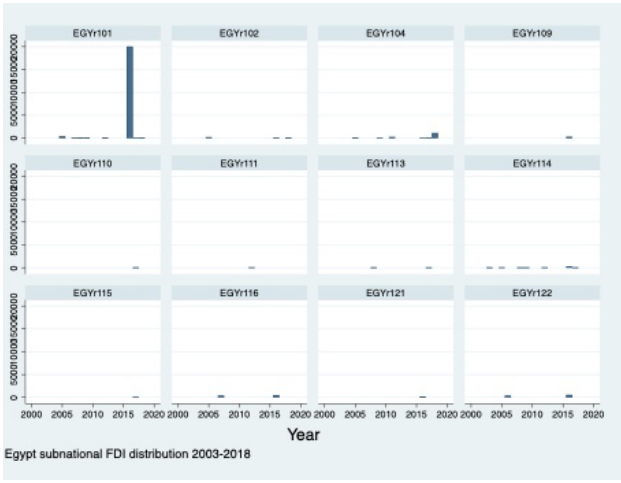
Graph 3.2 shows details of FDI inflow in all recipient subnational regions of the same 5 countries. The FDI inflow shows heterogeneous distribution on the subnational level. Some regions only occasionally receive investment and in small amounts such as Northern Ghana and Ogun (Nigeria). Some regions frequently receive investment, and in other cases a few spikes of high volume of investment are seen in some less regular recipients. As it is also shown in Table 3.1, the probability of a subnational region receiving FDI inflow varies significantly, the most regular recipient subnational region is observed with positive inflow in 13 occasions out of 16 years (0.8125%).

Variable	Obs	Mean	Std. dev.	Min	Max
FDI_primary	33	566.3673	684.2575	6.5	1991.2
FDI_second-y	150	233.9532	668.244	.02	6000
FDI_tertiary	111	362.6811	2012.818	.03	20015.8
C_primary	23	693.0704	715.8134	18.1	1991.2
P_primary	10	274.95	526.1642	6.5	1734.3
C_secondary	61	302.1377	868.971	1.3	6000
P_secondary	106	157.1942	438.8356	.02	4000
C_tertiary	33	153.3497	625.9883	4.2	3535
P_tertiary	88	399.9666	2230.433	.03	20015.8
FDI_total	260	361.695	1439.299	.02	20015.8
FDI_C	109	361.7574	822.6811	1.3	6000
FDI_P	182	300.0503	1601.741	.02	20015.8
p_FDI	1,744	.1513761	.1457698	.0625	.8125

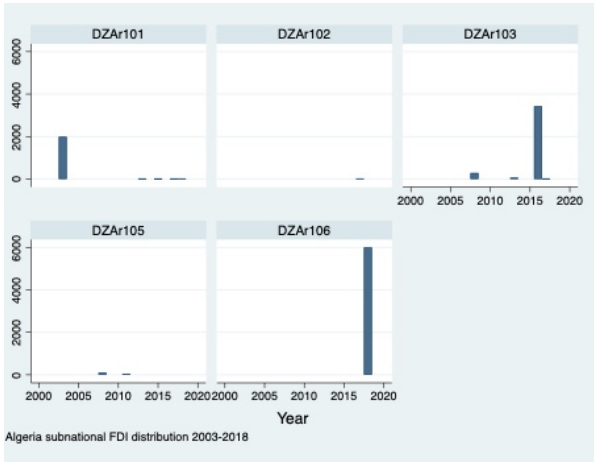
Table 3.1 Summary statistics of FDI inflow from 2003-2018

	Raw_material	Manufacturing	Service_Business	SOE	POE	total_amount
COUNTRY						
Algeria	1991.20	9929.43	61.20	11689.73	292.10	11981.83
Egypt	1505.70	1617.10	22137.60	1963.40	23297.00	25260.40
Ghana	203.80	4293.20	912.80	159.00	5250.80	5409.80
Nigeria	3072.20	3835.66	353.20	1500.00	5761.06	7261.06
South Africa	221.40	2148.95	7053.60	789.75	8634.20	9423.95
Total	1679.33	3700.59	7725.90	2567.45	10538.37	13105.82

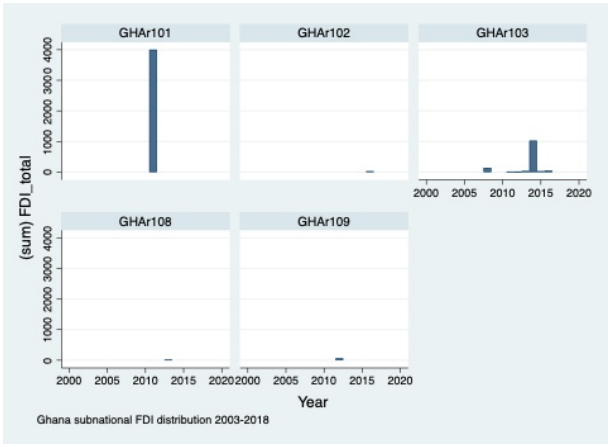
Table 3.2 Top 5 recipient countries FDI total inflow, by sector and by ownership type, in million US dollars



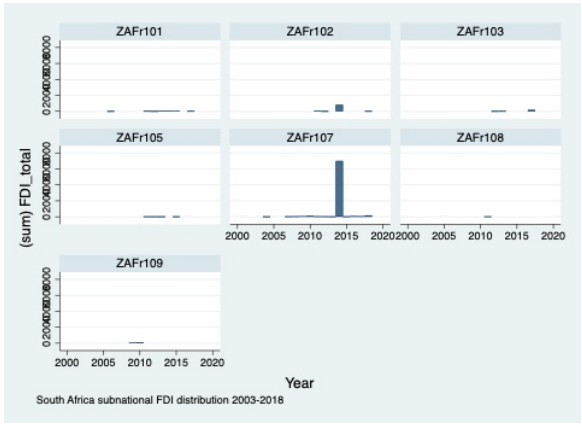
Egypt



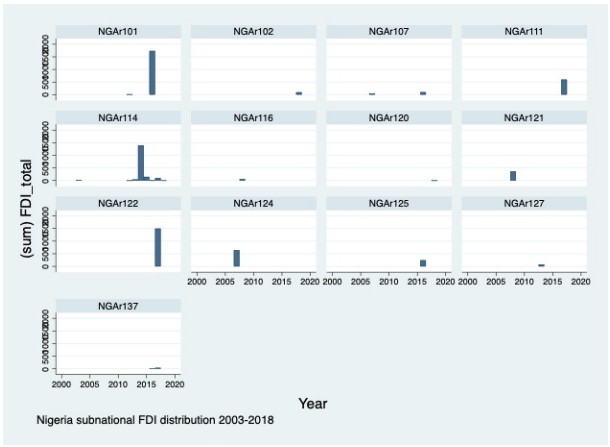
Algeria



Ghana



South Africa



Nigeria

Graph 3.1 Subnational FDI inflow time trend of the top 5 recipient countries

3.3.2 Summary statistics of dependent variables

The subnational population used in this research is from the Global Data Lab, Area Database (GDL-AD). We chose this database because it is the same population Smits and Permanyer (2019) used to reweight subnational indicators. The limitation is population only available from 2003 to 2017.

Table 3.3 shows summary statistics of NTL, SHDI and the subdimensions. All dependent variables of interest show huge variations, and it is clear to see that even though all subnational regions in our sample are part of the most undeveloped world, still there exists huge differences between better-off regions and the lowest ones. More detailed statistics of our sample (see appendix) shows in 2003, the first quartile line of SHDI was 0.616, and this number was changed to 0.711 in 2018. UNDP HDI draws the line of high development level at 0.700. This shows some of the subnational regions in African countries in our sample are comparable to the level of development even in many developed countries. On the other end of the extreme, the numbers are also striking. In our sample, the subnational region with the lowest SHDI is Sokoto, Nigeria in 2003. Furthermore, in the subdimensions, the mean year of education is less than 1 year, life expectancy is 47 years, with gross national income per capita of 1513 (measured in 2011 US$, PPP adjusted)

Acknowledging the subnational and year variation, table 3.4 and 3.5 shows comparisons of the subnational regions with the highest and lowest SHDI in 2003 and in 2018, respectively. Two things are worth mentioning. One is the overall improvement in both of the most developed and least developed subnational regions. Second is the composition of the most developed and least developed groups. The most developed regions in 2003 are Suez, Cairo and the Grand Tunis area with the highest SHDI. In 2018, the Grand Tunis area is ranked third, and with South-East Botswana and North Mauritus rank as the highest. However on the other end, Zinder (Niger) and Sokoto ranked as the two lowest in 2003 and in 2018. From this observation, one may conclude that the development condition did not improve much for the least developed regions, compared to the developed regions. This conclusion would face challenges from a closer look at the data. Sokoto, although ranked as the least developed region throughout the study years, in terms of mean years of education for example, it doubled to 1.75 , and the mean night time light intensity almost improved by one magnitude. When interpreting

composed indexes, it is therefore important to include the composition dimensions into analysis to gain a holistic view on the results.

Variable	Obs	Mean	Std. dev.	Min	Max
shdi_	1,744	.5728062	.1148352	.24	.805
healthindex_	1,744	.6420573	.1143475	.355	.881
incindex_	1,744	.5826898	.1274794	.28	.849
edindex_	1,744	.5172523	.1462583	.081	.846
esch_	1,744	10.93476	2.525731	1.869	16.66
msch_	1,744	6.405398	2.638276	.762	13.676
lifexp_	1,744	61.73399	7.431968	43.088	77.27
lgnic_	1,744	8.462651	.843916	6.46	10.227
pop	1,541	3.995685	4.765196	.01	41.7
nls_mea_	1,744	10.41459	14.57503	.0018647	61.32609

Table 3.3 Summary statistics of dependent variables

	shdi_	esch_	msch_	lifexp_	lgnic_	(mean) nls_mea_
GDLCODE						
EGYr101	0.72	12.73	9.05	71.58	9.27	24.03
EGYr104	0.70	12.05	8.17	71.80	9.31	5.58
NERr107	0.25	2.35	0.79	51.20	6.83	0.01
NGAr121	0.24	1.87	0.86	47.18	7.32	0.37
NGAr125	0.26	2.36	0.93	47.67	7.36	0.13
TUNr101	0.72	14.65	6.67	75.60	9.22	52.28
Total	0.48	7.67	4.41	60.84	8.22	13.73

Table 3.4 Details of subnational regions with highest and lowest SHDI in 2003

	shdi_	esch_	msch_	lifexp_	lgnic_	(mean) nls_mea_
GDLCODE						
BWAr108	0.80	14.04	13.68	65.50	10.23	47.16
MUSr101	0.81	14.85	9.99	74.92	10.09	45.96
NERr102	0.38	4.53	1.45	69.97	7.29	0.18
NERr107	0.36	5.78	1.39	61.76	6.96	0.16
NGAr121	0.33	4.18	1.75	47.69	7.92	2.70
TUNr101	0.79	16.66	8.85	77.27	9.45	58.42
Total	0.58	10.01	6.18	66.19	8.66	25.76

Table 3.5 Details of subnational regions with highest and lowest SHDI in 2018

4. Results

4.1 Regress main dependent variables NTL and SHDI on FDI

Table 4.1 and table 4.2 report the second stage of IV regression. As specified in the main model, country-year fixed effect, subnational fixed effect and subnational population are controlled in all regression.

Table 4.1 shows estimated coefficients regressed on $FDI\_total_{i,t-n}$, where the first row reports when $n = 2$ and second row $n = 3$, and instrument $Reserves_{t-m}$ use $m = 4$ and $m = 5$, respectively. Both instruments have F-statistics and are above 30 and therefore we are less likely to have the concern of using weak instruments. In the short-run, within 2 to 3 after the announcement, Chinese FDI shows a negative impact on the income index. On average every 10 billion USD worth investment causes a decrease in income index by 0.03 in 2 years, or 0.02 in 3 years, controlled for population, regional differences and country-year specific shocks. The results are both significant at 1% level. This is likely to be the reason that causes decrease in the overall SHDI index, but the impact is likely mitigated for the health index and education index are not affected. FDI inflow is also likely to contribute to more economic activity in 3 years, column 6 shows per 10 billion dollar worth FDI inflow increases night-time light by almost 0.2 units. Column 10 reports a positive impact on the education index. Although the impact on local economic activity and on education is only significant at 10%, in the second row when taking 3 lag years, FDI shows an overall more significant impact on almost all indicators. This is comprehensible to our intuition, that not only local development takes time to make changes to happen, investment also takes time to the recipient location and become part of the economy.

Regression NTL and SHDI on FDI, lag 2 and 3 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	nls_mea_	shdi_	healthindex_	incindex_	edindex_	nls_mea_	shdi_	healthindex_	incindex_	edindex_
FDI_total_-2	0.0000199	-0.00000102***	-0.000000749	-0.00000269***	1.82e-08					
	(0.27)	(-5.83)	(-1.42)	(-7.37)	(0.07)					
FDI_total_-3						0.0000992**	-0.000000337*	-0.000000785	-0.00000174***	0.000000938**
						(2.28)	(-1.72)	(-1.06)	(-6.12)	(2.11)
_cons	44.97***	0.772***	0.762***	0.859***	0.722***	49.79***	0.798***	0.798***	0.807***	0.809***
	(24.13)	(172.99)	(56.76)	(92.55)	(114.99)	(46.53)	(166.08)	(44.07)	(115.86)	(74.22)
R-squared	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Observations	160	160	160	160	160	140	140	140	140	140

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4.1 Regress NTL and SHDI on FDI (lag2 and lag3 years)

Following the same logic that development change and investment flow takes time to be fully realised, we also report on the results regressed on higher lag years of FDI. One thing to note is with each year of lags taken, the number of observations reduces. To prevent the sample size becoming too small to

compromise the statistical power of our results, we stop at lag 5 years (remaining 108 observations). Table 4.2 report on the results shows a very different picture from our previous estimates. When regressing on FDI of 4 and 5 lagged years, investment seems to have a strongly negative impact on local economic activity measured by night-time light, and significant improvement in income index. This result not only contradicts Table 4.1, also notice it is not comprehensible to interpret the coefficients. Results from column (1) and (6) would mean every 10 billion dollar investment causes night-time light intensity to decrease 36.9 units, and cause a 0.1 point increase in income index. Although all reported at 1% significance, this read is of a different magnitude from the previous results.

This obviously error result is likely caused by the weak instrument. Because the disadvantage of taking even more lags for reserve is we limit the time period of observations. When taking 5 lag years for FDI and 7 lag years for reserve, the time span for which we claim correlation becomes FDI during 2003-2013 and reserve during 2001-2011. The variation in reserve change before and after 2010 are very different. According to World Bank data, the holding of the international reserve in China was steady around 100 billion (current US$) prior to 2000. This figure jumped to 1 trillion in 2006 and doubled to 2 trillion in 2 years. This exponential growth of reserve holding continued in the following years and only hit the break in 2015. This dramatic change in variation between 2010-2015 is also reflected in Figure 1 where I plot the time trend of detrended net changes in Chinese international reserve holding. Excluding the reserve, specifically of the post exponential growth years, sacrifices the already limited variation and weakens the instrument.

The results of OLS regression, (controlled for the same fixed-effects) of all dependent variables on FDI with 4 lagged years, will not be reported here. Because the coefficients are all statistically insignificant ,we from here limit the lag within 2 and 3 years in the following regressions.

Regression NTL and SHDI on FDI, lag 4 and 5 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	nls_mea_	shdi_	healthindex_	incindex_	edindex_	nls_mea_	shdi_	healthindex_	incindex_	edindex_
FDI_total_−4	-0.00369**	0.0000119**	-0.000135***	0.0000199**	0.0000964***					
	(-1.99)	(2.02)	(-4.99)	(2.32)	(4.65)					
FDI_total_−5						-0.00966***	-0.0000101***	-0.000113***	0.0000108***	0.0000646***
						(-5.87)	(-3.47)	(-9.40)	(3.57)	(7.21)
_cons	49.11***	0.794***	0.700***	0.806***	0.848***	43.16***	0.767***	0.688***	0.796***	0.819***
	(30.32)	(153.81)	(29.60)	(107.19)	(46.74)	(21.76)	(218.39)	(47.30)	(218.22)	(75.81)
R-squared	1.000	1.000	0.999	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Observations	126	126	126	126	126	108	108	108	108	108

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4.2 Regress NTL and SHDI on FDI (lag 4 and lag 5 years)

4.2 Regression results of SHDI components on FDI

Table 4.3 provides a detailed picture of how FDI impacts local development in different dimensions. Column (4) reports on average, per 10 billion Chinese FDI causes 18% decrease in gross national income per capita (PPP, 2011 USD) in 2 years of a subnational region, holding everything constant. This impact is persistent even in the year after, as it shows in Column (8), per 10 billion Chinese FDI inflow continues to cause a 12% decrease in income. Results on education show an interesting picture. Column (1) and (5) reports FDI inflow has a positive impact on expected years of schooling, however no impact on mean years of schooling as in column (2) and (6). The calculation of mean years of schooling is drawn from the population aged 25+, and the expected year of schooling is from children aged 6. The changes in expectation would not affect the actual education adults that already received and completed. To interpret the coefficient at face value, this means in 2 years, every 10 billion USD of FDI inflow causes on average an 0.12 years of increase in expected years of schooling, or 0.19 years of increase in 3 years. The impact on education and on income are both statistically significant at 1%, however, the impact on education is rather subtle and it is not reflected in the education index itself.

Table 4.4 reports OLS regression of all dependent variables on FDI (lagged 2 years), controlled for the same fixed effects and covariant. Although it shows overall significant estimates, the results are counter-intuitive and hard to have meaningful interpretations. Firstly, column (1) suggests every 10 billion USD FDI inflow would on average increase NTL by 2.4 units in 2 years. This would be very unlikely, considering the average delta NTL of subnational regions in our sample is only 0.38. Column (8) also suggests FDI would significantly improve life expectancy (on average 1 year longer per 10 billion USD inflow!) which is also too good to be true in such a short period.

Regression channels on FDI, lag 2 and 3 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	esch_	msch_	lifexp_	lgnic_	esch_	msch_	lifexp_	lgnic_
FDI_total_~2	0.0000123***	-0.00000794	-0.0000414	-0.0000180***				
	(2.98)	(-1.63)	(-1.21)	(-7.38)				
FDI_total_~3					0.0000191***	0.0000111	-0.0000529	-0.0000120***
					(2.84)	(1.32)	(-1.10)	(-6.29)
_cons	14.39***	9.679***	69.61***	10.28***	15.30***	11.45***	71.93***	9.933***
	(137.06)	(77.81)	(79.87)	(165.29)	(92.74)	(55.37)	(60.78)	(212.58)
R-squared	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000
Observations	160	160	160	160	140	140	140	140

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4.3 Regress SHDI compositions on FDI (lag2 and lag3 years)

OLS regression of the main dependent variables on FDI lag 2 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	nls_mea_	shdi_	healthindex_	incindex_	edindex_	esch_	msch_	lifexp_	lgnic_
FDI_total_~2	0.000243***	-0.000000458	0.00000179**	-0.000000850**	-0.00000180***	-0.0000301***	-0.0000286***	0.000119***	-0.00000566**
	(3.38)	(-1.26)	(2.77)	(-2.31)	(-3.39)	(-3.16)	(-3.31)	(2.83)	(-2.31)
_cons	37.34***	0.727***	0.649***	0.841***	0.704***	14.19***	9.321***	62.22***	10.16***
	(15.63)	(60.23)	(30.20)	(68.89)	(40.01)	(44.80)	(32.49)	(44.66)	(124.91)
R-squared	0.999	1.000	0.999	1.000	0.999	0.999	1.000	0.999	1.000
Observations	193	193	193	193	193	193	193	193	193

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4.4 OLS regression on FDI (lag2 and lag3 years)

5. Robustness tests

5.1 Robustness test with regression on FDI project

Table 5.1 and table 5.2 report the main dependent variables regressed on the number of FDI projects, instead of inflow amount, controlled for country-year fixed effect, subnational fixed effect and population. We used the same instrument, and presents two set of results using different lag years of FDI, $n = 2$ in the first row and second row $n = 3$. The results are overall consistent with our reported main results regressed on FDI inflow amount, implying negative impact on income index and mildly positive impact on local economic activity measured by NTL. To be more specifically, column (4) and (9) of Table 5.1 both confirm that on average, holding other factors constant, one additional project assigned to a subnational region would cause income index decrease by 0.00112 in 2 years, or 0.00168 in 3 years, both coefficients are statistically significant at 1% level. Column (4) and (8) of Table 5.2 shows specifically an additional FDI project would cause 1.88% decrease in gross national income in 2 years, or 1.11% decrease in 3 years. What is different is in the education aspect, results from column (1) and (2) of Table 5.2 suggesta an additional FDI project cause 0.02 less years in expected years of schooling and 0.01 less years of mean years of schooling in 2 years after the assignment of projects. Although these two coefficients are significant statistically, in terms of actual year, this result is rather insignificant. The coefficients are also insignificant when regressed on lag 3 years of FDI.

It is important to point out that the F-statistic for the same instrument but for the FDI project is 11.3, closely approaching 10, which brings the concern of weak instruments. The main reason is when switching from FDI inflow to the number of projects, we face a lack of variations between subnational regions at a given year. Amongst the 288 observations, most of the time a subnational region receives only 1 FDI project in a year, which account for 45% of the projects (208 out of total 449 projects). Only on one occasion, Gauteng (South Africa) received 11 projects within a year. In fact, in terms of number of projects, the distribution is extremely left screwed. As the distribution plotted in Graph 5.1 on the right side, the amount of FDI inflow, measured in million USD, shows more variation across observation units (i.e., subnational region i in year t).

Regression NTL and SHDI on FDI project, lag 2 and 3 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	nls_mea_	shdi_	healthindex_	incindex_	edindex_	nls_mea_	shdi_	healthindex_	incindex_	edindex_
FDI_projec~2	0.0606	-0.00137***	-0.000758	-0.00281***	-0.00112***					
	(0.46)	(-5.69)	(-1.51)	(-5.28)	(-3.99)					
FDI_projec~3						0.149**	-0.000611***	-0.00105	-0.00168***	-0.00000312
						(2.08)	(-2.67)	(-1.63)	(-3.64)	(-0.01)
_cons	25.15***	0.773***	0.710***	0.897***	0.718***	35.64***	0.790***	0.719***	0.867***	0.785***
	(12.61)	(210.39)	(92.69)	(110.75)	(167.30)	(27.45)	(191.09)	(61.81)	(103.91)	(109.67)
R-squared	0.999	1.000	0.999	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Observations	182	182	182	182	182	160	160	160	160	160

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5.1 Regress NTL and SHDI on FDI projects (lag2 and lag3 years)

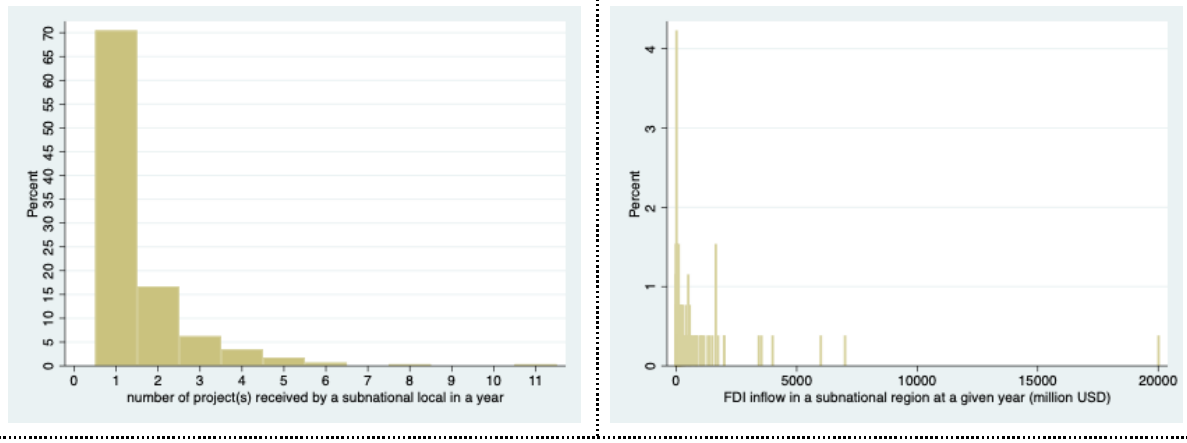
Regression channels on FDI, lag 2 and 3 years

	(1) esch_	(2) msch_	(3) lifexp_	(4) lgnic_	(5) esch_	(6) msch_	(7) lifexp_	(8) lgnic_
FDI_projec~2	-0.0236***	-0.0134**	-0.0472	-0.0188***				
	(-3.41)	(-2.52)	(-1.44)	(-5.34)				
FDI_projec~3					-0.00458	0.00298	-0.0609	-0.0111***
					(-0.69)	(0.39)	(-1.45)	(-3.64)
_cons	14.52***	9.422***	66.19***	10.54***	15.56***	10.59***	66.71***	10.34***
	(137.61)	(116.50)	(133.00)	(196.44)	(130.30)	(77.22)	(87.91)	(186.73)
R-squared	1.000	1.000	0.999	1.000	1.000	1.000	0.999	1.000
Observations	182	182	182	182	160	160	160	160

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5.2 Regress SHDI components on FDI projects (lag2 and lag3 years)



Graph 5.1 Distribution of FDI projects (left) and FDI inflow (right), Y axis shows number of projects/ FDI inflow total share %

5.2 Robustness test: control for Chinese aid project

For the Chinese aid project, we draw from AidData which contains in total 3485 Chinese official aid projects from 2000-2014, coded with geo-reference. Amongst 747 projects to subnational regions in Africa, we merged 252 observations that are allocated to the subnational regions of our study. Additionally we created a dummy variable of $Aid\_receiver\_lag4$, which takes value of 1 if a subnational region is recorded with a positive aid amount from China in lag 4 years, and 0 otherwise. This is to compensate for the missing values between 2014-2018 to ensure the variation in the control variables. It is a time-varying dummy variable and it is not controlled by the fixed effects.

Table 5.3 reports the second-stage regression of all dependent variables of interest on FDI inflow (lagged 2 years), controlled for subnational population, aid-receiving dummy, subnational fixed effect and country-year fixed effect. After controlling for Chinese aid, FDI inflow remains to have significant negative impact on gross national income per capita and on income index, and positive impact on expectation of years of schooling. The coefficient per 10 billion USD is about the same with the reported main results from Table 4.1 and Table 4.3.

The two robustness tests, first regression on FDI project and second adding Chinese aid as control variable, shows consistency with our main result.

Regression dependent variables on FDI, control for aid receiving

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	nls_mea_	shdi_	healthindex_	incindex_	edindex_	esch_	msch_	lifexp_	lgnic_
FDI_total_~2	0.0000302	-0.000000996***	-0.000000687	-0.00000268***	4.72e-08	0.0000126***	-0.00000728	-0.0000375	-0.0000180***
	(0.43)	(-5.93)	(-1.34)	(-7.36)	(0.20)	(3.07)	(-1.55)	(-1.13)	(-7.38)
Aid_receiv~4	-1.508***	-0.00347***	-0.00908***	-0.000557	-0.00421***	-0.0384	-0.0954***	-0.566***	-0.00259
	(-3.66)	(-3.51)	(-3.02)	(-0.26)	(-2.98)	(-1.60)	(-3.45)	(-2.89)	(-0.18)
_cons	47.16***	0.777***	0.775***	0.860***	0.728***	14.45***	9.818***	70.43***	10.28***
	(25.02)	(172.15)	(56.51)	(87.97)	(113.00)	(131.51)	(77.62)	(78.89)	(157.01)
R-squared	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Observations	160	160	160	160	160	160	160	160	160

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5.3 Regress dependent variables on FDI investment, control for Aid receiving in the past (lag 4 years)

6. Conclusion and discussion

This study is the first empirical analysis that regresses subnational human development indicators on subnational FDI inflow, to the best of the author's knowledge. In this paper, FDI is instrumented by the Chinese international reserve combined with probability factors. The panel data covers observations of 109 subnational regions in African countries ranging 2003-2018. Our results show FDI in the short run has a negative impact on standard of living, which is a monetary measurement based on GNI per capita. We also find a positive but less persistent and less significant impact on expected years of schooling. This result remains robust after regress on FDI project number, and after controlling for aid receiving history.

Our finding is inconsistent with the country-level analysis by Atitianti and Dai (2021), where they find Chinese FDI to have significant positive impact on HDI index. However, the novelty of our study provides new insight at subnational level. The result of our study should be subject to further rigorous tests, such as including a more complete Chinese aid project allocation as control variable. The FDI project raw data from the replication for Wang (et al., 2021) is also only a portion of the full fDi Market investment tracker data. Expanding the sample size would not only bolster the statistical power of the findings but also enhance the validity of our conclusions. More dependent variables, such as insurance coverage, unemployment rate, or even the number of people speaking more than one language (as proxy for education level) could be included to explore the channel of which FDI has an impact.

Another limitation of this study is the mechanism through which FDI can be instrumented by reserve is rather unclear. Although the correlation seems intuitive, the use of reserves as an instrument in regression analysis presents challenges. In this study, $Reserves_{t-m} * p_i$ is only a valid instrument (F>>10) when $m = n - 2$. In other words, the instrument "weakens" when reserves are lagged by years other than 2 relative to FDI. Unfortunately the Chinese government does not disclose information on the detailed composition of international reserve holding, the lagged use remains a puzzle in this research.

7. Bibliography

Acquah, A. M., & Ibrahim, M. (2019). Foreign direct investment, economic growth and Financial Sector Development in Africa. *Journal of Sustainable Finance & Investment*, *10*(4), 315–334. https://doi.org/10.1080/20430795.2019.1683504

Amendola, N., Gabbuti, G., & Vecchi, G. (2023). On some problems of using the human development index in economic history. *European Review of Economic History*, *27*(4), 477–505. https://doi.org/10.1093/ereh/head008

Asher, S., Lunt, T., Matsuura, R., & Novosad, P. (2021). Development research at high geographic resolution: An analysis of night-lights, firms, and poverty in India using the shrug open data platform. *The World Bank Economic Review*, *35*(4), 845–871. https://doi.org/10.1093/wber/lhab003

Atitianti, P. A., & Dai, Q. (2021). Does Chinese foreign direct investment improve the welfare of Africans? *Journal of African Business*, *23*(4), 964–983. https://doi.org/10.1080/15228916.2021.1969192

Benfratello, L., D'Ambrosio, A., & Sangrigoli, A. (2023). Foreign Direct Investments in Africa: Are Chinese investors different? *Journal of Business Research*, *155*, 113383. https://doi.org/10.1016/j.jbusres.2022.113383

Biglaiser, G., & Lu, K. (2022). Political risk and economic sectors: Chinese overseas public and private investment in the developing world. *Foreign Policy Analysis*, *18*(3). https://doi.org/10.1093/fpa/orac013

Cheung, Y., & Qian, X. (2009). Empirics of China's outward direct investment. *Pacific Economic Review*, *14*(3), 312–341. https://doi.org/10.1111/j.1468-0106.2009.00451.x

Colen, L., Maertens, M., & Swinnen, J. (2012). Foreign direct investment as an engine for economic growth and human development: A review of the arguments and empirical evidence. *Foreign Direct Investment and Human Development*, 80–125. https://doi.org/10.4324/9780203076880-9

Cruzatti C., J., Dreher, A., & Matzat, J. (2023). Chinese aid and health at the country and local level. *World Development*, *167*, 106214. https://doi.org/10.1016/j.worlddev.2023.106214

De Groot, O. (2014). (rep.). *NACIONES UNIDAS*. Retrieved 2024, from https://hdl.handle.net/11362/37137.

Dinh, T. T.-H., Vo, D. H., The Vo, A., & Nguyen, T. C. (2019). Foreign direct investment and economic growth in the short run and long run: Empirical evidence from developing countries. *Journal of Risk and Financial Management*, *12*(4), 176. https://doi.org/10.3390/jrfm12040176

Donou-Adonsou, F., & Lim, S. (2018). On the importance of Chinese investment in Africa. *Review of Development Finance*, *8*(1), 63–73. https://doi.org/10.1016/j.rdf.2018.05.003

Dreher, A., Fuchs, A., Hodler, R., Parks, B. C., Raschky, P. A., & Tierney, M. J. (2021). Is favoritism a threat to Chinese Aid Effectiveness? A subnational analysis of Chinese development projects. *World Development*, *139*, 105291. https://doi.org/10.1016/j.worlddev.2020.105291

Eshete, Z. S. (2020). China's unprecedent move and its repercussion on African economies: Empirical evidence from Ethiopia. *Frontiers in African Business Research*, 283–303. https://doi.org/10.1007/978-981-15-4510-8_14

Iamsiraroj, S. (2016). The Foreign Direct Investment–Economic Growth Nexus. *International Review of Economics & Finance*, *42*, 116–133. https://doi.org/10.1016/j.iref.2015.10.044

Kimiagari, S., Mahbobi, M., & Toolsee, T. (2023). Attracting and retaining FDI: Africa Gas and Oil Sector. *Resources Policy*, *80*, 103219. https://doi.org/10.1016/j.resourpol.2022.103219

Kosack, S., & Tobin, J. (2006). Funding self-sustaining development: The role of aid, FDI and government in economic success. *International Organization*, *60*(01). https://doi.org/10.1017/s0020818306060097

Kpolovie, P. J., Ewansiha, S., & Esara, M. (2017). Continental comparison of Human Development Index (HDI). *International Journal of Humanities, Social Sciences and Education*, *4*(1). https://doi.org/10.20431/2349-0381.0401002

Li, X., Zhou, Y., Zhao, M., & Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, *7*(1). https://doi.org/10.1038/s41597-020-0510-y

Nunn, N., & Qian, N. (2014). US Food Aid and civil conflict. *American Economic Review*, *104*(6), 1630–1666. https://doi.org/10.1257/aer.104.6.1630

Obstfeld, M., Shambaugh, J. C., & Taylor, A. M. (2010). Financial Stability, the trilemma, and international reserves. *American Economic Journal: Macroeconomics*, *2*(2), 57–94. https://doi.org/10.1257/mac.2.2.57

Our World in Data, & Roser, M. (2024, March 25). *Our world in data*. Our World in Data. https://ourworldindata.org/

Permanyer, I., & Smits, J. (2019). *Inequality in Human Development across the Globe*. https://doi.org/10.31235/osf.io/hskue

Prados de la Escosura, L. (2021). Augmented human development in the age of globalization†. *The Economic History Review*, *74*(4), 946–975. https://doi.org/10.1111/ehr.13064

SAFE. (2022). (rep.). *State Administration of Foreign Exchange*. Retrieved 2024, from https://www.safe.gov.cn/en/2020/1221/1779.html.

Salidjanova, N. (2011). (rep.). *https://www.govinfo.gov/*. Retrieved March 25, 2024, from https://www.govinfo.gov/content/pkg/GOVPUB-Y3-PURL-gpo24706/pdf/GOVPUB-Y3-PURL-gpo24706.pdf.

Sanfilippo, M. (2010). Chinese FDI to Africa: What is the Nexus with foreign economic cooperation?*. *African Development Review*, *22*(s1), 599–614. https://doi.org/10.1111/j.1467-8268.2010.00261.x

Sharma, B., & Gani, A. (2004). The effects of foreign direct investment on Human Development. *Global Economy Journal*, *4*(2), 1850025. https://doi.org/10.2202/1524-5861.1049

Titiloye Ademola, O., Bankole, A. S., & Adewuyi, A. O. (2009). China–africa trade relations: Insights from AERC scoping studies. *The European Journal of Development Research*, *21*(4), 485–505. https://doi.org/10.1057/ejdr.2009.28

Total reserves (includes gold, current US$). World Bank Open Data. (n.d.). https://data.worldbank.org/indicator/FI.RES.TOTL.CD

Utesch-Xiong, F., & Kambhampati, U. S. (2021). Determinants of Chinese foreign direct investment in Africa. *Journal of African Business*, *23*(4), 833–850. https://doi.org/10.1080/15228916.2021.1954446

Wei, W. X., & Alon, I. (2010). Chinese Outward Direct Investment: A study on macroeconomic determinants. *International Journal of Business and Emerging Markets*, *2*(4), 352. https://doi.org/10.1504/ijbem.2010.035663

World Investment Report 2022. (2022). *United Nations Conference on Trade and Development (UNCTAD) World Investment Report (WIR)*. https://doi.org/10.18356/9789210015431