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Economic Complexity and Poverty in Developing Countries

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Abstract

This paper has examined the effect of economic complexity on poverty in developing countries. The analysis has used a sample of 84 countries over the period 1980-2017. Results indicate that greater economic complexity results in lower poverty headcount rates. This is particularly the case for countries that enjoy higher economic growth rates, lower levels of income inequality and lower degrees of economic growth volatility, including due to lower sizes of export demand and financial flows shocks. These findings have important policy implications for developing countries that are exploring ways and means to recover from the current COVID-19 pandemic crisis, and prepare for future crises.

KEYWORDS: Economic complexity; Poverty headcount; Economic Growth; Economic growth volatility; Income inequality; External shocks.

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1. Introduction

Does economic complexity reduce poverty in developing countries? The current paper aims to contribute to the relatively nascent literature on the macroeconomic effects of economic complexity by addressing this question. The relevance of this question lies on the fact that poverty reduction is a shared objective of all countries in the world, including developing countries. This explains why the goal of 'reducing poverty' is at the heart (and even appears as the first goal) of the sustainable development goals[2].

'Economic complexity' is a relatively recent complex, which refers, for a given country, to the productive knowledge embedded in domestically produced goods as well as the diversification of goods exported (e.g., Albeaik et al., 2017a, 2017b; Bustos et al., 2012; Hausmann and Hidalgo, 2009; Hausmann and Hidalgo, 2011; Hidalgo et al., 2007). One of the main features of the concept of 'economic complexity' is its relation to the competitive advantage: a country with a high level of economic complexity enjoys a competitive advantage in the global economy, and through the creation of sophisticated products, would likely experience higher returns compared to countries that create less sophisticated products (see also Le Caous and Huarng, 2020). The production of complex goods requires a wide range of diverse and exclusive capabilities. Economic complexity measures the sophistication of a country's productive structure, which reflects the diversity of this country (i.e., the number of products it exports) and the ubiquity of its products (i.e., the number of countries that also export these products) (e.g., Hausmann and Hidalgo, 2009). Thus, products are qualified as 'complex' or 'sophisticated' when they cannot be easily reproduced by other countries (i.e., they are less ubiquitous – they have a low ubiquity) and when they are produced by few countries that are endowed with a wide range of diverse and exclusive capabilities.

Both the research community and policymakers are increasingly showing attention to the usefulness of 'economic complexity'. This is exemplified by a growing number of studies on issues related to economic sophistication. For example, some works have looked at the determinants of economic complexity (e.g., Albeaik et al., 2017a, 2017b; Chu, 2020; Hausmann and Hidalgo, 2014; Lapatinas, 2019; Lapatinas and Litina, 2018; Sepehrdoust et al., 2019). Other studies have shown that economic complexity helps to promote economic development (e.g., Caldarelli et al., 2012; Cristelli et al., 2015; Felipe et al., 2012; Hidalgo et al., 2007), enhance economic growth (e.g., Hausmann and Hidalgo, 2009; Poncet and Starosta de Waldemar, 2013; Stojkoski et al., 2016), reduce income inequality (e.g., Hartmann et al., 2017; Le Caous and Huarng, 2020), improve

[2] The document "Transforming our world: the 2030 Agenda for Sustainable Development" (reference number A/RES/70/1) contains sustainable development goals adopted by the General Assembly of the United Nations.

human development (e.g., Le Caous and Huarng, 2020), reduce economic growth volatility (e.g., Güneri and Yalta, 2020; Maggioni et al., 2016; Miranda-Pinto, 2021), dampen economic growth cycles (e.g., Canh and Thanh, 2020) and increase labor share notably in the context of (e.g., Arif, 2021).

Building on the aforementioned existing empirical literature on the effect of economic complexity, the present article examines the effect of economic complexity on poverty in developing countries through the channels of economic growth, income inequality and economic growth volatility. An extensive literature has shown that these three channels (i.e., economic growth, income inequality and economic growth volatility) can influence poverty rates (e.g., Banerjee et al., 2015; Bhagwati, 2001; Bourguignon, 2004; Datt and Ravallion, 2002; Dollar and Kraay, 2002; Fosu, 2015, 2018; Perera et al., 2013; Ravallion, 2004). For example, if economic complexity influences positively a country's economic growth (e.g., Hausmann and Hidalgo, 2009), and reduces the prevailing income inequality in this country (e.g., Hartmann et al., 2017), then it can be a potential driver of poverty reduction in that country, in particular if economic growth contributes to lowering poverty rates (e.g., Banerjee et al., 2015; Bhagwati, 2001; Dollar and Kraay, 2002; Fosu, 2015, 2018; Perera et al., 2013; Ravallion, 2004) and if income inequality is associated with poverty reduction (e.g., Fosu, 2010; Kulkarnia and Gaiha, 2020).

We test empirically the effect of economic complexity on poverty through the three channels mentioned above by using a sample of 84 countries over the period 1980-2017. The results, based on the two-step system Generalized Methods of Moments (GMM), show that economic complexity reduces poverty, notably in countries that experience a higher economic growth rate, lower levels of income inequality, and lower degree of economic growth volatility, including through lower extent of external shocks.

The rest of the paper contains five sections. Section 2 discusses the theoretical effects of economic complexity on poverty through the economic growth and income inequality avenues. Section 3 describes the model specification used to undertake the empirical analysis, and briefly presents the econometric approach used to estimate this model. Section 4 presents estimations' outcomes. Section 5 deepens the analysis by examining whether economic growth volatility matters for the effect of economic complexity on poverty. Section 6 concludes.

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2. Discussion on the effect of economic complexity on poverty

We postulate that economic complexity can affect poverty through its effect on economic growth and income inequality, insofar as economic growth and income inequality can influence poverty. Before discussing how these effects could materialize, it is important to note that greater economic complexity can generate new jobs, increase income for both low-skilled workers and high-skilled workers, in particular if the production and export of complex products are part of a supply chain that utilizes both high-skilled and low-skilled workers. Additionally, a complex economy provides its individuals with more freedom of choices, more capabilities, a variety of ideas and lifestyles, and can adapt easily to its people's needs (e.g., Hartmann and Pyka, 2013; Le Caous and Huarng, 2020). In so doing, a complex economy can improve standards of living, and provide its citizen with better education, healthcare, and other needed social services. Therefore, we can expect that through these various channels, economic complexity can help reduce poverty.

Let us now consider how economic complexity can influence poverty through economic growth and income inequality channels. We start by discussing the effect of economic complexity on economic growth and income inequality. We then consider how economic growth and income inequality affect poverty.

It is now well established in the literature that economic complexity is strongly and positively associated with economic growth. For example, Hausmann and Hidalgo (2009) have shown that a country's economic complexity is positively correlated with its income level, and this relationship is a good predictor of the country's future growth. Hence, economic complexity contributes strongly to sustainable growth and prosperity. Poncet, and Starosta de Waldemar (2013) have considered the relationship between economic complexity and growth in China's cities. They have found that the greater the complexity of a city's productive structure, the faster is its per capita income growth rate. Stojkoski et al. (2016) have reported, *inter alia*, that a country's economic complexity measured in the product space (including goods and services) influences positively its income per capita, adjusted for purchasing power parity.

As noted in the introduction, few studies have shown that economic complexity contributes significantly to reducing income inequality (e.g., Caous and Huarng, 2020; Hartmann et al. 2017). The empirical analysis carried out by Hartmann et al. (2017) has demonstrated that economic complexity exerts a strong negative effect on income inequality: over time, countries that export complex products enjoy lower levels of income inequality than countries that export simpler products. Le Caous and Huarng (2020) have obtained empirically that by reducing income inequality, economic complexity helps improve human development in developing countries. On the theoretical front, Hartmann et al. (2017) have noted that the effect of economic complexity on income inequality is similar to that of structural changes on income distribution (referred to as the Kuznets-Lewis wave). This means that economic complexity would result in lower income inequality as it is the case for structural changes. One argument is that the production of complex goods by a given country involves some constraints on occupational choices, learning opportunities and bargaining power of its workers and unions. Thus, industrialization in emerging countries has allowed the creation of new jobs and generated new opportunities for workers, and all of these have contributed to the emergence of a new middle class that helps reduce income inequality. In contrast, income inequality has risen in industrialized countries that have experienced a greater competition in the world market, and de-unionization. The widening in income inequality in these countries has arisen from job losses, lower wages, and reduced ability of unions to compress wage inequality. The other argument put forth by Hartmann et al. (2017) is that complex industrial products are more than single products featured by a higher degree of tacit knowledge and a greater distribution of knowledge. These features can help enhance unions' power to negotiate high wages, and reduce wage inequality. Along the same lines, Le Caous and Huarng (2020) have built on the work by Constantine and Khemraj (2016) to argue that economies with low-value added products (i.e., less complex economies) experience low wages shares, a small middle class, and consequently a rise in income inequality. This is because low-value added products are simple, have a low technological content, embed low knowledge, and are endowed with low-skilled individuals. Additionally, the returns from activities generated by such products are usually captured by small groups of individuals, which widens the income disparities vis-à-vis the rest of the population.

In the meantime, economic complexity can be associated with higher income inequality. This could be explained by the skill-biased technical change (SBTC) that can arise from the technological change induced by greater complexification of the economy (i.e., the production of increasingly complex goods). In fact, the technological progress associated with the rise in economic complexity can result in a higher demand for high-skilled workers relatively to low-skilled workers, and widen wage inequality, which could in turn, generate a rise in income inequality. Many studies have provided empirical support for the SBTC theory (e.g., Card and DiNardo, 2002; Feenstra and Hanson, 1999; Hahn and Choi, 2017; Lee and Wie, 2015).

From the afore-mentioned discussion, it is likely that economic complexity would be positively associated with economic growth, and negatively associated with income inequality. Now, how do economic growth and income inequality influence poverty? The direction(s) of these effects would determine the direction of the effect of economic complexity on poverty. For example, if it appears that higher economic growth reduces poverty, then by improving economic growth, economic complexity will result in lower poverty rates. Likewise, if lower income inequality contributes to reducing poverty, then by reducing the level of income inequality, economic complexity will result in lower poverty rates. The literature on the relationship between economic growth and poverty on the one hand, and between income inequality and poverty on the other hand, is extensive and inconclusive as to the direction of the effects. Additionally, a strand of this literature has shown that the effect of economic growth on poverty is altered by the level of income inequality. As a result, the relationship between economic complexity and poverty could be mitigated by the prevailing income inequality.

Starting with the literature on the effect of economic growth on poverty, various studies have revealed that economic growth has been an important driver of poverty reduction (e.g., Banerjee et al., 2015; Bhagwati, 2001; Bourguignon, 2004; Datt and Ravallion, 2002; Dollar and Kraay, 2002; Fosu, 2015, 2018; Perera et al., 2013; Ravallion, 2004). However, in investigating the factors underpinning the slow pace of poverty reduction between the mid-1980s and the mid-2000s in Brazil, Ferreira et al. (2010) have found that economic growth has played a negligible role in Brazil's poverty reduction. Services sector growth has contributed much more to poverty reduction than growth in agriculture or industry sectors, although growth in the industry sector has exerted different effects on poverty across different states depending on initial conditions related to human development and worker empowerment. Mwabu and Thorbecke (2004) have uncovered that rural development plays a key role in transforming economic growth into poverty reduction in African countries. Grimm and Günther (2007) have obtained for Burkina Faso that poverty has increased between 1994 and 1998 despite a good macroeconomic performance, which may signify that economic growth has not been associated with poverty reduction during this period of time in Burkina Faso.

Meanwhile, many works[3] have shown that lower income inequality can be instrumental in ensuring that economic growth genuinely translates into poverty reduction (e.g., Adams, 2004; Bigsten et al., 2003; Bourguignon, 2003; Fosu, 2009; Kalwij and Verschoor, 2007; Salvatore, 2004; Ravallion, 1997). For example, Kulkarnia and Gaiha (2020) have obtained empirically that in India, the gap between the income share of the top 1% and share of the bottom 50% has resulted in greater poverty. Bigsten et al. (2003) have found that the potential poverty reduction effect associated with a rise in real per capita income can be counteracted by the rise in income inequality. In other words, despite good economic growth performance, poverty can increase due to the

[3] Thorbecke (2013) has provided a literature review on the nexus between economic growth, income inequality, and poverty nexus.

worsening of income distribution. Kalwij and Verschoor (2007) have explored the effect of both economic growth and income inequality on poverty, as well as whether income distribution matters for the responsiveness of poverty to income growth in developing countries. Their findings suggest that income growth reduces poverty, while income inequality increases it, with income growth elasticity to poverty, and the elasticity of income inequality to poverty varying across various regions in the sample. Additionally, the differences in the responsiveness of poverty to income growth across regions is explained by the differences in the rates of changes in income inequality. Goh et al. (2009) have found for eight provinces in China that while poverty has fallen further to income growth in all segments of the population, the growth in income has nevertheless been uneven, as income has increased more rapidly in coastal areas, and among the educated. Fosu (2009) has uncovered for both Sub-Saharan Africa and non-Sub-Saharan Africa that the poverty reduction effect of economic growth decreases with the level of initial income inequality. Fosu (2010) has undertaken a comparative global perspective on the role of inequality relative to income growth in poverty reduction. He has observed that poverty is reduced when income increases in the context of decreasing income inequality, although there is a large variation across countries in the relative effects of inequality on poverty. Likewise, Fosu (2015) has observed for Sub-Saharan African countries that while economic growth is relevant for poverty reduction, its ultimate effect depends on income inequality, as a fall in income inequality results in lower poverty rates, holding constant the country's income level. Fosu (2017) has reported for developing countries that the extent to which a higher economic growth can result in poverty reduction could be limited by growing income inequality. According to Fosu (2018), while income growth has been the main driver behind poverty reduction in Africa, there appears to be striking differences across countries and poverty measures concerning the relative roles played by income inequality and economic growth.

Summing-up, while the direction of the effect of economic growth on poverty remains unclear (as it could be negative or positive), it appears that this effect can be mediated by the level of income inequality. As a consequence, it would be difficult at this stage of the analysis to anticipate the direction of the effect of economic complexity on poverty through the economic growth channel or the income inequality channel. For this reason, in the empirical analysis below, we examine the effect of economic complexity on poverty through these two channels by including in the same model specification both the variables capturing the economic growth rate, and the income inequality (as well as the interaction between each of these variables and the economic complexity indicator). In so doing, we will ensure that we are genuinely capturing the effect of

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economic complexity on poverty through one channel regardless of its effect through the other channel.

3. Model specification

To examine the effect of economic complexity on poverty, including through the economic growth and income inequality channels, we drawn from the recent study by Gnangnon (2021) as well as previous studies on the macroeconomic determinants of poverty in developing countries (e.g., Fosu, 2018; Kpodar and Singh, 2011; Gnangnon, 2019, 2020, 2021; Lacalle-Calderon, Perez-Trujillo, & Neira, 2018; Le Goff & Singh, 2014; Singh & Huang, 2015). The model postulated is as follows:

$$POVHC_{it} = \beta_0 + \alpha_1 \mathrm{POVHC}_{it-1} + \beta_2\, \mathrm{ECI}_{it} + \beta_3[ECI_{it} * VAR_{it}] + \beta_4\, \mathrm{VAR}_{it} + \beta_5\, \mathrm{OPEN}_{it} + \beta_6 \mathrm{FINDEV}_{it} + \beta_7 \mathrm{EDU}_{it} + \beta_8 \mathrm{Log(GDPC)}_{it} + \beta_9 \mathrm{POLITY2}_{it} + \beta_{10} \mathrm{Log(POP)}_{it} + \vartheta_t + \mu_i + \omega_{it} \quad \textbf{(1)}$$

The subscripts i and t stand respectively for a country, and time period. Our measure of poverty is the poverty headcount rate at $1.90 a day, which is denoted 'POVH'. The poverty headcount rate at $1.90 a day is the percentage of the population living on less than $1.90 a day at 2011 international prices. As it contains many zeros and is skewed, this variable has been transformed into the dependent variable 'POVHC' following the procedure proposed by Yeyati et al. (2007) (see Appendix 1). For the sake of brevity, we henceforth use 'poverty' to refer to 'poverty headcount rate'. The variable 'ECI' is the key variable of interest, and represents the economic complexity index. It is calculated using Hidalgo and Hausmann's (2009) methodology, and reflects the diversity and ubiquity of a country's export structure (see Appendix 1 for more details). The variable 'VAR' is what we term the channel-variable, i.e., the channel through which economic complexity can influence poverty. Thus, 'VAR' can be either the economic growth rate, denoted 'GROWTH' or the income inequality level, denoted 'GINI'.

The other regressors in model (1) are control variables drawn from the extensive literature on the macroeconomic determinants of poverty (see in particular Gnangnon, 2021). They include the degree of trade openness ('OPEN'); a proxy for the level of financial development ('FINDEV'); the level of education ('EDU'); the real per capita income (GDPC'), which is a proxy for the development level; the quality of institutions proxied by the level of democracy (POLITY2'); and the population size (POP'). The source of all variables contained in model (1) (as well as other variables that would be used later in the analysis) are described in Appendix 1.

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While the sign and significance of the coefficient β_2 in model (1) are of key interest to us (including when the variable 'VAR' and the interaction variable '$[ECI_{it} * VAR_{it}]$' are absent from the model), we are also interesting in the sign and significance of the interaction term β_3, which represents the coefficient of the interaction between the index of economic complexity and each of the channel-variable (i.e., economic growth or income inequality).

Model (1) is estimated using an unbalanced panel dataset containing 84 countries over the period 1980-2017. The list of the 84 countries is provided in Appendix 2. Following the practice in the macro-empirical literature, we use non-overlapping sub-periods of 5-year average for data so as to smooth out the effect of business cycles on variables (see for example the recent studies by Gnangnon, 2020, 2021). These sub-periods are 1980-84; 1985-89; 1990-94; 1995-99; 2000-04; 2005-09; 2010-14, and 2015-17 (the last sub-period contains three years). The parameters β_0 to β_{10} are to be estimated. μ_i represents countries' time-invariant fixed effects. ω_{it} is an idiosyncratic error-term. ϑ_t are time dummies, and capture global shocks that affect all countries' poverty rates. Descriptive statistics on variables used in the analysis are presented in Appendix 3. It is worth noting that other descriptive statistics (that could be obtained upon request) on the within-country variation and between-country variation of all variables in model (1) have shown that for the majority of variables (of which 'POVHC' and 'ECI'), the between-country variation dominates the within-country variation.

We have included the one-period lag of the dependent variable in model (1) in order to account for the fact that poverty is persistent over time (see for example Kpodar and Singh, 2011; Gnangnon, 2019, 2020, 2021; Le Goff & Singh, 2014).

[Insert Figure 1, here]

Figure 1 illustrates the correlation pattern between economic complexity and poverty. It clearly shows a negative correlation between these two indicators regardless of whether the poverty variable has not been transformed (i.e., 'POVH') (see the left-hand graph) or transformed (i.e., 'POVHC') (see the right-hand graph). We also observe that the use of the transformed indicator of poverty helps address the skewness of the poverty index 'POVH' - particularly around 0 - observed in the left-hand graph (this skewness no longer appears in the right-hand graph).

Following many previous studies (e.g., Kpodar and Singh, 2011; Gnangnon, 2019, 2020, 2021; Le Goff & Singh, 2014), we estimate model (1) by using primarily the two-step system generalised methods of moments[4] (GMM) approach suggested by Blundell and Bond (1998). This estimator helps address many endogeneity problems, including the ones arising from the reverse

[4] For the sake of brevity, we refer the readers to recent studies such as Gnangnon (2020, 2021) concerning the rationale for using this indicator.

causality (i.e., from the dependent variable to some regressors), as well as the endogeneity concern stemming from the correlation between the one-period lag of the dependent variable and countries' time invariant specific effects[5]. Using the two-step system GMM estimator involves estimating a system of equations that includes an equation in differences and an equation in levels where lagged first differences are used as instruments for the levels equation, and lagged levels are used as instruments for the first-difference equation. In the current analysis, we have treated as endogenous (due to the potential reverse causality problem) the variables 'ECI', 'GROWTH', 'GINI', 'OPEN', 'FINDEV', 'EDU', and 'POLITY2'. For example, the bi-directional causality between 'POVHC' and 'ECI' can be explained by the fact that while economic complexity can affect poverty, it is also possible that countries that aim to reduce poverty, would implement a package of policies and measures aiming at 'complexifying' their export products structure.

Three standard tests are used to assess the consistency of the two-step system GMM estimator. These tests are the Arellano-Bond test of first-order serial correlation (AR(1)) in the error term; the Arellano–Bond test of no second-order autocorrelation (AR(2)) in the error term; and the standard Sargan-Hansen test of over-identifying restrictions (OID), which determines the validity of the instruments used in the regressions. To ensure that the above-mentioned requirements of the two-step system GMM estimator are met, we estimate model (1) using a maximum of 3 lags of the dependent variable as instruments, and 2 lags of endogenous variables as instruments. Additionally, in performing the regressions, we have noticed that the requirements of the two-step system GMM are met only when two lags of the dependent variable in model (1) are included in the regressions (as with only one lag of the dependent variable, these requirements were not met). Therefore, all our estimations of the dynamic model (1) henceforth include a one-period lag of the dependent variable and a two-period lag of the dependent variable.

Even though the two-step system GMM estimator is our main estimator in the analysis, we also use two standard econometric estimators to estimate a variant of model (1): the fixed effects estimator (along with the Driscoll and Kraay (1998) technique to correct standard errors) and the feasible generalized least squares. The objective of doing so is to compare results based on the two-step system GMM estimator with those arising from the use of each of these two estimators, even though the latter can generate biased results as they do not deal with the endogeneity concerns raised above. The variant of model (1) estimated using these two estimators is a static form of model (1) (i.e., model (1) from which we remove the lagged dependent variable as regressors) that

[5] The correlation between the one-period lag of the dependent variable and countries' time invariant specific effects generates biased estimates if the model is estimated using standard econometric estimators such as the ordinary least squares estimator, or the fixed effects estimator. The GMM estimator helps to address this endogeneity problem.

does not include the variable 'VAR' and the interaction variable. This specification of model (1) allows examining how economic complexity influences poverty regardless of channels through which this effect takes place.

4. Empirical outcomes

The outcomes of the estimations of different variants of model (1), including with the three estimators highlighted above, are provided in Table 1. Columns [1] and [2] of the Table report results concerning the estimation of the static form of model (1) described above using respectively the fixed effects estimator and the feasible generalized least squares estimator. Results in column [1] suggest that economic complexity does not affect significantly poverty headcount rate (the coefficient of 'ECI' is not statistically significant at the 10% level), while results in column [2] indicate that economic complexity exerts a negative and significant effect on poverty headcount rate (the coefficient of 'ECI' is negative and significant at the 1% level). These differences in the outcomes can be explained by the dominance of between-country variation over the within-country variations of the majority of variables used in the analysis, including for our key variables of interest. In fact, in such a case, the fixed effects estimator loses efficiency at the benefit of the feasible generalized least squares estimator. Results based on column [2] suggests that a one percentage point increase in the index of economic complexity reduces the index of poverty headcount rate by 12.6% (= 0.126*100). Concerning control variables, estimates based on the fixed effects estimator suggest that a rise in the real per capita income, greater financial development and a rise in the population size are associated with poverty reduction (at the 1% level), while greater trade openness raises poverty (also at the 1% level). The institutional quality variable does not affect significantly poverty at the 10% level. Results relating to control variables in column [2] of the Table indicate that a higher real per capita income, greater financial development and an improvement in the education level contribute to reducing poverty, while all other variables (trade openness, the institutional quality, and the population size) exert no significant effect on poverty at the 10% level. As noted above, the estimates displayed in columns [1] and [2] of Table 1 can be biased due to the endogeneity concerns of some regressors raised above.

[Insert Table 1, here]

Columns [3] and [4] of Table 1 contain the outcomes arising from the estimation of two different specifications of model (1). In fact, results presented in column [3] of the Table stem from the estimation of the dynamic form of model (1) that allows exploring the effect of economic complexity on poverty regardless of channels through which this effect takes place. Hence, the specification of this model is nothing else than the dynamic model (1) (i.e., with the two lags of the dependent variable) from which we remove the regressor 'VAR' (i..e, the channel-variable) as well as the interaction between the channel-variable and the indicator 'ECI'. Column [4] contains the outcomes obtained from estimating model (1) as it stands: these outcomes help examine whether the effects of economic complexity on poverty translate through the economic growth and the income inequality channels. As noted above, we have included both channel-variables along with their interaction with 'ECI' in the model so as to ensure that the effect of economic complexity on poverty through one channel would be independent from the effect of economic complexity on poverty through the other channel. Results in columns [3] and [4] of the Table suggest that poverty is persistent over time. The coefficients of both the one-period lag and the two-period lag of the dependent variable are significant at the 1% level. In particular, the coefficient of the one-period lag of the dependent variable is positive, while the coefficient of the two-period lag of the same variable is negative across the two columns. These results indicate that a rise in poverty headcount rate in period t-1 influences positively poverty headcount rate in period t, while an increase in poverty headcount rate in period t-2 influences negatively poverty headcount rate in period t. Interestingly, and as expected, the null hypotheses of Arellano-Bond tests of first, second-order autocorrelations in the error term cannot be rejected in columns [3] and [4] of the Table, and the p-values of the Sargan test are higher than 0.10 (i.e., the 10% level of statistical significance). On the basis of these outcomes, we can infer that the two-step system GMM estimator generates consistent and efficient estimates, at least compared to those based on the fixed effects and feasible generalized least squares estimators. As for the estimates in column [3], we find that greater economic complexity is negatively associated with poverty headcount rate (the coefficient of 'ECI' is negative and significant at the 5% level). This outcome shows that, on average, developing countries that export complex products experience lower poverty rates. Specifically, a one percentage point increase in the index of economic complexity reduces the poverty headcount rate by 9.2% (= 0.092*100). It is interesting to note that the magnitude of this effect is slightly lower compared to the one obtained from the regression based on the feasible generalized least squares. Estimates related to control variables indicate that at the 1% level, an increase in the real per capita income and greater trade openness are associated with poverty reduction. At the 10% level, financial development, the education level, and the population size do not influence significantly poverty. We note, with surprise, that greater democracy, which reflects here an improvement in the institutional quality, raises poverty (at the 1% level). This outcome, which reflects, an average effect across countries in the full sample, may hide positive and significant, negative and significant, but also non-significant effects across countries. This outcome may also reflect the fact that democracies' spending including on education and health tend to benefit much more middle-and upper-income groups than non-democracies (Ross, 2006). In such a situation, greater democracy can result in higher poverty rates (particularly among low-income groups).

The finding of a negative and significant effect of economic complexity on poverty in column [3] of the Table raises question as to "through which avenues does the economic complexity help reduce poverty?" Results presented in column [4] of the Table help to respond to this question. They suggest that the coefficient of 'ECI' and the interaction term of the variable 'ECI*GROWTH' are both negative and significant at the 1% level. We conclude that the effect of economic complexity on poverty headcount rate genuinely depends on the economic growth prevailing in countries: regardless of the rate of economic growth, economic complexity always leads to lower poverty rates, and the higher the economic growth rate, the greater is the magnitude of the negative effect of economic complexity on poverty. At the same time, the interaction term of the variable 'ECI*GINI' is positive and significant at the 1% level. This outcome suggests that economic complexity leads to poverty reduction in countries that experience lower levels of income inequality. As the coefficient of 'ECI' is negative and significant at the 1% level, economic complexity influences positively poverty when the level of income inequality is higher than 38 (= 0.543/0.0143) (values of 'GINI' range between 22.2 and 68.3 - interval that contains the threshold '38' found above). Hence, for levels of income inequality higher than 38, economic complexity results in higher poverty rates. However, for levels of income inequality lower than 38, economic complexity influences is associated with poverty reduction, and the lower the degree of income inequality, the higher is the magnitude of the effect of economic complexity on poverty. Summing-up results in column [3], we can conclude that greater economic complexity consistently leads to poverty reduction in countries with higher economic growth rates, but reduces poverty in countries with low levels of income inequality. On another note, higher economic growth rates lead to lower poverty, and an increase in the level of income inequality results in higher poverty (the coefficients of 'GROWTH' and 'GINI' are respectively negative and positive, while significant at the 1% level).

5. Further analysis

We complement the previous analysis by investigating in this section whether the effect of economic complexity on poverty can translate through the economic growth volatility channel. This is because on the one hand, a recent literature has shown that economic complexity is associated with lower aggregate output volatility (e.g., Güneri and Yalta, 2020; Miranda-Pinto, 2021), lower firms' output volatility (e.g., Maggioni et al., 2016), and dampens economic growth

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cycles (e.g., Canh and Thanh, 2020). On the other hand, a large body of the literature has now well established that greater macroeconomic volatility (e.g., output volatility) due, *inter alia*, to external shocks (e.g., financial crises and economic crises such as severe commodity prices shocks) adversely affects poor people, and raises poverty in developing countries[6]. More recently, Gnangnon (2020) has demonstrated empirically that the exchange rate pressure (ERP), which is a proxy for export demand and foreign financial flows shocks raise poverty in developing countries.

Against this backdrop, we postulate that producing and exporting complex products will enable countries to mitigate the effect of output volatility (or economic growth volatility) on their economies, and consequently dampen any adverse effects of external shocks on poverty. Put it differently, by reducing economic growth volatility as well as the adverse effects of external shocks, greater economic complexity would alleviate poverty.

To test this hypothesis, we use model (1) where the variable 'VAR' is alternatively measured by economic growth volatility denoted 'GRVOL' and the exchange rate pressure, which as indicated above, is a proxy for export demand and foreign financial flows shocks (see also for example, Morrissey et al., 2016). Therefore, we estimate two different specifications of model (1) (with two lags of the dependent variable as right-hand side regressors): the first one contains the economic growth volatility indicator (as the measure of 'VAR') along with its interaction with the variable 'ECI', and the second model contains the variable 'ERP' (as the measure of 'VAR') and its interaction with 'ECI'. The description and source of 'GRVOL' and 'ERP' are provided in Appendix 1, and their related descriptive statistics are presented in Appendix 3. The results of the estimation of these two model specifications by means of the two-step system GMM approach are displayed in columns [1] and [2] of Table 2. It is important to note here that all requirements of the two-step system GMM estimator are met (see results at the bottom of Table 2). We observe in column [1] of the Table that the coefficient of 'ECI' is negative and significant at the 1% level, while the coefficient of the variable 'ECI*Log(GRVOL)' is positive and significant at the 1% level. Taken jointly, these outcomes suggest that the effect of economic complexity on poverty genuinely depends on the level of economic growth volatility: economic complexity results in lower poverty in countries that experience lower degrees of economic growth volatility, in particular if the latter are lower than 1.98 (= 0.118/0.0597) (values of 'GRVOL' range between 0.09 and 16.3 - see Appendix 3). Overall, economic complexity reduces poverty in countries that experience a degree of economic growth volatility lower than 1.98, and for these countries, the lower the economic

[6] These studies include for example Alimi and Aflouk (2017); Barrot et al. (2018); Dabla-Norris and Gündüz (2014); Ivanic and Martin (2008); Loayza and Raddatz (2007); Moncarz et al. (2018); Raddatz (2007); and Rewilak (2018). See also Gnangnon (2020) for a literature review on the effect of macroeconomic volatility on poverty, including through external shocks.

growth volatility level, the higher is the magnitude of the reducing effect of economic complexity on poverty. In contrast, in countries that experience a degree of economic growth volatility higher than 1.98, economic complexity raises poverty, and the higher the economic growth volatility, the higher is the magnitude of the positive effect of economic complexity on poverty.

[Insert Table 2, here]

Likewise, estimates in column [2] of Table 2 show a positive coefficient of 'ECI', but a negative coefficient of the interaction variable 'ECI*ERP', both being significant at the 1% level. We deduce that the effect of economic complexity on poverty also translates through the external shocks channel. Specifically, greater economic complexity leads to lower poverty rates in countries that experience a low extent of external shocks, i.e., of export demand and foreign financial flows shocks. This is the case when the extent of external shocks (i.e., of the indicator ERP) is lower than 0.65 (= 0.162/0.249) (values of 'ERP' range between -0.18 and 7.2 - see Appendix 3). As a consequence, countries whose size of external shocks is lower than 0.65 enjoy a reducing poverty effect of greater economic complexity, and the lower the size of external shocks, the greater is the magnitude of the negative effect of economic complexity on poverty. On the other hand, in countries whose extent of external shocks is greater than 0.65, economic complexity raises poverty, and the greater the extent of external shocks, the higher is the magnitude of the positive effect of economic complexity on poverty.

Overall, the outcomes in column [2] of Table 2 suggest that economic complexity can contribute to poverty reduction through its dampening effect on economic growth volatility, as well as its ability to withstand the adverse effects of external shocks on domestic economies.

6. Conclusion

This paper aims to complement the recent literature on the macroeconomic effects of economic complexity by investigating whether economic complexity influences poverty in developing countries, and if so, whether this effect translates through three mains channels, including economic growth, income inequality, economic growth volatility (as well as external shocks). The analysis has revealed that greater economic complexity results in lower poverty headcount rates, and this effect genuinely translates through the channels mentioned above. Specially, economic complexity leads to lower poverty headcount rates in countries that enjoy higher economic growth rates, lower levels of income inequality, lower degrees of economic growth volatility as well as lower extents of external shocks (i.e., lower degrees of export demand and financial flows shocks).

The current COVID-19 pandemic is a severe blow to all economies in the world, as it has hit more severely developing countries than developed countries. This crisis has exposed the vulnerabilities of developing economies to future crises, and their need to explore ways to recover quicky and prepare for any future crisis. The findings of the present analysis show that one important means that could allow developing countries to prevent future crises from severely hitting their economies and raising poverty is to elaborate strategies, and implement appropriate policies and measures in favour of producing and exporting increasingly complex products. In that way, they would ensure a sustainable economic growth, and prepare their economies to cope with future major crises, including economic, financial, and health crises.

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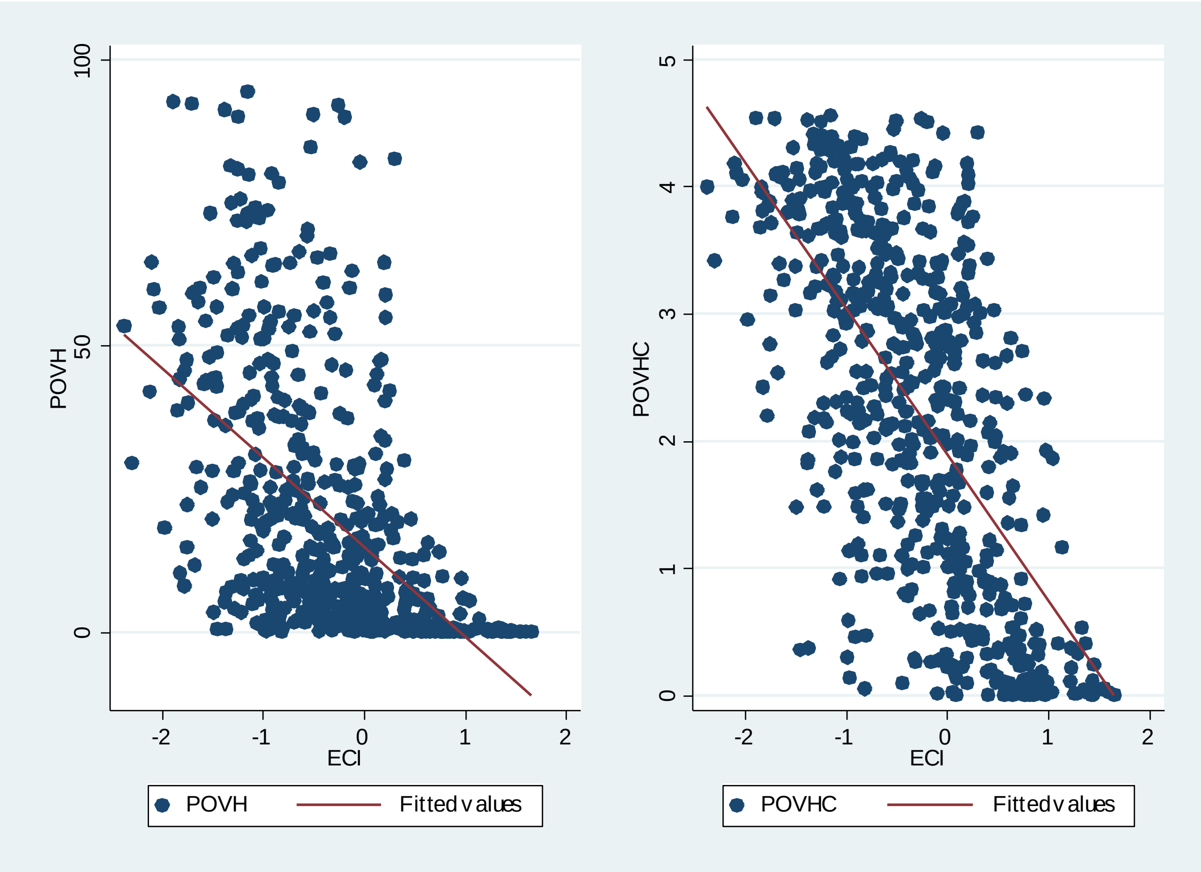
FIGURE

Figure 1: Economic complexity and poverty



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TABLES and APPENDICES

Table 1: Effect of economic complexity on poverty for varying economic growth rates, and varying levels of income inequality

Estimators: Within Fixed effects (with Driscoll-Kraay standard errors) and FGLS (with panel-specific first order Autocorrelation)

	FE	FGLS	Two-Step System GMM	
Variables	**POVHC**	**POVHC**	**POVHC**	**POVHC**
	(1)	**(2)**	**(3)**	**(4)**
$POVHC_{t-1}$			1.042***	0.942***
			(0.0344)	(0.0228)
$POVHC_{t-2}$			-0.238***	-0.184***
			(0.0256)	(0.0174)
ECI	0.0360	-0.126***	-0.0923**	-0.543***
	(0.0506)	(0.0353)	(0.0455)	(0.182)
ECI*GROWTH				-0.0322***
				(0.00480)
ECI*GINI				0.0143***
				(0.00417)
GROWTH				-0.0544***
				(0.00221)
GINI				0.0426***
				(0.00203)
OPEN	0.00595***	-0.000602	-0.00210***	0.00108**
	(0.00124)	(0.000681)	(0.000413)	(0.000495)
FINDEV	-0.00741***	-0.00389***	0.000993	-0.00419***
	(0.00199)	(0.000829)	(0.000634)	(0.000518)
EDU	-0.00112***	-0.00151***	0.000138	0.000355
	(0.000383)	(0.000378)	(0.000386)	(0.000245)
Log(GDPC)	-1.299***	-0.826***	-0.117***	-0.217***
	(0.0711)	(0.0418)	(0.0367)	(0.0220)
POLITY2	-0.000994	-0.00172	0.0111***	-0.00404**
	(0.00328)	(0.00356)	(0.00243)	(0.00202)
Log(POP)	-0.217***	0.0293	-0.0420*	0.0707***
	(0.0521)	(0.0317)	(0.0217)	(0.0136)
Constant	16.18***	8.893***	2.194***	-0.603
	(0.924)	(0.687)	(0.576)	(0.376)
Observations - Countries	501 - 84	496 - 79	408 - 84	384 - 82
Within R^2 / Pseudo R^2	0.5723	0.8085		
Number of Instruments			69	93
AR1 (P-Value)			0.0010	0.0012
AR2 (P-Value)			0.7240	0.3592
Sargan (P-Value)			0.1224	0.7729

*Note: *p-value < 0,1; **p-value < 0,05; ***p-value < 0,01. Robust Standard errors are in parenthesis. Robust Standard errors are in parenthesis. The Pseudo R^2 has been calculated for regressions based on the FGLS estimator, as the correlation coefficient between the dependent variable and its predicted values. For the Two-Step System GMM estimator, the variables "ECI", "GROWTH", "GINI", "OPEN", "FINDEV", "EDU", and*

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"POLITY2" and the interaction variables have been considered as endogenous. Time dummies have been included in the regressions. The regressions have used a maximum of 3 lags of the dependent variable as instruments, and 2 lags of endogenous variables as instruments.

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Table 2: Effect of economic complexity on poverty for varying levels of economic growth volatility/Exchange Rate Pressure
Estimator: Two-Step System GMM

Variables	POVHC	POVHC
	(1)	(2)
$POVHC_{t-1}$	1.044***	1.046***
	(0.0330)	(0.0386)
$POVHC_{t-2}$	-0.228***	-0.233***
	(0.0226)	(0.0300)
ECI	-0.118**	-0.162***
	(0.0470)	(0.0417)
ECI*Log(GRVOL)	0.0597***	
	(0.0130)	
ECI*ERP		0.249***
		(0.0425)
Log(GRVOL)	0.0913***	
	(0.0149)	
ERP		0.306***
		(0.0299)
OPEN	-0.00157***	-0.00188***
	(0.000498)	(0.000431)
FINDEV	0.000875	0.00114*
	(0.000546)	(0.000613)
EDU	0.000348	-0.000830**
	(0.000428)	(0.000406)
Log(GDPC)	-0.136***	-0.00323
	(0.0343)	(0.0266)
POLITY2	0.0117***	0.0175***
	(0.00300)	(0.00374)
Log(POP)	-0.0480**	0.0174
	(0.0207)	(0.0202)
Constant	2.243***	0.106
	(0.594)	(0.491)
Observations - Countries	408 - 84	374 - 80
Number of Instruments	71	71
AR1 (P-Value)	0.0010	0.0001
AR2 (P-Value)	0.6134	0.4899
Sargan (P-Value)	0.1110	0.1846

*Note: *p-value < 0,1; **p-value < 0,05; ***p-value < 0,01. Robust Standard errors are in parenthesis. Robust Standard errors are in parenthesis. The variables "ECI", "OPEN", "FINDEV", "EDU", and "POLITY2" and the interaction variables have been considered as endogenous. Time dummies have been included in the regressions. The regressions have used a maximum of 3 lags of the dependent variable as instruments, and 2 lags of endogenous variables as instruments.*

Appendix 1: Definition and Source of variables

Variables	Definition	Sources
POVHC	This is the transformed measure of poverty headcount ratio at $1.90 a day is the percentage of the population living on less than $1.90 a day at 2011 international prices. Let us denote "POVH" the measure of poverty headcount ratio at $1.90. As this variable contains many zeros, and is skewed, it has been transformed using the following formula (see Yeyati et al. 2007): POVHC $= sign(POVH) * \log(1 + \lvert POVH \rvert)$, where $\lvert POVH \rvert$ refers to the absolute value of the indicator "POVH", and "POVHC" is the transformed variable.	Data on this indicator are collected from the Word Development Indicators (WDI) of the World Bank (https://datatopics.worldbank.org/world-development-indicators/) and POVCALNET of the World Bank (http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx). Missing data have been completed by using linear interpolation technique over two to four years (see also Santos-Paulino, 2017 who has adopted the same procedure, although she has not mentioned it explicitly in her article).
ECI	This is the economic complexity index. It is calculated using Hidalgo and Hausmann's (2009) formula for economic complexity, and reflects the diversity and ubiquity of a country's export structure.	MIT's Observatory of Economic Complexity (https://atlas.media.mit.edu/rankings)
GDPC	Per capita Gross Domestic Product (constant 2010 US$).	WDI
GROWTH	Real GDP growth (constant 2010 US$) (annual %).	WDI
GINI	This is the measure of the market Gini (Gini of incomes before taxes and transfers). The Gini index ranges between 0 and 100, with higher values reflecting a more unequal income distribution.	Standardized World Income Inequality Database (SWIID) - SWIID Version 8.0, February 2019 (see Solt, 2019). See online at: https://fsolt.org/swiid/
GRVOL	Economic growth volatility, calculated as the standard deviation of the annual economic growth rate (growth rate of real GDP) over non-overlapping sub-periods of 5-year.	Authors' calculation based on inflation data extracted from the WDI.

ERP	The variable "ERP" represents the transformed measure of the exchange rate pressure. This transformation has been made using the technique proposed by Yeyati et al. (2007) (see also Gnangnon, 2020; Morrissey et al., 2016) ERP $= sign(PI) * \log(1 + \lvert PI \rvert)$ (2), where $\lvert PI \rvert$ refers to the absolute value of the Exchange Rate Pressure, denoted "PI", and where $\mathrm{PI}_{\mathrm{it}} = w_{E,i}\frac{\Delta E_{it}}{E_{i,t-1}} - w_{RES,i}\frac{\Delta RES_{it}}{RES_{i,t-1}}$ ***E*** is the exchange rate in local currency units per USD; ***RES*** is the size of reserves, $w_{E,i}$ and $w_{RES,i}$ are country-specific weights: $w_{E,i} = \frac{\sigma_{RES,i}}{\sigma_{RES,i}+\sigma_{E,i}}$ and $w_{RES,i} = \frac{\sigma_{E,i}}{\sigma_{RES,i}+\sigma_{E,i}}$. $\sigma_{RES,i}$ stands for the standard deviation of $\frac{\Delta RES_{it}}{RES_{i,t-1}}$ over the full period of the analysis (here, 1980-2014). Similarly, $\sigma_{E,i}$ is the standard deviation of $\frac{\Delta E_{it}}{E_{i,t-1}}$ over the full period of the analysis (here, 1980-2014). The variable "PI" has been computed using the annual data over the period 1980-2014.	Author's calculation based on data from the WDI.
OPEN	Measure of trade openness calculated as the share of sum of exports and imports of goods and services in GDP.	Authors' calculation based on data extracted from the WDI
FINDEV	Domestic credit to private sector as % of GDP. It stands for the measure of the depth of domestic financial development.	WDI
EDU	This is the measure of the education level. It is calculated as the sum of the gross primary school enrolment rate (in percentage), secondary school enrolment rate (in percentage) and tertiary school enrolment rate (in percentage).	WDI
POLITY2	An index extracted from Polity IV Database. It represents the degree of democracy based on competitiveness of political participation, the openness and competitiveness of executive recruitment and constraints on the chief executive. Its values range between –10 and +10, with lower values reflecting autocratic regimes and greater values indicating democratic regimes. Specifically, the value +10 for this index represents a strong democratic regime, while the value –10 stands for strong autocratic regime.	Polity IV Database (Marshall, Gurr, & Jaggers, 2018).
POP	The measure of the total population	WDI

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Appendix 2: List of countries contained in the Full Sample

Full sample			
Albania	Dominican Republic	Liberia	Russian Federation
Angola	Ecuador	Lithuania	Senegal
Argentina	Egypt, Arab Rep.	Madagascar	Serbia
Azerbaijan	El Salvador	Malawi	Slovak Republic
Bangladesh	Estonia	Malaysia	Slovenia
Belarus	Gabon	Mauritania	South Africa
Bolivia	Georgia	Mexico	Sri Lanka
Botswana	Ghana	Moldova	Sudan
Brazil	Guatemala	Mongolia	Tajikistan
Bulgaria	Guinea	Morocco	Tanzania
Cambodia	Honduras	Mozambique	Thailand
Cameroon	Hungary	Nicaragua	Togo
Chile	India	Nigeria	Tunisia
China	Indonesia	North Macedonia	Turkey
Colombia	Iran, Islamic Rep.	Pakistan	Uganda
Congo, Dem. Rep.	Jordan	Panama	Ukraine
Congo, Rep.	Kazakhstan	Paraguay	Uruguay
Costa Rica	Kenya	Peru	Venezuela, RB
Cote d'Ivoire	Kyrgyz Republic	Philippines	Vietnam
Croatia	Lao PDR	Poland	Zambia
Czech Republic	Latvia	Romania	Zimbabwe

Appendix 3: Descriptive statistics on variables used in the model

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
POVH	501	18.882	21.783	0.000	94.402
POVHC	501	2.264	1.330	0.000	4.558
ECI	501	-0.327	0.767	-2.373	1.658
GROWTH	501	3.698	3.299	-16.525	21.570
GINI	444	44.161	7.006	22.220	68.260
GRVOL	501	2.921	2.375	0.092	16.317
PI	458	3.548	62.910	-0.200	1341.902
ERP	458	0.185	0.547	-0.182	7.203
OPEN	501	72.450	35.619	12.876	205.539
FINDEV	501	32.493	25.266	0.186	155.930
EDU	501	169.027	60.274	6.525	305.700
GDPC	501	4528.843	4489.532	153.903	24600.910
POLITY2	501	3.024	6.155	-9	10
POP	501	62,500,000	189,000,000	764826	1380,000,000