# Economic complexity (ECI) and output volatility: A panel data analysis.

Pau Vila Soler

Universitat de Barcelona
Faculty of Economics and Business

Supervisor: Esther Vayá Valcarce

Bachelor in Economics

2021-2022

# *Acknowledgements*

*I would like to thank my supervisor, Esther, for helping me throughout this thesis despite the unfavorable conditions.*

*I would also like to thank the university and the city of Groningen for giving me the opportunity to learn how to be myself and for providing me with six months of my life that I shall never forget.*

*Pau Vila Soler*
*June 26, 2022*

## Abstract

This paper aims to investigate the relationship between economic complexity and output volatility. We analyze whether Economic Complexity Index (ECI) ratings affect macroeconomic volatility. Given that the ECI aims to measure productive knowledge, we expect to see that countries with a higher ECI score are more resilient to economic shocks and, hence, have lower volatility. We estimate a fixed effects model for a series of 84 countries for the period between 1995 and 2018. The results indicate an ambiguous relationship between ECI and output volatility.



*Keywords: ECI (Economic Complexity Index), output volatility, panel data, Fixed Effects, multivariate analysis*



## Resumen

Esta tesis pretende investigar la relación entre la complejidad económica y la volatilidad del output. En concreto, nos proponemos analizar si los valores del índice Economic Complexity Index (ECI) afectan a la volatilidad macroeconómica de los países. Dado que el ECI pretende mesurar el conocimiento productivo, esperamos encontrar que los países con un índice ECI más elevado sean más resistentes a los choques económicos y, por lo tanto, tengan menos volatilidad. Procedemos estimando un modelo de efectos fijos para una serie de 87 países para el período entre 1995 y 2018. Los resultados apuntan hacia una relación ambigua entre el índice ECI y la volatilidad del output.



*Palabras clave: ECI (Economic Complexity Index), volatilidad del output, datos de panel, Efectos Fijos, análisis multivariante*

# Index

**1. Introduction**…………………………………………………………………………………………………….7

**2. Analytical framework**………………………………………………………………………………………9

**2.1. Output Volatility**……………………………………………………………………………………9

**2.2. Economic Complexity**…………………………………………………………………………10

**2.1.1. Economic Complexity Index (ECI)**…………………………………………11

**2.2. Review of the literature.**…………………………………………………………………14

**3. Empirical framework**…………………………………………………………………………………16

**3.1. Methodology**……………………………………………………………………………………16

**3.2. Data**……………………………………………………………………………………………………17

**3.2.1. Descriptive statistics**………………………………………………………………18

**3.3. Bivariate analysis**……………………………………………………………………………21

**4. Results**…………………………………………………………………………………………………………24

**4.1. Fixed Effects…**……………………………………………………………………………………24

**4.2. Specification analysis.**……………………………………………………………………26

**4.4. Discussion of the results**………………………………………………………………29

**5. Conclusions**…………………………………………………………………………………………………31

**6. References**……………………………………………………………………………………………………32

**6.1. Academic writings and articles**……………………………………………………32

**6.2. Databases**……………………………………………………………………………………………37

**7. Annex**……………………………………………………………………………………………………………38

**7.1. List of Countries**………………………………………………………………………………38

**7.2. Alternative models**……………………………………………………………………………41

## List of figures and tables

Figure 1: Density function of GDP per capita Levels……………………..…………………………………….20

Figure 2: Bivariate analysis: ECI-Volatility…………………………………………………………………………….21

Figure 3: Bivariate analysis: Volatility-Control Variables……………..…………………………….…………22

Figure 4: Bivariate analysis: Volatility-Institutional Variables…………………………………….…………23

Figure 5: Fixed Effects model…………………………………………………………………………………………….24

Figure 6: Pooled OLS model………………………………………………………………………………………………26

Figure 7: Panel specification test #1………………………………………………………………………………….27

Figure 8: Panel specification test #2………………………………………………………………………………….28

Table 1: Correlation Matrix……………………………………………………………………………………………….19

Table 2: Summary statistics for output volatility…………………………………………………………………20

Table 3: Summary statistics for ECI……………………………………………………………………………………20

## 1. Introduction

This paper aims to investigate whether Economic Complexity Index (ECI) ratings affect output volatility. The main hypothesis driving our study is that, given that the ECI aims to measure productive knowledge, countries with a higher ECI score can leverage their productive capabilities to better adapt to economic shocks and should, therefore, exhibit less macroeconomic volatility.

The literature regarding economic complexity has taken off in the last decade. There is now considerable evidence linking economic complexity to economic growth (Hausmann and Hidalgo, 2009; Hausmann et al., 2014), as well as some evidence linking it to inequality (Hidalgo et al., 2016), gender parity (Ben Saâd and Assoumou-Ella, 2019; Barza et al., 2020) and greenhouse gas emissions (Romero and Gramkow, 2021; Neagu and Teodoru, 2019). As such, economic complexity methods and topics are becoming increasingly prominent in economic research. Despite this, however, the literature studying the relationship between economic complexity and macroeconomic volatility remains scarce.

The detrimental effect of output volatility on the development of countries is also well established in the literature. Important papers like Lucas (1988), Ramey and Ramey (1995), and Mobarak (2005) have shown the negative link between macroeconomic instability and economic growth. Given the negative effects of volatility, it should be a priority of economics research to try to understand its underlying causes. As such, there is a vast literature examining the determinants of economic volatility. Variables like trade openness (Haddad et al., 2013), financial development (Hausmann and Gavin, 1996; Silva et al., 2017), country size (Furceri and Karras, 2009; Alouini and Hubert, 2010), institutional quality (Rodrik, 1999) and GDP per capita levels (Koren and Tenreyro, 2007) have all been found in the literature to affect countries volatility in one way or another.

The underlying assumptions of our hypothesis can be summarized in three points:

I. The ECI correctly measures productive capabilities, hence, countries with higher ECI ratings possess more sophisticated productive knowledge.
II. Countries with more sophisticated productive knowledge are more adaptable to economic shocks.
III. Countries that are more adaptable to economic shocks exhibit less output volatility.

The objectives of this study, thus, are both to contribute to the volatility literature by trying to understand its underlying causes and to help further understand the role that economic complexity plays in macroeconomic dynamics.

We employ a panel data series consisting of 87 countries for the period between 1995 and 2018. Our empirical strategy consists of the estimation of a Fixed Effects model. We also include a set of control variables that have been chosen in accordance with the role that the literature has attributed to them for influencing output volatility. The control variables are GDP per capita levels, financial development, trade openness, inward FDI inflows, country size, as well as a set of institutional indicators provided by the World Bank Worldwide Governance Indicators that capture six different institutional aspects: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence, Regulatory Quality, Rule of Law and Voice and Accountability. A more detailed discussion these variables as well as the measures we use to proxy for them is provided in section 3.1.

The structure of the paper is set as follows: In section 2 we provide the theorical background for our study and particularly for our two variables of interest, namely output volatility and economic complexity. We also provide an overview methodology behind the Economic Complexity Index (ECI) as well as a discussion of some of the criticisms that It has received and other alternative measures. We then discuss the relevant literature connecting the ECI with output volatility, both at the macroeconomic level as well as some studies focusing at the firm and industry level. In section 3 we describe our empirical strategy starting first with a description of our choice of variables as well a description of the data sources that we used. We also include the summary statistics for our relevant variables. In section 4 we provide the results of our model as well as a discussion of some of the insights. We end the study by providing our conclusions as shown in section 5.

# 2. Analytical Framework

## 2.1. Output Volatility

In a seminal 2001 paper titled "The long and large decline in U.S. Output Volatility" Olivier Blanchard and Jon Simon argued that the two long economic expansions that the U.S. went through between the late 1980s and the mid-2000s were actually a symptom of a much broader general decline in U.S. volatility starting in the 1950s. There has been a wide interest ever since in trying to explain the causes for this so-calledd "The Great Moderation". The great recession of the late 2000s brought some economists to claim that the decline of U.S. output volatility had come to an end and that it had been, after all, just an empirical anomaly brought by the lack of any major adverse shock (Stock and Watson, 2003). A decade after, the U.S. economy had just again surpassed for the longest economic expansion in its history, highlighting, once again, the fact that this observed decline in U.S. volatility was a manifestation of a much deeper and systemic downward trend.

There have been ever since a broad range of explanations given for this decline. These have ranged from purely monetary-based explanations to more structural dynamics like a restructuring into a more flexible labor market (Bruno Coric, 2011). The fact remains, however, that trying to explain the causes of output volatility in developed countries has become an important goal for economic research.

The importance of macroeconomic volatility seems to be perhaps even more evident for developing countries. In another seminal 1988 paper titled "On the mechanics of Economic Development" Robert E. Lucas, Jr. points out the disparities in volatility levels between developed countries and developing countries, with the latter showing much higher rates of growth volatility than their developed counterparts. Other papers that have also highlighted these differences include Pritchett (2000) as well as Mobarak (2005). The link between level of development and volatility seems to be even more reinforced considering the vast literature pointing to a negative relationship between volatility and GDP growth rates, with countries that are more volatile showing lower levels of economic growth (Ramey and Ramey, 1994). Other negative mechanisms of output volatility have been highlighted by papers such as Fogli and Perri (2015), where they showed that macroeconomic instability tends to incentivize people to hold assets in foreign countries, with a 0.5 percent increase in volatility levels leading to an 8 percent increase in foreign assets.

Considering these findings, it is not surprising that output volatility has come to be regarded as a macroeconomic peril that needs to be addressed both by policy makers and by economic researchers.

A quick inspection of the volatility literature also shows a wide variety of measures for estimating volatility. Criolle (2012) provides different three different ways to measure it. The first, and most widely used in the literature, is by taking the standard deviation of the GDP growth rate. This approach implicitly assumes that the underlying series is stationary. However, given that macroeconomic indicators, including GDP growth rates, generally exhibit a trend, this approach tends to exaggerate volatility (Hnatkovska and Loayza, 2003). The second approach is to measure volatility through an auxiliary economic regression. Pritchett (2000) proposes three different measures based on this approach. The first is by looking at the coefficient of determination of a growth-rate regression on a linear temporal trend. If the coefficient of determination is low it means that the temporal trend has low predictive power and thus, volatility is higher. The second one is by taking the standard deviation of the residual of an economic growth regression. This approach, however, has an important caveat as Criolle (2012) points out, which is whether the interpretation of this residual as an indication of economic volatility is actually correct. The third approach is by measuring the difference in growth rates before and after a break year that has been chosen as to minimize the sum of the squares of the residuals of a regression on a simple linear trend. This last approach also happens to be one of the least commonly used in the literature.

A different set of approaches are based on measuring volatility as the standard deviation of a cycle isolated by a statistical filter. The most commonly used filter is probably the Hodrick-Proscott filter which has been used in some studies including Chauvet and Guillaumont (2007) and Becker and Mauro (2006). The other filter that is also commonly used is the Baxter and King filter. The key advantage that the statistical filter-based approach presents is that it does not make any assumptions about the behavior or stationarity of a series and thus, does not exaggerate volatility as other approaches do.

For this paper, however, we will use the standard deviation of the GDP per capita growth owing to mostly to its simplicity and we will do so by diving the study into 8 sub-periods of 3 years each in order to calculate the standard deviation.

## 2.2. Economic complexity

We should also start by describing what is meant by economic complexity. Economic complexity is an emerging field in economics that adopts techniques from complexity science, networks, and artificial intelligence in order to study the geography and the dynamics of economic activities. As such, it is easy to see why the rise of economic complexity methods should go hand in hand with the rise of AI, machine learning as well as the study of complex systems. (Hidalgo, 2021) There are various ways of measuring economic complexity. This study adopts the approach by Hausmann and Hidalgo (2009) with the Economic Complexity Index and, as such, a description of the Index and its methodology is necessary. A detailed discussion on some of the criticisms that it has received as well as some of its alternative measures will follow.

### 2.2.1. Economic Complexity Index

The methodology behind the Economic Complexity Index is described in Hidalgo and Hausmann (2009) as well as in Hausmann et al. (2014). The main philosophy behind the construction of the index is to first interpret trade data as a bipartite network[1] that connects countries to the products that they export and to then assume that this bipartite network is the result of a larger tripartite network connecting countries to the productive capabilities that they have and products with the productive capabilities that they require.

An easy way to grasp this idea intuitively is with the following thought experiment provided by The Observatory of Economic Complexity (Simoes and Hidalgo, 2011). We can imagine a teacher who is asked to grade a multiple-choice exam in a language he doesn't speak and who is given an answer key to help him. He is also told that he should give more points for challenging questions, however, given that he cannot understand the content of the questions, he doesn't have a direct way of knowing which questions are more challenging. So, in order to measure how challenging a given question is, he assumes that easy questions will have been answered correctly by most students while difficult questions will have been answered correctly by very few students and so he decides to measure the difficulty of a question by looking at the students that have answered that question correctly. He also realizes, however, that some of the students who have answered the hard questions correctly will have done so merely by guessing their answers and thus, when counting how many students have answered a question correctly, he decides to give a higher weight to students who have answered most questions right. This means that the difficulty of a question is a function of how good the students who have answered that question are, while in turn, how good the students are is a function of the difficulty of the questions they have answered correctly.

This form of circular reasoning can be explained in terms of countries and products, and we should note that the way the ECI measures economic complexity is similar to the way the teacher measures the difficulty of a question. First, it looks at how complex a given product is by looking at the complexity of the countries producing it, and then it looks at how complex a country is by looking at the complexity ofthet products that it produces. Hence why the authors refer to this method as the "Method of Reflections" (Hausmann and Hidalgo, 2009).

Mathematically speaking this can be expressed in the following equations, where $K_c$ is the complexity of a given location *c*, $K_p$ is the complexity of a given activity *p,* and $M_{cp}$ is a matrix summarizing whether an activity *p* is present in location c and thus, if location *c* produces product *p* then $M_{cp} = 1$.

$$K_c = f(M_{cp}, K_p) \tag{1}$$

$$K_p = g(M_{cp}, K_c) \tag{2}$$

[1] By bipartite network meaning a network whose elements can be split in two diferent sets so that each element is connected only with members of the other set.

If we substitute the preceding into each other, we get the following expressions:

$$K_c = f\ \left(M_{cp}, g\ \left(M_{cp}, K_c\right)\right) \tag{3}$$

$$K_p = g\ \left(\ M_{cp}, f\left(M_{cp}, K_p\right)\right) \tag{4}$$

These equations, in turn, mean that the complexity of a location or product can be seen as a solution to self-consistent equations which can be further reduced into equations (5) and (6). What this also implies is that these measures of complexity are relative measures given that the complexity of a given country depends on the complexity of other countries and the same goes with the complexity products with other products.

$$K_c = \ \widetilde{M}_{cc'} K_{c'} \tag{5}$$

$$K_p = \ \widetilde{M}_{cc'} K_{c'} \tag{6}$$

More formally, the ECI is the solution of the following set of equations, where $M_c$ is the number of activities present in a location or, in other words, the diversity of a location. And where $M_p$ is the number of locations where an activity is present or, in other words, the ubiquity of an activity.

$$K_c = \frac{1}{M_c} \sum_p M_{cp} K_{p'} \tag{7}$$

$$K_p = \frac{1}{M_p} \sum_c M_{cp} K_{c'} \tag{8}$$

After putting the first equation into the second one and defining the matrix $\widetilde{M}_{cc'}$ as shown in equation (9), we get the expressions shown in equations (7) and (8).

$$\widetilde{M}_{cc'} = \sum_p \frac{M_{cp} M_{c'p}}{M_c M_p} \tag{9}$$

Given that the ECI is a relative measure, equations (7) and (8) are then transformed using a Z-transform into the following expressions respectively:

$$ECI = \frac{K_c - \widetilde{K}_c}{stdev\ (K_c)} \tag{11}$$

$$PCI = \frac{K_p - \widetilde{K}_p}{stdev\ (K_p)} \tag{12}$$

Where $\widetilde{K}_c$ and $\widetilde{K}_p$ are the averages of $K_c$ and $K_p$, and PCI is the Product Complexity Index, the product oriented version of the ECI.

A few things stand out from analyzing the way the index is measured. First is the relative nature of the index. This means that the value of the index for a given country is dependent on the value of the index of all other countries. The same goes with the PCI with regards to products. This, in turn, stems from the fact that, as highlighted by the thought experiment provided before, the way that the complexity of a given location is calculated is by looking at the complexity of the products that it produces while the complexity of the products is, subsequently, calculated by looking at the complexity of the countries producing it. The other thing that stands out from analyzing the index is the central role that the concepts of ubiquity and diversity play, as illustrated by the thought experiment of the teacher grading the exam. It should be important to note, however, that although the Economic Complexity Index is conceptually related to export diversification, some studies have shown that these two measures are orthogonal. (Mealy et al., 2017) This means that the ECI and export diversification capture different information and thus, it is not correct to extract conclusions on one by studying the other and vice versa.

We should also mention some of the criticisms that have been made against the ECI, perhaps the most prominent of which were made by Tacchella et al. (2012) and Christelli et al. (2013). In their work, they criticize the index for measuring the complexity of a product by the average complexity of the countries producing it. This procedure, they argue, hides the assumption that developed countries, or high-complexity countries, specialize in very complex products while in reality they produce products across the entire complexity spectrum, both high-complexity and low-complexity products. This in turn means that the average complexity of the countries producing a low-complexity product is actually higher than the ECI methodology assumes given that developed countries also produce those products. Tacchella et al. (2012) go on to propose a new measure of economic complexity, which they call the “Fitness” of a country. This new measure also takes an iterative approach similar to the one used by the ECI, but it instead adopts a nonlinear approach when measuring the complexity of a product in order to give more weight to low-complexity countries. This way they are able to capture the fact that if a low-complexity produces a product it must mean that this product is also low-complexity.

Similar related approaches measuring economic complexity include the GENEPY proposed by Sciarra et al. (2020), which unites the ECI and the Fitness concepts into a single framework, as well as the production ability concept introduced by Bustos and Yildirim (2021).

All of these concepts have their own benefits and they try to capture similar information as the Economic Complexity Index. For this study, however, the ECI will be used owing to the availability of the Data as well as its higher prevalence in previous studies regarding this topic.

## 2.3. Review of the literature

As mentioned before, the literature studying the relationship between economic complexity and output volatility is somewhat limited. As of our knowledge, only two studies have tried to analyze the direct relationship between economic complexity and output volatility. In the first one, Breitenbach, Chisadza, and Clance (2021) studied the relationship between the ECI and macroeconomic volatility using panel data analysis for low-income and high-income countries for the short and the medium to long-term periods. They found that, for low-income countries, the ECI showed a negative relationship with volatility in the long term only when allowing for longer lags of the ECI, while for high-income countries, the ECI was negatively associated with volatility both in the long term and in the short term. The study also highlighted differences between regions for the attenuating effect of economic complexity, namely between Africa and Asia, with the former needing a longer time for the effects of the ECI to lessen output volatility. The authors end the study by suggesting that diversifying exports should help countries achieve lower levels of volatility. This conclusion, however, seems to conflict with the findings by previous studies regarding the orthogonality of the ECI with export diversification (Mealy et al., 2017).

The other study was carried out by Güneri (2019) using a VAR analysis approach on a series of countries between 1981 and 2015. The results indicated a negative relationship between ECI and macroeconomic volatility even after controlling for variables like GDP growth, financial openness and institutional quality.

There have also been similar studies focusing on the relationship between ECI and output volatility at the industry and firm levels. Krishna and Levchenko (2013) proposed a theoretical model in which less developed countries, given that they have less developed institutions and lower levels of human capital, will tend to specialize in low complexity products which are associated with higher levels of volatility. They then showed some empirical evidence suggesting that less complex industries show higher levels of volatility. Maggioni, Turco and Gall,egati (2014) also analyzed the relationship between economic complexity and output volatility by looking at micro-evidence at the firm level. They found that firms producing more complex goods are subject less sales volatility. Their findings are also in line with Koren and Tenreyno (2013) who found that, using a related measure to ECI, output volatility showed a negative relationship with what they call “technological diversification”.

Other studies have also focused on related measures of output volatility. Phuc Canh and Dinh Thanh (2020) studied the relationship between ECI and economic growth cycles and found uni-directional Granger causality between ECI and growth cycles for high-income countries between 1996 and 2007. Another study by Gómez-Zaldívar and Llanos-Guerrero (2021) studied the synchronization of the business cycles of Mexican states and found that the ECI was a better predictor alone than an entire seven-variables model proposed by an earlier study.

Thus, it seems to be a consensus of the literature on this topic that economic complexity negatively affects output volatility. This in turn reinforces our hypothesis that more complex countries are more adaptable to economic shocks and, as a consequence, are less volatile.

In the following section we describe our empirical strategy for this study and we provide a brief description of our choice of variables.

# 3. Empirical Framework

## 3.1. Methodology

The methodology that we employ consists of the estimation of a Fixed Effects model.

$$Y_{it} = \alpha_i + \delta_t + \beta_1 ECI_{it} + \beta_2 X_{it} + \mu_{it} \tag{13}$$

The overall specification that we use is given by equation (13) where $Y_{ii}$ stands for output volatility measured as the standard deviation of the GDP growth rate for 3-year subperiods, $\alpha_i$ and $\delta_t$ stand for fixd country and year effects, $ECI_{it}$ stands for the Economic Complexity Index and $X_{it}$ stands for the set of control variables that have been chosen according to the literature on the determinants of output volatility. Estimating by Fixed Effects (FE) allows us to capture potentially unobserved country and time differences. This way, the results obtained by FE are more precise than the ones that would be obtained by estimating with OLS. This specification is also similar to the one used by Breitenbach et al. (2021), however, the control variables used for their study are different from the ones used here.

The set of control variables that we use for the study consists of the following:

- GDP per Capita PPP (current international $): We control for the GDP per capita level following the extensive literature mentioned previously connecting it with output volatility. Furthermore, as Güneri (2019) points out, GDP per capita helps capture general macroeconomic conditions which could have an impact on macroeconomic instability.
- Trade openness: The literature connecting macroeconomic volatility with trade openness is not as unambiguous as the literature connecting volatility with GDP per capita. There seems to be, however, some evidence that, for certain countries, trade openness does affect output volatility. Haddad et al. (2013) for instance, found that trade openness tended to attenuate output volatility when countries had a well-diversified export basket. Another study conducted by Cavallo (2007) found that, even though trade openness raised volatility by exposing countries to terms of trade volatility, this effect was counteracted by a larger effect by which exposure to trade tended to stabilize country's outputs. These results seem to be in contrast with a yet another previous study by Bejan (2007) who found a positive relationship between output volatility and trade openness. However, in that study, when the sample was divided into developed countries and developing countries, the relationship turned negative for the former but stayed positive for the latter.
  The measure that we use for trade openness is the Trade to GDP ratio, as is standard in the literature.

- Private credit to GDP ratio: We also use the ratio of private credit to GDP to proxy for financial development. This is perhaps the most straightforward way of measuring financial development in the literature and so, for this study we also adopt this approach. Financial development, in turn, is thought to affect output volatility by acting as a shock absorber in times of crisis. (Hausmann and Gavin, 1996), This line of reasoning is also in tune with the justification provided by Breitenbach et al. (2021) for including financial development as a control variable in their study.
- Inward FDI Inflows: We adopt inward FDI inflows in accordance with the findings by Mensah and Kwasi Mensah (2021) that Inward FDI inflows positively affect volatility. We use the series "Foreign direct investment, net inflows (% of GDP)" from the World Bank, which in turn is calculated as the ratio between total new investment inflows minus disinvestment and GDP.
- Country size: We control for country size, in terms of population numbers given the findings by Furceri and Karras (2007) as well as Alouini and Hubert (2010) that show that output volatility is negatively associated with the population size of countries.
- Institutional indicators: For the institutional indicators, we use, as mentioned before, the Worldwide Governance Indicators by the World Bank. These indicators consists of six different estimates that measure different aspects of institutional quality. Hence the quality of institutions is controlled for by using six different indicators. These estimates are Control of Corruption (CCE), Government Effectiveness (GEE), Political Stability and Absence of Violence (PSAV), Regulatory Quality (RQE), Rule of Law (RoLE) and Voice and Accountability (VAE). The methodology behind these measures is provided in Kaufmann et al. (2010) and the procedure is built by obtaining different data sources corresponding to each individual institutional quality and then averaging all the values for each country. The results are then rescaled so that they fall between -2.5 and 2.5.
  ratio

## 3.2. Data

We use panel data from 87 countries spread from 1995 to 2018. This data has been extracted from three different data sets. For the variables Output Volatility, Financial Development, Trade Openness and Foreign Direct Investment we use the World Development Indicators from the World Bank. For the institutional variables we use the Worldwide Governance Indicators, which includes data on six different aspects of institutional quality: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence, Regulatory Quality, Rule of Law and Voice and Accountability. Finally, for the Economic Complexity Index, we use the data provided by the Atlas of Economic Complexity.

As for the measurement of output volatility, we use, as mentioned previously, the standard deviation of a three-year period. This means that the study will consist of 8 time periods in total. The data of the other variables is taken to be the value of the first observation at each subperiod.

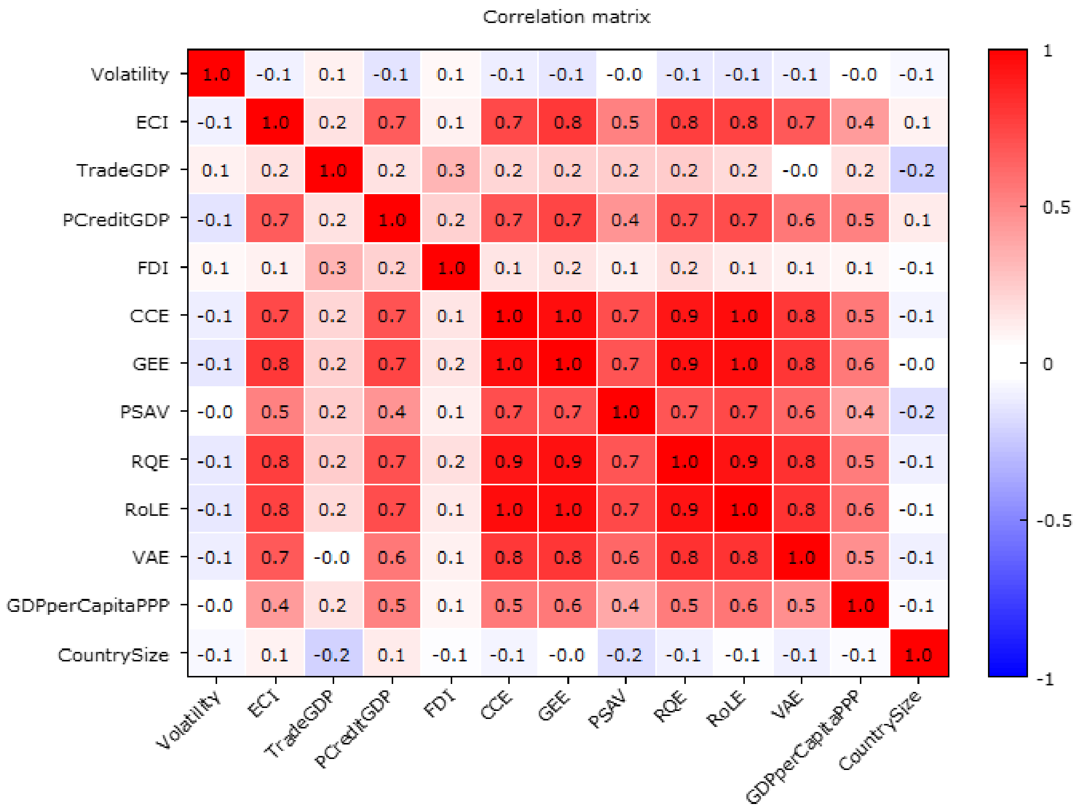
This approach towards measuring economic volatility, while being the most commonly used in the volatility literature, has some limitations. As Hnatkovska and Loayza (2003) point out and as we mention in section 2.1., the standard deviation of GDP exaggerates output volatility when there is an upward or downward trend in GDP growth, as is the case in developing countries. Another limitation of this approach is highlighted by Iseringhausen and Vierke (2018) who also point out that measuring volatility in this manner results in complex dynamics being averaged out and, in the process, some information is lost inevitably. Nevertheless, the standard deviation remains the most common and most straightforward way of measuring the volatility of a variable in the literature and so we adopt this procedure.

In order to measure economic complexity, we use, as has been mentioned, the Economic Complexity Index by the Atlas of Economic Complexity. The index, in turn, is built from trade data from the United Nations Statistical Division (COMTRADE) and the International Monetary Fund (IMF) Direction of Trade Statistics database.

### 3.2.1. Descriptive statistics

We should also provide a brief analysis of the structure and behavior of our dataset by first looking at the correlations as shown in Table 1. It becomes quite clear upon a simple first inspection that some variables exhibit very high correlations, which could forecast potential multicollinearity problems. Most of these high correlations involve the institutional indicators which, perhaps not surprisingly, are very much correlated with each other. They also show very high correlations with the ECI which in turn falls in line with the findings by Vu (2020) suggesting that the Economic Complexity Index is positively associated with institutional quality. Other high correlations include the institutional variables with Domestic credit to GDP, the institutional variables with GDP per Capita, and the ECI with Domestic credit to GDP. Interestingly, the ECI shows a higher correlation with Domestic credit to GDP than with GDP per capita levels which is surprising given the extended literature connecting the ECI with GDP levels. All of these high correlations imply that, when estimating our models, we will need to be aware of the presence multicollinearity in our dataset.

**Table 1: Correlation matrix (Own elaboration using data from World Bank and Atlas Of Economic Complexity (2011)**




Looking now at the rest of the correlations we find mostly what we would expect from the literature: GDP per capita levels are positively associated with the Economic Complexity Index as well as the institutional variables, FDI inflows are positively associated with Trade Openness, and Trade Openness in turn is positively associated with institutional variables.

We also provide the relative frequency distribution of the GDP per capita levels of our sample shown in Figure 1. It is interesting to look at the relative distribution of GDP per capita levels so that we can get an idea of the relative development levels of our sample which, by looking at the figure, we can see that it contains considerably more low-income observations than high-income observations. This is in turn interesting to analyze given the conditional effect that some studies have found on output volatility for variable like trade openness based on country’s level of development (Haddad et al., 2013).

**Figure 1: Relative frequency distribution of GDP per capita levels**

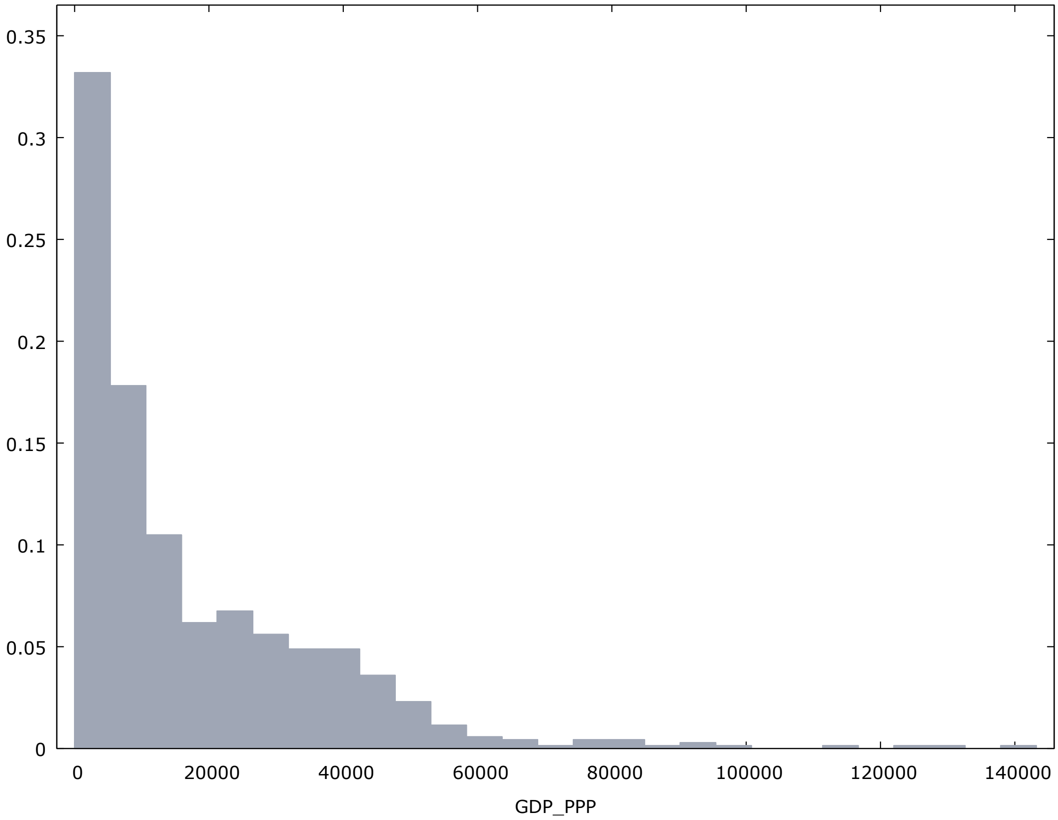



Table 2 shows the summary statistics for output volatility. It should perhaps be noted the very high maximum value of 14.6 which, considering that both the mean and the S.D. are 1.86, could imply the presence of anomalous observations in our study. Upon some investigation, we discover that this observation corresponds to the country of Zimbabwe for the period between 2007 and 2010 and we decide to include it in the study given that is not the result of erroneous data and that it could actually help capture valuable information about our variables.

**Table 2: Summary Statistics for output volatility**

Summary Statistics, using the observations 1:1 - 87:8

| Variable | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|
| Volatility | 1.86 | 1.21 | 1.86 | 1.55e-006 | 14.6 |

We also provide the summary statistics for the ECI, as shown in table 3.

**Table 3: Summary Statistics for Economic Complexity Index (ECI)**

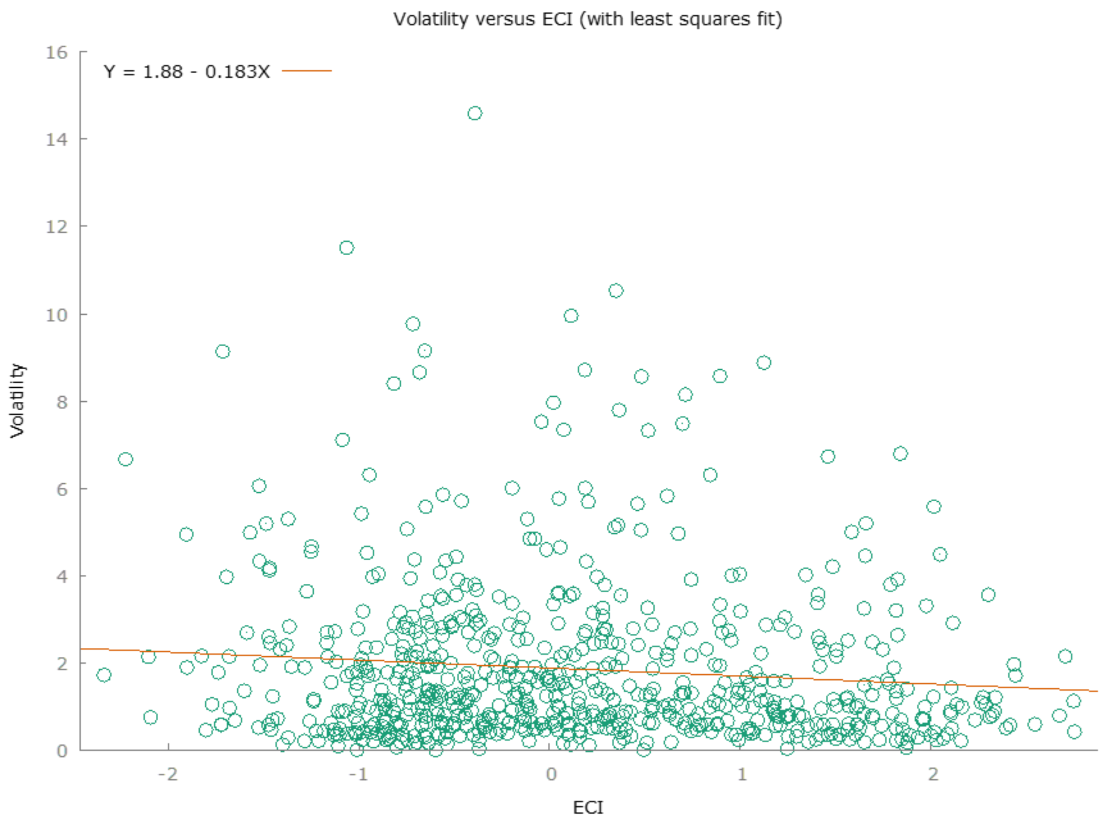
Summary Statistics, using the observations 1:1 - 87:8

| Variable | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|
| ECI | 0.135 | 0.0182 | 1.04 | -2.34 | 2.76 |

### 3.2.2. Bivariate analysis

We continue our analysis by looking at the bivariate relationships between Volatility and the rest of our variables. The results indicate a significant negative correlation between Volatility and the ECI as they are shown in Figure 2.

**Figure 2: Bivariate analysis: ECI-Volatility**



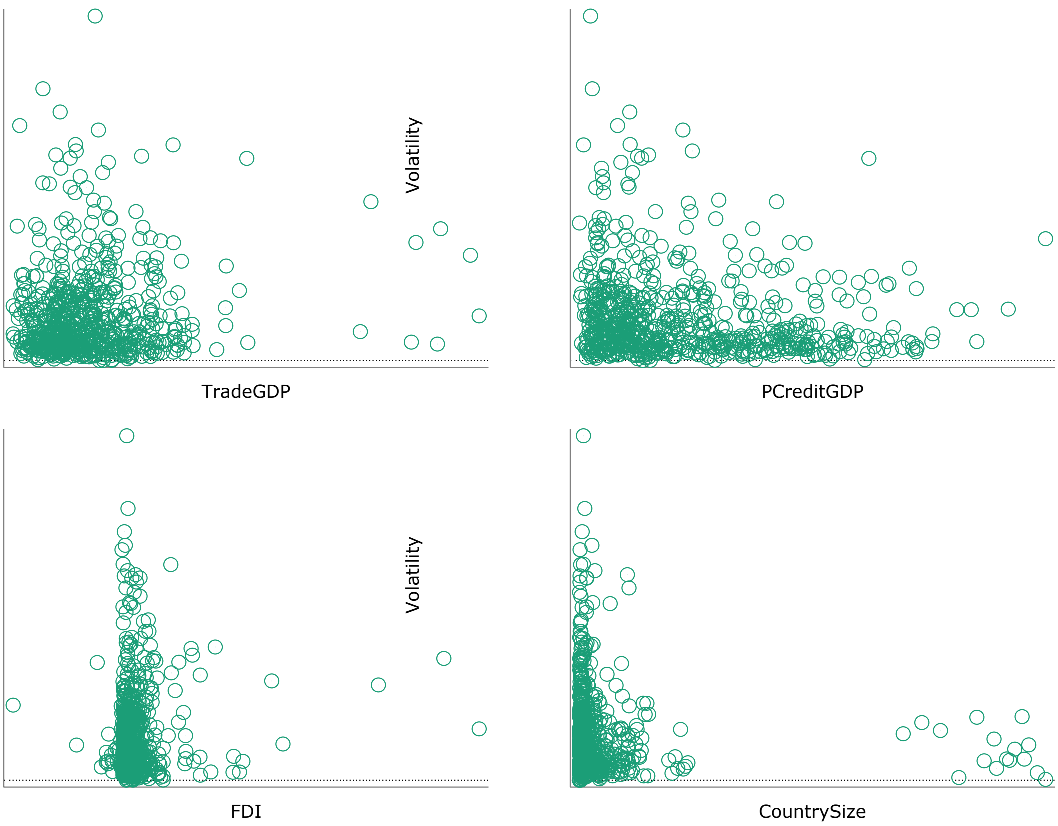

These results fall in line both with our hypothesis as well as the previous literature on this topic.

We also provide a bivariate analysis for the rest of our control variables which show a statistically significant relationship with volatility on an individual basis. Surprisingly enough, GDP per capita levels did not prove to be a significant predictor of output volatility. This is contrary to the results found by the literature previously mentioned and it would seem to suggest that country's level of development doesn't influence volatility levels. Another variable that didn't show significance at the individual level is Political Stability and Absence of Violence. This is once again surprising given the implication that county's level of political stability doesn't affect output volatility.

In figure 2 and figure 3 we provide the rest of the scatter plots for the control variables variables that have proven to be significant at the individual level.

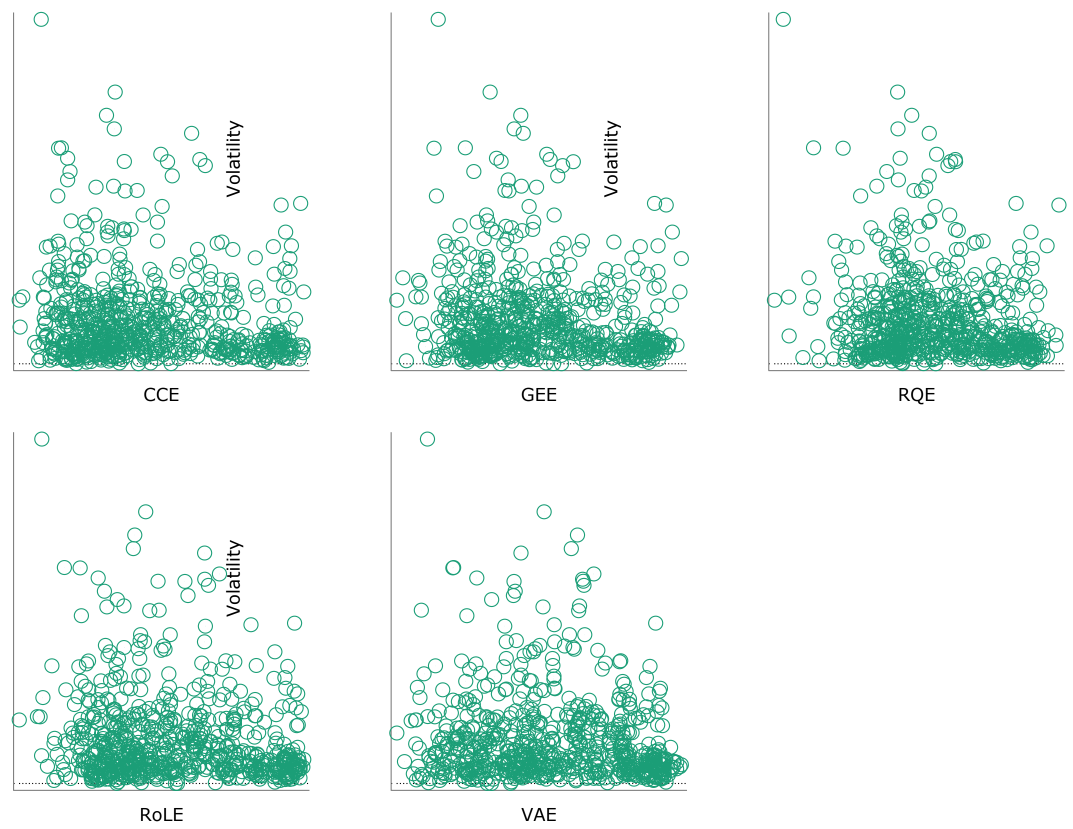
A couple of aspects about the graphs deserves mention. First, is the negative values of the variable FDI Inflows. This occurs because the variable is defined by the World Bank as the net FDI inflows calculated as the ratio between total new investment inflows minus disinvestment and GDP. The second one are the extreme observations associated with Trade to GDP, Country Size and FDI Inflows. There are eight observations of the variable Trade to GDP that stand out, all of them corresponding to the country of Singapore with values between 300% and 400%. This is not surprising given traditional standing of Singapore as a trading hub as well as its small size. There are also sixteen observations of Country Size that stand out and that correspond, understandably, to China and India. And finally, there are some observations that stand out for FDI inflows both on the positive side as well as the negative side. On the positive side, three observations take values of 88%, 108% and 120%. The first observation corresponds to the country of the Netherlands for the year 2007 and the other two correspond to the country of Cyprus for 2010 and 2013 respectively. One observation also stands out on the negative side with a value of -37% associated with Mongolia for the year 2016.

**Figure 3: Bivariate analysis: Volatility-Control Variables**



When it comes to the institutional variables the behavior of our dataset seems much more consistent and doesn't really exhibit any outlier values as with other variables. This is probably due to the fact that, as described by Kaufmann et al. (2010), the methodology behind the estimates of the WGI's is designed in a way so that all the values fall between -2.5 and 2.5.

**Figure 4: Bivariate analysis: Volatility-Institutional Variables**




In the following section we present a more detailed empirical analysis of our dataset and we also provide a more thorough verbal discussion of the results.

## 4. Results

As mentioned before, for the estimation of our multivariate analysis we use a Fixed Effects (FE) model. This allows us to capture potential unobserved year and country effects and to control for the possibility of heteroscedasticity in our regression assuming that this heteroscedasticity is correlated with the independent variables. In section 4.1. we present the results of this estimation. In section 4.2. we deepen our analysis by contrasting the Fixed Effects methodology that we employed with a pooled OLS and with a Random Effects specification. And we conclude in section 4.3. by providing a more detailed verbal analysis of the results of our model.

### 4.1. Fixed Effects

We begin by presenting the results of our Fixed Effects (FE) model with output volatility as the dependent variable and the ECI as well as the control variables as the regressors. Given the problems with multicollinearity discussed in section 3.2.1. however, we decide to use different combinations of control variables for the study. We chose between different specifications by looking at the Aikaike criterion. The institutional variable that we employ is Government Effectiveness and we chose it because it is the variable associated with the lowest p-value in the individual regressions of our bivariate analysis. The results are shown in the figure 5.

Figure 5: Fixed Effects model

Model 1: Fixed-effects, using 609 observations
Included 87 cross-sectional units
Time-series length = 7
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 0.432493 | 0.379081 | 1.141 | 0.2571 | |
| ECI | 0.0879912 | 0.366348 | 0.2402 | 0.8108 | |
| ECI_1 | −0.495180 | 0.295473 | −1.676 | 0.0974 | * |
| PCreditGDP | 0.0107762 | 0.00482470 | 2.234 | 0.0281 | ** |
| FDI | 0.0156487 | 0.00510619 | 3.065 | 0.0029 | *** |
| GEE | −0.954252 | 0.454584 | −2.099 | 0.0387 | ** |
| dt_2 | 1.44125 | 0.248706 | 5.795 | <0.0001 | *** |
| dt_3 | 1.30005 | 0.252823 | 5.142 | <0.0001 | *** |
| dt_4 | 0.537102 | 0.158915 | 3.380 | 0.0011 | *** |
| dt_5 | 2.48792 | 0.237895 | 10.46 | <0.0001 | *** |
| dt_6 | 0.937267 | 0.156878 | 5.975 | <0.0001 | *** |
| dt_7 | 0.354220 | 0.139069 | 2.547 | 0.0126 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.855227 | S.D. dependent var | 1.861685 |
| Sum squared resid | 1141.674 | S.E. of regression | 1.494723 |
| LSDV R-squared | 0.458216 | Within R-squared | 0.250030 |
| Log-likelihood | −1055.491 | Akaike criterion | 2306.983 |
| Schwarz criterion | 2739.341 | Hannan-Quinn | 2475.179 |
| rho | −0.220318 | Durbin-Watson | 2.148313 |

Looking at this findings we can see what looks to be an ambiguous relationship between volatility and the ECI. On the one hand, the one-year lagged version of the ECI shows significance at the 10% level, while on the other, the contemporary version of the ECI shows no significance with a corresponding p-value of 0.81. A more detailed interpretation of this ambiguous relationship will be provided in sections 4.3. and 5.

When it comes to the rest of the variables, the results are somewhat in line with what we expect from the literature. First, the coefficient associated with the one year lagged version of the ECI is negative suggesting that, as countries become more complex, their volatility levels decrease. The coefficient associated with the contemporary version of the ECI is positive, however, as mentioned before, the p-value is clearly insignificant. Second, Government Effectiveness, the institutional variable that we have chosen for the estimation, shows a significant and negative relationship with volatility and it suggests that as countries achieve higher levels of institutional quality they become more stable. And third, FDI inflows shows a positive relationship with volatility, implying that higher levels of FDI inflows make countries more volatile.

There is perhaps one observation from the results that, at first sight, could be somewhat confusing. Private credit to GDP shows a significant but positive relationship with volatility. This is in contradiction with the work by Hausmann and Gavin (1996) that suggested that developed financial systems can act as shock absorbers. We discuss this contrasting result in more detail in section 4.3.

Also worth discussing is the associated R-squared. The within R-squared has a value of 0.25 which means that our model explains 25% of the variance within the panel units of our dataset. This relatively low value could perhaps be interpreted as to signal that our regressors, while significant, are not good predictors for volatility. The LDVS R-squared, on the other hand, has a value of 45%. These different measures, while related, are actually meant for different approaches, as Cotrell and Luchetti (2022) point out:

*"Fixed-effects models can be thought of in two equally defensible ways. From one perspective they provide a nice, clean way of sweeping out individual effects by using the fact that in the linear model a sufficient statistic is easy to compute. Alternatively, they provide a clever way to estimate the "important" parameters of a model in which you want to include (for whatever reason) a full set of individual dummies. If you take the second of these perspectives, your dependent variable is unmodified y and your model includes the unit dummies; the appropriate R^2 measure is then the squared correlation between y and the yˆ computed using both the measured individual effects and the effects of the explicitly named regressors. This is reported by gretl as the "LSDV R-squared". If you take the first point of view, on the other hand, your dependent variable is really yit − y¯i and your model just includes the β terms, the coefficients of deviations of the x variables from their per-unit means. In this case, the relevant measure of R^2 is the so-called "within" R^2 ; this variant is printed by gretl for fixed-effects model in place of the adjusted R^2."*

Given that this study is interested in capturing the potential fixed year and country effects, the first interpretation of Fixed Effects models is the one that we assume and so we should focus on the "within" R-squared of our model.

In the following section, we provide a more thorough justification in favor of a Fixed Effects estimation as opposed to a pooled OLS or a Random Effects model.

## 4.2. Specification analysis

In order to justify our choice for a Fixed Effects estimation of our model as opposed to a pooled OLS or a Random Effects, we provide the following results based on the alternative pooled OLS estimation of our model. The results are shown in figure 6.

**Figure 6: Pooled OLS model**

Model 2: Pooled OLS, using 609 observations
Included 87 cross-sectional units
Time-series length = 7
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 1.13692 | 0.200981 | 5.657 | <0.0001 | *** |
| ECI | 0.187365 | 0.282769 | 0.6626 | 0.5094 | |
| ECI_1 | −0.206567 | 0.300756 | −0.6868 | 0.4940 | |
| PCreditGDP | −0.00283981 | 0.00292986 | −0.9693 | 0.3351 | |
| FDI | 0.0153640 | 0.00690030 | 2.227 | 0.0286 | ** |
| GEE | −0.140852 | 0.199362 | −0.7065 | 0.4818 | |
| dt_2 | 1.09626 | 0.244902 | 4.476 | <0.0001 | *** |
| dt_3 | 1.01737 | 0.228426 | 4.454 | <0.0001 | *** |
| dt_4 | 0.282002 | 0.139964 | 2.015 | 0.0470 | ** |
| dt_5 | 2.35477 | 0.228272 | 10.32 | <0.0001 | *** |
| dt_6 | 0.865040 | 0.150943 | 5.731 | <0.0001 | *** |
| dt_7 | 0.318458 | 0.136570 | 2.332 | 0.0220 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.855227 | S.D. dependent var | 1.861685 |
| Sum squared resid | 1718.017 | S.E. of regression | 1.696393 |
| R-squared | 0.184711 | Adjusted R-squared | 0.169689 |
| F(11, 86) | 15.67262 | P-value(F) | 2.75e-16 |
| Log-likelihood | −1179.933 | Akaike criterion | 2383.866 |
| Schwarz criterion | 2436.807 | Hannan-Quinn | 2404.461 |
| rho | 0.169181 | Durbin-Watson | 1.437713 |

Some observations stand out from this specification. First, as opposed to the results in the Fixed Effects estimation, the ECI shows no significance for either the contemporary version or the one-year lagged version. Second, the institutional variable Government Effectiveness shows no significant relationship with volatility, which would seem to imply that the quality of institutions has no effect on the stability of countries. And third, the coefficient associated with Private credit to GDP, which was significant in the Fixed Effects estimation, has turned out to be insignificant for the pooled OLS approach.

Other factors worth noting are the higher Akaike and Hannan-Quinn criterions and the lower Schwarz criterion when compared to the Fixed Effects estimation, as well as the lower value associated with the R-squared, which stands at 0.17.

We next provide the results of the panel specification test provided by Gretl for this pooled OLS specification to further consolidate the choice between different estimation methods in favor of the Fixed Effects method. The results are shown in figure 7.

**Figure 7: Panel specification test #1**

```
Diagnostics: using n = 87 cross-sectional units

Fixed effects estimator
allows for differing intercepts by cross-sectional unit

               coefficient   std. error   t-ratio    p-value
  -----------------------------------------------------------
  const         0.432493     0.360604      1.199    0.2309
  ECI           0.0879912    0.305542      0.2880   0.7735
  ECI_1        -0.495180     0.298730     -1.658    0.0980    *
  PCreditGDP    0.0107762    0.00462613    2.329    0.0202    **
  FDI           0.0156487    0.00845489    1.851    0.0648    *
  GEE          -0.954252     0.378847     -2.519    0.0121    **
  dt_2          1.44125      0.250671      5.750    1.54e-08  ***
  dt_3          1.30005      0.244051      5.327    1.50e-07  ***
  dt_4          0.537102     0.240963      2.229    0.0262    **
  dt_5          2.48792      0.233497     10.66     4.48e-024 ***
  dt_6          0.937267     0.228460      4.103    4.75e-05  ***
  dt_7          0.354220     0.227490      1.557    0.1201

Residual variance: 1141.67/(609 - 98) = 2.2342

Joint significance of differing group means:
 F(86, 511) = 2.99958 with p-value 2.07303e-014
(A low p-value counts against the null hypothesis that the pooled
OLS model
is adequate, in favor of the fixed effects alternative.)

Variance estimators:
 between = 0.617514
 within = 2.2342
theta used for quasi-demeaning = 0.416266
```

**Figure 8: Panel specification test #2**

```
Random effects estimator
allows for a unit-specific component to the error term

               coefficient   std. error   t-ratio    p-value
  ----------------------------------------------------------
  const         0.871253     0.256638      3.395    0.0007    ***
  ECI           0.234519     0.250240      0.9372   0.3490
  ECI_1        -0.276093     0.250583     -1.102    0.2710
  PCreditGDP    0.00158782   0.00294465    0.5392   0.5899
  FDI           0.0159467    0.00769599    2.072    0.0387    **
  GEE          -0.317296     0.181778     -1.746    0.0814    *
  dt_2          1.20787      0.239068      5.052    5.81e-07  ***
  dt_3          1.10786      0.235946      4.695    3.30e-06  ***
  dt_4          0.365370     0.234452      1.558    0.1197
  dt_5          2.39810      0.231594     10.35     3.20e-023 ***
  dt_6          0.887625     0.229070      3.875    0.0001    ***
  dt_7          0.331679     0.228761      1.450    0.1476

Breusch-Pagan test statistic:
 LM = 75.0538 with p-value = prob(chi-square(1) > 75.0538) = 4.58052e-
018
(A low p-value counts against the null hypothesis that the pooled OLS
model
is adequate, in favor of the random effects alternative.)

Hausman test statistic:
 H = 14.2773 with p-value = prob(chi-square(5) > 14.2773) = 0.0139408
(A low p-value counts against the null hypothesis that the random
effects
model is consistent, in favor of the fixed effects model.)
```

Looking at the different tests shown in these figures we can clearly see the superiority of the Fixed Effects approach. The joint significance of different group means test clearly shows that the pooled OLS estimation is not an adequate one and it falls in favor of the FE estimation. The Breusch-Pagan test, on the other hand, highlights a clear superiority of the RE as opposed to the pooled OLS.

In order to settle the debate between the Random Effects approach and the Fixed Effects approach, we can look at the results from the Hausman test. The associated p-value is 0.14, which implies that the correct way to estimate is through Fixed Effects and not Random Effects. This means that the heteroscedasticity present in our regression is correlated with the independent variables and thus, the correct way to estimate is through Fixed Effects.

### 4.3. Discussion of the results

The results shown in the previous sections are somewhat surprising given the relevant literature. Even though the one-year lagged version of the ECI shows significance in the Fixed Effects model, the relationship between the ECI and output volatility, according to those results, can also be interpreted as being somewhat ambiguous. On the one hand, the bivariate analysis shows an attenuating effect of economic complexity with volatility, and on the other, the Fixed Effects model showed no significance for the contemporary version of the ECI and it only did so for the one year lagged version. This seems to be at odds with the findings of the previous two studies on this topic mentioned in section 2.2. (Breitenbach et al. 2022; Güneri 2019).

We should mention however a couple of things about those papers. First, both the study conducted by Breitenbach et al. (2022) as well as the one conducted by Güneri (2019) differ in some way or another in terms of methodology from this study. Breitenbach et al. (2022) also use a fixed effects estimation for their model, but they divide their sample into low and high income countries and their time frame into long and short-term time horizons. They also include up to 5-year lags in the specification of the ECI. Güneri (2019), on the other hand, includes a similar sample to ours (87 countries for the period between 1981 and 2015), but instead he uses a panel VAR approach for his study which, as stated by Grossman et al. (2014), can capture dynamic effects that other panel regression cannot. Second, the significant relationship between the ECI and volatility found in these studies, and in particular, the one found by Breitenbach et al. (2022), doesn't look as straightforward as it seemed upon a closer inspection. For one, even though the authors report a negative and significant correlation between ECI and output volatility, the ECI really only shows a clear relationship with output volatility for the high-income countries. For the low-income countries in the short term, it shows no significant relationship and, in the long term, it only does so for the five-year lagged version of the ECI. The theoretical framework by which there could be a relationship between ECI and volatility for a five-year lag but not for a one-year lag or a three-year lag is perhaps somewhat hard to understand. Furthermore, when looking at the sign of the coefficients, it becomes even more clear that this is far from an unambiguous relationship, as high-income countries show a negative relationship between the ECI and volatility for a three-year lag of the ECI, but they show a positive relationship for a one-year lag of the ECI. The relationship in the short term for high-income countries also shows surprising results considering the positive coefficient associated with the ECI, which would seem to suggest that contrary to both the hypothesis in this study as well the one in Breitenbach et al (2022), for high-income countries in the short term, economic complexity contributes positively to output volatility.

The results of this study also diverge somewhat from the literature when it comes to the control variables. Variables like GDP per capita and country size have also shown an ambiguous relationship, with GDP per capita not showing significance in the bivariate analysis and country size not showing significance in the Fixed Effects model. The relationship attributed in this study to Trade Openness with output volatility contrasts even more unequivocally with the literature, having shown a significant relationship only at the individual level of the bivariate analysis. This contrast in one way or another with the previously mentioned studies connecting output volatility with GDP per capita (Koren and Tenreyro, 2007), Trade Openness (Haddad et al., 2013; Cavallo, 2007; Bejan, 2007) and country size (Furceri and Karras, 2007; Alouini and Hubert, 2010).

Also worth discussing is the coefficient associated with Private credit to GDP in model 1. The coefficient is 0.010, which indicates a positive relationship between financial development and output volatility. These results are in contrast with some of the studies on output volatility. Hausmann and Gavin (1996), for instance, argued that well-developed financial markets can act as shock absorbers during times of crisis and should thus help lower volatility. Da Silva et al. (2017) also studied the relationship between volatility and domestic credit to GDP and found a significant relationship between the two. However, this relationship, rather than being a linear one, actually showed an “inverted-U” shape, which could help explain the positive sign found in this study. These results also contrast with the individual correlations presented in section 3.2.1., where the correlation between Private credit to GDP and volatility is actually negative. This seeming contradiction could be due to high correlations between Private credit to GDP and other variables or simply due to a higher accuracy of the Fixed Effects estimation for capturing the real relationship between two variables.

## 5. Conclusions

To conclude, our findings suggest an ambiguous relationship between the Economic Complexity Index and output volatility. There are various aspects that could be producing this ambiguity. First is the high correlation between the ECI, Private credit to GDP, GDP per capita levels and Government Effectiveness. This study has tried to exclude the presence of multicollinearity by estimating various regressions with different combinations of independent variables. However, there may be still some degree of multicollinearity in our models given the significant changes in results whenever different combinations of explanatory variables were used.

It is also possible that the method we used for measuring economic volatility has influenced the results of this study. As mentioned before, even though most studies focusing on volatility chose the standard deviation of GDP growth as a measurement, there have been some studies taking different approaches. Nevertheless, the two previous studies on this topic that found a significant relationship between the ECI and volatility did so by measuring volatility as the standard deviation. This would seem to suggest that we need to look elsewhere to explain our contrasting results.

Another factor that could be influencing this observed ambiguity could be a misspecification of our theoretical framework. As stated in section 1, the assumptions for the hypothesis of our study can be summarized in three points:

I. The ECI correctly measures productive capabilities, hence, countries with higher ECI ratings possess more sophisticated productive knowledge.
II. Countries with more sophisticated productive knowledge are more adaptable to economic shocks.
III. Countries that are more adaptable to economic shocks exhibit less output volatility.

This is the conceptual framework that has guided both the purpose of this study as well as the structure of our empirical models but it could be possible that economic complexity affects output volatility through different unaccounted mechanisms other than the higher adaptability mechanism that we proposed.

And lastly, we should also acknowledge the possibility that this ambiguity in our results is just the empirical manifestation of the lack of a real causal relationship between economic complexity and output volatility.

# 6. References

## 6.1. Academic writings and articles


Alouini, O. & Hubert, P. (2019). *Country size, economic performance and volatility.* Revue de l'OFCE, 164, 139-163. https://doi.org/10.3917/reof.164.0139

Balland, P. A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). *The new paradigm of economic complexity*. Research policy, 51(3), 104450. https://doi.org/10.1016/j.respol.2021.104450

Bejan, M., *Trade Openness and Output Volatility* (2006). SSRN Electronic Journal. Available at SSRN: https://ssrn.com/abstract=965824 or http://dx.doi.org/10.2139/ssrn.965824

Caldarelli, G., Cristelli, M., Gabrielli, A., Pietronero, L., Scala, A., Tacchella, A. (2012) *A Network Analysis of Countries' Export Flows: Firm Grounds for the Building Blocks of the Economy.* PLoS ONE 7(10). https://doi.org/10.1371/journal.pone.0047278

Canh, N. P., & Thanh, S. D. (2022). *The Dynamics of Export Diversification, Economic Complexity and Economic Growth Cycles: Global Evidence.* Foreign Trade Review, 57(3), 234–260. https://doi.org/10.1177/0015732520970441

Cariolle, J. (2012). *Measuring macroeconomic volatility - Applications to export revenue data*. Working Papers I14, FERDI.

Cotrell, A. & Lucchetti, R. (2022) "*Gretl User's Guide*". Gnu Regression, Econometrics and Time-series Library.

Cristelli, M., Gabrielli, A., Tacchella, A., Caldarelli, G. & Pietronero, L. (2013) *Measuring the Intangibles: A Metrics for the Economic Complexity of Countries and Products.* PLoS ONE 8(8): e70726. https://doi.org/10.1371/journal.pone.0070726

Maggioni, D., Lo Turco, A. & Gallegati, M.  (2014) *"Does export complexity matter for firms' output volatility?,"* Working Papers 407, Universita' Politecnica delle Marche (I), Dipartimento di Scienze Economiche e Sociali.

Cavallo, E. (2008) *"Output Volatility and Openness to Trade: a Reassessment,"* Economía Journal, The Latin American and Caribbean Economic Association - LACEA, vol. 0(Fall 2008), pages 105-152, September.

Furceri, D. & Karras, G. (2007). *Country Size and Business Cycle Volatility: Scale Really Matters.* Journal of the Japanese and International Economies. 21. 424-434. 10.1016/j.jjie.2007.04.001.

Gómez-Zaldívar, M., & Llanos-Guerrero, A. (2021). *On the synchronization of the business cycles of Mexican states and its relationship to their economic complexity*, 2000–2014. Growth and Change, 52, 1576– 1592. https://doi.org/10.1111/grow.12525

Grossmann, A., Love, I. & Orlov, A. (2014). *The Dynamics of Exchange Rate Volatility: A Panel VAR Approach.* Journal of International Financial Markets, Institutions and Money. 33. 10.1016/j.intfin.2014.07.008.

Güneri, B. & Yalta, A. Y. (2020) *Does economic complexity reduce output volatility in developing countries?* Bull. Econ. Res. https://doi.org/10.1111/boer.12257

Hartmann, D.,  Guevara, M., Jara Figueroa, C., Aristarán, M. & Hidalgo, C. (2017). *Linking Economic Complexity, Institutions and Income Inequality*. World Development. 93. 10.1016/j.worlddev.2016.12.020.

Hausman, J. A. (1978). *Specification Tests in Econometrics*. Econometrica, 46(6), 1251–1271. https://doi.org/10.2307/1913827

Hausmann, R. , Hidalgo, C.A., Bustos, S., Coscia, M., Chung, S.,  Simoes, A. & Yildirim, M.A. (2014) *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. MIT Press: Cambridge

Hidalgo, C.A. (2021) *Economic complexity theory and applications*. Nat Rev Phys 3, 92–11 https://doi.org/10.1038/s42254-020-00275-1

Hidalgo, C. & Hausmann, R. (2009). *The Building Blocks of Economic Complexity.* Proceedings of the National Academy of Sciences of the United States of America. 106. 10570-5. 10.1073/pnas.0900943106.

Hnatkovska, V. & Loayza, N. (2004) *"Volatility and growth"* Policy Research Working Paper Series 3184, The World Bank.

Mensah, I. & Kwasi Mensah, E. (2021) *The impact of inward FDI on output growth volatility: A country-sector analysis.* Research in Globalization,Volume 3,2021,100063,ISSN 2590-051X, https://doi.org/10.1016/j.resglo.2021.100063.

Stock, J.H. & Watson, M.W. (2003) *"Has the Business Cycle Changed and Why?,"* NBER Chapters, in: NBER Macroeconomics Annual 2002, Volume 17, pages 159-230, National Bureau of Economic Research, Inc.

Kaufmann, D. & Kraay, A. & Mastruzzi, M. (2010). *The Worldwide Governance Indicators: Methodology and Analytical Issues.* World Bank, Working Paper Series 5430. 3. 10.1017/S1876404511200046.

Kemp-Benedict, E. (2014). *An interpretation and critique of the Method of Reflections.* Munich Personal RePEc Archive (MPRA), 18 December 2014 .

Krishna, P. & Levchenko, A. (2009) *Comparative Advantage, Complexity and Volatility*, NBER: National Bureau of Economic Research. Retrieved from https://policycommons.net/artifacts/1399942/comparative-advantage-complexity-and-volatility/2014206/ on 15 Jun 2022. CID: 20.500.12592/m6k6x8.

Pritchett, L. (2000) *Understanding Patterns of Economic Growth: Searching for Hills among Plateaus, Mountains, and Plains*, The World Bank Economic Review, Volume 14, Issue 2, Pages 221–250, https://doi.org/10.1093/wber/14.2.221

Langbein L. & Knack S. (2010) *The Worldwide Governance Indicators: Six, One, or None?*, The Journal of Development Studies, 46:2, 350-370, DOI: 10.1080/00220380902952399

Lensink, R. & Morrissey, O. (2006). *Foreign Direct Investment: Flows, Volatility, and the Impact on Growth*. Review of International Economics. 14. 478-493. 10.1111/j.1467-9396.2006.00632.x.

Lucas, R. Jr. (1988) *"On the mechanics of economic development,"* Journal of Monetary Economics, Elsevier, vol. 22(1), pages 3-42, July.

Majeed, M. & Noreen, A. (2018). *Financial Development and Output Volatility: A Cross-Sectional Panel Data Analysis*. The Lahore Journal of Economics. 23. 97-141. 10.35536/lje.2018.v23.i1.A5.

Breitenbach, M. C., Chisadza, C. & Clance, M. (2022) *The Economic Complexity Index (ECI) and output volatility: High vs. low income countries*, The Journal of International Trade & Economic Development, 31:4, 566-580, DOI: 10.1080/09638199.2021.1995467

Iseringhausen, M. & Vierke, H. (2018) *"What Drives Output Volatility? The Role of Demographics and Government Size Revisited,"* European Economy - Discussion

Mealy, P., Farmer, J. & Teytelboym, A. (2017). *A New Interpretation of the Economic Complexity Index*. SSRN Electronic Journal. 10.2139/ssrn.3075591.

Koren, M. & Tenreyro, S. (2005) *"Volatility and Development,"* CEP Discussion Papers dp0706, Centre for Economic Performance, LSE.

Becker, T.I. & Mauro, P. (2006) *"Output Drops and the Shocks That Matter,"* IMF Working Papers 2006/172, International Monetary Fund.

Blanchard, O. & Simon, J. (2001) *"The Long and Large Decline in U.S. Output Volatility,"* Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, vol. 32(1), pages 135-174.

Guillamont, P. & Chauvet, L. (2007) *"Aid, Volatility and Growth Again When Aid Volatility Matters and When it Does Not,"* Working Papers 200707, CERDI.

Ramey, G., & Ramey, V. A. (1995). *Cross-Country Evidence on the Link Between Volatility and Growth.* The American Economic Review, 85(5), 1138–1151. http://www.jstor.org/stable/2950979

Rose, A. (2004). *Defining and Measuring Economic Resilience to Disasters*. Disaster Prevention and Management. 13. 307-314. 10.1108/09653560410556528.

Sciarra, C., Chiarotti, G., Ridolfi, L., & Laio, F. (2020). *Reconciling contrasting views on economic complexity*. Nature communications, 11(1), 3352. https://doi.org/10.1038/s41467-020-16992-1

Da Silva, S.H.R., Tabak, B.M., Cajueiro, D.O. & Fazio, Dimas M. (2017) *"Economic growth, volatility and their interaction: What's the role of finance?,"* Economic Systems, Elsevier, vol. 41(3), pages 433-444.

Tang, C. F., & Abosedra, S. (2020). *Does Financial Development Moderate the Effects on Growth Volatility? The Experience of Malaysia.* Margin: The Journal of Applied Economic Research, 14(4), 361–381. https://doi.org/10.1177/0973801020953400

Thomas, M. (2010) *What Do the Worldwide Governance Indicators Measure?.* Eur J Dev Res 22, 31–54 https://doi.org/10.1057/ejdr.2009.32

Vu, T. (2022). *Does institutional quality foster economic complexity? The fundamental drivers of productive capabilities*. Empirical Economics. 10.1007/s00181-021-02175-4.

Simoes, A.G.J. & Hidalgo, C.A. (2011) *The Economic Complexity Observatory: An Analytical Tool for Understanding the Dynamics of Economic Development*. Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence.

## 6.2. Databases

World development indicators. Washington, D.C. :The World Bank.

Worldwide Governance Indicators (WGI) Project. The World Bank, Washington DC, USA (2011)

The Growth Lab at Harvard University. (2019). "Growth Projections and Complexity Rankings, V2" [Data set]. https://doi.org/10.7910/dvn/xtaqmc

# 7. Annex

## 7.1. List of countries

- Algeria
- Argentina
- Australia
- Austria
- Bahrain
- Bangladesh
- Belgium
- Botswana
- Brazil
- Bulgaria
- Burkina Faso
- Cambodia
- Cameroon
- Canada
- Chile
- China
- Colombia
- Congo, Dem. Rep.
- Congo, Rep.
- Cote d'Ivore
- Croatia
- Cyprus
- Czech Republic
- Denmark
- Ecuador
- Egypt
- El Salvador
- Eswatini
- Finland
- France
- Gabon
- Germany
- Ghana
- Greece
- Guatemala
- Guinea
- Honduras

- Hungary
- India
- Israel
- Italy
- Jamaica
- Japan
- Jordan
- Kenya
- Korea, Rep.
- Kuwait
- Kyrgyz Republic
- Lao PDR
- Lebanon
- Madagascar
- Malaysia
- Mali
- Mauritius
- Mexico
- Mongolia
- Mozambique
- Netherlands
- Nicaragua
- Nigeria
- Norway
- Oman
- Pakistan
- Paraguay
- Peru
- Philippines
- Polan
- Portugal
- Qatar
- Romania
- Russian Federation
- Saudi Arabia
- Senegal
- Singapore
- South Africa
- Spain
- Sri Lanka
- Sweden

- Switzerland
- Tanzania
- Togo
- Tunisia
- UK
- Usa
- Uruguay
- Vietnam
- Zimbabwe

## 7.2. Alternative models

**Model 17**

Model 17: Fixed-effects, using 696 observations
Included 87 cross-sectional units
Time-series length = 8
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 1.24334 | 0.539833 | 2.303 | 0.0237 | ** |
| ECI | −0.120480 | 0.358587 | −0.3360 | 0.7377 | |
| TradeGDP | −0.00318580 | 0.00534725 | −0.5958 | 0.5529 | |
| FDI | 0.0127772 | 0.00583690 | 2.189 | 0.0313 | ** |
| CountrySize | −1.35065e-011 | 1.89519e-09 | −0.007127 | 0.9943 | |
| GDPperCapitaPPP | 2.75663e-06 | 1.27944e-05 | 0.2155 | 0.8299 | |
| GEE | −0.522223 | 0.325435 | −1.605 | 0.1122 | |
| dt_1 | 0.934367 | 0.295711 | 3.160 | 0.0022 | *** |
| dt_2 | 1.16767 | 0.274792 | 4.249 | <0.0001 | *** |
| dt_3 | 1.09688 | 0.250552 | 4.378 | <0.0001 | *** |
| dt_4 | 0.347695 | 0.176897 | 1.966 | 0.0526 | * |
| dt_5 | 2.41916 | 0.242171 | 9.989 | <0.0001 | *** |
| dt_6 | 0.899157 | 0.156806 | 5.734 | <0.0001 | *** |
| dt_7 | 0.332003 | 0.150244 | 2.210 | 0.0298 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.858268 | S.D. dependent var | 1.859438 |
| Sum squared resid | 1398.921 | S.E. of regression | 1.532052 |
| LSDV R-squared | 0.417837 | Within R-squared | 0.201040 |
| Log-likelihood | −1230.522 | Akaike criterion | 2661.045 |
| Schwarz criterion | 3115.580 | Hannan-Quinn | 2836.796 |
| rho | −0.143614 | Durbin-Watson | 2.058271 |

**Model 18**

Model 18: Fixed-effects, using 609 observations
Included 87 cross-sectional units
Time-series length = 7
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 1.31860 | 0.648817 | 2.032 | 0.0452 | ** |
| ECI | 0.0798135 | 0.381415 | 0.2093 | 0.8347 | |
| ECI_1 | −0.501239 | 0.304794 | −1.645 | 0.1037 | |
| TradeGDP | −0.000253082 | 0.00578583 | −0.04374 | 0.9652 | |
| FDI | 0.0187217 | 0.00638397 | 2.933 | 0.0043 | *** |
| GDPperCapitaPPP | −6.58845e-06 | 1.50644e-05 | −0.4374 | 0.6630 | |
| GEE | −0.883437 | 0.445994 | −1.981 | 0.0508 | * |
| dt_2 | 1.12938 | 0.278208 | 4.059 | 0.0001 | *** |
| dt_3 | 1.03597 | 0.258827 | 4.003 | 0.0001 | *** |
| dt_4 | 0.306028 | 0.181640 | 1.685 | 0.0957 | * |
| dt_5 | 2.34818 | 0.238280 | 9.855 | <0.0001 | *** |
| dt_6 | 0.859490 | 0.152336 | 5.642 | <0.0001 | *** |
| dt_7 | 0.320364 | 0.142320 | 2.251 | 0.0269 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.855227 | S.D. dependent var | 1.861685 |
| Sum squared resid | 1153.297 | S.E. of regression | 1.503784 |
| LSDV R-squared | 0.452700 | Within R-squared | 0.242395 |
| Log-likelihood | −1058.576 | Akaike criterion | 2315.151 |
| Schwarz criterion | 2751.921 | Hannan-Quinn | 2485.063 |
| rho | −0.211025 | Durbin-Watson | 2.132004 |

**Model 19**

Model 19: Fixed-effects, using 609 observations
Included 87 cross-sectional units
Time-series length = 7
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 1.18043 | 0.464577 | 2.541 | 0.0129 | ** |
| ECI | 0.0955469 | 0.376272 | 0.2539 | 0.8002 | |
| ECI_1 | −0.506544 | 0.309796 | −1.635 | 0.1057 | |
| TradeGDP | −0.00041543<br>1 | 0.00586837 | −0.07079 | 0.9437 | |
| FDI | 0.0186900 | 0.00639113 | 2.924 | 0.0044 | *** |
| GEE | −0.894003 | 0.444620 | −2.011 | 0.0475 | ** |
| dt_2 | 1.19609 | 0.236442 | 5.059 | <0.0001 | *** |
| dt_3 | 1.09201 | 0.227052 | 4.810 | <0.0001 | *** |
| dt_4 | 0.349828 | 0.136613 | 2.561 | 0.0122 | ** |
| dt_5 | 2.37152 | 0.228010 | 10.40 | <0.0001 | *** |
| dt_6 | 0.874533 | 0.155862 | 5.611 | <0.0001 | *** |
| dt_7 | 0.322813 | 0.143332 | 2.252 | 0.0269 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.855227 | S.D. dependent var | 1.861685 |
| Sum squared resid | 1153.782 | S.E. of regression | 1.502628 |
| LSDV R-squared | 0.452470 | Within R-squared | 0.242077 |
| Log-likelihood | −1058.704 | Akaike criterion | 2313.407 |
| Schwarz criterion | 2745.765 | Hannan-Quinn | 2481.603 |
| rho | −0.211755 | Durbin-Watson | 2.133192 |

## Model 21

Model 21: Fixed-effects, using 696 observations
Included 87 cross-sectional units
Time-series length = 8
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 0.624289 | 0.505800 | 1.234 | 0.2205 | |
| ECI | −0.127005 | 0.353337 | −0.3594 | 0.7201 | |
| TradeGDP | −0.00398977 | 0.00516972 | −0.7718 | 0.4424 | |
| PCreditGDP | 0.0112414 | 0.00388094 | 2.897 | 0.0048 | *** |
| FDI | 0.00999037 | 0.00479619 | 2.083 | 0.0402 | ** |
| GEE | −0.593294 | 0.325626 | −1.822 | 0.0719 | * |
| dt_1 | 1.18755 | 0.246357 | 4.820 | <0.0001 | *** |
| dt_2 | 1.38822 | 0.248440 | 5.588 | <0.0001 | *** |
| dt_3 | 1.28632 | 0.248221 | 5.182 | <0.0001 | *** |
| dt_4 | 0.527042 | 0.153303 | 3.438 | 0.0009 | *** |
| dt_5 | 2.53927 | 0.234237 | 10.84 | <0.0001 | *** |
| dt_6 | 0.961443 | 0.159876 | 6.014 | <0.0001 | *** |
| dt_7 | 0.372086 | 0.146367 | 2.542 | 0.0128 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.858268 | S.D. dependent var | 1.859438 |
| Sum squared resid | 1380.930 | S.E. of regression | 1.520893 |
| LSDV R-squared | 0.425323 | Within R-squared | 0.211315 |
| Log-likelihood | −1226.018 | Akaike criterion | 2650.036 |
| Schwarz criterion | 3100.026 | Hannan-Quinn | 2824.029 |
| rho | −0.147624 | Durbin-Watson | 2.066983 |

**Model 22**

Model 22: Fixed-effects, using 696 observations
Included 87 cross-sectional units
Time-series length = 8
Dependent variable: Volatility
Robust (HAC) standard errors

| | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* | |
|---|---|---|---|---|---|
| const | 0.666810 | 0.562084 | 1.186 | 0.2388 | |
| ECI | −0.130804 | 0.354296 | −0.3692 | 0.7129 | |
| TradeGDP | −0.00393435 | 0.00515747 | −0.7628 | 0.4476 | |
| PCreditGDP | 0.0113482 | 0.00396356 | 2.863 | 0.0053 | *** |
| FDI | 0.00999042 | 0.00477606 | 2.092 | 0.0394 | ** |
| GEE | −0.590028 | 0.327779 | −1.800 | 0.0754 | * |
| GDPperCapitaPPP | −2.36067e-06 | 1.19112e-05 | −0.1982 | 0.8434 | |
| dt_1 | 1.16396 | 0.287919 | 4.043 | 0.0001 | *** |
| dt_2 | 1.36681 | 0.264595 | 5.166 | <0.0001 | *** |
| dt_3 | 1.26826 | 0.259300 | 4.891 | <0.0001 | *** |
| dt_4 | 0.513290 | 0.177019 | 2.900 | 0.0047 | *** |
| dt_5 | 2.53207 | 0.240516 | 10.53 | <0.0001 | *** |
| dt_6 | 0.956651 | 0.159252 | 6.007 | <0.0001 | *** |
| dt_7 | 0.371641 | 0.146114 | 2.544 | 0.0128 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var | 1.858268 | S.D. dependent var | 1.859438 |
| Sum squared resid | 1380.852 | S.E. of regression | 1.522125 |
| LSDV R-squared | 0.425356 | Within R-squared | 0.211360 |
| Log-likelihood | −1225.998 | Akaike criterion | 2651.996 |
| Schwarz criterion | 3106.531 | Hannan-Quinn | 2827.747 |
| rho | −0.147273 | Durbin-Watson | 2.066263 |