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Growth Accounting and Regressions: a new methodological approach to capital and technology

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Dedication

“Truth is treason in the empire of lies.

— Ron Paul, U.S. Representative from Texas

“The best method for estimating the intelligence of a ruler is to look at the men he has around him.

— Niccolò Machiavelli, Italian - Writer | 1469 – 1527

“Gold Is Money, Everything Else Is Credit.

— J. P. Morgan, American - Banker | 1837 – 1913

“I would remind you that extremism in the defense of liberty is no vice! And let me remind you also that moderation in the pursuit of justice is no virtue!”

— Barry Goldwater, U.S. Senator from Arizona

“Speech was given to man to disguise his thoughts.

— Charles Maurice de Talleyrand, French - Diplomat | 1754 – 1838

“I have no trouble with my enemies. I can take care of my enemies in a fight. But my friends, my goddamned friends, they’re the ones who keep me walking the floor at nights!”

— Warren G. Harding, 29th President of the United States

“Never presume that I will not act on my worst instincts.

— Cesare Borgia, Italian - Philosopher | 1475 – 1507

“Should I change my style now? Hmpf... How stupid of me... I already know the answer I am not going to change at all... it would be a crowning achievement of the dumb moves to me to do something like that. A disciplined person knows when needs to control himself. I just gotta stick to the basics.

— Sudō Kyōichi, Team leader of Emperor

"You can rid yourself of many useless things among those that disturb you, for they lie entirely in your imagination; and you will then gain for yourself ample space by comprehending the whole universe in your mind, and by contemplating the eternity of time, and observing the rapid change of every part of everything, how short is the time from birth to dissolution, and the illimitable time before birth as well as the equally boundless time after dissolution.

— Marcus Aurelius, Roman - Soldier | 121 - 180

"Remember that all we have is 'on loan' from Fortune, which can reclaim it without our permission—indeed, without even advance notice. Thus, we should love all our dear ones, but always with the thought that we have no promise that we may keep them forever—nay, no promise even that we may keep them for long.

— Seneca, Roman - Philosopher | 4 BC – 65

"But neither a bull nor a noble-spirited man comes to be what he is all at once; he must undertake hard winter training, and prepare himself, and not propel himself rashly into what is not appropriate to him.

— Epictetus, Greek - Philosopher | 55 – 135

Thanks

I am very grateful to my supervisor Professor Tiago Sequeira for the privilege of having his excellent guidance and constant support during this work which certainly without his expertise would not be possible to reach this high level of standards. I am enormously grateful to my friends Estefano, André, Zé, Fábio, João, Rúben, Alexandra, Paulo, Cátia, Filipa and my old friend Samuel for all friendship and support during this master's, also thankful to all teachers that shared their knowledge during the courses. Especially warm thanks go to my parents Vítor and Ana and my brother and sister Marco and Neide for their constant support during this dissertation.

Resumo

Foi aplicado um método inédito da contabilidade de crescimento em que assume proporções de factores produtivos variáveis em vez de constantes como é comum. As contribuições da acumulação de factores de produção para o crescimento económico tem sido um assunto amplamente analisado e testado na literatura económica. No entanto, várias questões têm posto em causa a fiabilidade dos resultados provenientes das regressões do crescimento tais como a existência de outliers e a de potencial causalidade reversa. O estudo alberga um painel de dados de 101 países entre 1950 e 2015 em que associações entre países e períodos de tempo como choques comuns, características persistentes específicas a cada país e ciclos económicos são analisados e corrigidos. A metodologia aplicada contorna várias críticas apontadas ás regressões do crescimento que até ao momento ainda não tinham sido visadas pela literatura mais recente. A evidência mais importante aponta para que a despesa corrente do governo diminua as contribuições do capital e trabalho no crescimento mas não que não tenha efeito aparente sobre a produtividade total dos factores (PTF). O comércio externo afecta as contribuições da PTF e do progresso tecnológico enviesado (PTE), porém reduzindo as contribuições associadas á acumulação de factores. Além disso, o capital humano diminui a contribuição do PTF, mas aumenta a contribuição do PTE para o crescimento.

Palavras-chave

Crescimento Económico, Contabilidade do Crescimento, Dados em Painel, Contribuições Variáveis de Factores, Despesa Corrente, Capital Humano, Comércio Externo, Factores Historicamente Enraízados, Bootstrapping, Multi-Clustering

Resumo alargado

A relação entre as contribuições dos factores produtivos para o crescimento económico é um tema que tem sido amplamente analisado na literatura. Desde Solow (1956) que a contabilidade do crescimento ganhou lugar na ciência económica para acessar as fontes mais importantes de crescimento económico. Uma das questões mais importantes na explicação do crescimento económico é a importância da acumulação de factores de produção e tecnologia como impulsionadores da taxa de crescimento económico. Em artigos influentes, Hall and Jones (1999) e Easterly and Levine (2001) concluíram que a fonte mais importante de crescimento é a produtividade total dos factores (PTF) sendo que o primeiro apresentou como explicação as diferenças na PTF são baseadas essencialmente em diferenças institucionais entreas nações. A grande maioria dos artigos que implementam metodologia de contabilidade de crescimento baseiam-se no pressuposto que as contribuições dos factores são consideradas constantes, seguindo aquilo que se conhece como o facto estilizado de Kaldor. No entanto, estudos sobre as proporções de factores feitos como o de Zuleta (2008) concluem que elas variam consistentemente entre os países. Neste estudo, aplicamos a metodologia Zuleta (2012) para obter as proporções da acumulação de capital e tecnologia numa grande variedade de países ao longo de um grande horizonte temporal usando períodos gerados a partir de médias de 5 anos de modo a evitar choques não relacionados com o crescimento de longo prazo. Este trabalho também inova ao incluir o progresso técnico enviesado (PTE) que representa o viés no crescimento a favor dos factores com maior intensidade em capital humano logo mais produtivos. Métodos avançados de econometria em painel são usados para avaliar como a instabilidade, o peso do governo na economia, a abertura ao comércio e o capital humano os afectam. Neste sentido, estamos a ir além da questão central do crescimento económico 'Por que é que alguns países crescem mais do que outros?' Na verdade, desejamos perguntar 'Por que alguns países dependem mais da acumulação de factores ou da tecnologia para crescer?' Embora possam ser tiradas várias lições dos resultados mais robustos (e recentes) das regressões do crescimento, as razões pelas quais alguns países dependem mais da acumulação de factores ou do progresso tecnológico ainda não foram plenamente comprendidas. Esta é a primeira contribuição desta dissertação: obter uma primeira avaliação do motivo pelo qual os países dependem mais do acumulação de factores, do crescimento da PTF ou da PTE para apoiar o seu próprio processo de crescimento económico. Ao contrário do que acontece em microeconometria, em painéis macroeconómicos as distribuições e as correlações dos erros e das variáveis explicativas representam características especiais dos países e/ou dos períodos em causa. Em termos da forma com as observações estão distribuídas é evidente a presença de outliers dado que eles reflectem a existência de casos de sucesso e os fracassos de políticas económicas, desde sempre foieste um tema relevante para a temática do crescimento em que vários trabalhos referem que os outliers tendem conduzir as regressões levando a resultados significantes quando na realidade não o são bastando apenas pequenas alterações na amostra para o resultados se modificarem completamente. Segundo, as observações entre si possuem dispersões díspares o que remete para uma natureza distinta da composição das taxas de crescimento de país para país. Fenómenos de correlação ao longo do tempo e de país para país estão presentes nas diferentes variáveis explicativas e nos erros o que reflecte que esses países compartilham certos padrões espaciais como choques comuns e características persistentes que são específicas a cada país, também se verificou que a existência de efeitos tipo ciclo económico em que choques comuns são persistentes no tempo. A adequação dos

estimadores ás especificidades é bem e discutida ao dados do painel. Para o factor capital e progresso técnico foi usado um estimador á la Thompson (2011). Para o factor trabalho foi usado estimador á lá Petersen (2009) e para o progresso técnico enviesado um mais tradicional que é o Arellano (1987). A evidência mais importante revela que o gasto corrente do governo reduz o crescimento dos factores porém não tem efeito sobre a PTF. O comércio externo, no entanto, afecta a PTF e a contribuição do PTE ao mesmo tempo também tende a diminuir a contribuição do capital. Além disso, o capital humano diminui a contribuição da PTF, mas aumenta a contribuição do BTC para o crescimento. Determinantes do desenvolvimento mais profundamente enraízados, como a diversidade étnica e a densidade populacional histórica, também afectam a acumulação dos factores, a PTF e a PTE de diferentes maneiras. Por exemplo, a densidade populacional histórica tende a diminuir a contribuição do trabalho, mas aumenta a contribuição do PTE para o crescimento. Além disso, a diversidade étnica tende a elevar as contribuições do trabalho e de PTE, mas diminui a contribuição do capital físico. Finalmente, a temperatura tende a aumentar a contribuição do trabalho no crescimento. Olhando para os resultados de uma perspectiva diferente, a participação de capital diminui devido ao comércio externo, despesa em consumo do governo e à diversidade étnica. A participação do trabalho diminui devido aos mesmos determinantes, mas aumenta com a temperatura e diversidade étnica. A contribuição da PTF aumenta devido ao comércio internacional, mas diminui devido ao capital humano. Finalmente, a contribuição do progresso técnico enviesado aumenta devido ao comércio, capital humano, densidade populacional histórica e diversidade étnica. Entre os diferentes métodos de estimação, um dos resultados mais robustos é o efeito negativo do consumo do governo sobre as contribuições da acumulação de factores. O nosso trabalho abre vários caminhos para futura investigação. No lado metodológico, oferece uma nova abordagem baseada em métodos econométricos recentemente desenvolvidos. Para lidar com aspectos críticos em regressões de crescimento. Do lado dos resultados, destaca-se que diferentes determinantes podem explicar diferentes fontes de crescimento (factores de produção e tecnologia) e que as regressões de crescimento podem ser enganosas quando se tenta explicar o crescimento geral. Uma sugestão directa para pesquisas futuras é considerar os diferentes determinantes do crescimento dos factores de produção e tecnologia. Essa sugestão inclui o estudo da influência de determinantes imediatos do crescimento, como o capital humano e determinantes mais profundamente enraizados historicamente, como a temperatura ou a densidade populacional histórica.

Abstract

We apply a variable shares growth accounting method for 101 countries between 1950 and 2015. Then we estimate regressions for those factor shares and technology using a panel data estimator robust to temporary country-wide common shocks, persistent country characteristics, business cycles shocks, reverse causality and high influential observations outliers. This way our applied methodology takes into account the specific features of the data and overcomes most criticisms previously raised on growth regressions, which received only few attention in the economic literature yet. The most important evidence reveals that government current expenditure decreases the factor contribution and has no effect on total factor productivity (TFP). Trade, affects the TFP and the Biased Technical Change (BTC) contributions, decreasing the factor shares. Moreover, human capital decreases TFP and increases the BTC contribution to growth.

Keywords

Economic Growth, Growth Accounting, Cross-Country Data, Variable Factor Share, Total Factor Productivity, Skill-biased Technical Change, Government Expenditure, Human Capital, Trade, Deep-root factors, Multi-Way Clustering, Wild-cluster Bootstrap

Contents

List of Figures

List of Tables

List of Algorithms

List of Acronyms

UBI	Universidade da Beira Interior
OLS	Ordinary Least Squares
TFP	Total Factor Productivity
BTC	Biased Technological Change
GDP	Gross Domestic Product
PWT	Penn World Tables
CNTS	Cross-National Time-Series Data Archive
G-ECON	Geographically based Economic data
EU	European Union
EZ	Euro Zone
WTO	World Trade Organization
CE	Century
OECD	Organisation for Economic Co-operation and Development
AR(1)	First Order Autoregression
MA	Moving Average
VIF	Variance Inflation Factor
RESET	Regression Equation Specification Error Test
DK	Driscoll-Kraay
VCE	Variance-covariance Matrix

Chapter 1

Introduction

[1] Production factor shares and economic growth have been extensively analyzed in the literature. With Solow (1956), growth accounting entered into economics science in an effort to identify the most important sources of economic growth. One of the most important issues is the importance of factors of production and technology as contributors to the economic growth rate and income. In influential articles, Hall and Jones (1999) and Easterly and Levine (2001) concluded that the most important source of growth is total factor productivity (TFP). In particular, Hall and Jones (1999) present evidence according to which differences in TFP are based on institutional differences among countries. However, in most of the articles implementing growth accounting methodology, factor shares are assumed constant, following the well-known Kaldor stylized fact for the US. However, factor shares studies made by Zuleta (2008), for example, conclude that they routinely vary across the countries.

In this study we apply Zuleta (2012) methodology to obtain the shares of capital accumulation and technology across a large cross-section of countries over several years. Then, we use econometrics to evaluate how instability, government weight in the economy, openness to trade and human capital affect them. In that sense we are going beyond the important question 'why do some countries grow more than others?' In fact, we wish to ask 'why do some countries rely more on factor accumulation or on technology to grow?' While several lessons can be taken from the most robust (and recent) results on growth regressions, the reasons why some countries rely more on factor accumulation or on technological change have not been assessed yet. This is the first contribution of this paper: to gain a first assessment of why countries rely more on factor accumulation, TFP growth or biased technical change (BTC) to support their own process of economic growth.

We also deal with common problems affecting the study of the relationship between growth and its determinants, namely the criticism in the literature on the growth regressions literature (e.g. Sala-i Martin (1997)). It is not rare to see cross-country studies tending to disregard heterogeneity and some possible interdependence across countries (Eberhardt, 2011).[2] In our econometric estimations, we deal with heterogeneity, endogeneity, and extreme observations following recent contributions for panel data estimations in small samples. First, Nakamura et al. (2017) show that when estimating growth regressions in panel datasets it is crucial to consider both country-specific shocks and worldwide shocks that have mid-term half-life, and serious biases

[1] This dissertation was written in XƎLaTeX using Paulo (2016) template following the principal order nº 49 / R / 2010.

[2] Many studies simultaneously handle country and time-period effects employing dummies even though this procedure has serious limitations. Both fixed-effects have problems in dealing with complex error structures. Country-dummies do not model accurately the autoregressive process and time-period dummies do not capture some specific country dynamics. Second, the use of dummies restricts the number of covariates that can be used due to collinearity with other regressors and country-dummies inflate the standard errors when the covariates do not vary much across time-periods (see e.g. Thompson (2011)).

will emerge if we fail to take into account implying e.g. overrejection of the null, which will deceive the researcher by suggesting statistical significance where it does not exist. Second, Thompson (2011) makes a strong case for robust standard errors estimation in panel models where the errors and regressors have both time and country effects and persistent idiosyncratic shocks that affect different countries in different time periods. We use robust standard-error in line with the contributions of Millo (2017). Third, a common concern about growth regressions is the endogeneity bias which in our case is solved by including country-effects that wipe out individual heterogeneity potentially correlated to the regressors. Finally, another of the main criticisms of empirical works using cross-section growth regressions that is usually neglected is that the presence of extreme observations generates weak and dubious economic inference (Easterly, 2005; Kaffine and Davis, 2017). To tackle this problem we integrate in our covariance estimation the Cribari-Neto and da Silva (2011) weighting function, which surpasses the other methods in the presence of very influential observations.

In fact, we think that overcoming those main criticisms raised against the growth regressions methodology is our second contribution to the literature. In that sense, this paper is also related to the contributions of Sala-i Martin (1997); Brock and Durlauf (2001); Durlauf (2005); Ley and Steel (2009). All these papers criticize traditional growth regressions questioning their usefulness to obtain lessons for the understanding of economic growth or for design policy. Some of them also suggest some ways to improve their inference properties. In this paper we apply alternative econometric approaches developed recently (Thompson, 2011; Cribari-Neto and da Silva, 2011; Yu, 2013; Millo, 2017) to address this issue.

The most important evidence from our empirical exercise reveals that government current expenditure (as a ratio to GDP) decreases the factor contribution and has no effect on total factor productivity (TFP), highlighting very important long-run crowding-out effects or Ricardian-like intertemporal effects. Trade, however, affects the TFP and the Biased Technical Change (BTC) contributions, tending to decrease the factor contribution. Moreover, human capital decreases the TFP contributions but increases the BTC contribution to growth. More deeply rooted determinants of development such as ethnic diversity and historical population density also affect factor accumulation, TFP, and BTC in different ways. Finally, temperature tends to raise the labor contribution and decrease the TFP contribution.

The structure of the paper is the following. In chapter 2 we review the relevant literature. In chapter 3 we show how we applied the growth accounting methodology and built the variables. In chapter 4 we explain and present the growth accounting methodoloy for the factors accumulation and technology obtained in the previous chapters and present our results. In chapter 5, we conclude.

Chapter 2

Literature Review

Although the doubt about the constancy of shares was already expressed by Keynes (1939) and Solow (1957), most of the field researchers continue to allege that factor shares are constant, as is the case of Brown and Weber (1953) and this evidence has been restated by Kaldor (1961), as a stylized fact of Macroeconomics. This stylized fact has been extensively used in both exogenous and endogenous growth theories, without much questioning of its empirical validity over years and countries, and especially in growth accounting aplications (Barro, 1999).

Kahn and Lim (1998) show evidence that the income shares of equipment, production workers and non-production workers have clear trends. In Blanchard (1997) it is observed that the share of labor decreases in Europe after the 1980's and the reason for the decline is pointed out to be the technological bias. Some other authors calculate the income share of reproducible factors, like human and physical capital, and non-reproducible factors and contend that the latter is correlated positively with the income level (Krueger, 1999; Caselli and Feyrer, 2007).

Despite the interest in biased technological change raised by the seminal work of Acemoglu (2002), there have been few attempts to correct the standard measure of total factor of productivity (TFP) according to the existence of biased technological change. In the US there is some evidence that technology has favored skilled workers since the 1980s in manufacturing (Mallick and Sousa, 2017). Sturgill (2012) decomposed the labor' share into reproducible and non-reproducible components with cross-country estimates, and finds that the labor' share is negatively correlated with output per worker.

Some economists draw attention to the ratio between capital and labor measured in efficiency units, which have remained steady since the 1980s. Bental and Demougin (2009) propose a model that predicts a decreasing ratio between labor in efficiency units and capital, falling wages per efficiency units and increase in labor productivity.

Sturgill (2014) analyzes the development accounting differently from the standard baseline, incorporating natural capital and treating factor shares as variables instead of constant parameters using translog multilateral indices of outputs, inputs and productivity. The results reveal that the correction for the mismatch between physical capital and its share, which is the weight assigned to physical capital input in development accounting, reduces the variation in output per worker.

Since the seminal article from Barro (1991), growth regressions have seen exponential applications trying to assess the most important determinants of economic growth. The so-called Barro regressions highlighted positive factors associated with growth such as investment in physical and human capital, openness to trade and negative factors associated with growth such as the government weight in the economy and distortions in the market (e.g. the black market exchange rate premium). Additionally, Easterly and Rebelo (1993) positively associated public investment in transport and communication with growth. Corruption was found to deter investment (e.g. Ades and Di Tella (1997)). Macroeconomic factors like inflation and budget deficits also have a role in growth by reducing both capital accumulation and TPF growth as in Fischer (1993). Financial markets development has been associated with growth (see Levine (1997) and Levine (2005) for important surveys). More institutional, historical and geographical factors associated with growth have been highlighted by Easterly and Levine (2003). However, outliers are the main driver of many big policy effects exposed in growth regressions because they typically represent very 'bad' policies (Easterly, 2005). As stated in Bertrand et al. (2002), only a small number of empirical studies using panel methods have employed clustered standard errors to deal with that problem.[1]

[1] Please see the technical problems pointed out to the growth regressions methodology discussed in the Introduction.

Chapter 3

Growth Accounting Methodology

In this section, we analysed the panel data collected from 1950 to 2015 for 101 countries A.1. The only selection criteria used was the data availability for the longest time span. All variables are quinquennial to avoid unrelated short run oscillations. The samples were collected from very well-known databases like PWT, G-Econ and CNTS. The econometric methods were executed using *R Studio* by R Development Core Team (2017) and *Stata 14* by StataCorp (2015). [1]
We also used *Excel* by Microsoft Corporation (2016) for some charts. The new Zuleta (2012) approach creates 4 growth shares assuming, contrary to the usual growth accounting method, variations in capital and labor shares. The outcome variables come in contributions which are Capital, Labor, Solow Residual and Biased Technological Change.

3.1 Applying the Growth Accounting Methodology

First, the central concept in the model is the production function with all the standard assumptions,

$$Y_t = A_t F(\theta_k K_t, \theta_l L_t) \quad (3.1)$$

where Y_t is Output-side real GDP at current PPPs (in mil. 2011US$), K_t is Capital stock at current PPPs (in mil. 2011US$), and L_t is Number of persons engaged (in millions). These raw variables were extracted from PWT. The factor shares vary over time so the relative abundance of factors becomes extremely important and, therefore, it is required to have accurate measures of capital and labor, θ_k and θ_l are used as parameters for this reason. The economy is labor abundant when $\theta_l L_t \geq \theta_k K_t$.

The annual compound growth of output rate is $g_y = \left(\frac{Y_t}{Y_{t-1}}\right)^{(1/5)} - 1$

Differentiating (3.1) we have,

$$g_y = \left[g_a + \alpha_t g_k + (1-\alpha_t) g_l + \Delta\alpha_t \ln\left(\frac{\theta_k K_t}{\theta_l L_t}\right)\right] \quad (3.2)$$

The Y_t elasticity with respect to capital is α_t and $(1-\alpha_t)$ is the elasticity of output with respect

[1] The Stata and R code are available in A.1 and A.2.

to labor. $g_k = \left(\frac{K_t}{K_{t-1}}\right)^{(1/5)} - 1$ $\quad g_l = \left(\frac{L_t}{L_{t-1}}\right)^{(1/5)} - 1$

$$S_t = g_y - (\alpha_t g_k + (1 - \alpha_t) g_l) \quad (3.3)$$

The Solow residual of Eq.(3.3) is the S_t variable. The Solow residual from (3.2) and (3.3) also contains the skill-biased technological change (BTC).

$$S_t = g_a + \Delta\alpha_t \ln\left(\frac{\theta_k K_t}{\theta_l L_t}\right) \quad (3.4)$$

Using this expression $\tilde{S}_t = S_t - \Delta\alpha_t \ln\left(\frac{K_t}{L_t}\right)$ we can rewrite (3.4) this way,

$$\tilde{S} = g_a + \Delta\alpha_t \ln\left(\frac{\theta_K}{\theta_L}\right) \quad (3.5)$$

The subsequent equation can be estimated

$$\tilde{S} = C_0 + C_1 \Delta\alpha_t + \tau_t \quad (3.6)$$

where $g_a = C_0 + \tau_t$ and $C_1 = \ln\left(\frac{\theta_K}{\theta_L}\right)$.

3.2 Graphical Analysis

3.2.1 By Country Region

In this section, we are going to analyse the contributions for the growth decomposition:

- K_comp - Capital Contribution
- L_comp - Labor Contribution
- A_comp - Productivity Contribution
- BTC_comp - Biased Technological Change Contribution

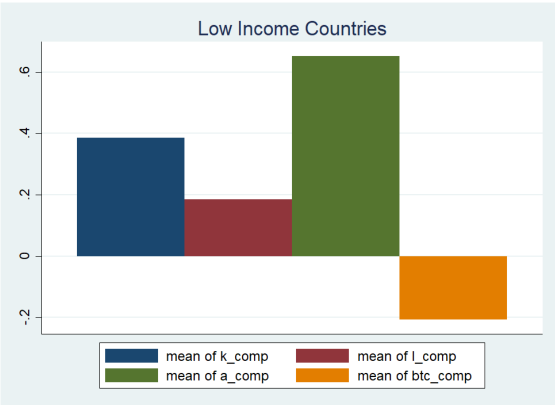
As an example of the data obtained we show a figure 3.1 for low and high income countries.[2]

[2] Figures for other groups of countries are available on appendix Additional Figures A.4.

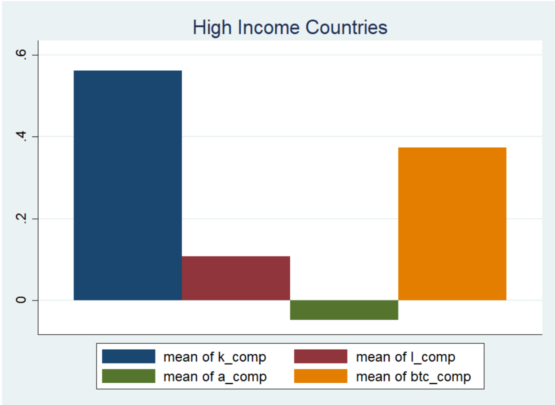
Table 3.1: List of regions

label	Region
h/l	high/low countries
africa	africa countries
lat	latin america countries
casia	central, south and east asia countries
meast	middle east countries
oceania	oceania countries
sasia	southeast and asian tigers countries
oecd	oecd countries
europe	non-oecd european countries

Figure 3.1: Contributions by Income Level (averaged 1950-2015)



Note: Bar charts created using *Stata*.



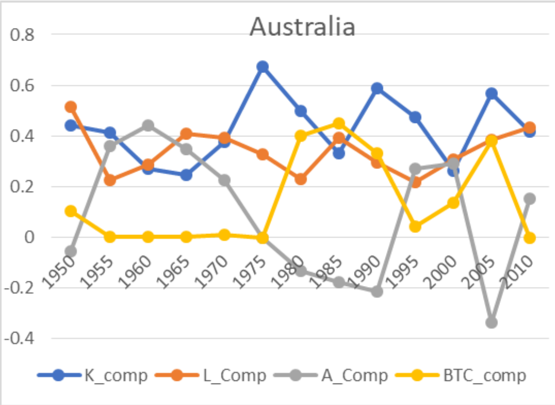
Note: Bar charts created using *Stata*.

Lower income countries obtained their growth most gains from productivity growth and capital accumulation. The negative biased tech may be explained by a brain drain effect that moved high productive workers to rich countries.

In rich countries, we can check on of the main problems of nowadays which is a stagnation of productivity and the improvements occurring from the labor and capital contributions as well as a positive biased technical change contribution.

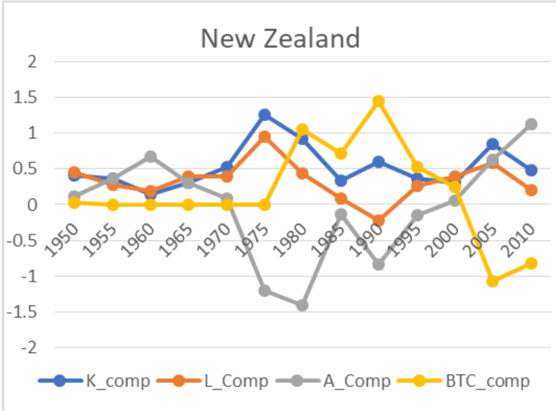
3.2.2 By Individual Countries

We took 4 from the sample countries (Australia, New Zealand, Portugal and Singapore).



Note: Line charts created using $Excel$.

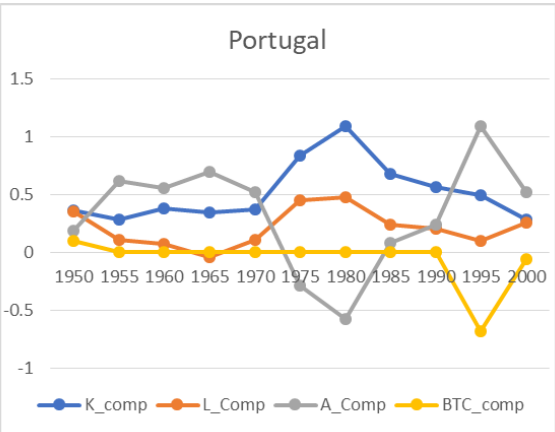
Figure 3.2: Factor Contribution Australia 1950-2015



Note: Line charts created using $Excel$.

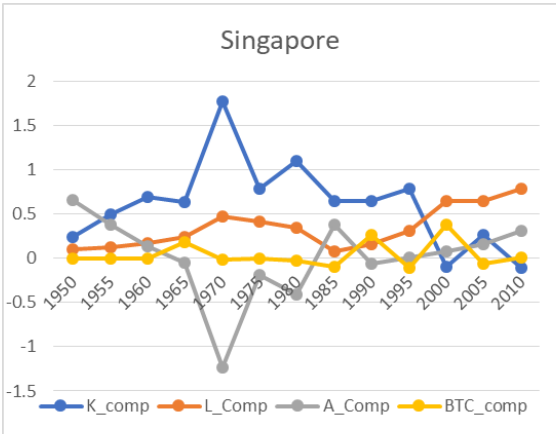
Figure 3.3: Factor Contribution New Zealand 1950-2015

Australia is a vibrant free-market economy with an impressive performance without a recession for more than 25 years. After the internationalization of the economy in 1980s the capital converged with labor with a good TPF growth. New Zealand largely liberated the economy in 1980s and 1990s which we can see on build-up of capital and labor and after a high productivity labor rise.



Note: Line charts created using $Excel$.

Figure 3.4: Factor Contribution Portugal 1950-2000



Note: Line charts created using $Excel$.

Figure 3.5: Factor Contribution Singapore 1950-2015

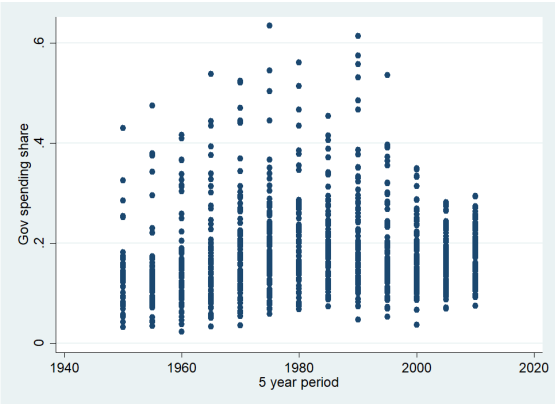
Portugal is an EU country that needs an urgent economic policy adjustment. 1950s and 1960s were a great period of expansion of the Portuguese economy with greater productivity improvement. Singapore is one of the world's most well-off nations that is characterized by a highly educated workforce and solid legal environment. Singapore shows a very interesting trend while financialization expands his labor contribution grows as well. As expected each country experienced different contributions of each factors, biased technical change and TFP depending on different each historical period. For example, capital accumulation tend to be more important in Australia, New Zealand and Singapore and TFP is more important in Portugal namely until the 1970s.

3.3 Variables and Data

3.3.1 Regressors

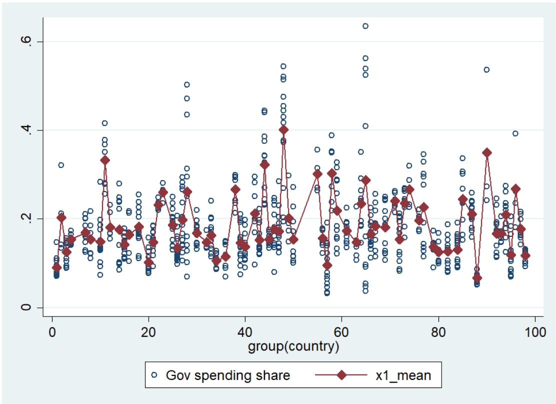
3.3.1.1 Government current expenditure

Economic growth is inversely related to the **government current expenditure (as a ratio to GDP)** (csh_g) meaning that lower government consumption enhances growth Barro (1997). This relationship is strong specially in developing countries which goes in line with Pritchett and Aiyar (2015) because only the richer countries tend to be able to afford for large governments. The contribution of the government expenditures or debts to growth has been particularly controversial after the now famous contribution of Reinhart and Rogoff (2010). However in most growth regressions, the government current expenditure (as a ratio to GDP) appear with a negative and significant sign. With our results we will be able to tell which contribution of growth this (an the other) variables is affecting more. In this case, from where comes the negative sign if it exists. The panel data for this variable was extracted from PWT. We can see a rising trend until mid-eighties coinciding with big deficits and inflation period and afterwards a declining since then specially on the top values.



Note: Scatterplot drawn using $Stata$.

Figure 3.6: Government Spending share 1950-2015



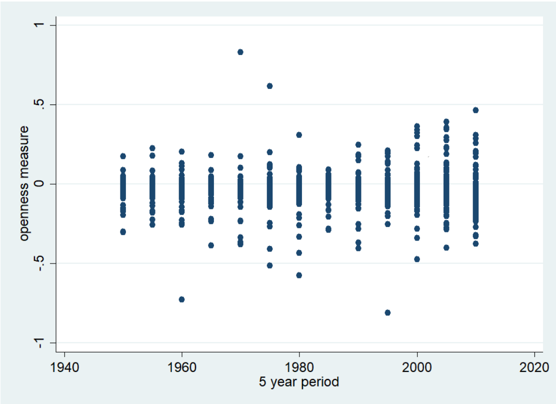
Note: Scatter created using $Stata$ command $twoway\ scatter$.

Figure 3.7: Country-specific effects

We can see a rising trend until mid-eighties coinciding with big deficits and inflation period and afterwards a declining since then specially on the top values.

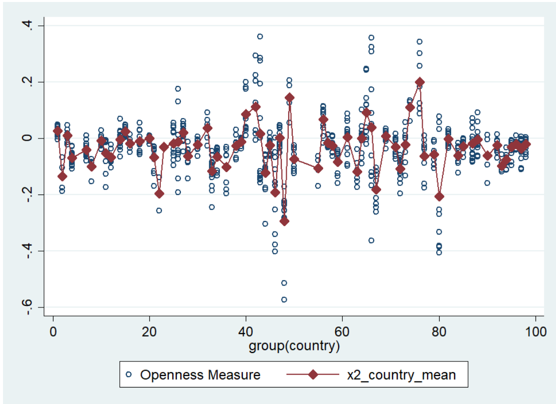
3.3.2 Trade openness

Trade openness (trade) is a openness measure which is obtained by summing exports and imports shares. The relationship between openness and economic growth has been regarded as positive by the literature (Dollar (1992), Frankel and Romer (1999) and Yanikkaya (2003)). In developing countries increased trade openness will not increase wage rates directly and may produce declines in real wages as increase distribution across wages, while in developed countries, wage earner will in general gain in medium run with increased trade, with wage dispersions not increasing and probably decline as result openness Majid (2004). The worldwide openness was stagnant until the early nineties when then started to grow caused by expansion of WTO deals.



Note: Scatterplot drawn using *Stata*.

Figure 3.8: Trade openness 1950-2015

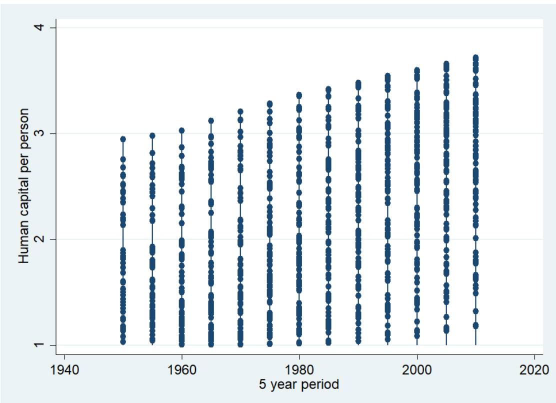


Note: Scatter created using *Stata* command *twoway scatter*.

Figure 3.9: Country-specific effects

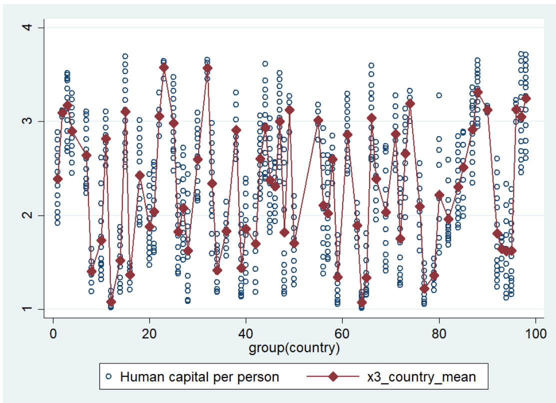
3.3.3 Human capital

In general, and despite some initial controversy (Benhabib (1994)), the most recent empirical literature confirms that **Human capital** (hc) is positively related to growth (Cohen and Soto (2007); Sunde and Vischer (2015); Teixeira and Queirós (2016)). Human capital in regions with high physical capital tend to have higher incomes for all workers (see e.g Mulligan and Sala-i Martin (1997)). The educational attainment rose from 9 years to 12 years and that explains why human capital is steadily growing.



Note: Scatterplot drawn using *Stata*.

Figure 3.10: Human capital per person 1950-2015

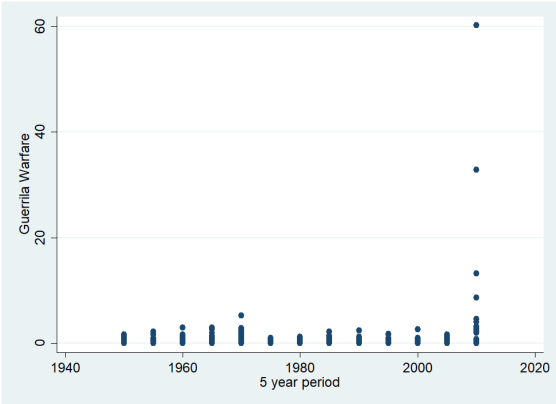


Note: Scatter created using *Stata* command *twoway scatter*.

Figure 3.11: Country-specific effects

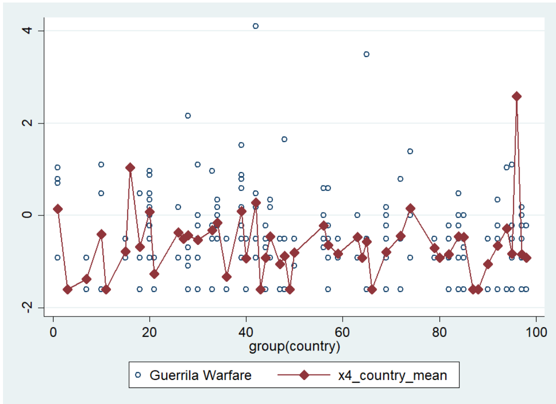
3.3.4 Guerrila warfare

Guerrila warfare (gwar) is used as a proxy for political and social instability as higher degrees of instability are correlated with lower growth rates (Alesina et al., 1996), because it also affects in lowering the rates of overall productivity growth as pointed out by Aisen and Veiga (2013). We have seen an increase of violence till the 70's and a significative lowering but in the last period we have explosive growth occurred provoked by recent events in Iraq, Nigeria and Ukraine.



Note: Scatterplot drawn using $Stata$.

Figure 3.12: Guerrila Warfare 1950-2015

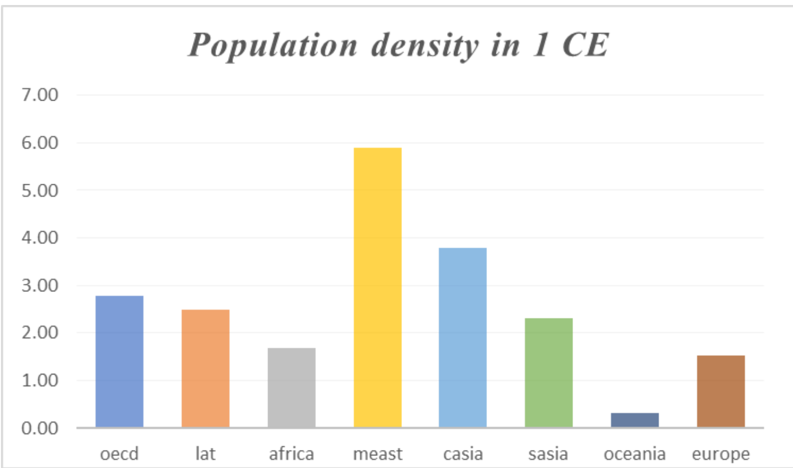


Note: Scatter created using $Stata$ command $twoway\ scatter$.

Figure 3.13: Country-specific effects

3.3.5 Deeply rooted variables

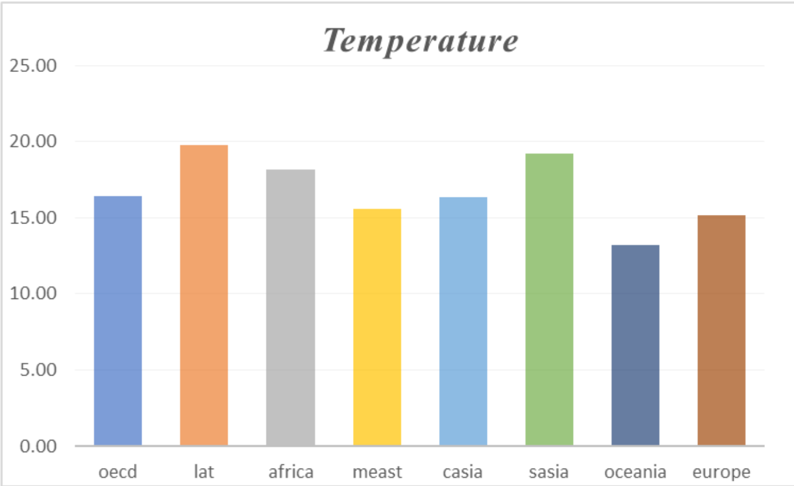
Additionally, we have included 3 time-invariant regressors that improve the explanatory power by adding some geographical factors into account. Ashraf and Galor (2012) show that **Population density in 1 CE** (pd1) embody some and significant economic development effects for countries that have long expanse of time. The Middle East and Central Asia were the regions with higher density because the first big civilizations started there.



Note: Bar chart created using $Excel$. Y-axis measured in pop/km^2

Figure 3.14: Population density in 1 CE (country region)

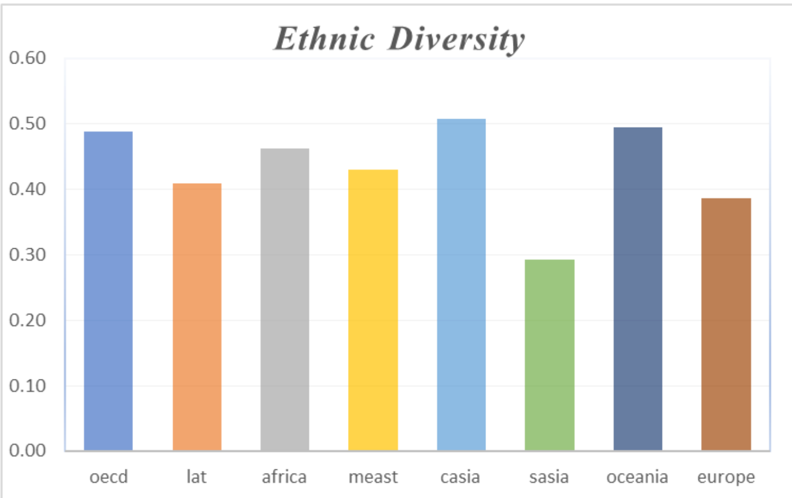
Some literature examined the association between average **Temperature** (temp) and aggregate economic variables using panel data. The main relationship found was a reduced economic growth rates and a lower level of output but the effects are only relevant in poor countries. Dell et al. (2012) Regions near Tropics have naturally higher temperatures average.



Note: Bar chart created using $Excel$. Y-axis measured in ºC.

Figure 3.15: Temperature (country region)

Ethnic Diversity (ethnic) tend to lower a country's economic growth rate because higher levels of ethnic fractionalization are related with unstable democracies Easterly and Levine (1997) and Alesina et al. (2003).
Central Asia and OECD are the economic regions with higher ethnic fractionalization.



Note: Bar chart created using $Excel$. Y-axis measured in %.

Figure 3.16: Ethnic Diversity (country region)

3.4 Descriptive Analysis

The raw variables were transformed using a cubic root transformation that fits better for data with zeros and negative numbers, and the share data we consider as dependent variables – see e.g. Cox (2011). The descriptive statistics (see Table 3.2) show that we have a very diversified unbalanced panel of countries. More than 70 countries with thirteen 5-years period make this a very good sample. The panel data for *csh_g*, *trade* and *hc* was extracted from Penn World Tables 9.0 (PWT) from Feenstra et al. (2015), *gwar* from databanks database (cross-national time-series data archive – CNTS, Wilson (2017)) and *temp*, *pd1* and *ethnic* from Geographically based Economic data (G-Econ) from Nordhaus and Chen (2006). [3]

Table 3.2: Descriptive statistics

Variables	***AR(1)***	***CSD***	***Mean***	***S.D.***	***Min***	***Max***
K_comp	3.47*	31.29***	0.677	.5692	-3.599	2.272
L_comp	8.77***	7.81***	0.435	.5856	-2.736	2.338
A_comp	3.86*	2.98***	0.218	.9210	-3.242	4.111
BTC_comp	0.21	1.26	0.096	.6609	-3.377	3.239
csh_g	169.3***	34.9***	0.179	.0840	.0324	.6342
trade	99.46***	8.56***	-0.034	.0989	-.5745	.3612
hc	6121.83***	110.22***	2.269	.7158	1.009	3.719
gwar	3.49***	1.74	0.402	2.663	0	60.2
pd1			3.176	4.403	.011	23.80
temp			16.60	8.764	-7.929	28.64
ethnic			0.418	.2490	.012	.887

Note: *K_comp* , *L_comp* , *A_comp* and *BTC_comp* are in cubic roots. H_0 of Pesaran (2015) Test: Variable is cross sectional independent. H_0 of Wooldridge (2002) Test: Variable follows an AR(1) process. *** $p < 0.01$, * $p < 0.1$. The $Stata$ commands $xtsum$, $xtcd2$ and $xtserial$ were used to reach the table. There are 719 observations in the sample, covering 71 countries, with a T-bar of 10.127.

[3] For a better view on variables, sources and reference see the appendix Additional Tables A.2.

Chapter 4

Econometric Methodology

4.1 Model Specification

A panel regression is the main method used to analyse two dimensions (country, period). Consider the following panel regression

$$y_{it} \equiv \sigma + v_t\gamma + z_{it}\psi + \varepsilon_{it} \equiv X'\beta + \varepsilon \quad (4.1)$$

with,

$$\beta_{K,1} = \begin{pmatrix} \sigma \\ \gamma \\ \psi \end{pmatrix} \quad (4.2)$$

y_{it} is the dependent variable, the production factor component or tecnology, X is a vector of covariates, β is an unknown coefficient vector. ε_{it} is a vector of errors terms which can be heteroskedastic but with zero conditional mean, thus $E(\varepsilon_{it}|x_{it}) = 0$. Index i refers to country-level observations and t to periods where i=1, ... ,N countries observed over t=1, ... ,T periods. The equation (4.2) error term ε_{it} and the regressand y_{it} contain three components: $\overline{\varepsilon}_i$ and $\overline{x}_i$ represent country-specific effects. f_t and g_t are both vectors of autocorrelated common factors that follow an $AR(1)$ process. ϕ_i and δ_i represent vectors of idiosyncratic factor sensitivities that follow $N(0,1)$. ω_{it} and ξ_{it} are the idiosyncratic errors.

$$\varepsilon_{it} = \overline{\varepsilon}_i + \phi_i f_t + \omega_{it} \quad and \quad x_{it} = \overline{x}_i + \delta_i g_t + \xi_{it} \quad (4.3)$$

If f_t is uncorrelated across time periods we are in presence of time effects but when f_t is persistent we have both time-period effects and persistent common shocks.

4.2 Assessing assumptions

The error term will probably include unobserved components like country-specific effects and business-cycle shocks that are common and persistent that affect all countries. Checking for eventual violations on assumptions is vital for a good estimation in a heterogeneous panel given their sensibility of usual panel estimator if some of the assumptions are violated a robust standard errors estimator will be required. To that end, we performed a set of tests on standardized residuals.

4.2.1 Specification Tests

Table 4.1: Langragian multiplier test of independence

	K_comp	*L_comp*	*A_comp*	*BTC_comp*
Statistics	$\chi^2(1) = 0.00$	$\chi^2(1) = 9.28$***	$\chi^2(1) = 0.69$	$\chi^2(4) = 0.00$

Note: *** $p < 0.01$. H_0 of Breusch and Pagan (1980) Test: $Var(u) = 0$. The $Stata$ command used was $xttest0$.

The Langragian multiplier test of independence was performed to verify if the variance across countries is 0. H_0 is rejected for *L_comp* which means that a random effects estimation is the correct approach for all the others a pooled estimation is the best option.

4.2.2 Distribution of model errors

Table 4.2: Breusch-Pagan and Doornik-Hansen Tests

	Homoskedasticity	Normality
Statistics	$F(1, 717) = 892.932$***	$\chi^2(2) = 1021.003$***

Note: *** $p < 0.01$. Tests executed for K as Dependent variable. H_0 of Breusch and Pagan (1979) Test: Constant variance. H_0 of Doornik and Hansen (2008) Test: Normality of residual term. The $Stata$ commands used were $hettest$ and $mvtest$.

We assess the violation of one of main assumptions of OLS estimation that is the normality of the residuals non-normal errors distorts p-values and confidence intervals. The Gaussian kernel and other normality tests also show the same problem. [1]

The existence of heteroskedasticity was checked using BP test enhanced by a Wooldridge (2013) F-statistic version that drops the normality assumption. Using the rejection of H_0 and a visual assessment [2] we can conclude that the residuals suffer from heteroskedasticity. Heteroskedastic residuals require robust standard errors estimation.

4.2.3 Correlation of model

Table 4.3: Pesaran and Wooldridge Tests

Equation \ Test	Spatial Correlation $N(0,1)$	Serial Correlation $F(1, 70)$
K_comp	11.347***	2.915*
L_comp	1.237	8.746***
A_comp	3.592***	3.843*
BTC_comp	-0.553	0.217

Note: *** $p < 0.01$, * $p < 0.1$. H_0 of Pesaran (2015) Test: Errors are cross sectional independent. H_0 of Wooldridge (2002) Test: Errors do not follow an AR(1) process. The $Stata$ commands used were $xtcd2$ and $xtserial$.

[1] see appendix Additional Figures A.1 for visual confirmation.
[2] see appendix Additional Figures A.2 for visual confirmation.

The Cross-Dependence test detected cross-sectional dependence which originating some complications derived from omitted-variables bias when the regressors are correlated with the unobserved common factors Pesaran (2006). This type of correlation may appear when countries or regions share common shocks Eberhardt (2011). The literature identifies two types of dependence when there is global wide interdependence in the panel – see e.g. Moscone and Tosetti (2010) and spatial dependence – see e.g. Anselin (2001). Goverment consumption, Human capital and Trade have relevant correlated common shocks between cross sections. To check the existence of a AR(1) process in the errors terms a Wooldridge (2002) Test was performed and confirmed the existence of autocorrelation.

4.2.4 Assessing model structure

First, we test the proposed model for omitted and redundant variable bias.

4.2.4.1 Omitted and Redundant Variable Bias

Table 4.4: Ramsey and Pregibon Tests

	Omitted Variables	Redundant Variables
Statistics	$F(3,708) = 1.42$	$N(0,1) = -0.39$

Note: Tests only executed for K as Dependent variable. H_0 of Ramsey (1969) RESET test: model has no omitted variables. Pregibon (1980) Test: Hatsq $p > 0.10$. The $Stata$ commands used were $ovtest$ and $linktest$.

The RESET Test check if we omitted some relevant variable in the specification process, which was not the case. $Linktest$ is a specification test that verify the existence of redundant variables that can warm the quality of the estimation by biasing the regressors, which also validate our specification.

4.2.4.2 Multicollinearity

Table 4.5: VIF and Condition Index

	Mean VIF	Condition Number
Value	1.35	2.62

Note: Tests only executed for K as Dependent variable. The $Stata$ command used was $collin$.

Second, Multicollinearity might be problematic when the VIF and condition number are bigger than 10 because it means that some regressors are closely correlated to one another's biasing the standard errors, distorting confidence intervals and providing less reliable probability values. The absence of multicollinearity is supported with very low conditions numbers and VIF.

4.2.5 Important group of observations

In literature, the first concerns about the unreliableness of the method of ordinary least squares (OLS) in presence of outliers came from Edgeworth (1887). The OLS estimation intends to minimize the squares of the error terms (ε_i).

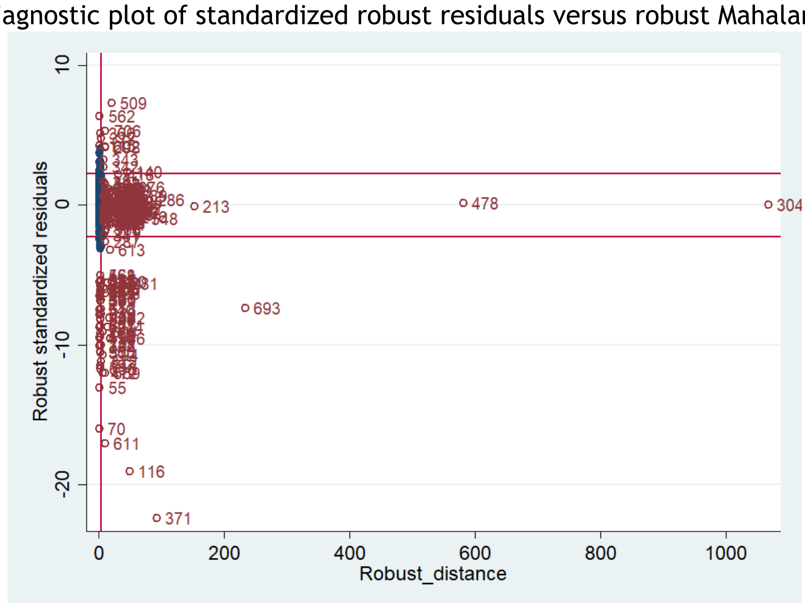
$$min\, J = \sum_{i=1}^{n} \varepsilon_i^2 \quad (4.4)$$

Rousseeuw and Leroy (2003) explain that some of them the vertical outliers and bad leverage points are particularly problematic. Vertical outliers affffect the estimated intercept since the observations have outlying values for the residuals whereas bad leverage points are observations that equally have outlying values but are also far away from the regression line.

We used a graphical tool made by Rousseeuw and van Zomeren (1990) to check them, which is created by plotting, on the Y-axis, the robust standardized residuals, defined as $r_i/\hat{\sigma}^S$, with $\hat{\theta}^S$ being a measure of dispersion robust against extreme values making the residuals less sensitive to these values, proposed by Rousseeuw (1984) for measuring the outlyingness in the fitted regression. On the X-axis is plotted the Mahalanobis (1936) distance that measures outlyingness of the explanatory variables. There are some ways to measuring robust Mahalanobis distance but the most robust that we used is the algorithm proposed by Rousseeuw and Van Driessen (1999) using a minimum covariance determinant. We set the limits proposed by Verardi and Croux (2009), where outside the observations are measured as outliers.

- y dimension, between -2.25 and $+2.25$.
- x dimension, $\sqrt{\chi_p^2, 0.975}$.

Figure 4.1: Diagnostic plot of standardized robust residuals versus robust Mahalanobis distance



Note: The outliers are flagged with red numbers. Scatterplot drawn using $Stata$ commands mcd and $sregress$.

This plot shows that we have some outliers in our dataset, which means that leverage points need to be accounted. Another two visual test using Studentized residuals A.3 and the leverage statistic A.4 reach out to similar conclusions. Table 4.6 summarizes for each of the dependent variable the diagnostic summary and consequently the necessary care to take in each of the regressions presented below.

Table 4.6: Errors diagnosis sum up

Panel	*SEs need to be robust against*
K_comp	overleverage, arbitrary heteroskedasticity, within-panel autocorrelation and cross-panel autocorrelated disturbances.
L_comp	overleverage, arbitrary heteroskedasticity and contemporaneous cross-panel correlation.
A_comp	overleverage, arbitrary heteroskedasticity, within-panel autocorrelation and cross-panel autocorrelated disturbances.
BTC_comp	overleverage and arbitrary heteroskedasticity.

Note: Arbitrary heteroskedasticity is tested in 4.2, overleverage and outliers were checked in 4.1, within-panel autocorrelation and cross-panel autocorrelation is tested in 4.3.

4.3 Robust Estimation

As a result of the last section results we need to address the violation of distribution and correlation of errors assumptions to assure the validity of statistical inference. In the presence of assumptions violated, we use some alternative ways to compute covariances matrix estimators in order to obtain robust standard errors. We made three error correlation assumptions. First, ε_{it} have country-effects when ε_{it} is correlated across time periods for a specific country $E(\varepsilon_{it}\varepsilon_{ik}|x_{it}, x_{ik}) \neq 0$. Second, time-period effects are present at some moment in time there is correlation beetween countries, $E(\varepsilon_{it}\varepsilon_{jt}|x_{it}, x_{jt}) \neq 0$. Lastly when, $E(\varepsilon_{it}\varepsilon_{jk}|x_{it}, x_{jk}) = 0$ if $i \neq j$ and $|t - k| > L$, we are in presence of persistent common shocks that disappear after L lags.

Table 4.7: Error and regressors correlation assumptions

	Errors				**Regressors**			
	K	*L*	*A*	*BTC*	*z1*	*z2*	*z3*	*z4*
Country-Effects	X	X	X	X	X	X	X	X
Time-Effects	X	X	X		X	X	X	X
Persistent common shocks	X		X		X	X	X	
S.E. type	ϑ	ϱ	ϑ	ϖ	-	-	-	-

Notes: ϑ stands for Thompson (2011) standard-errors; ϱ stands for Petersen (2009) standard-errors and ϖ for Arellano (1987) standard errors which is consistent with the information summarized in Table 4.6.

Multi-way clustering was firstly described by Petersen (2009) and generalized after in Cameron et al. (2011) Using the formula with the assumptions defined above

$$\hat{V}_{Double} = \hat{V}_{Country} + \hat{V}_{Period} - \hat{V}_{White} \quad (4.5)$$

where, $\hat{V}_{Country} = \hat{H}^{-1} \sum_{i=1}^{N} (\hat{c}_i \hat{c}_i') H^{-1}$ $\quad \hat{V}_{Period,l} = \hat{H}^{-1} \sum_{t=l+1}^{T} (\hat{s}_t \hat{s}_{t-1}) H^{-1}$

$\hat{V}_{White,l} = \hat{H}^{-1} \sum_{t=l+1}^{N} \sum_{l=1}^{T} (\hat{u}_{it}\hat{u}'_{i,t-1}) H^{-1}$
$\hat{V}_{Period,0}$ is the traditional formula for clustered SE's by Period. $\hat{V}_{White}$ is the common OLS SE's robust to arbitrary heteroskedasticity. $\hat{V}_{White,l}$ and $\hat{V}_{Period,l}$ correct for persistent common shock across panels.

Based on previous works Thompson (2011) upgraded the double-clustering with kernel-robust inference to manage business cycles shocks that disappear after some L periods.

$$\hat{V}_{Double,L|w} = \hat{V}_{Country} + \hat{V}_{Period} + \sum_{l=1}^{L} (\hat{V}_{Period,l} + \hat{V}'_{Period,l}) - \hat{V}_{White} - \sum_{l=1}^{L} (\hat{V}_{White,l} + \hat{V}'_{White,l}) \quad (4.6)$$

K_comp and *A_comp* panels errors and regressors display similar time and country effects which is when the double clustering matters the most. By clustering on country we produce SE's and statistics robust to autocorrelated within-panel disturbances and combining a kernel-based HAC with period clustering we correct for autocorrelated across-panel disturbances. *L_comp* common correlated disturbances are corrected by clustering period and by country – we use the Petersen (2009) standard-errors. For *BTC_comp* panel double clustering is not required, so we can get the right β by clustering on country – we use the Arellano (1987) standard-errors.

Additionally, we tune the variance-covariance matrix to account for the presence of overleverage points. Also some specifications related with HAC inference are done for *K_comp* and *A_comp* . This affects all the dependent variables and is explained in the following sub-sections.

4.3.1 Overleverage and Heteroskedasticity-Robust inference

A weighting function is used to control the effects of high leveraged observations on the calculation of the covariance

$$\omega_t = (1 - h_i)^{\frac{-\delta_i}{2}}, \qquad \delta_i = min(4, h_i/\overline{h}) \quad (4.7)$$

where $h_i = X'_t(X'X)^{-1}X_i$ are the diagonal components of the $H = X'(X'X)^{-1}X'$, $\overline{h}$ is their mean and δ_i is exponential discounting factor that is truncated. Cribari-Neto and da Silva (2011) discuss in detail the effects of these choices and why the *HC4* method is better than the bias-correcting *HC2* or pseudo-jackknife *HC3* proposed in MacKinnon and White (1985) to cope with the presence of influential observations.

4.3.2 Kernel-robust inference

The optimum number of lags is 2 which was calculated Newey and West (1994) lag selection formula the number of lags is reasonable taking into account the fact that we use 5-year averages.

$$m(T) = floor[4(T/100)^{2/9}] \quad (4.8)$$

The Newey and West (1987) kernel smoother function with linearly decaying weights based on HAC inference was employed.

$$\omega_\ell = \frac{\ell}{1+L} \quad (4.9)$$

4.3.3 Panel robust estimation results

Using the specifications mentioned in the previous sections the output came as follows. [3]

Table 4.8: Panel robust estimation results

Regressors \ Dependent Variable	K_comp (*1*)	L_comp (2)	A_comp (*3*)	BTC_comp (*4*)
csh_g	-0.841***	-0.799**	-0.26	0.321
	(0.211)	(0.248)	(0.366)	(0.283)
trade	-0.45***	-0.225	0.413*	0.51***
	(0.061)	(0.151)	(0.245)	(0.181)
hc	0.05	0.008	-0.224**	0.116***
	(0.067)	(0.054)	(0.102)	(0.042)
gwar	-0.002	-0.004	0.024	-0.011
	(0.074)	(0.028)	(0.137)	(0.108)
pd1	-0.001	0.01	-0.002	0.017***
	(0.003)	(0.006)	(0.006)	(0.005)
temp	0.001	0.005	-0.016***	0.0017
	(0.005)	(0.003)	(0.006)	(0.003)
ethnic	-0.201***	0.296**	-0.182	0.124
	(0.071)	(0.091)	(0.11)	(0.112)
Constant	0.765***	0.296*	1.127***	-0.337**
	(0.241)	(0.179)	(0.397)	(0.157)
Wald $F(7,711)$	3.349***	2.028**	2.68***	3.097***
Method	Pooled	Random	Pooled	Pooled

Note: Regressors are defined in the first column of the Table. Dependent Variables are defined in the first row of the Table. Values in parentheses below the observed coefficients are the Thompson (2011) two-way cluster and kernel-robust SE's (*1* and *3*), Petersen (2009) two-way clustered-robust SE's (2) and Arellano (1987) one-way cluster-robust SE's (*4*). Level of significance: *** for p-value > 0.01, ** for > 0.05, * for > 0.1. To reach the results we used R package plm created by Croissant et al. (2017). For (*1*) and (*3*) equations we applying a block building process which was built using the commands $vcovSCC$ and $vcovHC$. Equation (2) used the command $vcovDC$ and (*4*) the $vcovHC$. All *4* equations use Cribari-Neto and da Silva (2011) $HC4$ weighting function. (*1* and *3*) and Newey and West (1987) kernel-smother with 2 lags.

From the analysis of Table 4.8 we can note that the physical capital contribution is strongly influenced by the government share in the economy as well as by trade and ethnic diversification. This indicates a potentially strong crowding-out effect in the long run that can be associated with intertemporal Ricardian effects on the decision of investments when agents expect higher taxes in the future. This also indicates that the usually negative and significant sign of government expenditures on growth regressions come from the physical capital source of growth. The fact that trade is negatively influencing the physical capital contribution may be explained by an *infant industry argument* and an explanation why openness is not always significant in growth regressions. This also has some support in the literature. For example Madsen (2009) showed that openness is independent of economic growth in much of history but is clearly positively

[3] The algorithm used to reach the results is on appendix R code A.1.

associated with growth when technology is taken into account. This is exactly what our results seem to support, as trade has a positive and highly significant influence on both total factor productivity and biased technical change contribution of growth. Moreover, economic theory also has shown that in some conditions protectionism may increase welfare (see e.g. Tuinstra et al. (2014)). Finally, ethnic diversity has a highly negative effect on the physical capital contribution of growth, which is very much consistent with the empirical literature as in Easterly and Levine (1997) and Alesina et al. (2003).

Interestingly, the government share in income also has a negative effect on the labor share which reinforces our argument toward an intertemporal Ricardian effect in this case on the labor/leisure decisions. Additionally, ethnic diversity appears with a positive effect on the labor contribution, which highlights its potential positive effect on human capital and labor adaptability on the labor market, which also has some support in recent empirical contributions from Hoogendoorn and van Praag (2012) and Maestri (2016). This also indicates that the negative effect that ethnic diversity can have on overall economic growth may come from the investment in physical capital and not in the labor market. The remaining most important results are the significantly negative effect of human capital in the TFP contribution and positive effect in the BTC contribution and a positive effect of historical population density in the BTC contribution. On the one hand, negative effects of human capital in TFP are somewhat unexpected and can be obtained through high duplication effects (see e.g. Jones and Williams (2000)), or complexity effects which may lead to negative scale effects (see e.g. Sequeira et al. (2016)). On the other hand, positive effects of human capital on the biased technical change contribution is an expected result, as human capital is more adapted to work with new investments and thus contribute to a bias toward capital. Additionally this can be a direct consequence of the positive effect of human capital in wages of the more qualified which may lead to an increase in the capital-labor ratio (Acemoglu (2002); Violante (2012)). The positive effect of historical population density in the biased technical change contribution is an interesting effect in line with recent evidence that historically determined investments have influence in today's economic activity (e.g. Dalgaard et al. (2018)). In particular this means that historically more developed regions or countries tend to favor physical capital nowadays, suggesting a channel through which historical persistence of development can occur, i.e., through biased technical change. Finally higher temperatures seem to decrease TFP, suggesting a channel through which temperature (and climate change in general) may affect growth (as shown by e.g. Dell et al. (2012)).

4.3.4 Robustness

Thompson (2011) makes a strong case for double clustering in multivariate regression in which some regressors vary by time and some vary by country but sometimes the most robust method may not be the best option. Cameron et al. (2008) propose a wild-cluster bootstrap low asymptotic requirement that comes is an easy and very robust check even when the cluster number is midsized. Wild bootstrap as first described in Wu (1986) and further in studies Liu (1988) and Mammen (1993) improved the robustness of bootstrap in presence of heteroskedastic errors. Another popular option is pairs bootstrap that resamples the regressand and regressors from the original data (Freedman (1981)). Cameron and Miller (2015) offers a good overview for cluster-robust methods. Hagemann (2017) and Kayhan and Titman (2007) endorse wild bootstrap as viable option to deal with very heterogeneous data and break patterns of dependence, respectively. Cameron and Miller (2015) offers a good overview for cluster-robust methods. Webb (2014) states that wild cluster bootstrap outperforms pairs bootstrap in loss of power derived from asymptotic tests and high leverage observations.

$$y \equiv \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_G \end{bmatrix} = X\beta + \varepsilon \equiv \beta \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_G \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_G \end{bmatrix} \quad (4.10)$$

We have G clusters, index by j, stacked into a vector y and a matrix $X.\beta$ is a vector of unknown parameters. ε designate the OLS residuals for j^{th} cluster that are robust to heteroskedasticity and cluster-correlations. The procedure for a wild cluster bootstrap a la Cameron et al. (2008) comes

$$y_{ji} = X_{ji}\hat{\beta} + f(\hat{\varepsilon}_{ji})v_j \quad (4.11)$$

where j indexes clusters, i indexes observations, and the v derive from the Rademacher distribution. Davidson et al. (2007); Davidson and Flachaire (2008) recommend the usage of built-in Rademacher distribution weights $v_j\,\{-1,1\}$ since they outperform Mammen (1993) two-point distribution. The robustness check using wild-cluster bootstraped SE's gave us the following output results. [4]

Table 4.9: Estimation results with wild-cluster bootstraped SE's

Dependent Variable / Regressors	K_comp (*1*)	L_comp (2)	A_comp (*3*)	BTC_comp (*4*)
csh_g	-0.841***	-0.799**	-0.263	0.321***
	(0.224)	(0.341)	(0.458)	(0.121)
trade	-0.45**	-0.224	0.413	0.512***
	(0.035)	(0.169)	(0.302)	(0.05)
hc	0.05	0.008	-0.224***	0.116***
	(0.042)	(0.054)	(0.068)	(0.028)
gwar	-0.002	-0.004	0.024*	-0.011
	(0.01)	(0.005)	(0.013)	(0.021)
pd1	-0.001	-0.011**	-0.002	0.017***
	(0.007)	(0.005)	(0.007)	(0.006)
temp	0.001	0.004	-0.016***	0.0017
	(0.003)	(0.005)	(0.004)	(0.002)
ethnic	-0.201	0.279**	-0.182	0.124*
	(0.123)	(0.127)	(0.138)	(0.086)
Constant	0.765***	0.396	1.127***	-0.337***
	(0.147)	(0.238)	(0.208)	(0.086)

Note: Regressors are defined in the first column of the Table. Dependent Variables are defined in the first row of the Table. Values in parentheses below the observed coefficients are the Cameron et al. (2008) wild bootstrapped multi-way clustered SE's.Level of significance: *** for p-value > 0.01, ** for > 0.05, * for > 0.1. The number of replications used was 999. To reach the results we used the R package plm created by Graham et al. (2016) applying $cluster.boot$ command.

Monte Carlos simulations done in Yu (2013) proved that Driscoll-Kraay's SE's perform very well

[4] The algorithm used to reach the results is on appendix R code A.1.

in presence of arbitrary common autocorrelated errors but they are inconsistent when country-specific effects are strong and not removed. Despite of Driscoll and Kraay (1998) contribution do not allow fixed and time-period effects dummies in the model Kiefer and Vogelsang (2005) and Vogelsang (2012) provided asymptotic theory to back that prospect and very recently Hoechle (2017) upgraded his $Stata$ command $xtscc$ to handle fixed-effects dummies which is very useful for our situation that correcting country-specifics effects, individual heterogeneity and potential endogeneity is needed. A downside is that $HACSC$ inference is not compatible with $HC4$-style overleverage adjustments unlike Thompson's approach. *BTC_comp* panel errors does not have cross-sectional dependence so there is no need for DK SE's. [5]

Table 4.10: Estimation results with dummy DK SE's

Regressors \ **Dependent Variable**	K_comp (*1*)	L_comp (2)	A_comp (*3*)
csh_g	-0.837***	0.120	-0.62
	(0.267)	(0.310)	(0.563)
trade	-0.968***	-0.094	0.514
	(0.208)	(0.227)	(0.409)
hc	0.25***	0.047	-0.627***
	(0.060)	(0.054)	(0.145)
gwar	-0.004	-0.001	0.033***
	(0.007)	(0.005)	(0.009)
pd1	-0.001	-0.008	-0.013
	(0.011)	(0.014)	(0.025)
temp	0.016*	0.02**	-0.076***
	(0.007)	(0.008)	(0.013)
ethnic	-0.629	1.104***	-1.01**
	(0.396)	(0.262)	(0.465)
Constant	0.765***	-0.247	3.311***
	(0.21)	(0.256)	(0.417)
Fixed Dummy	Country	Country	Country
Wald $F(74, 12)$	12.40***	18.04***	24.13***
R^2	0.161	0.222	0.162

Note: Regressors are defined in the first column of the Table. Dependent Variables are defined in the first row of the Table. Values in parentheses below the observed coefficients are the Driscoll and Kraay (1998) one-way cluster and kernel-robust SE's with Vogelsang (2012) dummies. Level of significance: *** for p-value > 0.01, ** for > 0.05, * for > 0.1 The $Stata$ command $xtscc$ was used. The lag number is 2.

In the robustness results shown on Tables 4.9 and 4.10 most results presented and discussed below Table 4.8 are maintained. For example, physical capital contribution is strongly influenced by the government share in the economy as well as by trade. However the significant effect of ethnic fraccionalization disappears, maintaining its positive and significant effect in the explanation of labor contribution and now also with a marginally significantly positive positive sign in the BTC contribution. This new effect may suggest that more ethnic diversified regions tend to favor capital in detriment of labor. Another possible explanation consistent with the references cited above is that as ethnic diversification favors the labor share (with an effect in wages) it would contribute to firms substitute labor by capital. The government share now appears with a significant and positive effect of the contribution of BTC to growth. For instance, Cozzi and Impullitti (2010) argued that government spending played a significant role in stimulating the wave of innovation that hit the U.S. economy in the late 1970s and in the 1980s, as well as the

[5]The algorithm used to reach the results is on appendix Stata code A.2.

simultaneous increase in inequality and in education attainments. Thus this rise of wage may lead the economy to favor physical capital and thus increasing the capital to labor ratio, which would help to explain this result.

Trade maintains its highly significant and positive effect in the BTC contribution although it looses significance in explaining TFP. Effects of human capital and temperature are maintained. Historical population density appears with an additional significant sign explaining the labor contribution in growth, which together with the maintained positive sign in the explanation of the BTC contribution may suggest that the more developed countries in the past rely nowadays more in physical capital than in labor to grow, which is consistent with the historical persistence of development argued by recent research (see again Dalgaard et al. (2018)). Finally a marginal significant and positive positive effect of guerrilla warfare on the TFP contribution can only be explained by the fact that this TFP contribution cannot be completely associated with technological progress in growth accounting exercises, as it is part of a residual, as is well known in the literature.

Chapter 5

Conclusion

Growth accounting exercises and growth regressions are the most common empirical assessments of the economic growth phenomenon (Barro, 1991, 1997, 1999), one of the main fields of study in macroeconomics. However, those methodologies have been subjected to several criticisms. On the one hand growth accounting often relies on constant shares of the production factors which seems to be counter factual. On the other hand, growth regressions are subject to criticisms due to possible endogeneity led by reverse causality, omitted variables, heterogeneity, and the presence of outliers. In this paper we combine both techniques and address most of the main criticisms raised in the literature. First, we apply a methodology that allows for variable factor shares in growth accounting (due to Zuleta (2012)). Then, we use the growth regression methodology to assess the determinants of each of the contributions of growth. In this sense,we are going further answering the important question: why do some countries grow more than others? In fact, we obtain answers to the question: why do some countries rely more on factor accumulation or on technology to grow? Second, we specifically address the features of the data and account for overleverage points, arbitrary heteroskedasticity, within-panel autocorrelation, and cross-panel autocorrelated disturbances in panel data estimations. Overlooking those features has been at the center of the criticisms raised to growth regressions. Thus we estimate robust panel data regressions to the different factor contributions, total factor productivity and biased technical change contributions.

The most important evidence reveals that government current expenditure (as a ratio to GDP) decreases the factor contributions and has no effect on TFP. Trade, however, affects the TFP and the Biased Technical Change (BTC) contribution, tending to decrease the capital share. Moreover, human capital decreases TFP contribution but increases the BTC contribution to growth. More deeply rooted determinants of development such as ethnic diversity and historical population density also affect factor accumulation, TFP, and BTC in different ways. For example, historical population density tends to decrease the contribution of labor but increase the BTC contribution to growth. Additionally, ethnic diversity tends to raise both the labor and the BTC contribution, but decrease the physical capital contribution. Finally, temperature tends to raise the labor contribution to growth. Looking at the results from a different perspective, capital contribution decreases due to trade, the government consumption share, and ethnic diversity. Labor contribution decreases due to the same determinants but increases due to temperature and ethnic diversity. The TFP contribution increases due to trade but decreases due to human capital. Finally, the Biased Technical Change contribution increases due to trade, human capital, historical population density, and ethnic diversity. Across the different estimation methods, one of the most robust results is the negative effect of government consumption on the contribution of factor accumulation.

Our paper opens prospects for future research. On the methodological side it offers an new approach based on recently developed econometric methods[1] to deal with critical aspects in growth regressions. On the results side, it highlights that different determinants may explain different sources of growth (production factors and technology) and growth regressions may be misleading when trying to explain overall growth. A direct suggestion for future research is to account for different determinants of growth of production factors (e.g. capital) and technology. This suggestion includes the study of the influence of proximate determinants of growth such as human capital and more deeply historically rooted or geographical determinants such as temperature or historical population density.

[1]Those methods have been applied in other contexts, namely in microeconometrics, but never to approach the economic growth regressions problems.

Bibliography

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, 40(1):7–72. 3, 22

Ades, A. and Di Tella, R. (1997). National champions and corruption: some unpleasant interventionist arithmetic. *The Economic Journal*, 107(443):1023–42. 4

Aisen, A. and Veiga, F. J. (2013). How does political instability affect economic growth? *European Journal of Political Economy*, 29:151–167. 11

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003). Fractionalization. *Journal of Economic Growth*, 8(2):155–194. 12, 22

Alesina, A., Osler, S., Roubini, N., and Swagel, P. (1996). Political Instability and Economic Growth. *Journal of Economic Growth*, 1(2):189–211. 11

Anselin, L. (2001). Spatial Econometrics. In A companion to theoretical econometrics. *Baltagi B (ed), Oxford: Basil Blackwell*, pages 310–330. 17

Arellano, M. (1987). Computing Robust Standard Errors for Within-Group Estimators. *Oxford Bulletin of Economics and Statistics*, 49:431–434. x, 19, 20, 21

Ashraf, Q. and Galor, O. (2012). Human Genetic Diversity and Comparative Economic Development. *American Economic Review*, pages 1–73. 11

Barro, R. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2):407. 3, 27

Barro, R. (1997). Determinants of Economic Growth: A Cross-Country Empirical Study. *Foreign Affairs*, 76(6):154. 9, 27

Barro, R. (1999). Notes on Growth Accounting. *Journal of Economic Growth*, 4(2):119–137. 3, 27

Benhabib, S. (1994). The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data. *Journal of Monetary Economics*, 34:143–173. 10

Bental, B. and Demougin, D. (2009). Declining Labor Shares and Bargaining Power: An Institutional Explanation. *Journal of Macroeconomics*, 32(1):443–456. 3

Bertrand, M., Mullainathan, S., and Duflo, E. (2002). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, (May):1–36. 4

Blanchard, O. (1997). The Medium Run. *Brookings Papers on Economic Activity*, pages 89–158. 3

Breusch, T. and Pagan, A. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47(5):1287–1294. 16

Breusch, T. and Pagan, A. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, 47(1):239. 16

Brock, W. A. and Durlauf, S. N. (2001). Growth Empirics and Reality. *The World Bank Economic Review*, 15(2):229–272. 2

Brown, P. and Weber, B. (1953). Accumulation, Productivity and Distribution in the British Economy, 1870-1938. *The Economic Journal*, 63(250):263. 3

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). Bootstrap-Based Improvements for Inference with Clustered Errors. *Review of Economics and Statistics*, 90(3):414–427. 22, 23

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business and Economic Statistics*, 29(2):238–249. 19

Cameron, A. C. and Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, 50(2):317–372. 22, 23

Caselli, F. and Feyrer, J. (2007). The Marginal Product of Capital. *The Quarterly Journal of Economics*, 122(2):535–568. 3

Cohen, D. and Soto, M. (2007). Growth and human capital: good data, good results. *Journal of Economic Growth*, 12(1):51–76. 10

Cox, N. J. (2011). Stata tip 96: Cube roots. *Stata Journal*, 11(1):149–154. 13

Cozzi, G. and Impullitti, G. (2010). Government Spending Composition, Technical Change, and Wage Inequality. *Journal of the European Economic Association*, 8(6):1325–1358. 24

Cribari-Neto, F. and da Silva, W. B. (2011). A new heteroskedasticity-consistent covariance matrix estimator for the linear regression model. *AStA Advances in Statistical Analysis*, 95(2):129–146. 2, 20, 21

Croissant, Y., Millo, G., and Tappe, K. (2017). Linear Models for Panel Data. 21

Dalgaard, C.-J., Kaarsen, N., Olsson, O., and Selaya, P. (2018). Roman Roads to Prosperity: Persistence and Non-Persistence of Public Goods Provision. 22, 25

Davidson, J., Monticini, A., and Peel, D. (2007). Implementing the wild bootstrap using a two-point distribution. *Economics Letters*, 96(3):309–315. 23

Davidson, R. and Flachaire, E. (2008). The wild bootstrap, tamed at last. *Journal of Econometrics*, 146(1):162–169. 23

Dell, M., Jones, B., and Olken, B. (2012). Climate Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, 4(3):66ß95. 12, 22

Dollar, D. (1992). Outward-oriented developing economies really do. *Economic Development and Cultural Change*, 40 (3):523–544. 9

Doornik, J. A. and Hansen, H. (2008). An omnibus test for univariate and multivariate normality. *Oxford Bulletin of Economics and Statistics*, 70(SUPPL. 1):927–939. 16

Driscoll, J. and Kraay, A. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics*, 80(4):549-560. 24

Durlauf, S. N. (2005). Complexity and empirical economics. *Economic Journal*, 115(504). 2

Easterly, W. (2005). Chapter 15 National Policies and Economic Growth: A Reappraisal. In *Handbook of Economic Growth*, volume 1, pages 1015–1059. 2, 4

Easterly, W. and Levine, R. (1997). Africa's Growth Tragedy: Policies and Ethnic Divisions. *The Quarterly Journal of Economics*, 112(4):1203–1250. 12, 22

Easterly, W. and Levine, R. (2001). It's Not Factor Accumulation: Stylized Facts and Growth Models. *The World Bank Economic Review*, 15(2):177–219. ix, 1

Easterly, W. and Levine, R. (2003). Tropics, germs, and crops: How endowments influence economic development. *Journal of Monetary Economics*, 50(1):3–39. 4

Easterly, W. and Rebelo, S. (1993). Fiscal policy and economic growth. *Journal of Monetary Economics*, 32(3):417–458. 4

Eberhardt, M. (2011). Panel time-series modeling: New tools for analyzing xt data. *United Kingdom Stata Users' Group Meetings 2011*, (September):1–42. 1, 17

Edgeworth, F. (1887). On Observations Relating to Several Quantities. *Hermathena*, 6(13):279–285. 18

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the penn world table. *American Economic Review*, 105(10):3150–3182. 13

Fischer, S. (1993). The Role of Macroeconomic Factors in Growth. *National Bureau of Economic Research Working Paper Series*, No. 4565. 4

Frankel, J. A. and Romer, D. (1999). Does trade cause growth? *American Economic Review*, 89(3):379–399. 9

Freedman, D. (1981). Bootstrapping Regression Models. *The Annals of Statistics*, 9(6):1218–1228. 22

Graham, N., Arai, M., and Hagströmer, B. (2016). multiwayvcov: Multi-Way Standard Error Clustering. 23

Hagemann, A. (2017). Cluster-Robust Bootstrap Inference in Quantile Regression Models. *Journal of the American Statistical Association*, 112(517):446–456. 22

Hall, R. and Jones, C. (1999). Why do Some Countries Produce So Much More Output Per Worker than Others? *The Quarterly Journal of Economics*, 114(1):83–116. ix, 1

Hoechle, D. (2017). XTSCC: Stata module to calculate robust standard errors for panels with cross-sectional dependence. 24

Hoogendoorn, S. and van Praag, M. (2012). Ethnic Diversity and Team Performance: A Field Experiment. *IZA Discussion Papers*, (6731). 22

Jones, C. and Williams, J. (2000). Too Much of a Good Thing ? The Economics of Investment in R & D. *Journal of Economic Growth*, 85(March):65–85. 22

Kaffine, D. T. and Davis, G. A. (2017). A multi-row deletion diagnostic for influential observations in small-sample regressions. *Computational Statistics and Data Analysis*, 108:133–145. 2

Kahn, J. A. and Lim, J.-S. (1998). Skilled Labor-Augmenting Technical Progress in U. S. Manufacturing. *The Quarterly Journal of Economics*, 113(4):1281–1308. 3

Kaldor, N. (1961). Capital Accumulation and Economic Growth. *The Theory of Capital*, pages 177–222. 3

Kayhan, A. and Titman, S. (2007). Firms' histories and their capital structures. *Journal of Financial Economics*, 83(1):1–32. 22

Keynes, J. M. (1939). Relative Movement of Real Wages and Output. *The Economic Journal*, 49(193):34–51. 3

Kiefer, N. M. and Vogelsang, T. J. (2005). A new asymptotic theory for heteroskedasticity-autocorrelation robust tests. *Econometric Theory*, 21(6):1130–1164. 24

Krueger, A. (1999). Measuring labor's share. *American Economic Review*, 89(2):45–51. 3

Levine, R. (1997). Financial Development and Economic Growth : Views and Agenda. *Journal of Economic Literature*, XXXV(June):688–726. 4

Levine, R. (2005). *Finance and Growth: Theory and Evidence*. 4

Ley, E. and Steel, M. (2009). On the effect of prior assumptions in Bayesian model averaging with applications to growth regression. *Journal of Applied Econometrics*, 24(4):651–674. 2

Liu, R. Y. (1988). Bootstrap procedures under some non-i.i.d. models. *The Annals of Statistics*, 16(4):1696–1708. 22

MacKinnon, J. G. and White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics*, 29(3):305–325. 20

Madsen, J. B. (2009). Trade Barriers, Openness, and Economic Growth. *Southern Economic Journal*, 76(2):397–418. 21

Maestri, V. (2016). Can ethnic diversity have a positive effect on school achievement? *Education Economics*, 0(0):1–14. 22

Mahalanobis, P. (1936). On the generalised distance in statistics. *Proceedings of the National Institute of Sciences of India*, 2(1):49–55. 18

Majid, N. (2004). What is the effect of trade openness on wages ? *International Labour Office*. 10

Mallick, S. and Sousa, R. (2017). The Skill Premium Effect of Technological Change: New Evidence from the US Manufacturing Sector. *International Labour Review*, pages 113-131. 3

Mammen, E. (1993). Bootstrap and Wild Bootstrap for High Dimensional Linear Models. *The Annals of Statistics*, 21(1):255–285. 22, 23

Microsoft Corporation (2016). Microsoft Office Excel. 5

Millo, G. (2017). Robust Standard Error Estimators for Panel Models: A Unifying Approach. *Journal of Statistical Software*, 82(3). 2

Moscone, F. and Tosetti, E. (2010). Testing for error cross section independence with an application to US health expenditure. *Regional Science and Urban Economics*, 40(5):283–291. 17

Mulligan, C. and Sala-i Martin, X. (1997). A labor income-based measure of the value of human capital: An application to the states of the United States. *Japan and the World Economy*, 9(2):159–191. 10

Nakamura, E., Sergeyev, D., and Steinsson, J. (2017). Growth-rate and uncertainty shocks in consumption: Cross-country evidence. *American Economic Journal: Macroeconomics*, 9(1):1–39. 1

Newey, W. and West, K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703. 21

Newey, W. and West, K. (1994). Automatic Lag Selection in Covariance Matrix Estimation. *The Review of Economic Studies*, 61(4):631–653. 20

Nordhaus, W. and Chen, X. (2006). Geographically based Economic data (G-Econ). 13

Paulo, R. (2016). PhD Thesis Template for Universidade da Beira Interior. 1

Pesaran, M. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4):967–1012. 17

Pesaran, M. (2015). Testing Weak Cross-Sectional Dependence in Large Panels. *Econometric Reviews*, 34(6-10):1089–1117. 13, 16

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1):435–480. x, 19, 20, 21

Pregibon, D. (1980). Goodness of link tests for generalized linear models. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 29(1):15–23. 17

Pritchett, L. and Aiyar, Y. (2015). Taxes: Price of Civilization or Tribute to Leviathan. *SSRN Electronic Journal*, pages 1–20. 9

R Development Core Team (2017). R: A Language and Environment for Statistical Computing. 5

Ramsey, J. (1969). Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis. *Journal of the Royal Statistical Society. Series B (Methodological)*, 31(2):350–371. 17

Reinhart, C. M. and Rogoff, K. S. (2010). Growth in a time of debt. *American Economic Review*, 100(2):573–578. 9

Rousseeuw, P. (1984). Least median of squares regression. *Journal of the American Statistical Association*, 79(388):871–880. 18

Rousseeuw, P. and Leroy, A. (2003). *Robust regression and outlier detection*. Wiley-Interscience, New York. 18

Rousseeuw, P. and Van Driessen, K. (1999). A fast algorithm for the minimum covariance determinant estimator. *Technometrics*, 41(3):212–223. 18

Rousseeuw, P. and van Zomeren, B. (1990). Unmasking multivariate outliers and leverage points. *Journal of the American Statistical Association*, 85(411):633–639. 18

Sala-i Martin, X. X. (1997). I Just Ran Two Million Regressions. *American Economic Review*, 87(2):178–183. 1, 2

Sequeira, T., Gil, P. M., and Afonso, O. (2016). Growth without scale effects due to entropy. FEP Working Paper 575. 22

Solow, R. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of*

Economics, 70(1):65–94. ix, 1

Solow, R. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, 39(3):312. 3

StataCorp (2015). STATA Data Analysis & Statistical Software. 5

Sturgill, B. (2012). The relationship between factor shares and economic development. *Journal of Macroeconomics*, 34(4):1044–1062. 3

Sturgill, B. (2014). Back to the basics: Revisiting the development accounting methodology. *Journal of Macroeconomics*, 42:52–68. 3

Sunde, U. and Vischer, T. (2015). Human capital and growth: Specification matters. *Economica*, 82(326):368–390. 10

Teixeira, A. A. and Queirós, A. S. (2016). Economic growth, human capital and structural change: A dynamic panel data analysis. *Research Policy*, 45(8):1636–1648. 10

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics*, 99(1):1–10. x, 1, 2, 19, 20, 21, 22

Tuinstra, J., Wegener, M., and Westerhoff, F. (2014). Positive welfare effects of trade barriers in a dynamic partial equilibrium model. *Journal of Economic Dynamics and Control*, 48. 22

Verardi, V. and Croux, C. (2009). Robust regression in Stata. *Stata Journal*, 9(3):439–453. 18

Violante, G. L. (2012). Skill-biased Technical Change. *The New Palgrave Dictionary of Economics, 2012 Version*. 22

Vogelsang, T. J. (2012). Heteroskedasticity, autocorrelation, and spatial correlation robust inference in linear panel models with fixed-effects. *Journal of Econometrics*, 166(2):303–319. 24

Webb, M. (2014). Reworking Wild Bootstrap Based Inference for Clustered Errors. *Queen's Economics Department Working Paper*, 1315:1 – 23. 23

Wilson, K. A. (2017). Cross-National Time-Series Data Archive. 13

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. 13, 16, 17

Wooldridge, J. M. (2013). *Introductory econometrics: a modern approach*. Cengage Learning, sixth edit edition. 16

Wu, C.-F. (1986). Rejoinder: Jackknife, Bootstrap and Other Resampling Methods in Regression Analysis. *The Annals of Statistics*, 14(4):1343–1350. 22

Yanikkaya, H. (2003). Trade openness and economic growth: A cross-country empirical investigation. *Journal of Development Economics*, 72(1):57–89. 9

Yu, S. (2013). *"Three Essays on Robust Inference for Linear Panel Models with Many Time Periods*. PhD thesis, Michigan State University. 2, 23

Zuleta, H. (2008). An empirical note on factor shares. *Journal of International Trade and Economic Development*, 17(3):379–390. ix, 1

Zuleta, H. (2012). Variable factor shares, measurement and growth accounting. *Economics Letters*, 114(1):91–93. ix, 1, 5, 27

Appendix A

Appendix

A.1 R Code

Algorithm 1: R Code

```
install.packages("plm")
install.packages("lmtest")
install.packages("car")
install.packages("sandwich")
install.packages("multiwayvcov")
install.packages("readx1")

library(readx1)
library(plm)
library(lmtest)
library(car)
library(sandwich)
library(multiwayvcov)

library(readxl)
dataset <- read_excel("C:/Users/xxx/Desktop/dataset.xls")

mainData = dataset

mainData$k = as.numeric(mainData$k)
mainData$l = as.numeric(mainData$l)
mainData$a = as.numeric(mainData$a)
mainData$btc = as.numeric(mainData$btc)
mainData$x1 = as.numeric(mainData$x1)
mainData$x2 = as.numeric(mainData$x2)
mainData$x3 = as.numeric(mainData$x3)
mainData$x4 = as.numeric(mainData$x4)
mainData$v1 = as.numeric(mainData$v1)
mainData$v2 = as.numeric(mainData$v2)
mainData$v3 = as.numeric(mainData$v3)

 /* Define panel dataset */
dataset <- pdata.frame(mainData, index=c("panelid","timeid"))

```

```
 /* Define panel regression */
z1 <- plm(k~x1+x2+x3+x4+v1+v2+v3, data=dataset, model="pooling")
z2 <- plm(l~x1+x2+x3+x4+v1+v2+v3, data=dataset, model="random")
z3 <- plm(a~x1+x2+x3+x4+v1+v2+v3, data=dataset, model="pooling")
z4 <- plm(btc~x1+x2+x3+x4+v1+v2+v3, data=dataset, model="pooling")

 /* Define panel bootstrap regression */
b1 <- lm(k~x1+x2+x3+x4+v1+v2+v3, data=dataset)
b2 <- lm(l~x1+x2+x3+x4+v1+v2+v3, data=dataset)
b3 <- lm(a~x1+x2+x3+x4+v1+v2+v3, data=dataset)
b4 <- lm(btc~x1+x2+x3+x4+v1+v2+v3, data=dataset)

 /* Calculate Thompson (2011) VCE */
myvcovDCS <- function(x, maxlag = NULL, ...) {
  w1 <- function(j, maxlag) 1-j/(maxlag+1)
  VsccL.1 <- vcovSCC(x, maxlag = maxlag, wj = w1, ...)
  Vcx <- vcovHC(x, cluster = "group", method = "arellano", type="HC4",
      ...)
  VnwL.1 <- vcovSCC(x, maxlag = maxlag, inner = "white", wj = w1, ...)
  return(VsccL.1 + Vcx - VnwL.1)
}
/* Calculate Thompson (2011) SE's, Peterson SE's (2009) and Arellano (1987)
     SE's with Cribari correction */
coeftest(z1, vcov.=myvcovDCS, maxlag=2)
coeftest(z2, vcov.=function(x) vcovDC(x, type="HC4"))
coeftest(z3, vcov.=myvcovDCS, maxlag=2)
coeftest(z4, vcov.=function(x) vcovHC(x, cluster = "group", method = "
    arellano", type="HC4"))

 /* Statistics */
z1_summary <- summary(z1)
Fstat <- z1_summary[["fstatistic"]]
z2_summary <- summary(z2)
Fstat <- z1_summary[["fstatistic"]]
z3_summary <- summary(z3)
Fstat <- z3_summary[["fstatistic"]]
z4_summary <- summary(z4)
Fstat <- z4_summary[["fstatistic"]]

 /* Activate cores (4) for wild bootstrapping */
require(parallel)
cl <- makeCluster(4)
options(boot.ncpus = 4)

 /* Wild bootstrapping SE's estimation */
boot1<- cluster.boot(b1,~panelid+timeid, parallel = TRUE, R = 999,
    use_white=NULL, force_posdef = TRUE, boot_type = "wild", wild_type = "
```

```
    rademacher")
boot2<- cluster.boot(b2,~panelid+timeid, parallel = TRUE, R = 999,
    use_white=NULL, force_posdef = TRUE, boot_type = "wild", wild_type = "
    rademacher")
boot3<- cluster.boot(b3,~panelid+timeid, parallel = TRUE, R = 999,
    use_white=NULL, force_posdef = TRUE, boot_type = "wild", wild_type = "
    rademacher")
boot4<- cluster.boot(b4,~panelid+timeid, parallel = TRUE, R = 999,
    use_white=NULL, force_posdef = TRUE, boot_type = "wild", wild_type = "
    rademacher")
 /* Wild bootstrapping tables output */
coeftest(b1, boot1)
coeftest(b2, boot2)
coeftest(b3, boot3)
coeftest(b4, boot4)
```

A.2 Stata Code

Algorithm 2: Stata code

```
clear all
use statadataset1 , clear
set more off
ssc install xtscc, replace
ssc install xtserial
ssc install xtcd2
ssc install sregress
ssc install mcd

xtset panelid timeid  /* declare panel dataset */
xtsum k-v3  /* obtain the summary statistics: */

/* Driscoll-Kraay Dummies: */
xtscc k x1-v3 i.panelid, lag(2)
xtscc l x1-v3 i.panelid, lag(2)
xtscc a x1-v3 i.panelid, lag(2)

***
 /* Regression Analysis */
qui xtreg K x1-v3, fe
qui xtreg K x1-v3, re
xttest0 /* LM Test */

qui reg k x1-v3
predict r1, rstandard
```

```
collin k x1-v3, corr /* Multicollinearity */     /* or */
vif
hettest r1, fstat   /* heteroskedasticity */
ovtest    /* omitted variables */
linktest    /* redundancy */
mvtest normality r1  /* normality */
xtserial r1     /* AR(1) */
xtcd2 r1   /* CSD */

qui reg l x1-v3
predict r2, rstandard
hettest r2, fstat
mvtest normality r2
xtserial r2
xtcd2 r2

qui reg a x1-v3
predict r3, rstandard
hettest r3, fstat
mvtest normality r3
xtserial r3
xtcd2 r3

qui reg btc x1-v3
predict r4, rstandard
hettest r4, fstat
mvtest normality r4
xtserial r4
xtcd2 r4
***
/* Bar charts */
graph bar k l a btc if hl==0, ytitle(Low Income)
graph bar k l a btc if hl==1, ytitle(High Income)
***
/* Leverage plot */
sregress k x1-v3, graph
/* Scatterplots */
twoway (scatter x1 period)
twoway (scatter x2 period)
twoway (scatter x3 period)
twoway (scatter x4 period)
twoway (scatter v1 period)
twoway (scatter v2 period)
twoway (scatter v3 period)

/* Bar charts */
graph bar (mean) k l a btc if oecd==1, ytitle(OECD)
```

```
graph bar (mean) k l a btc if lat==1, ytitle(Latin America)
graph bar (mean) k l a btc if africa==1, ytitle(Africa)
graph bar (mean) k l a btc if casia==1, ytitle(Central Asia)
graph bar (mean) k l a btc if sasia==1, ytitle(South Asia)
graph bar (mean) k l a btc if oceania==1, ytitle(Oceania)
graph bar (mean) k l a btc if europe==1, ytitle(Europe)

/* Residual Analysis (Appendix) */
rvfplot2, ms(oh) yline(0)        /* Visual Heteroskedasticity */
kdensity r1, normal   /* Visual Residual Normality*/
indexplot, show(rstudent) ms(oh) yline(-3) yline(3) mlabe(n) /*Studentized Residuals */
lvr2plot, ms(oh) mlabel(n) /* Leverage */

/* Variable Construction - Dont run */
/* Cubic Root Transform */
gen K=sign(k_comp) * abs(k_comp)^(1/3)
gen L=sign(l_comp) * abs(l_comp)^(1/3)
gen A=sign(a_comp) * abs(a_comp)^(1/3)
gen BTC=sign(btc_comp) * abs(btc_comp)^(1/3)

/* Zuleta (2012) Methodology */
generate d1ksh=(1-labsh[_n])-(1-labsh[_n-1])
gen gy=((rgdpo[_n])/(rgdpo[_n-1]))^(1/5)-1
gen gk=((ck[_n])/(ck[_n-1]))^(1/5)-1
gen gl=((emp[_n])/(emp[_n-1]))^(1/5)-1
gen S=gY-(gK*(1-labsh)+labsh*gL)
gen Stilda=S-d1ksh*ln(ck/emp)
gen ga=Stilda-c1*d1ksh
by country: reg Stilda d1ksh, robust
```

A.3 Additional Tables

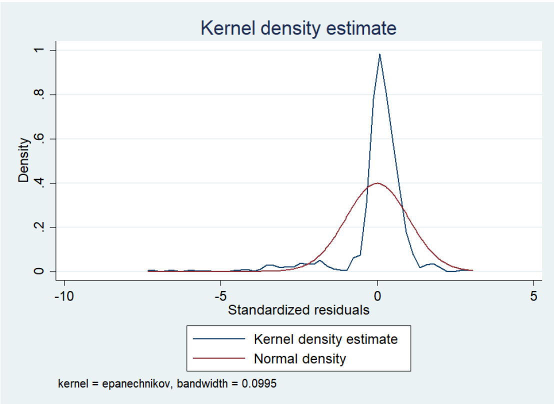
Table A.1: List of countries

Countries						
Australia	Argentina	France	Georgia	Mozambique	Kenya	Niger
Benin	Armenia	Côte d'Ivoire	Sierra Leone	New Zealand	Tajikistan	Central African Republic
China	Austria	United Kingdom	Taiwan	Panama	Poland	Croatia
Colombia	Azerbaijan	Japan	Greece	Peru	South Africa	Guatemala
Costa Rica	Bulgaria	Honduras	Lebanon	Sudan	Denmark	Kazakhstan
Czech Republic	Burkina Faso	Philippines	Burundi	Uruguay	Belarus	Israel
Dominican Republic	Cameroon	Nicaragua	Bolivia	Paraguay	Italy	Serbia
Ecuador	Canada	Guinea	United States	Portugal	Romania	Switzerland
Germany	Chad	Russian Federation	Belgium	Rwanda	Singapore	Senegal
Hong Kong	Chile	Ukraine	Netherlands	Saudi Arabia	Slovakia	Turkey
Indonesia	Egypt	Togo	Finland	Tanzania	Jordan	Mexico
Iraq	Hungary	Spain	Kyrgyzstan	Venezuela	Laos	Mongolia
Kuwait	Iran	Sweden	India	Zimbabwe	Malaysia	Nigeria
Lithuania	Ireland	Tunisia	Thailand	Brazil	Jamaica	Norway
Sri Lanka	South Korea	Morocco				

Table A.2: Variables, Label and Source

Regressors	Label	Source
Government current expenditure	csh_g	PWT
Trade openness	trade	PWT
Human capital per person	hc	PWT
Guerrila warfare	gwar	CNTS
Population density in 1 CE	pd1	G-ECON
Temperature	temp	G-ECON
Ethnic diversity	ethnic	G-ECON

A.4 Additional Figures

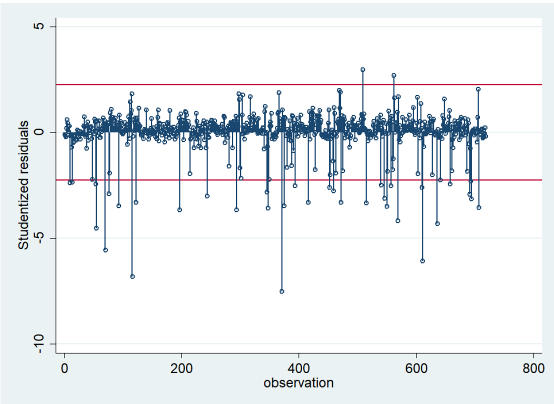


Note: Graph created using $Stata$ command $kdensity$.

Figure A.1: Gaussian kernel density estimation.

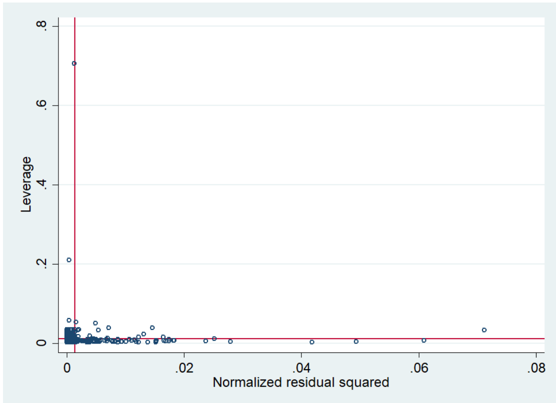
Note: Graph created using $Stata$ command $rvfplot2$.

Figure A.2: Heteroskedasticity Visual Test



Note: Plot created using $Stata$ command $indexplot$.

Figure A.3: Studentized (jackknifed) residuals.



Note: Plot created using $Stata$ command $lvr2plot$.

Figure A.4: Leverage against squared residual plot

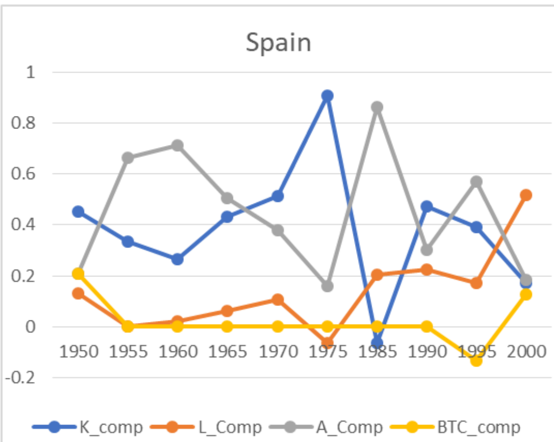


Figure A.5: Factor Contribution Spain 1950-2000

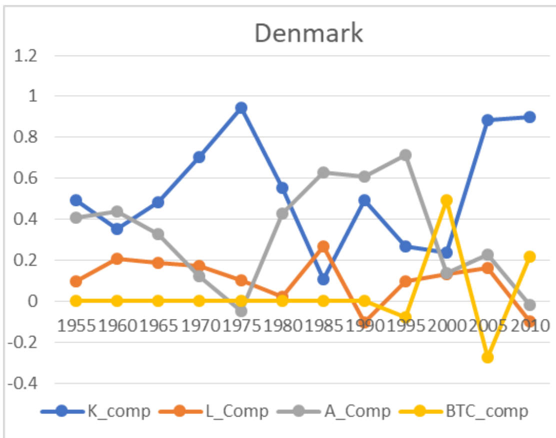


Figure A.6: Factor Contribution Denmark 1950-2015

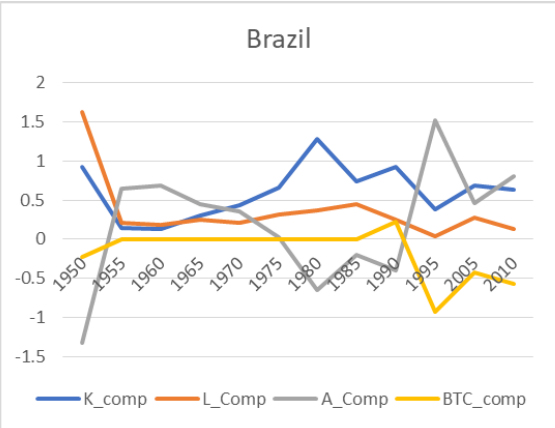


Figure A.7: Factor Contribution Brazil 1950-2015

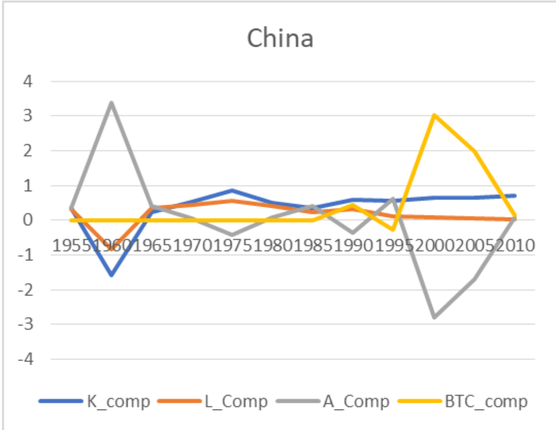


Figure A.8: Factor Contribution China 1950-2015

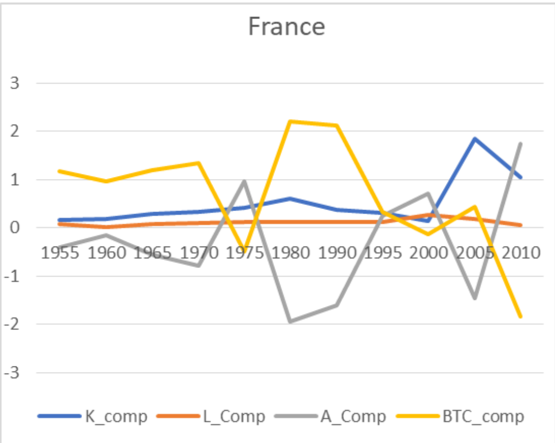


Figure A.9: Factor Contribution France 1950-2015

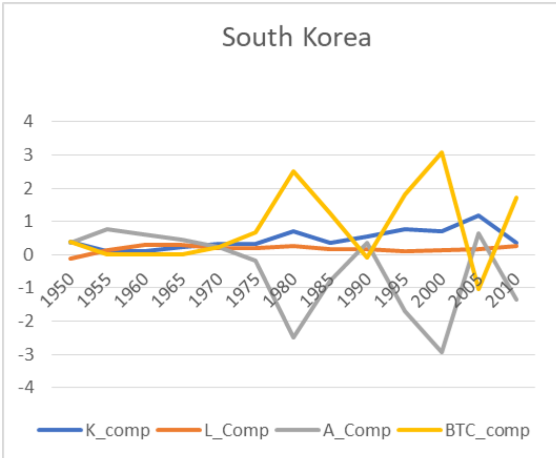


Figure A.10: Factor Contribution South Korea 1950-2015

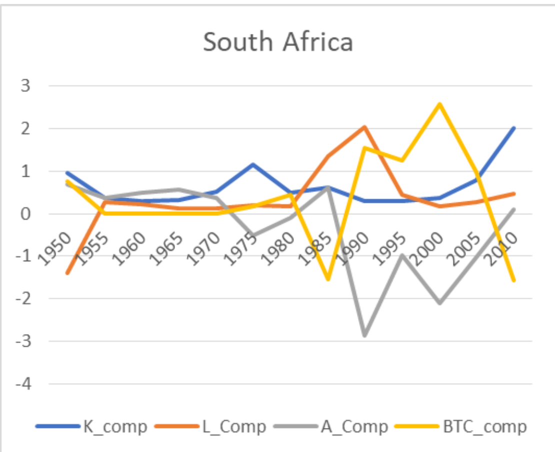


Figure A.11: Factor Contribution South Africa 1950-2015

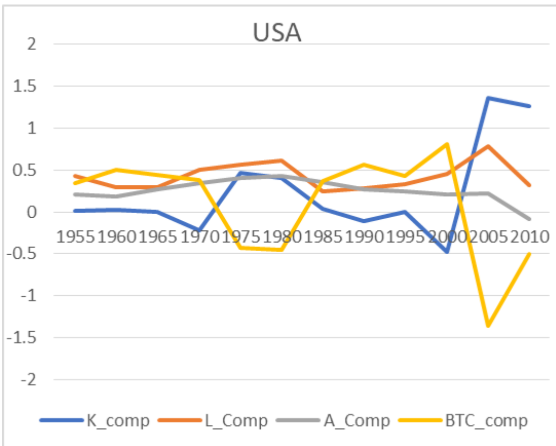


Figure A.12: Factor Contribution USA 1950-2015

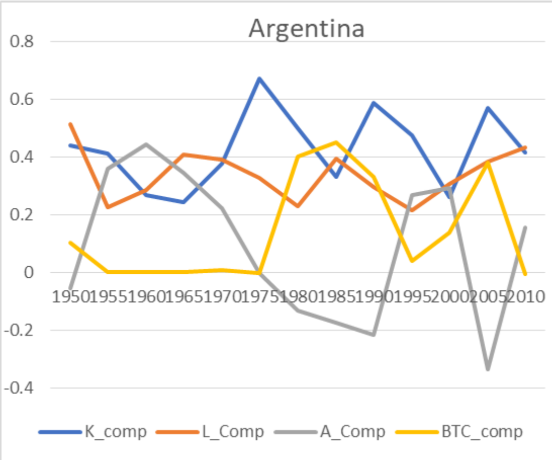


Figure A.13: Factor Contribution Argentina 1950-2015

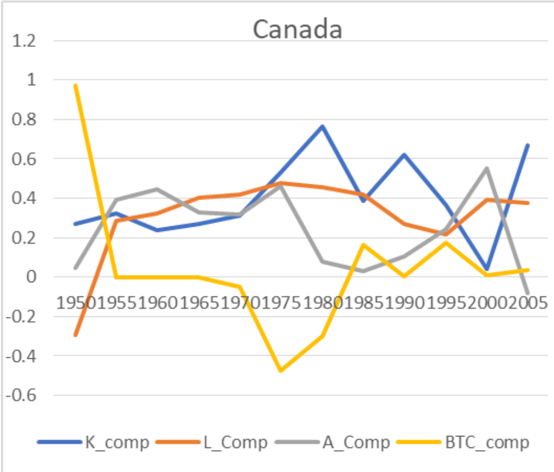


Figure A.14: Factor Contribution Canada 1950-2015

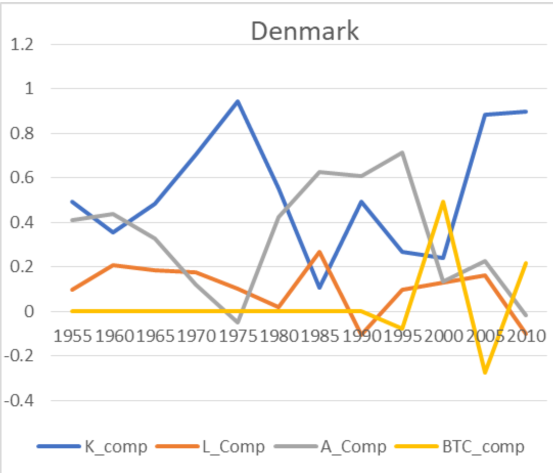


Figure A.15: Factor Contribution Denmark 1950-2015

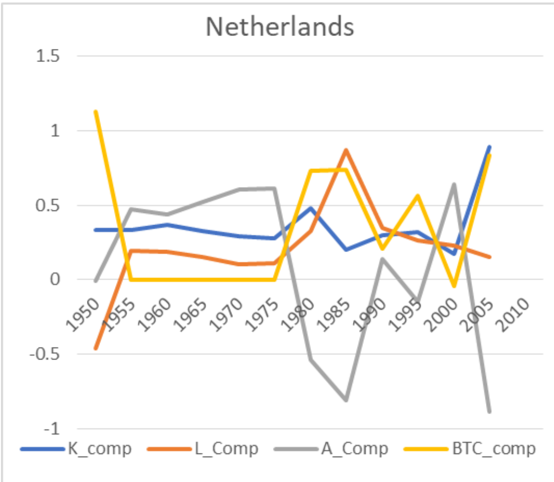


Figure A.16: Factor Contribution Netherlands 1950-2015

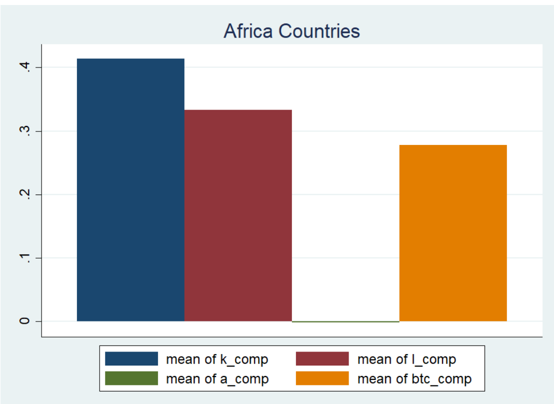


Figure A.17: Factor Contribution Africa countries 1950-2015

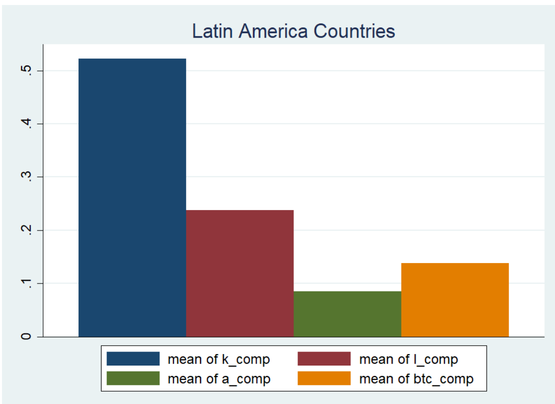


Figure A.18: Factor Contribution Latin America countries 1950-2015

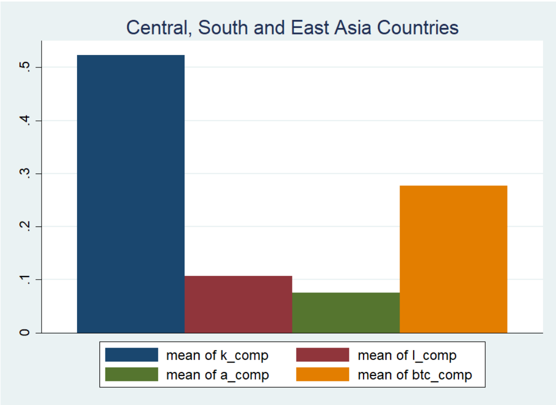


Figure A.19: Factor Contribution Central,South and East Asia 1950-2015

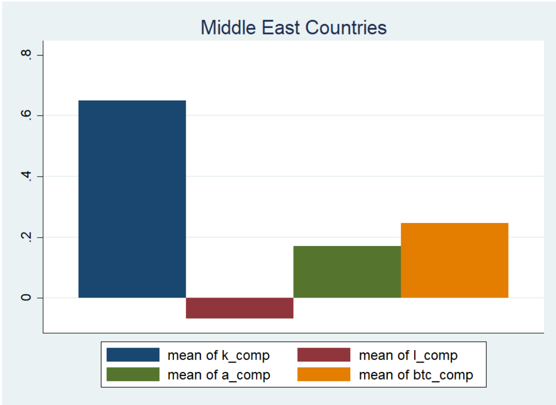


Figure A.20: Factor Contribution Middle East countries 1950-2015

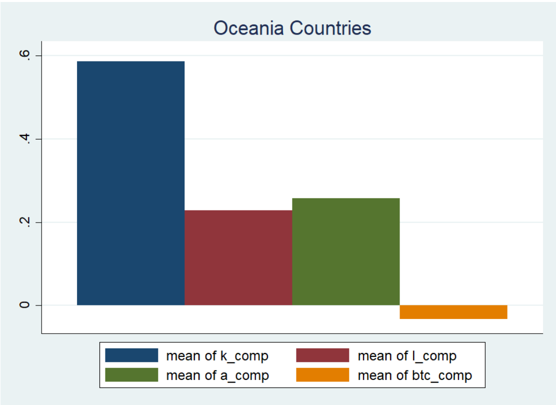


Figure A.21: Factor Contribution Oceania countries 1950-2015

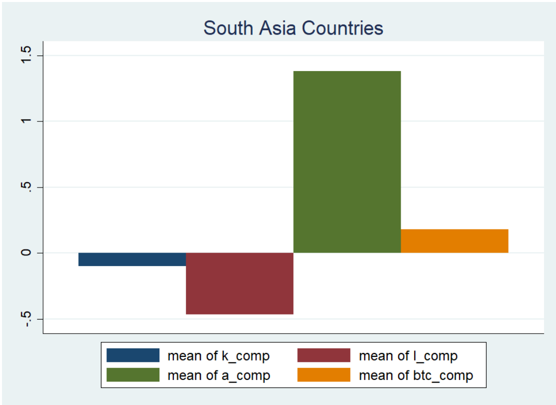


Figure A.22: Factor Contribution South Asia countries 1950-2015

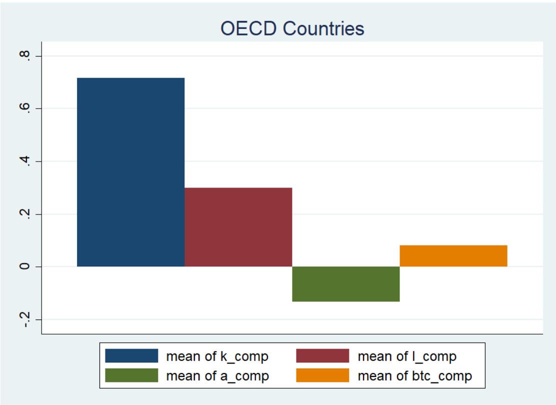


Figure A.23: Factor Contribution OECD countries 1950-2015

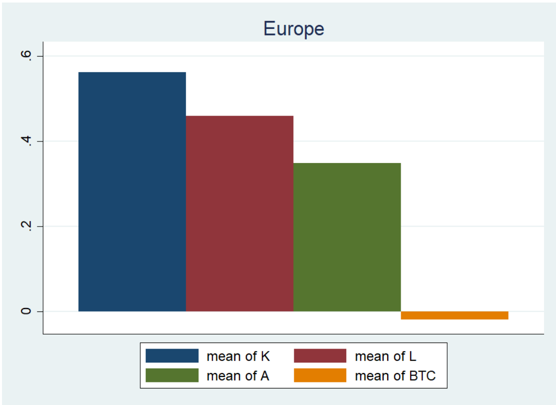


Figure A.24: Factor Contribution Europe countries 1950-2015