Typology Construction for Comparative Country Case Study Analysis of Patterns of Growth

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Abstract

This study has been motivated by the limitations of cross-country regressions and unstructured comparative case studies in providing policy-relevant findings on the determinants of patterns of growth. It presents a methodology to improve upon existing comparative case study research by situating cases withing a typological framework and subsequently using cluster analysis to improve the matching of cases with respect to a number of 'weakly exogenous' variables. Such an approach performs a taxonomic function, distinguishing different types of cases, and an explanatory function, by facilitating the comparison of similar cases in terms of variables in the typology ('like with like' comparisons) or of cases with one or more known differences with respect to these variables. The approach also constitutes a middle-ground between cross country regressions and unstructured case studies which has the potential to generate better comparative analysis of patterns of growth leading to more policy-relevant results.

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1. Introduction

Why do some countries have better growth and distributional outcomes than others? Or, more specifically in the present case, why are some countries in sub-Saharan Africa more successful in converting growth into poverty reduction? There are two main ways of addressing these types of questions in the literature, namely cross-country regressions and country case studies.

The literature on the cross-country econometrics of growth is extensive (Durlauf et al. 2005; Ciccone and Jarociński 2010). Similarly, a body of research exists relying on cross-country regressions to estimate growth elasticities of poverty and correlates of poverty (Balakrishnan et al. 2013, Dollar et al. 2013). There are a number of limitations, however, of cross-country regressions, in particular if such results are intended to provide policy-relevant information. A short list includes problems of endogeneity, uncertainty about model specification, heterogeneity of country experience which is inadequately captured in a regression framework, the endogeneity of policy choice in response to unobservables, and so on (e.g., Durlauf 2009, Rodrik 2012).

In light of such limitations, a literature has developed relying on comparative cases studies of growth (Rodrik, ed., 2003) and inclusive growth (Besley and Cord (eds.) 2007; Grimm et al. (eds.) (2007), including in sub-Saharan Africa (Arndt et al. (eds.), (2016)). Many such studies, however, are subject to two critiques. First, results tend to be characterized by a high level of generality, in that their findings often do not distinguish between types of countries. Second, there is a degree of explanatory imprecision, in that no attempt is made to compare 'like' with 'like' when making causal claims based on the cases.

The methodology presented in this paper has been motivated by the limitations of cross-country regressions along with these two shortcomings of comparative case study research. The reliance on a typological framework partly addresses the critique of excessive generality in that an attempt is made to distinguish different country types. Second, explanatory imprecision is partly addressed by comparing cases which are very similar in terms of variables in the typology (within-cell comparisons) to facilitate 'like with like' comparisons, or different in terms of one or more known variables (between-cell comparisons), and subsequently matched using cluster analysis. Comparative cases study analysis of this sorts constitutes a middle ground between cross-country regressions and unstructured case comparisons which has the potential to generate better comparative analysis of patterns of growth leading to more policy-relevant results.

The objective of this paper is to illustrate the logic and results of situating comparative case study analysis within a typological framework and grouping cases using statistical analysis. It makes three main contributions to the literature. First, the paper suggests ways of improving upon existing comparative case study research to make it more analytically robust and potentially more policy-relevant. Second, it relies on a range of techniques of cluster analysis which have not been widely used in development economics and development studies.[1] Third, while typologies abound, including some applied to patterns of growth in sub-Saharan Africa (Thorbecke 2012a, 2012b, 2013), they have generally not been linked to theoretical

[1] There are exceptions, including Berlage and Terweduwe, (1988) and Vazquez and Sumner (2013, 2016), for example.

literatures on typological frameworks (e.g. Bailey 1994) nor to their potential role in facilitating comparative case study analysis.

As mentioned, the analytical focus of this study is on the conversion of growth into poverty reduction, represented by Growth (semi) Elasticities of Poverty (GEPs), rather than on growth or poverty per se. There are three reasons. First, GEPs in sub-Saharan Africa tend to be lower than in other regions, sometimes quite significantly, depending on the time period, and the growth and poverty measures used (Fosu 2009 2017). Second, there has been much more analytical work undertaken on the determinants of (the volume of) growth than on determinants of the pattern of growth generally, and in sub-Saharan Africa specifically (e.g. Ndulu et al. (eds.)). Third, there is quite significant variation in GEPs across sub-Saharan African countries including cases of so-called Immiserizing Growth, where growth has coexisted with increasing or stationary levels of poverty (Shaffer et al. 2019).

The format of the paper is as follows: Section 2 provides background by discussing the underlying concepts of causation in econometrics, in typology-based comparative analysis and in unstructured case studies and to show how the second can constitute a middle ground between the other two. Section 3 discusses the logic of comparative case study analysis within a typological framework and presents an illustrative typology drawing on the literature on typologies of growth and poverty reduction in sub-Saharan Africa. Section 4 outlines the methodology of case selection to populate the typology drawing on the cluster analysis. Section 5 reviews the data and section 6 presents results of the cluster analysis. A final section concludes.

2. Causation in Econometrics and Typology-based Comparative Analysis

An entry point to understanding the role of typology-based comparative analysis in supporting causal analysis is to compare it with the underlying concept of causation in econometrics. The logics of both are quite similar despite some differences. It is important to clarify these points to show how typological analysis can serve as a middle ground between cross-country regressions and unstructured case studies in facilitating comparative analysis of patterns of growth.

The approach to causation which underpins econometrics is known as conditional association (Shaffer 2013). Historically, it is linked to probabilistic theories of causation, notably developed by Reichenbach (1956) and Suppes (1970), which maintain that causes increase the conditional probability of their effects. Translated into an econometric context, variables are more likely to be causal if their coefficient values are significant after conditioning on other relevant variables.

The theoretical and practical deficiencies associated with this approach to causation are well-known and it is widely recognised that inferring causation from conditional association requires additional information to address problems arising from endogeneity, misspecification and so on. Such information may come from knowledge about the underlying causal system or temporal ordering drawing on theory or empirical information (Hoover 2008). Examples include theory-based hypothesis testing (causal system/a priori); Granger-causality (temporal ordering/empirical), instrumentation (causal system/empirical) and so on. Much of modern econometrics has, in fact, been devoted to addressing such challenges to causal inference.

Despite its limitations, the logic of causal analysis in econometrics ultimately rests on this notion of conditional association. More formally, an econometric model of the form $y = g(x_1, \dots, x_k) + \varepsilon$ can be alternatively specified as $E(y|x, \dots, x_k)$ or the expected value of y conditional on x. In the context of a linear regression $y = \beta_1 + \beta_2 x_2 + \ldots \beta_k x_k + \varepsilon$, beta coefficients represent the conditional expectation on y of a unit change in the value of x, holding all other xs constant (Kennedy1993, p. 51). This is precisely the logic of conditional association.

The use of typological frameworks in the context of comparative case study analysis follows a similar logic. From the point of view of causal analysis, the core rationale for situating cases within a typology, and proceeding to compare them, is to control for at least some variables which could be affecting outcomes.[2] Accordingly, if different outcomes persist after conditioning on a number of key variables, causal claims are strengthened, *ceteris parabis*. At this point, the logic of conditional association is quite similar in the econometric and typological contexts.

There are at least three important differences however in the application of this logic of conditional association to typological frameworks.

First, the objective is to select cases to populate different typology cells to allow for more structured cross-case comparisons. The cases maybe very similar in terms of the conditioning variables in the typology (within-cell comparisons) to facilitate 'like with like' comparisons, or different in terms of one or more known variables (between-cell comparisons). In either case, this differs from the econometric context where the objective is to estimate parameter values directly.

Second, case selection drawing on conditional association is playing a secondary role in causal analysis. Most of the causal claims about outcomes stem from the analyses presented within the individual cases drawing on any number of research strategies and analytical techniques.

Third, practical problems typically pose bigger challenges to typological frameworks than for econometric estimation. There are only a limited number of variables which may be used in the construction of a typology before it becomes unmanageable. For binary variables, cell size increases at the rate of 2^n where n represents the number of variables (George and Bennett 2004). In addition, depending on sample size, it may be very hard to find good cases to populate typology cells to facilitate within or between-cell comparisons.

Despite these differences, the same logic of conditional association in econometrics underpins causal inference in typology-based comparative case study by facilitating the comparison of similar cases in terms of conditioning variables in the typology ('like with like' comparisons) or of cases with known differences with respect to one or more conditioning variables.

It is in this sense that comparative case study analysis within a typological framework represents a middle ground between cross country regressions and unstructured case study comparisons. As with cross-country econometrics, it relies on conditional association, though only to do a limited part of the causal work (related to case selection). As with typical unstructured case studies, it draws on within-case analysis to do most, though not all, of the heavy causal lifting. Combining the two thus constitutes a middle ground which in principle should allow for stronger comparative analysis and stronger causal claims.

[2] The objective of the cluster analysis discussed in section 4 is simply to control for an additional number of variables, thereby improving the matching between cases.

3. Typologies for Comparative Case Study Analysis

3.1 The Logic of Comparative Case Study Research within a Typological Framework

The logic of typological analysis depends on the purposes for which they have been constructed. The most famous example is Weber's (1949) ideal-type notion which was a non-empirical mental construct, likely intended as a device to sharpen analytical categorization (Bailey 1994). Alternatively, typologies have been used for purely conceptual clarification, as for example, when disentangling distinct attributes of a compound concept (Elman 2005). A different example concerns so-called explanatory typologies which assess the predictions of a theoretical framework based on empirical cases which populate typology cells (Elman 2005).

The present typology differs in that it is primarily empirical and serves two distinct purposes. First, it fulfills a taxonomic function in assigning cases to relevant types, based on relevant differentiating characteristics. Second, it strengthens explanation by facilitating the comparison of similar cases in terms of conditioning variables in the typology ('like with like' comparisons) or of cases with one or more known differences with respect to these variables. These two functions, taxonomic and explanatory, partly address the shortcomings of unstructured case study research mentioned in the introduction, namely excessive generality and causal imprecision, respectively.

To clarify, there are three distinct levels of analysis undertaken within an empirical typological framework of this type namely, within-case, within-cell and between-cell.

> *Within-Case Analysis*: This is the level at which most unstructured comparative case studies are conducted. Analyses of particular cases are undertaken using a range of research strategies and analytical techniques to address the research questions at hand.
>
> *Within-Cell Comparative Analysis:* This comparison is between cases which are similar in terms of all the conditioning variables in the typology to facilitate 'like with like' comparisons. In this way, an attempt is made is address the problem of explanatory imprecision on unstructured case studies (the explanatory function).
>
> *Between-Cell Comparative Analysis:* The comparison here are between cases which differ in terms of one or more known variables in the typology while holding others constant. There are two main objectives. First, between-cell comparisons examine similarities and differences across different types of cases with known properties, addressing the problem of excessive generality of unstructured case studies (the taxonomic function). Second, as with within-cell analysis, it facilitates a more controlled comparison of cases with the objective of improving explanatory precision (the explanatory function).

3.2 The Logic of This Study

To render the discussion more concrete, consider the broad strategy of this study in terms of the within-case, within-cell and between-cell analyses.

Within-Case Analysis: The object of inquiry is the conversion of growth into poverty reduction, (growth (semi) elasticities of poverty) reflected in cases of inclusive and non-inclusive, or immiserizing, growth. The within-cell analysis focuses on the policy mix as the primary explanatory factor for the different patterns of growth. A range of research strategies and analytical techniques may be employed to facilitate this type of analysis.

Within-Cell Analysis: The variables used to construct the typology are 'weakly exogenous', in the sense that they are not *directly or entirely* determined by policy within the relatively short time periods of the country spells. Examples include variables related to geography, demography, size and so on. Cluster analysis is used to enhance the matching of cases drawing on other weakly exogenous variables which are not included in the typology. Accordingly, within-cell comparisons of cases of inclusive and non-inclusive, or immiserising, growth facilitate a comparison of countries which are similar with respect to all typology and cluster variables yet have different patterns of growth. If different policies are found to be associated with such patterns of growth, the typological framework strengthens the case for their causal relevance, as it controls for potentially confounding 'weakly exogenous' factors (the explanatory function).

Between-Cell Analysis: The between-cell analysis extends the comparison to cases with known differences in terms of the variables used in the typology, for example, between resource rich and resource poor countries. The objective is to determine if findings on the policy-related determinants of patterns of growth systematically different between cell types (the taxonomic function). In addition, by comparing cases with known differences in terms of the typology variables, while holding others constant, it facilitates a more structured comparison of cases with the objective of improving explanatory precision (the explanatory function).

The base logic, then, of the study can be presented schematically in the following 2x2 matrix where the subscripts *p* and *n* represent positive outcomes (inclusive growth) and negative outcomes (non-inclusive, or immiserising, growth) respectively:

Table 1 – The Logic of Comparative Case Studies in a Typological Framework

		Variable 1	
		Low	**High**
Variable2	**Low**	a_p, a_n	b_p, b_n
	High	c_p, c_n	d_p, d_n

In terms of the types of analyses discussed above:

Within-case analysis is represented by individual case studies of a_p thru d_n.

Within-cell analysis is represented by comparative analyses of (a_p & a_n); (b_p & b_n); (c_p & c_n); and (d_p & d_n).

Between-cell analysis, when allowing only one variable to vary, is represented by comparisons between a cell and its off-diagonal neighbours (in the 2x2 matrix), for example [(a_p & a_n) & (b_p & b_n)], [(a_p & a_n) & (c_p & c_n)].

Between-cell analysis when allowing more than one variables to vary, is represented by comparisons between a cell and its diagonal neighbour (in the 2x2 matrix), for example [(a_p & a_n) & (d_p & d_n)]

It should be emphasised that the role of the cluster analysis for both the within and between cell comparison is to condition on additional variables. In the within-cell case, the effect is to bolster the claim of comparing 'like with like'. In the between-cell case, it serves to strengthen the claim that the comparison is between cases with known differences with respect to the typology variables but 'well-matched' in terms of other 'weakly exogenous' variables found in the cluster analysis.

3.3 An Illustrative Typology of Patterns of Growth in Sub-Saharan Africa

The variables, then, used for the typology of patterns of growth in sub-Saharan Africa are 'at least weakly exogenous, in the sense that they are not *directly or entirely* determined by policy within the relatively short time periods of the country spells. There are many ways to construct a typology based on this criteria of weak endogeneity.

A good starting point is the typological framework for Growth/Inequality/Inequality in sub-Saharan Africa proposed by Thorbecke (2012a, 2012b 2013), drawing on existing typologies from the AERC (Collier and O'Connell 2008), World Bank (2008), IFPRI (Diao et al. 2007) and others. Thorbecke relies on five main variables, namely: i) failed or functioning states; ii) agricultural-based or 'transforming' economies; iii) more or less favourable agricultural potential; iv) the abundance or scarcity of natural resources; v) whether countries are land-locked or coastal.

I have retained four of five variables used in the Thorbecke typology though in slightly modified form. The 'transforming' vs. agricultural-based variable from the *World Development Report 2008* was dropped, because there are very so few cases of the former. The WDR definition of 'transforming', whereby agriculture is no longer a major contributor to GDP growth but poverty remains primarily rural, applies mainly or exclusively to South Africa (WB 2008, pp. 5, 31).

The failed state category was renamed 'higher conflict' given definitional ambiguities about the failed state terminology and the fact that conflict may be intimately related to poverty in the context of non-failed states, such as parts of India (Shaffer et al. 2019). The natural resource abundance/scarcity category was also slightly re-specified to align more closely with the so-called natural resource curse. Specifically, it was defined as the total of natural gas, oil and mineral rents as percentage of GDP.[3] The issues of conflict and natural resource extraction are of particular relevance because they have been associated with instances of immiserising growth (Shaffer et al., 2019).

[3] As such, it differs from Natural Resource Rents in the World Development Indicators, which also includes rents from coal and forestry.

The landlocked vs. coastal category was retained unchanged as was the 'more or less favorable' agriculture category. This category does raise a number of definitional issues[4] and practical problems because the original data set was not accessible.[5] Still, it is retained as an important and policy-relevant category.

Table 2 presents the modified Thorbecke typology as a 4x4 matrix comprised of sixteen mutually exclusive categories. We revisit the typology in section 6 after it has been populated with cases for comparative analysis.

Table 2 Typology of Patterns of Growth in Sub-Saharan Africa

		Natural Resource Poorer		Natural Resource Richer	
		Land Locked	Coastal	Land Locked	Coastal
Lower Conflict	More Favourable Agriculture				
	Less Favourable Agriculture				
Higher Conflict	More Favourable Agriculture				
	Less Favourable Agriculture				

[4] Diao et al. (2007: 20-21) state that the category is based on the results of FAO country level farming system assessments which themselves are based on a range of measures such as 'agroecological conditions and population densities'. For the latter, they cite (Dixon et al. 2001), which discusses a range of farming systems across the world but does not provide information on the FAO country assessments.
[5] Personal correspondence with Xinshen Diao, Sept. 16, 2019.

4. Methodology

There are a number of analytical techniques which may be used to group cases (Eshghi et al. 2011). This study relies on cluster analysis using a number of clustering procedures to determine the robustness of results.There are six key methodological steps which will be reviewed in turn, involving selection of:

1. Variables for the cluster analysis;
2. Methods of standardisation of the cluster variables;
3. Dissimilarity measures;
4. Clustering procedures for the base model and the pairwise probability matching;
5. Stopping rules to determine the optimum number of clusters;
6. Growth and poverty measures.

We will review each of these steps in turn.

4.1 Selection of Variables for the Cluster Analysis

In principle, there are two main ways to select cluster variable. The first would draw primarily on theory, teasing out relevant from non-relevant variables and further differentiating between those that are exogenous and endogenous. Empirical estimation in the growth literature provides a good example of this approach (Helpman 2004). Unfortunately, there is no comparable body of theory related to inclusive or immiserising growth on which to draw to perform an analogous exercise for this study.[6]

Accordingly, we opt for the second main way to select variables, which is empirical. The selection process was guided by four main considerations.

First, we did not use the same four typology variables because the effect would be to double count them.

Second, we chose a limited number of variables which could reasonably be considered as at least 'weakly exogenous' to the country spells under examination. To recall, the focus of the within-case analysis is on the policy mix and accordingly, in the cluster analysis, we searched for variables that are not *directly or entirely* determined by policy within the relatively short time periods of the country spells. *It should be emphasised that this criterion very significantly reduces the pool of potential variables for inclusion.* In fact, a review of the growth literature (in Sala-i-Martin et al. 2004 and Ciccone and Jarociński 2010), led us to fifteen candidate variables[7] in five thematic areas shown in Table 3.[8]

Third, in cluster analysis, there are a number of rules of thumb about the relationship between sample size and the number of cluster variables in the presence of sampling and measurement error. It is often suggested that a minimal ratio is 10:1 with optimal ratios hovering around 70:1 (Dolcinar et al. 2016, Mooi et al.

[6] There are theoretical contributions in the literature but they tend to differ widely in terms of conceptual categories used and substantive conclusions reached (Pritchett and Worker 2012, Gupta et al. 2015, Pritchett et al. 2018).

[7] We opted to remove inequality because there were a significant number of missing variables from the *All the Ginis* (2014) database for the spells in question and certain of the data points appear quite questionable.

[8] One significant omission from this list concerns institutions, in light of the importance afforded them in the recent literature as long-term drivers of present-day outcomes (for example, Sokoloff and Engerman 2000, Acemoglu et al. 2001, Austin 2010). They are not included because there is a high degree of arbitrariness in specifying, operationalising and measuring the institutions in questions, and it is unclear how relevant they are for the explanation of relatively short spells.

2018). Our sample of seventy-five country spells then strongly suggested selection of a limited number of variables.

Table 3: Candidate Cluster Variables

Thematic Area	Variables
Size	1. Total population (Pop), Source: World Development Indicators (WDI) 2. Land Area, km2 (Areakm2), Source: Gallup et al. 2010 3. Aggregate GDP/cap PPP (TGDP), Source: WDI
Stage of Structural Transformation	4. Ag, Forestry and Fishing value added % of GDP (AgFsh), Source: WDI 5. Rural Population % of Total (RurPop), Source: WDI
Inequality	6. Gini Coefficient (Gini), Source: All the Ginis database, version 2014
Geography	7. Latitude of Capital City (WDI) 8. Population Percentage in Koeppen-Geiger (K-G) tropical zone (KG-Pop), Source: Gallup et al. 2010 9. Land area Percentage in K-G tropical zone (KG-Land,) Source: Gallup et al. 2010 10. Population Percentage within 100 km of ice-free coast/navigable river (100K-Pop), Source: Gallup et al. 2010 11. Land area Percentage within 100 km of ice-free coast/navigable river (100K-Land), Source: Gallup et al. 2010
Demography	12. Age Dependency Ratio, % of working-age population (AgeDep), Source: WDI 13. Population Growth, % annual (PopGrth), Source: WDI 14. Population Ages 0-14, % of total (Pop14), Source: WDI 15. Population Ages 65 and above, % of total (Pop65), Source: WDI

Fourth, we examined the correlation between these measures and the growth (semi-) elasticities of poverty (further discussed in section 4.6). An initial choice rule was to select highly correlated across the (semi-) elasticities presented in Table 4. Generally, the correlations were low and never exceeded a value of 0.25. Accordingly, we opted to choose the variable within each thematic category most highly correlated across the (semi-) elasticities, arriving at the following selection:

1. Total Population;
2. Agriculture, Forestry and Fishing Value Added as a Percentage of GDP;
3. Latitude of the Capital City and
4. The Age Dependency Ratio as a Percentage of the Working-Age Population.

Table 4: Correlation Coefficients between Growth (semi-) Elasticities of Poverty and Cluster Variables

	E-P0_GDP	E-P0_SM	E-Q2_GDP	E-Q2_SM	Gini	AgFsh	RurPop	AgeDep	PopGrth	Pop14	Pop65	Pop	TGDP	Latitude	KG-Land	KG-Pop	Areakm2	100K-Land	100K_Pop
E-P0_GDP	1																		
E-P0_SM	0.3008	1																	
E-Q2_GDP	0.8345	0.1615	1																
E-Q2_SM	0.1814	0.8367	0.1971	1															
Gini	0.2217	-0.0852	0.374	-0.0215	1														
AgFsh	-0.0672	0.2017	-0.0105	0.1482	-0.4614	1													
RurPop	-0.1038	0.193	-0.018	0.1202	-0.2264	0.5439	1												
AgeDep	0.1396	0.0844	0.1629	0.0537	-0.274	0.5727	0.6584	1											
PopGrth	0.0928	0.06	0.1023	0.0621	-0.2181	0.3746	0.3202	0.4953	1										
Pop14	0.1235	0.0943	0.1359	0.0688	-0.2763	0.568	0.6214	0.9822	0.5134	1									
Pop65	-0.0478	-0.0935	-0.0161	-0.0876	0.1855	-0.416	-0.3849	-0.7318	-0.4695	-0.8345	1								
Pop	-0.1782	0.167	-0.1853	0.2337	-0.2374	0.0683	0.0389	-0.073	0.013	-0.0437	-0.0918	1							
TGDP	-0.1343	-0.0537	-0.1394	0.0409	0.1681	-0.355	-0.4201	-0.5032	-0.2876	-0.4686	0.1672	0.6773	1						
Latitude	0.2196	0.2465	0.1008	0.2497	-0.4612	0.4857	0.0242	0.3246	0.3654	0.3175	-0.2135	0.0562	-0.2308	1					
KG-Land	-0.0358	-0.0421	0.0312	0.0349	-0.3087	0.3469	-0.0258	0.2226	0.2401	0.2458	-0.2217	-0.0084	-0.1554	0.3325	1				
KG-Pop	-0.0461	-0.0547	0.0298	0.04	-0.2724	0.3107	-0.0666	0.2022	0.2254	0.2282	-0.22	-0.0064	-0.1279	0.32	0.9872	1			
Areakm2	-0.036	0.0646	-0.1153	0.0652	-0.0793	-0.0743	-0.1822	-0.2825	-0.0317	-0.3013	0.2125	0.4858	0.4443	-0.0694	-0.4799	-0.4605	1		
100K-Land	0.1114	-0.0415	0.0927	-0.0078	0.1703	-0.0577	-0.4192	-0.059	-0.023	-0.0281	-0.0973	-0.1968	-0.0456	0.0847	0.3007	0.3209	-0.3173	1	
100K-Pop	0.1252	-0.0478	0.0935	0.0022	0.1375	-0.1195	-0.5277	-0.1604	-0.0526	-0.1283	-0.041	-0.0928	0.096	0.1029	0.3213	0.3597	-0.2734	0.9493	1

Notes: E-P0_GDP = Growth (GDP) semi-elasticity of poverty(incidence); E-P0_SM = Growth (Survey Mean) semi-elasticity of poverty(incidence); E-Q2_GDP = Growth (GDP) elasticity of poverty(bottom quintile consumption growth); E-Q2_SM = Growth (Survey Mean) elasticity of poverty(bottom quintile consumption growth);
See Table 3 for variable definitions

Sensitivity analysis was performed to gauge the robustness of the cluster results to the choice of variables selected. We experimented with seven different combinations of size, demography and geography variables to determine if it affected the cluster groupings using the base model discussed in section 4.4.[9] In seventy percent of cases, variable choice did not matter as the cluster groupings were identical (the main differences involved the demography variables only). This finding provides additional insurance that results are not being driven primarily by variable choice.

4.2 Standardisation of the Cluster Variables

When variables are not measured in the same units, as in this study, cluster analysis requires some type of standardisation. Otherwise, the interpretation of distances across variables is unclear. A common approach is to standardise to unit variance, as in autoscaling or z-scoring. An alternative is to standardise by the range, which has been found to be superior to z-scoring in many applications (Everitt et al.: 67). Accordingly, we will rely on range standardisation in our base model and use both range and unit variance standardisation in the pairwise probability matching discussed next.

4.3 Selection of Dissimilarity Measures[10]

Dissimilarity measures are metrics of difference between objects or clusters with respect to select variables. Dissimilarity measures for continuous variables, such as those selected for this analysis, subdivide broadly into distance and correlation measures. The interpretation of correlation measures in the context of cluster analysis is difficult because it is not possible to measure the difference in size between any two observations as an identical correlation coefficient between observations is consistent with very different variable values.

Accordingly, in the base cluster model we rely on a widely used distance measure with the Ward's procedure in cluster analysis, squared Euclidean distance, which may be represented as:

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[9] The land-area based geography variables, #9 and #11 in Table 3, were removed from this exercise as they were highly collinear with the population-based geography variables, #10 and #12 in Table 3.

[10] This section draws on Everitt et al. (2010: 49-53).

$$d_{ij} = \sum_{k=1}^{p} \left(x_{ij} - x_{jk}\right)^2$$

where x_{ij} an x_{jk} represent for individuals i and j, the value of the kth variable of the p-dimensional matrix (Everitt et al 2011: 49-50).

In the pairwise probability matching exercise, we also use the (non-squared) Euclidean distance as a dissimilarity measure.

4.4 Clustering Procedures (Hierarchical Agglomerative and K-Means)

Base Model

Our analysis begins with hierarchical agglomerative clustering. Such techniques combine individual objects into a successively smaller number of clusters. They are appropriate for this study as we do not know a priori the optimum number of clusters to use (see discussion of stopping rules). Following the completion of hierarchical clustering exercise and the determination of the optimum number of clusters, we run a k-means cluster analysis to optimise within-cluster homogeneity.

Our base agglomerative clustering procedure relies on the Ward's method. This approach has consistently fared well in studies examining the performance of clustering techniques using either simulated data or actual empirical studies.[11] It has also been the method of choice in related studies in development economics (Vazquez and Sumner 2013, 2016). It merges clusters according to a rule which minimises the increase in the total within-group error sum of squares, *E,* where:

$$E = \sum_{m=1}^{g} E_m$$

and

$$E_m = \sum_{l=1}^{n_m} \sum_{k=1}^{p_k} \left(x_{ml,k} - \overline{x}_{m,k}\right)^2$$

whereby $\overline{x}_{m,k}$ is the mean of the *m*th cluster of the *k*th variable; $x_{ml,k}$ represents the value of the *k*th variable (k = 1, …, *p*) for the *l*th (*l* = 1, …,n_m) object in the *m*th cluster (*m* = 1, …, *g*) (Everitt et al. 2011: 77-78).

The final step in the base model is to run the k-means procedure using the optimum number of clusters generating from the agglomerative clustering approach. K-means is an iterative algorithm which relocates units to the cluster with the closest mean value and iteratively recalculates group means. It optimises clusters according to an algorithm which minimises the within-group sum of squares. In this sense, it is similar to Ward's procedure but the algorithm is different leading to potentially different cluster groupings (see section 6.1). A major shortcoming of k-means is that it is sensitive to the starting point. Accordingly, we rely on cluster means from the agglomerative method to seed the k-means clustering.

[11] Everitt et al. (2011: 83-84) provide a survey this literature.

Pairwise 'Probability' Matching

In light of the sensitivity of cluster outcomes to the choice of clustering procedure (Everitt et al. 2010) and other procedures for grouping cases (Eshghi et al. 2011), we experimented with six additional clustering approaches (using both agglomerative and k-means techniques) to calculate the 'probability' that any two cases are assigned to the same cluster regardless of the clustering procedure, data standardisation rules and dissimilarity measures, discussed in sections 4.2 and 4.3 respectively, to arrive at 55 total cluster runs.[12]

The specific procedure involved first generating all pairwise cases of country spells that fell within the two clusters of the base model, leading to 1326 pairs in cluster 1 and 254 pairs in cluster 2. The 'probability' of a pairwise match was calculated for each pair based on whether or not they were assigned to the same cluster across the 55 total cluster runs. We allowed the number of clusters to vary for each run of the agglomerative clustering, depending on the optimum cluster size as suggested by the Calinski-Harabasz pseudo-F statistic (discussed in section 4.5). Accordingly, the 'probability' statistic varies between 0 and 1, with the former denoting no cluster assignment matches and the latter representing complete cluster assignment matching.

The six addition clustering procedures are based on the following rules of cluster formation:

i. *Single linkage (nearest neighbour)*, which fuses clusters based on the shortest distance between any two members of each cluster.
ii. *Complete linkage (furthest neighbour)*, by contrast, which joins cluster based on the largest distance between any two cluster members
iii. *Average Linkage*, which combines clusters based on the shortest average distance between all pairs of members in the two clusters.
iv. *Weighted Average Linkage*, which simply weights cluster averages by the number of cluster members (so that smaller clusters receive greater weight).
v. *Centroid Linkage*, which combines clusters based on the shortest distance between their geometric means (centroids)
vi. *Median Linkage*, which simply weights cluster centroids by the number of cluster members.

A more formal treatment of these clustering procedures is provided in Appendix A which expresses these differences in terms of parameter values of intergroup distances in the so-called recurrence formula proposed by Lance and Williams (1967).

4.5 Stopping Rules

There are a number of ways to determining the optimum number of clusters. We rely on two methods, namely visual inspection of the so-called dendrogram along with examination of the *Calinski-Harabasz pseudo-F* measure.

Dendrograms provide a graphic depiction of the hierarchical clustering process. They show the levels of the dissimilarity or distance measure at which objects are successively combined into fewer and fewer clusters. Prior to cluster formation, the dissimilarity measure takes a value of zero, as there is no within-group heterogeneity, and increases as clusters are formed. Dendograms provide suggestive information on

[12] Specifically, we rely on seven clustering procedures in total using both agglomerative and k-means techniques, two dissimilarity measures, and two data standardisation rules. Our base model results are removed.

the optimum number of clusters if no cluster mergers occur over large distances, as represented by long vertical lines. The intuitive interpretation is that such breaks in the data mark a point after which within-group heterogeneity rises very rapidly.

The *Calinski-Harabasz* (CH) *pseudo-F* formalises certain of these insights following the logic of a one-way ANOVA. It has fared well in comparative assessments of stopping rules in the literature (Milligan and Cooper (1985) cited in Everitt et al. (2011: 127). The measure presents the ratio of between-group variance to the within-group variance. The associated CH cluster optimisation rule is based on the maximisation of this statistic, C(g) expressed as:

$$c(g) = \frac{trace(\mathbf{B})}{(g-1)} \Big/ \frac{trace\ (\mathbf{W})}{(n-g)}$$

where (**B**) and (**W**) represent the between-group and within-group dispersion matrices, respectively; g equals the number of groups or clusters and n denotes the number of cluster members.

4.6 Growth and Poverty Measures

After conducting the cluster exercise to determine cases which are well-matched in terms of our cluster variables, we then turn to the data on Growth (semi-) elasticities of Poverty (GEPs) to select cases of inclusive and non-inclusive, or immiserising, growth.

We rely on two measures of growth and two measures of poverty. The growth measures are PPP-adjusted GDP/cap ($2011) and PPP-adjusted survey mean income or consumption expenditure. The poverty measures used include percentage point changes in poverty incidence (at the poverty line of $PPP 1.90/day) and changes in consumption expenditure of the bottom quintile.

The (semi) elasticities were adjusted in a number of ways to facilitate interpretation of results. First, the signs of the elasticities have been changed so that if poverty outcomes improve then elasticities are positive. In the case of poverty incidence this entailed two changes: i) if the growth measure is positive and poverty incidence falls, the sign of the elasticity switches from negative to positive; ii) if the growth measure is positive and poverty incidence increases (the sign is positive), the sign of the elasticity switches from positive to negative. In the case of income growth of the bottom 20 percent the following two analogous changes were made: i) if the growth measure is negative and income growth of the bottom 20 percent is positive the sign of the elasticity switches from negative to positive; ii) if the growth measure is negative and income growth of the bottom 20 percent the sign of the elasticity switches from positive to negative.

The second adjustment to the GEPs concerns the so-called denominator problem, or the fact that as growth rates approach zero, GEPs become extremely large. So, an extremely large elasticity value need not reflect a positive case of inclusive growth, but simply a near zero rate of growth.[13] This problem does not affect the choice of individual countries for our case studies, as such anomalous cases can be spotted, but it may affect the correlation matrix used to select variables for the cluster analysis (discussed later on this section). Accordingly, we trimmed the (semi) elasticities if they were in excess of two standard deviations from the mean and if annual growth rates were below the absolute value of 0.25. In practice, only nine observations were removed, most with extreme values.

[13] The reverse issue, 'the numerator problem', does not pose the same type of interpretational difficulties because it is appropriate to consider a very low elasticity value associated with a near zero change in poverty, as a 'bad' outcome.

5. Data

The country-spell data is an updated version of Dollar et al.'s (2013) 'minimum five-year-spell' poverty dataset based on the World Bank's PovcalNet database. If consists of all possible consecutive non-overlapping country spells with a minimum length of five years per spell. Seventy-five spells were identified in sub-Saharan Africa.

The household survey-based data on poverty and growth are based on PovcalNet data as of March 14, 2019. Data on poverty incidence are based on the $1.90/day poverty line, using the 2011 revisions to the international Purchasing Power Parity (PPP) estimates.

The source of GDP/cap growth and all of the cluster analysis is the World Bank's World Development Indicators. Data on other candidate cluster variables are from Harvard's Centre for International Development's Geography and Economic Development online database (Gallup et al. 2010) presented in Table 3.

6. Results

There are three main components of the analysis for which results have been generated namely, the base cluster model, the pairwise probability matching and final case selection.

6.1 The Base Cluster Model

To recall, the base model of the cluster analysis relied first, on hierarchical agglomerative clustering based on Ward's procedure, squared Euclidian distance as the dissimilarity measure and variable standardisation by the range. The optimum number of clusters was chosen on the basis of visual inspection of the dendrogram and results of the Calinski-Harabasz (CH) Pseudo-F statistic (section 4.5). Subsequently, the k-means procedure was run.

Figure 1 presents the dendogram which suggests either a two or three cluster solution. To recall, longer vertical lines appearing prior to a cluster merger point marks a threshold after which within-group heterogeneity rises more rapidly.[14]

Figure 2 presents the results of the CH test which suggests that the optimal number of clusters is indeed two.

[14] The longest lines in the dendogram occur prior to the one-cluster solution but the procedure requires a minimum of two clusters.

Figure 1: Dendogram, Base Model

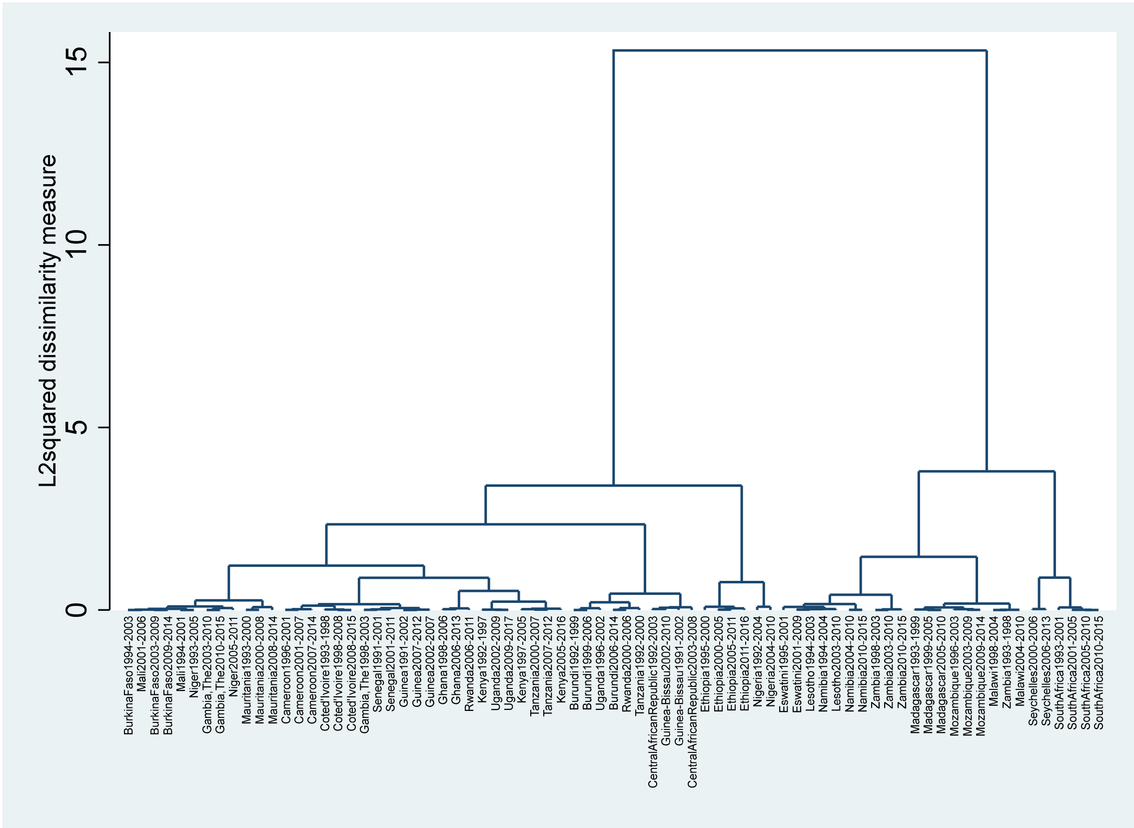
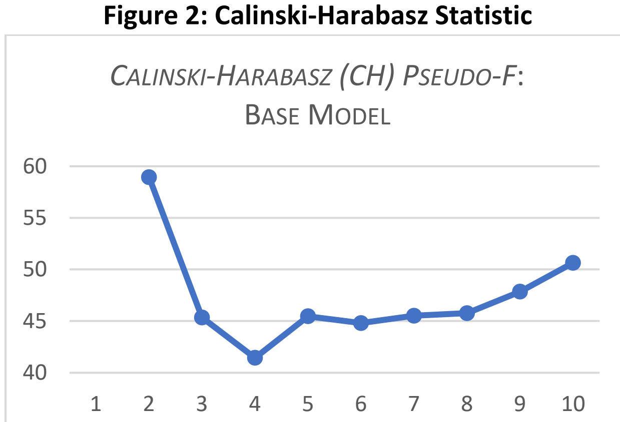


Figure 2: Calinski-Harabasz Statistic



On the basis of the two-cluster solution, we present in Appendix B the cluster assignments of all 75 country spells for the base cluster model for both the hierarchical agglomerative and the k-means procedures. The hierarchical agglomerative results place fifty-one of seventy-five spells in cluster 1. The K-means results are very similar with only the two spells from Malawi flipping from cluster 2 to cluster 1, resulting in fifty-three spells in Cluster 1. In selecting cases for comparison, we draw only on those spells which fall under Cluster 1.

To provide a better idea of how the clusters differ, table 5 presents descriptive statistics on the values of the clustering variables in Clusters 1 and 2 and in the full sample. Relative to Cluster 2 cases, counties in Cluster 1 are situated closer to the equator, are at a lower stage of the structural transformation with higher age dependency rates and larger populations. There are two striking differences in mean values between the clusters. The mean value of the structural transformation variable, the percentage of value-added in GDP due to agriculture, forestry and fishing, is 32% as compared to 14% in Cluster 2 cases. Similarly, there is a large difference in the mean values of the latitude of the capital city between Clusters 1 and 2 at around 6 and -21, respectively.

Table 5: Descriptive Statistics of Clusters

Cluster		mean	range	max	min	n
1	Ag/Fsh	31.58	41.09	54.27	13.18	52
	AgeDep	94.41	32.60	110.65	78.05	52
	Pop	2.20E+07	1.34E+08	1.35E+08	1.04E+06	52
	Latitude	5.93	32.06	18.09	-13.97	52
2	Ag/Fsh	13.99	29.46	31.85	2.39	23
	AgeDep	81.93	53.44	100.14	46.70	23
	Pop	1.51E+07	5.15E+07	5.16E+07	8.11E+04	23
	Latitude	-21.19	24.70	-4.62	-29.32	23
Total	Ag/Fsh	26.18	51.88	54.27	2.39	75
	AgeDep	90.59	63.95	110.65	46.70	75
	Pop	1.99E+07	1.35E+08	1.35E+08	8.11E+04	75
	Latitude	-2.38	47.41	18.09	-29.32	75

6.2 The Pairwise Probability Matching

The next stage was the pairwise probability matching exercise which entailed calculated the 'probability' that county-spells are assigned to the same cluster across 55 cluster runs (using different clustering procedures, standardisation methods and distance measures). The 'probability' statistic varies between 0 and 1, with the former denoting no cluster assignment matches and the latter representing complete cluster assignment matching. The analysis was conducted for all pairwise combinations of cases that fell within the two clusters of the base model, leading to statistics generated for 1326 pairs in cluster 1 and 254 pairs in cluster 2.[15]

As discussed in section 6.3, the cases selected to populate the typology were grouped into the same cluster in over 90 percent of the cluster runs. To provide a frame of comparison, Table 6 presents descriptive statistics on the probability values for the clusters. One encouraging finding is that mean values are quite high, in particular for Cluster 1, suggesting that results are generally robust to the clustering procedure, standardisation method and distance measure.

[15] These data are available from the author.

Table 6: Descriptive Statistics of Pairwise Probability Matching

Cluster	mean	range	max	min	n
1	0.81	0.75	1.00	0.25	1326
2	0.71	0.64	1.00	0.36	254

6.3 Final Case Selection

This final stage entailed selecting cases to populate the typology. Cases were selected drawing on four sets of information, namely:

i. Membership in Cluster 1 in the Base Model (Appendix B);
ii. High Probability of Same Cluster Assignment in the Pairwise Probability Matching;
iii. Representation of spells of inclusive and non-inclusive, or immiserising, growth based on percentage point changes in poverty incidence and the four growth (semi) elasticities of poverty discussed in section 4.6.
iv. Representation of specific cells in the typology based on combinations of the four typology variables, namely natural resource abundance or scarcity, landlocked or coastal status, lower or higher levels of conflict and more or less favourable agriculture.

Table 7 presents of a populated version of the typology drawing on these four sets of information with three proposed sets of comparative case study analyses.

Table 7: The Populated Typology

		Natural Resource Poorer		Natural Resource Richer	
		Land Locked	Coastal	Land Locked	Coastal
Lower Conflict	More Favourable Agriculture		Ghana (1998-2006)		Cameroon (2001-2007) Tanzania (2007-2012)
	Less Favourable Agriculture	Niger (1993-2005)		Mali (1994-2001)	
Higher Conflict	More Favourable Agriculture		Cote d'Ivoire (1998-2008)		
	Less Favourable Agriculture				

Cameroon (2001-2007) & Tanzania (2007-2012)

This comparative case study is an example of a within-cell design discussed in section 3 whereby the cases are similar with respect to all typology variables (and matched to be similar in terms of the cluster analysis). It is an attempt to compare 'like with like' with respect to a set of weakly exogenous variables as explained in section 3.

In terms of the cluster analysis, both cases fall within Cluster 1 and have a 93% 'probability' of being matched in the same cluster across different clustering procedures, dissimilarity measures, and data standardisation rules (see section 4.4).

Data presented in Table 8 show marked differences in terms of poverty and growth outcomes and related elasticities. Tanzania (2007-2012) is a case of inclusive growth, ranking in the top quarter of all country spells in terms of the annualised percentage point rate of poverty reduction and two of four elasticity measures.[16] Cameroon (2001-2007) represents the opposite scenario, situated in the bottom twenty per cent of all country spells in terms of poverty reduction and all elasticity values. It should be mentioned that survey mean-based data shows negative growth whereas GDP/cap growth appears positive. In this latter case, Cameroon may be viewed as an example of immiserising growth.

Table 8 Poverty and Growth Statistics: Cameroon and Tanzania

	P0	Q2	SM	GDPcap	E-P0_GDP	E-P0_SM	E-Q2_GDP	E_Q2_SM	IG
Cameroon2001-2007	1.03	-1.87	-0.94	1.57	-0.65	-2.11	-1.20	-8.76	Y
Tanzania2007-2012	-2.27	6.85	3.37	2.78	0.82	0.68	2.47	2.03	

Notes: P0 = Annualised percentage point reduction in poverty; Q2 = Annualised consumption expenditure growth of bottom quintile; SM = Annualised growth in survey mean consumption expenditure; GDPcap = Annualised growth in GDP/cap; E-P0_GDP = Growth (GDP) semi-elasticity of poverty(incidence); E-P0_SM = Growth (Survey Mean) semi-elasticity of poverty(incidence); E-Q2_GDP = Growth (GDP) elasticity of poverty(bottom quintile consumption growth); E-Q2_SM = Growth (Survey Mean) elasticity of poverty(bottom quintile consumption growth); IG = Case of Immiserising growth if either P0 increases or Q2 falls AND either SM or GDP/cap is positive.

In terms of the typology variables, both country spells were ranked in the richer natural resource category. Cameroon (2001-2007) was ranked 13th of all country spells mainly due to the presence of rents from oil, whereas Tanzania (2007-2012) was ranked 19th due primarily to rents from minerals and to a lesser extent from natural gas. They are both also categorised as low conflict countries. In the case of Cameroon, the long simmering conflict between anglophone and francophone regions only erupted into widespread open confliction following the end of the spell in question.

[16] The full data set is available from the author.

Mali (1994-2001) & Niger (1993-2005)

This comparative case study is an example of a between-cell design discussed in section 3, whereby the cases are similar with respect to some, but not all, typology variables (and matched to be similar in terms of the cluster analysis).

In terms of the cluster analysis, both cases fall within Cluster 1 and have a 100% 'probability' of being matched in the same cluster across different clustering procedures, dissimilarity measures, and data standardisation rules (see section 4.4).

Data presented in Table 9 show marked differences in terms of poverty and growth outcomes and related elasticities. Mali (1994-2001) is a case of inclusive growth, ranking in the top quarter of all country spells in terms of the annualised percentage point rate of poverty reduction and two of four elasticity measures. Niger (1993-2005) represents the opposite scenario, situated in the bottom third of all country spells in terms of poverty reduction and three of four elasticity values. It should be noted that survey mean-based data shows positive growth whereas GDP/cap growth appears negative. In the former case, Cameroon may be viewed as an example of immiserising growth.

Table 9 Poverty and Growth Statistics: Mali and Niger

	P0	Q2	SM	GDPcap	E-P0_GDP	E-P0_SM	E-Q2_GDP	E_Q2_SM	IG
Mali1994-2001	-3.76	13.75	8.84	3	1.25	0.43	4.59	1.56	
Niger1993-2005	-0.27	-1.11	0.91	-0.27	1.01	0.29	-10.28	-1.21	Y

Notes: P0 = Annualised percentage point reduction in poverty; Q2 = Annualised consumption expenditure growth of bottom quintile; SM = Annualised growth in survey mean consumption expenditure; GDPcap = Annualised growth in GDP/cap; E-P0_GDP = Growth (GDP) semi-elasticity of poverty(incidence); E-P0_SM = Growth (Survey Mean) semi-elasticity of poverty(incidence); E-Q2_GDP = Growth (GDP) elasticity of poverty(bottom quintile consumption growth); E-Q2_SM = Growth (Survey Mean) elasticity of poverty(bottom quintile consumption growth); IG = Case of Immiserising growth if either P0 increases or Q2 falls AND either SM or GDP/cap is positive.

In terms of the typology variables, Mali (1994-2001) was ranked 24th of all country spells mainly due to the presence of rents from minerals whereas Niger (1993-2005) registered zero rents from natural sources (as defined in section 3.2).

Cote d'Ivoire (1998-2008) & Ghana (1998-2006)

This comparative case study is also an example of a between-cell design discussed in section 3, whereby the cases are similar with respect to some, but not all, typology variables (and matched to be similar in terms of the cluster analysis).

In terms of the cluster analysis, both cases fall within Cluster 1 and have a 96% 'probability' of being matched in the same cluster across different clustering procedures, dissimilarity measures, and data standardisation rules (see section 4.4).

Data presented in Table 10 show marked differences in terms of poverty and growth outcomes and related elasticities. Cote d'Ivoire (1993-2005) represents a clear case of non-inclusive growth. It is situated in the bottom twenty per cent of all country spells in terms of poverty reduction and all elasticity values. It should be mentioned that survey mean-based data shows positive growth whereas GDP/cap growth appears negative. In former case, Cote d'Ivoire may be viewed as an example of immiserising growth. Ghana (1998-2006) is not a stellar case of Inclusive Growth, ranking generally in the middle of the pack with respect to the annualised percentage point rate of poverty reduction and the four elasticity measures. It does, however, contrast starkly with Cote d'Ivoire's experience.

Table 10 Poverty and Growth Statistics: Cote d'Ivoire and Ghana

	P0	Q2	SM	GDPcap	E-P0_GDP	E-P0_SM	E-Q2_GDP	E_Q2_SM	IG
Coted'Ivoire1998-2008	0.33	-1.94	0.2	-1.51	-0.22	-1.65	-13.15	-9.68	Y
Ghana1998-2006	-1.49	2.57	3.89	2.32	0.64	0.38	1.11	0.66	

Notes: P0 = Annualised percentage point reduction in poverty; Q2 = Annualised consumption expenditure growth of bottom quintile; SM = Annualised growth in survey mean consumption expenditure; GDPcap = Annualised growth in GDP/cap; E-P0_GDP = Growth (GDP) semi-elasticity of poverty(incidence); E-P0_SM = Growth (Survey Mean) semi-elasticity of poverty(incidence); E-Q2_GDP = Growth (GDP) elasticity of poverty(bottom quintile consumption growth); E-Q2_SM = Growth (Survey Mean) elasticity of poverty(bottom quintile consumption growth); IG = Case of Immiserising growth if either P0 increases or Q2 falls AND either SM or GDP/cap is positive.

In terms of the typology variables, the key point of differentiation concerns the high conflict environment of Cote d'Ivoire throughout this time period which contrast with the low conflict environment prevailing in Ghana.

7. Conclusion

The objective of this study has been to suggest a methodological approach which has the potential to generate better comparative analysis of patterns of growth leading to more policy-relevant results. It responds to the limitations of cross-country regressions in providing policy-relevant results and to the problems of excessive generality and explanatory imprecision associated with unstructured case studies.

The alternative suggested in this paper is a middle ground between these two approaches. It structures case studies within a typological framework and subsequently uses cluster analysis to improve the matching of cases with respect to a number of 'weakly exogenous' variables. Such an approach performs a taxonomic function, distinguishing different types of cases, and an explanatory function, by facilitating the comparison of similar cases in terms of variables in the typology ('like with like' comparisons) or of cases with one or more known differences with respect to these variables. The role of cluster analysis is to enhance the matching of cases in terms of other 'weakly exogenous' variables which are not included in the typology. In so doing, it partly addresses the aforementioned problems of excessive generality and explanatory imprecision associated with unstructured case studies..

The specific methodology steps outlined in section 4, are not meant to constitute a definitive methodological position. They are intended only to illustrate one research strategy which constitutes a middle ground approach between cross-country regressions and unstructured case studies. They do however, suggest other areas for further research, namely: i) selecting cases along the broad lines suggested in this paper, conducted detailed case studies, and then examining whether they lead to better comparative analysis with more policy-relevant information; ii) experimenting with a great range of grouping techniques, such as Kohonen Maps (Kohonen 2001), to see if they generate more robust cluster groupings when using data on growth, inequality and poverty.

Sources

Acemoglu, D., Johnson, S. and Robinson, J. (2001). 'The Colonial Origins of Comparative Development: An Empirical Investigation', *American Economic Review*, 91: 1369-1401.

All the Ginis Database (version November 2014), http: //econ.worldbank.org/projects/inequality.

Arndt, C., A. McKay and F. Tarp (eds) (2016). *Growth and Poverty in Sub-Saharan Africa*. Oxford: Oxford University Press.

Austin, G. 2010. 'African Economic Development and Colonial Legacies', *International development Policy* 78: 11-22.

Bailey, K. (1994). *Typologies and Taxonomies*. Thousand Oaks: Sage Publications.

Balakrishnan, R., Steinberg, C., and Syed, M. (2013). 'The Elusive Quest for Inclusive Growth: Growth, Poverty, and Inequality in Asia', *IMF Working Paper 13/152.* International Monetary Fund, Washington, D.C.

Beegle, K., Christiaensen, L., Dabalen A., Gaddis, I. (2016). *Poverty in a Rising Africa. Africa Poverty Report.* Washington, D.C.: The World Bank.

Berlage, L. and Terweduwe, D. (1988). 'The Classification of Countries by Cluster and by Factor Analysis', *World Development*, 16(12): 1527-1545.

Besley, T. and Cord, L. (eds) (2007). *Delivering on the Promise of Pro-Poor Growth.* Washington, D.C: the World Bank.

Ciccone, A. and Jarociński, M. (2010). 'Determinants of Economic Growth: Will Data Tell?' *American Economic Journal: Macroeconomics*, 2(4): 222-246.

Collier, P. and O'Connell, S. (2008) 'Opportunities and Choices' in Ndulu, B., O'Connell, S., Bates, R., Collier, P. and Soludo, C. (eds.), *The Political Economy of Economic Growth in Africa 1960-2000. Vol. 1.* Cambridge: Cambridge University Press.

Dixon, J., Gulliver, A. and Gibbon, D. (2001). *Farming Systems and poverty. Improving Farmer's Livelihoods in a Changing World*. Rome and Washington, D.C.: FAO and World Bank

Dolcinar, S., Grun, B. and Leisch, F. (2016). 'Increasing Sample Size Compensates for Data Problems in Segmentation Studies', *Journal of Business Research*, 69: 992-999.

Dollar, D., Kleineberg, T., and Kraay, A. (2016). 'Growth is Still Good for the Poor', *European Economic Review,* 81(C): 68-65.

Durlauf, S. (2009). 'The Rise and Fall of Cross-Country Growth Regressions.' *History of Political Economy*, 41 (annual suppl.): 315-333.

Durlauf, S., Johnson, P. and Temple, J. (2005). 'Growth Econometrics', in Aghion, P. and Durlauf S. (Eds.), *Handbook of Economic Growth, Volume 1A.* Amsterdam: North Holland.

Elman, C. (2005). 'Explanatory Typologies in Qualitative Studies of International Politics', *International Organization*, 59(2): 293-326.

Eshghi, A. et al. (2011). 'Identifying Groups: A Comparison of Methodologies.' *Journal of Data Science*, 9: 271-291.

Everitt, B., Landau, S., Leese, M. and Stahl, D. (2011). *Cluster Analysis. 5th Edition*. London: Wiley.

Fosu, A. (2009). 'Inequality and the Impact of Growth on Poverty: Comparative Evidence for Sub-Saharan Africa', *Journal of Development Studies*, 45(5): 726-745.

Fosu, A. (2017). 'Growth, Inequality and Poverty Reduction in Developing Countries: Recent Global Evidence.' *Research in Economics*, 71(2): 306-336.

Gallup, J., Mellinger, A. and Sachs, J. (2010). 'Geography and Economic Development", https://doi.org/10.7910/DVN/WR9XEX, Harvard Dataverse, V1,.

George, A. and Bennett, A. (2004). *Case Studies and Theory Development in the Social Sciences. Cambridge*, Mass: The MIT Press.

Government of Malawi (GoM) 2017. ‘Second Integrated Household Survey 2004-2005 – Study Description’. National Statistical Office.

Grimm, M., Klasen, S. and McKay, A. (Eds.) (2007). *Determinants of Pro-Poor Growth*. New York: Palgrave MacMilllan.

Gupta, J., Pouw, N. and Ros-Tonen, M. (2015). ‘Towards an Elaborated Theory of Inclusive Development.’ *European Journal of Development Research*, 27(4): 541-559.

Hoover, K. (2008). ‘Causality in Economic and Econometrics’, in S. Durlauf and L. Blume (eds), *The New Palgrave Dictionary of Economics. Second Edition.* Palgrave Macmillan. [online dictionary], http://www.dictionaryofeconomics.com/article?id=pde2008_C000569 doi:10.1057/9780230226203.0209, (accessed September 1, 2012).

Diao, X, Hazell, P., Resnick, D. and Thurlow, J., (2007). ‘The Role of Agriculture in Development. Implications for Sub-Saharan Africa’, *Research Report 153*. Washtingon, D.C.: International Food and Policy Research Institute

Kennedy, P. (1993). *A Guide to Econometrics*. Third Edition. Cambridge, Mass.: The MIT Press.

Kohonen, T. (2001). *Self-Organizing Maps. 3rd Edition*. Berlin: Springer.

Lance, G. and Williams, W. (1967). ‘A General Theory of Classificatory Sorting Strategies: Hierarchicial Systems’. *Computer Journal*, 9: 373-380.

Milligan, G. and Cooper, M. (1985). ‘An Examination of Procedures for Determining the Number of Clusters in a Data Set’, *Psychometrika*, 50(2): 159-179.

Mooi, E., Sarstedt, M. and Mooi-Reci, I. (2018). *Market Research*. Singapore: Springer.

Ndulu, B. et al. (Eds.) (2008). *The Political Economy of Economic Growth in Africa 1960-2000. Vol. 1*. Cambridge: Cambridge University Press.

Pritchett, L. and Werker, E. (2012). ‘Developing the Guts (Grand United Theory): Elite Commitment and Inclusive Growth’. *Effective States and Inclusive Development (ESID) Working Paper 16/12*, University of Manchester.

Pritchett, L., Sen, K. and Werker, E. (2018) ‘Deals and Development: An Introduction to the Conceptual Framework’, in Pritchett, L., Sen, K. and Werker (eds), *Deals and Development*. Oxford: Oxford University Press, 1-38.

Reichenbach, H. (1956). *The Direction of Time*. Berkeley and Los Angeles: University of California Press.

Rodrik, D. (Ed.) (2003). *In Search of Prosperity. Analytical Narratives on Economic Growth*. Princeton: Princeton University Press.

Rodrik, D. (2012). ‘Why we Learn Nothing from Regressing Economic Growth on Policies.’ *Seoul Journal of Economics*, 25(2): 137-151.

Salai-i-Martin X., Doppelhofer, G. and Miller, R. (2004). ‘Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach’, *American Economic Review*, 94(4): 813-835.

Shaffer, P. *Q-Squared. Combining Qualitative and Quantitative Approaches in Poverty Analysis*. Oxford: Oxford University Press.

Shaffer, P., Kanbur, R. and Sandbrook, R. (2019). *Immiserizing Growth. When Growth Fails the Poor*. Oxford: Oxford University Press.

Sokoloff, L. and Engerman, S. (2000). ‘History Lessons: Institutions, Factor Endowments, and Paths of Development in the New World’, *Journal of Economic Perspectives,* 14: 217-232.

Suppes, F. (1970). *A Probabilistic Theory of Causality*. Amsterdam: North-Holland Publications.

Thorbecke, E. (2012a). ‘The Anatomy of Growth and Development in Sub-Saharan Africa.’ In McKay, A. and Thorbecke, E. (Eds), *Economic Growth and Poverty Reduction in Sub-Saharan Africa.* Oxford: Oxford University Press.

Thorbecke, E. (2012b). ‘Poverty and Inequality in Sub-Saharan Africa,’ in Aryeetey, E. et al. (eds.), *The Oxford Companion to the Economics of Africa.* Oxford: Oxford University Press.

Thorbecke, E. (2013). 'The Interrelationship linking Growth, Inequality and Poverty in Sub-Saharan Africa.' *Journal of African Economies*, 22(AERC Supplement 1)" i15-i48.

Vazquez, S. and Sumner, A. (2013). 'Revisiting the Meaning of Development: A Multidimensional Taxonomy of Developing Countries.' *The Journal of Development Studies*, 49(12): 1728-1745.

Vazquez, S. and Sumner, A. (2016). 'Is the "Developing World" Changing? A Dynamic and Multidimensional Taxonomy of the Developing Countries.' European Journal of Development Research, 28(5): 847-874.

Weber, M. (1949). *Max Weber on The Methodology of the Social Sciences* (Translated and Edited by Shils, E. and Finch, H.). Glencoe, Illinois: The Free Press.

World Bank (2008). *World Development Report 2008. Agriculture for Development*. Washington, DC: The World Bank.

Appendix A – CLUSTERING PROCEDURES: THE RECURRENCE FORMULA

As discussed in the main text, we rely in this analysis on seven different clustering procedures. The base model relies on Ward's approach, and six additional methods are used when calculating the 'probability' of a pairwise match between cases. The distinct characteristics of these approaches may be represented formally in terms of parameter values in Lance and William's (1967) recurrence formula, namely[17]:

$$d_{k(ij)} = \alpha_i d_{ki} + \alpha_j d_{kj} + \beta_{dij} + \gamma|d_{ki} - d_{kj}|$$

where $d_{k(ij)}$ represents the distance between group k and a newly formed group ij, all other subscripts associated with d refer to pairwise intergroup differences and $\alpha_i,\ \alpha_j, \beta\ and\ \gamma$ are parameters which take different values based on the clustering procedures used. These values for six of the seven clustering approaches used in this study are as follows:

	α_i	α_j	β	γ
Single Linkage	½	½	0	-½
Complete Linkage	½	½	0	½
Average Linkage	$n_i/(n_i + n_j)$	$n_i/(n_i + n_j)$	0	0
Centroid Linkage	$n_i/(n_i + n_j)$	$n_i/(n_i + n_j)$	$-n_i n_j (n_i+n_j)^2$	0
Median Linkage	½	½	-¼	0
Ward's Method	$(n_k+n_i)/(n_k+n_i+n_j)$	$(n_k+n_i)/(n_k+n_i+n_j)$	$-n_k/(n_k+n_i+n_j)$	0

[17] This discussion is based closely on Everitt et al. (2011: 78-80).

APPENDIX B – BASE MODEL RESULTS

	countryyear	Agglom.	K-Means			Agglom.	K-Means
1	BurkinaFaso1994-2003	1	1	39	Malawi1998-2004	2	1
2	BurkinaFaso2003-2009	1	1	40	Malawi2004-2010	2	1
3	BurkinaFaso2009-2014	1	1	41	Mali1994-2001	1	1
4	Burundi1992-1999	1	1	42	Mali2001-2006	1	1
5	Burundi1999-2006	1	1	43	Mauritania1993-2000	1	1
6	Burundi2006-2014	1	1	44	Mauritania2000-2008	1	1
7	Cameroon1996-2001	1	1	45	Mauritania2008-2014	1	1
8	Cameroon2001-2007	1	1	46	Mozambique1996-2003	2	2
9	Cameroon2007-2014	1	1	47	Mozambique2003-2009	2	2
10	CentralAfricanRepublic1992-2003	1	1	48	Mozambique2009-2014	2	2
11	CentralAfricanRepublic2003-2008	1	1	49	Namibia1994-2004	2	2
12	Coted'Ivoire1993-1998	1	1	50	Namibia2004-2010	2	2
13	Coted'Ivoire1998-2008	1	1	51	Namibia2010-2015	2	2
14	Coted'Ivoire2008-2015	1	1	52	Niger1993-2005	1	1
15	Eswatini1995-2001	2	2	53	Niger2005-2011	1	1
16	Eswatini2001-2009	2	2	54	Nigeria1992-2004	1	1
17	Ethiopia1995-2000	1	1	55	Nigeria2004-2010	1	1
18	Ethiopia2000-2005	1	1	56	Rwanda2000-2006	1	1
19	Ethiopia2005-2011	1	1	57	Rwanda2006-2011	1	1
20	Ethiopia2011-2016	1	1	58	Senegal1991-2001	1	1
21	Gambia,The1998-2003	1	1	59	Senegal2001-2011	1	1
22	Gambia,The2003-2010	1	1	60	Seychelles2000-2006	2	2
23	Gambia,The2010-2015	1	1	61	Seychelles2006-2013	2	2
24	Ghana1998-2006	1	1	62	SouthAfrica1993-2001	2	2
25	Ghana2006-2013	1	1	63	SouthAfrica2001-2005	2	2
26	Guinea1991-2002	1	1	64	SouthAfrica2005-2010	2	2
27	Guinea2002-2007	1	1	65	SouthAfrica2010-2015	2	2
28	Guinea2007-2012	1	1	66	Tanzania1992-2000	1	1
29	Guinea-Bissau1991-2002	1	1	67	Tanzania2000-2007	1	1
30	Guinea-Bissau2002-2010	1	1	68	Tanzania2007-2012	1	1
31	Kenya1992-1997	1	1	69	Uganda1996-2002	1	1
32	Kenya1997-2005	1	1	70	Uganda2002-2009	1	1
33	Kenya2005-2016	1	1	71	Uganda2009-2017	1	1
34	Lesotho1994-2003	2	2	72	Zambia1993-1998	2	2
35	Lesotho2003-2010	2	2	73	Zambia1998-2003	2	2
36	Madagascar1993-1999	2	2	74	Zambia2003-2010	2	2
37	Madagascar1999-2005	2	2	75	Zambia2010-2015	2	2
38	Madagascar2005-2010	2	2				