Inclusive Growth and Employment: Conceptual and Methodological Challenges*

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Abstract

This paper presents a review of several recent studies dealing with issues related to labour markets and employability in the framework of inclusive growth diagnostics. The methodological framework used by existing studies is highlighted and we put forward new tools for the analysis of the transition to employment, the assessment of heterogeneity in returns to education and propose the use of models that explicitly account for spatial spillovers in labour market variables.

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1. Introduction

Employment lies at the heart of the concept of inclusive growth. The methodological framework constructed around the idea of inclusiveness in economic growth patterns focuses on the concept of productive employment and thus differs from other conceptual settings where concepts based on direct income redistribution lie in the centre of the paradigm (see Ianchovichina and Lundstrom, 2009). The focus on productive employment is justified by Ianchovichina and Lundstrom (2009) on the basis of the long-run perspective of the concept, as well as by the role that employment plays in the framework as the means which should allow excluded individuals to achieve sustainably high(er) income levels.

From an analytical point of view, inclusive growth analysis expands the growth diagnostics framework proposed by Hausmann, Rodrik and Velasco (2005, 2006, henceforth HRV). It does so by moving away from aggregated analysis and the search for binding constraints at the macroeconomic level and instead concentrating on potentially heterogeneous groups of the labour force. While this partly implies a different focus as compared to the HRV approach, the interaction between returns to investment and returns to employment links both approaches and emphasizes the need for a combined analysis when it comes to unveiling the constraints to inclusive growth.

As is the case with the HRV approach, inclusive growth diagnostics is eclectic in terms of the methodological toolkit applied to assess the nature of binding constraint(s). In particular, concerning issues related to employment and labour markets, which is the subject of this note, many different empirical methods have been used.

The aim of this contribution is twofold. On the one hand, we present a concise critical review of some of the main analytical tools which have been used to assess issues related to employment in recent studies which concentrate on inclusive growth. On the other hand, we highlight several useful analytical tools which have, in our opinion, been underutilized or ignored. In this sense, our study contributes to the discussion of inclusive growth analysis by proposing meaningful expansions to the set of available techniques for diagnostic. In particular, from a conceptual point of view, we concentrate on the pivotal role played by human capital accumulation as a determinant of employability and wages (and thus poverty) and as a potential binding constraint to inclusive growth. In terms of methodology, we emphasize the spatial dimension of economic growth and poverty, which has hitherto been at least partly ignored in existing research pieces on inclusive growth diagnostics.

This paper is structured as follows. In section 2 we offer a general description of the role played by labour markets in the framework of inclusive growth and review the different methodological approaches used to unveil potential binding constraints to inclusive growth in labour markets. Section 3 tackles the issue of human capital as a determinant of employability and wages and proposes several analytical tools such as the analysis of subnational dynamics of returns to education to assess constraints to inclusive growth in developing countries. Section 4 discusses the direct role of geography as a (direct or indirect) determinant of poverty outcomes and proposes the explicit modelling of spatial spillovers to analyze subnational poverty trends and to carry out policy
2. Employment and Inclusive Growth: Methods and Tools

As a methodological framework, inclusive growth moves the focus of analysis away from the pace to the pattern of economic growth. High growth rates alone may not be a sufficient condition to reduce poverty, since for growth to be sustainable it needs to be broad-based across sectors and inclusive of a large part of the labor force (see Ianchovichina and Lundstrom, 2009). Within this paradigm, productive employment appears as the main instrument to reach inclusive growth. Productive employment, in turn, is thought of as subsuming employment growth as well as productivity growth, and thus causing increases not only employment opportunities for currently unemployed individuals but also wages and income from the (self) employed. Since it is a stylized fact that the poor derive most of their income from work or self-employment (see for instance Gutierrez, 2007), well-functioning labor markets, sufficient employment opportunities and productivity improvements are thus keys for ensuring inclusive growth. As opposed to pure income redistribution, productive employment has the potential to increase the income of excluded groups permanently and is thus understood as the main instrument to reduce poverty.

Understanding the challenges of productive employment requires an in-depth analysis of employability at the individual level, as well as an assessment of the opportunities (or lack thereof) of being productively employed in the economy under study. Acquiring such knowledge about potential barriers to productive employment requires a detailed assessment of both supply and demand forces in the labour market, taking into account the institutional setting in which labour market interactions take place.

Addressing barriers to productive employment from the labour supply side concentrates on the analysis of issues related to human capital (both formal education and eventually informal forms of skill acquisition, as well as health), which plays a central role as a determinant of labour market entry. Inclusive growth tools related to the labour demand side, on the other hand, tend to concentrate on the question of whether and how employment opportunities could be extended. A common approach to address this question is by carrying out business environment analyses in the spirit of the decision tree framework laid down by standard growth diagnostics. Arguing that low private investment occurs either if the returns to economic activity are low or if the costs of finance are high, the methodology sheds light on the institutional environment, infrastructure, macroeconomic stability and international and domestic financial markets, all considered as important determinants of sustained job creation.

In the following pages we review some of the methodological tools that have been used in studies conducted with the aim of finding binding constraints to inclusive growth in human capital and labour markets. The two concepts introduced above, employability analysis and business environment analysis, constitute the basic framework in which a manifold of different analytical tools are applied. A word of caution should be spoken beforehand. On the one hand, inclusive growth studies need to acknowledge explicitly the peculiarities of the country, region or sub-population under consideration in terms of its economic, cultural, political and social specificities. On the other hand, the deeper
analysis of particular aspects related to employability is often very limited due to data availability and reliability. It is thus the case that many of the tools that would be available for inclusive growth diagnostics cannot be applied to some countries due to lack of data. Furthermore, it means that specific ad-hoc methods have to be used in many inclusive growth studies to overcome (at least partly) the problems caused by the limited and fragmented nature of the data in some countries.

Inclusive growth analysis has been recently applied in various country studies conducted by the World Bank and the concept of inclusive growth has shaped several recent Country Economic Memoranda. This section discusses a selection of the methods used in these studies, with a special focus on the tools used to detect binding constraints to inclusive growth in human capital and the labour market.

The main instrument used for identifying signals of restrictions in broad-based, inclusive growth is benchmarking of key indicators. Common benchmarks are contingent countries, countries of similar size or geographic conditions or countries that enjoy exemplary status in the region. It lies in the nature of inclusive growth diagnostics that such benchmarking exercises do not only concentrate exclusively on macroeconomic indicators, but tend to include individual-level and firm-level information by employing statistics obtained from household or firm surveys. In addition, when available, the utilization of subnational level data allows to draw conclusions about spatial heterogeneities and potential regional asymmetries that remain undetected when focusing exclusively on national-level data.

The central role of human capital (comprising both health and education) as a determinant of employment, productivity and wages in developing countries has been repeatedly shown in empirical studies (see Sahn and Alderman, 1988 or Strauss and Thomas, 1998, just to name two of the most cited works on the issue). The assessment of school attainment statistics and other formal education measures, as well as their relative level with respect to other countries or regions is thus a natural step that is taken when investigating binding constraints to inclusive growth. In a labour market segmented by skills, such a comparison allows to investigate the quantity side of the respective supply of labour. The price signals, which are the central measure to investigate binding constraints in the setting of inclusive growth diagnostics, are inferred from estimates of returns to education, eventually for different school attainment levels.

From the labour supply side, some of the measures used in growth diagnostics to gauge the quantity dimension of human capital accumulation include unemployment rates by skill level, literacy rates, school attainment statistics, enrolment rates and school quality data (pupil-to-teacher ratios, school infrastructure measures). The analysis based on labour supply characteristics tends to be enhanced by assessing the potential existence of constraints on the labour demand side. For this purpose, business environment analysis in the spirit of the growth diagnostics framework by HRV has been used in some cases. The rationale for the analysis relies on the relationship between private investment and employment opportunities: lack of private investment decreases employment opportunities and thus the chances for productive employment. Following the constraint assessment mentality embodied in growth diagnostics, low private
investment can originate either in low access to finance or in low returns to economic activity. To assess the first, key indicators are sometimes used to investigate whether subnational economies differ in terms of the conditions that firms face concerning labour markets and access to finance. In particular, benchmarking indicators such as credit to GDP ratio, the share of credits that are used for investment and working capital, lending rates for loans and the number of banks per person has proved useful in offering a quantitative picture of access, cost and supply of finance.

Unemployment dynamics can reveal important signals in inclusive growth studies. The importance of job creation in unemployment dynamics has been assessed by analyzing trends in key variables such as working age population and labour force participation, as well as labour productivity and wages. Such type of analysis is carried out by sector and gender and thus provides a first investigation related to the inclusiveness of the recent economic growth experience in the country under study. Methods for measuring skill mismatch include the analysis of unemployment or underemployment rates of particular skilled workers, by identifying skilled-labour shortages or by comparing emigration rates of individuals with different skill level.

The HRV and inclusive growth approaches, however, rely on unveiling (shadow) price signals as indicators of constraints to inclusive growth. HRV propose the identification of potential constraints to growth by concentrating on several stylized facts that should be (in principle jointly) observed in the market which is affected by the binding constraint: (a) the (shadow) price of the constraint should be high; (b) changes in the constraint should produce significant movements in the objective; (c) agents should attempt to overcome the constraint informally; (d) agents less intensive in the binding constraint should be more likely to be successful in the market. In terms of inclusive growth, which concentrates on constrained agents among heterogeneous groups, the stylized facts may be present in certain groups of individuals of firms, which would thus be affected by the binding constraint, but not in others.

From a theoretical point of view, the focus on the (shadow) price component is aimed at identifying supply and demand constraints. The approach interprets thus low quantity signals as potential restrictions in the market only if they are accompanied by relatively high prices. For the case of constraints to employability related to human capital accumulation, the study of returns to education is the key analysis to pinpoint potential labour market imperfections limiting inclusive growth. The coupling of a low level of some educational attainment with low returns to that type of skill would tend to be interpreted as lack of demand for skilled individuals from the side of firms, while low attainment together with high returns would signal a possible constraint to growth. Expanding the analysis to labour demand and labour supply for particular segments of the population and/or sectors or firms would further allow assessing constraints to inclusive growth. The existence of regional constraints can be further investigated by obtaining price signals in subnational units, eventually with an emphasis on differences between rural and urban areas.

If data are available, changes in overall returns to education can be studied by making use of Mincerian wage regressions applied to micro-datasets which span several years. However, education quality may also play a central role as an inclusive growth
constraints. Measuring education quality and interpreting whether the qualitative side of schooling is constraining inclusive growth requires the use of specific methods and data that go beyond the usual attainment statistics. Scores from international homogenized tests allow for benchmarking the country under study against other economies, but they are not always available for developing countries. The existence of national test scores for past years may also contribute to the analysis by informing about the variability of education quality over time. In particular, comparing the dynamics of enrolment figures and quality measures may be important to unveil first signals of capacity constraints in schools which would materialize in decreasing test scores with increases in enrolment.

Besides benchmarking general test results, the method put forward by Bratsberg and Terrell (2002) has proved helpful in providing an indicator of the relative quality of education in developing countries. The method relies on the estimation of returns to education of migrants to the US who received education in their respective home countries. Differences in the returns to education across sending countries are thus interpreted as an indicator for quality differentials of the educational outcomes of the various source economies. Studying the link between education and migration rates across population groups offers further information about links between human capital accumulation and employability, adding the returns to education in terms of migration possibilities to the analysis, as well as potential problems related to retaining high skilled workers in the country.

For developing countries which are expected to experience significant falls in fertility rates or changes in age structure whose source is related to demographic transition effects, a deeper analysis of demographic trends is in place when setting up the inclusive growth diagnostics design. Indicators such as unemployment rates, labour force participation and poverty rates by age group, as well as overall population dynamics and demographic trends are examined in order to obtain a detailed profile of the characteristics of the labour force. The demographic transition caused by the fall in fertility rates could change radically the labour market characteristics of the affected countries, as well as the challenges faced by the health and educational sectors and such dynamics should be explicitly accounted for in the analysis carried out in inclusive growth studies.

The existing inclusive growth studies reveal a very agnostic methodological approach, where the particular characteristics of the country and data availability appear as important determinants of the techniques employed to approach the identification of labour market constraints to inclusive growth. From a theoretical point of view, it is the case that the detailed study of returns to education, including the assessment of their differences across groups of the population and educational attainment levels and their dynamics over time (if data availability allows) should be a central part of the employability analysis in inclusive growth studies. In addition to the effort carried out by the studies reviewed in order to perform sensible inclusive growth analysis when it comes to issues related to employability, several methodological challenges and potential improvements can be proposed:

3 In certain cases, the lack of data can be itself a binding constraint for the performance of a sensible inclusive growth analysis.
Macro-econometric evidence on the transition to employment among different groups of the labour force, a key element of inclusive growth analytics, should play a more central role in the analysis, data permitting.

b) The assessment of heterogeneity in returns to education across groups of the population can offer extremely valuable information to the analysis.

c) The analysis of subnational data on labour markets, economic growth and poverty should explicitly account for the potential existence of spatial spillovers, thus improving the realism of policy analysis at the regional level.

In the following section we refer to the points raised in a) and b), while section 4 deals with the problem of empirically accounting for spatial clustering and spatial spillovers in inclusive growth analysis.

3. Heterogeneity, employability and returns to education

Which are the main determinants of participation in the labour market? How do these determinants change between rural and urban areas? How do they change between men and women? Are there obstacles to the integration of some societal groups in the labour market? These questions lie at the heart of inclusive growth analytics but cannot be assessed empirically unless we perform an analysis that moves away from benchmarking aggregated figures and concentrates on modelling precisely the differences between heterogeneous groups of the population instead of concentrating on their similarities.

Dealing with such issues requires empirical specifications that model the labour market status of individuals and thus the transition to employment. Such models can provide very valuable information for policymakers interested in making economic growth inclusive but have not become a workhorse of inclusive growth analytics. Admittedly, data availability may limit the possibilities of carrying out such an analysis, but in principle the information contained in labour force surveys should be sufficient for this assessment.

As an illustrative example that shows how such type of analysis can be a powerful tool to identify deficiencies in the labour market, we present below some estimations for Uganda which aim at answering questions as those posed above. We use the Uganda National Household Survey for 2005/6 in order to estimate multinomial logit models which aim to identify the determinants of labour market status and measure the relative effect of different factors on labour participation. We consider four possible values of the dependent variable, corresponding to the individual being unemployed \((y=0)\), employed in the wage sector \((y=1)\), self-employed \((y=2)\) or employed in agriculture \((y=3)\). Our multinomial logit model implies that
\[ P(y = j) = \frac{\exp \left( \sum_{f=1}^{k} \beta_j f x_f \right)}{1 + \sum_{j=0}^{3} \exp \left( \sum_{f=1}^{k} \beta_j f x_f \right)}, \]

for \( j = 1, 2, 3 \), and

\[ P(y = 0) = \frac{1}{1 + \sum_{j=0}^{3} \exp \left( \sum_{f=1}^{k} \beta_j f x_f \right)}, \]

where the group of \( x \)-variables summarizes the factors affecting the probability of being unemployed or employed in each one of the sectors (wage sector, self-employed or agricultural sector). We use socio-demographic variables (education attainment, age, place of residence, household characteristics) as regressors and the results of the estimation are presented in Table 2 for the subsamples of men and women in the sample, so as to stress the differences between the two groups. Similar subsample analysis can be carried out for rural versus urban areas, or by subnational regions. Focusing on such heterogeneity is a necessary condition in the framework of inclusive growth analysis.

The importance of assessing parameter heterogeneity in the econometric models used to inform inclusive growth analysis can be exemplified by comparing the marginal effect estimates for labour market status reported in Table 2. Comparing the results for the female and male sample, the role of primary education in offering opportunities in the self-employment sector is present in the male subsample, while females with primary education are more likely to remain in the agricultural sector. Secondary education, on the other hand, contributes to move from the agricultural sector to employment in the wage sector for both subsamples. The differences in terms of labour participation across regions in Uganda once that the characteristics of individuals are controlled for are also particularly interesting and can inform policymakers about labour market policies to achieve inclusive growth.
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Coefficients are marginal effects, evaluated at the means of the independent variables. Survey-corrected standard errors in parenthesis. *(**)[***] stands for significance at the 10% (5%) [1%] level.

Table 2: Multinomial logit estimates: Labour participation, Uganda National Household Survey for 2005/6

As mentioned in the previous section, demographic change adds a new heterogeneity metric which can be very important for countries undergoing falls in fertility rates, as is the case in many developing countries. Changes in the age structure of societies can have strong effects on the labour market, and these effects can be magnified by the differences in acquired skills across cohorts after fertility declines take place. The smaller size of cohorts after the decrease in fertility creates a window of opportunity both in terms of liberating resources from dependent individuals and allowing for higher per-capita investments in human capital. As demographic dividend

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4 Both of these effects are central elements of the so-called demographic dividend (see for example Bloom and Williamson, 1998).
(see Lutz et al., 2007, and Barro and Lee, 2010). These data can be used for benchmarking, building economic growth models and assessing future demographic developments in the form of projections (see KC et al. 2010), but has been hitherto relatively underutilized in inclusive growth studies.

A similar proposal concerning the importance of explicit modelling of heterogeneity can be put forward when it comes to assessing returns to education in inclusive growth studies. The estimation of aggregated returns to education, as well as benchmarking exercises based on this measure, is a valuable starting point for growth diagnostics, but an inclusive growth diagnostics exercise needs to take a step further and measure differences in returns in the corresponding heterogeneity metric. In terms of Mincerian wage regressions, which are the usual methodological workhorse to estimate returns to education, such heterogeneity can be easily captured by estimating the wage regression over subsamples of the data or using the corresponding interaction terms in the regression based on the full sample.

If estimates of returns to education are available over long periods of time, a detailed analysis of their dynamics between and within regions is a powerful tool to unveil constraints to inclusive growth related to human capital accumulation and labour markets which has been ignored in previous studies. This is a particularly important technique, since returns to education are the most important “price signal” when it comes to evaluating binding constraints to inclusive growth in terms of human capital. The evaluation of whether an observation of relatively high returns to education is related to labour market deficiencies that require policy action should only be carried out after making sure that such “high price” information is indeed atypical. Such labour market imperfections would exist if differences in returns to education across and within regions are not being eroded over time through forces related to the demand and supply of skilled labour (through mechanisms such as migration or changes in human capital investment and skilled labour demand strategies).

Proceeding further with the example of Uganda that has been presented above, we used the Uganda National Household Surveys for 2002/03 and 2005/06 to obtain district-specific estimates of returns to education. If (labour) market forces are in place and price signals are functioning, we would expect districts with high returns to education in 2002/03 to have decreased their returns (for example, through migration of skilled individuals to that region, attracted by the relatively higher wage) and we would expect the opposite to occur in districts with low wage premia for skilled individuals. This implies that lack of convergence in returns to education across subnational regions may be interpreted as a signal of inclusive growth constraints in regional labour markets. Using the returns by district for Uganda in 2002/03 and 2005/06 obtained from Mincerian wage regressions, Crespo Cuaresma and Raggl (2011) propose to estimate beta-convergence regressions in order to evaluate the degree of convergence in returns and thus assess inclusive growth constraints. Convergence regressions are built by using the change in the corresponding measure of interest (in our case, returns to education) as a dependent variable and the value of the measure in the initial period as explanatory variable. A negative estimated parameter for the initial value indicates that convergence in returns to education took place over the period under study, since regions with relatively low returns to education at the beginning of our observation period tended to
increase them more than those where returns where relatively high. The opposite case, reflected in positive estimates of the parameter, indicates divergence in returns to education. The absolute value of the estimated parameter is related to the speed of convergence over the corresponding period, with higher values of the estimate indicating higher speed of income convergence.

The usefulness of this method to inform policymakers about constraints to inclusive growth can be illustrated using the model used in Crespo Cuaresma and Raggl (2011) for assessing dynamics in returns to education at the subnational level in Uganda. Following the framework set up above, the empirical model is given by

\[ \Delta \hat{r}_j = \gamma_{0,j} + \sum_j \gamma_{1,j} \hat{r}_{0,j} + \nu_j, \]

where \( \hat{r}_{0,j} \) is the estimate of returns to education for district \( i \) in region \( j \) in 2002/03 and \( \Delta \hat{r}_j \) is the corresponding change in returns to schooling in that district. This model can be used to account for convergence between and within regions through the use of region-specific fixed effects and, eventually, region-specific speeds of convergence which are captured by the parameters \( \gamma_{1,j} \). Differences in these parameters are signals of barriers to “price equalization” in labour markets in terms of returns to human capital. The estimates of the model are presented in Table 3, making use of 55 observations for districts in Uganda. Three different specifications are used. In the first column, we evaluate overall convergence in returns to education across districts and regions, setting thus an overall intercept in the specification. The second column assesses within-region convergence of returns to education assuming a common speed of convergence, which is done by including region-specific intercepts in the model. Finally, the third model allows for region-specific speed of convergence in returns to education by breaking the assumption \( \gamma_{1,j} = \gamma_1 \) and thus allowing for convergence speeds that differ across the four broadly defined regions of Uganda.

The results in Table 3 indicate a strong trend of convergence across districts. On average, returns to schooling also converged within regions, as can be observed from the estimates of the second column, which includes region-specific fixed effects. However, estimating region-specific speeds of within-region convergence leads to important differences in the speed of correction of labour market disequilibria in terms of returns to education. In particular, the correction of return differences in Northern Uganda (a post-conflict region) appears significantly slower than in the rest of the country. Standard tests for equality of parameters for all regions strongly rejects the null hypothesis of equal speed of convergence across regions, but excluding the Northern region the test cannot reject equality. A more detailed analysis of such differences can explain the divergent results at least partly through conflict-related displacement and infrastructure problems, coupled with teacher-supply related problems (see Crespo Cuaresma and Raggl, 2011).
Common intercept Region fixed effects Region fixed effects and region-specific convergence speed

<table>
<thead>
<tr>
<th>Initial return</th>
<th>-1.079*** (0.141)</th>
<th>-1.070*** (0.155)</th>
<th>-1.564*** (0.319)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial return, Central</td>
<td>-1.564*** (0.319)</td>
<td>-1.253*** (0.177)</td>
<td>-0.573*** (0.052)</td>
</tr>
<tr>
<td>Initial return, East</td>
<td>-1.253*** (0.177)</td>
<td>-0.573*** (0.052)</td>
<td>-1.352*** (0.147)</td>
</tr>
<tr>
<td>Initial return, North</td>
<td>-0.573*** (0.052)</td>
<td>-1.352*** (0.147)</td>
<td></td>
</tr>
<tr>
<td>Initial return, West</td>
<td>-1.352*** (0.147)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>55</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>R²</td>
<td>0.5848</td>
<td>0.5948</td>
<td>0.658</td>
</tr>
</tbody>
</table>

**Table 3: Convergence equations for returns to education in Uganda (2002-2006)**

The aggregate analysis that has been carried out in several other inclusive growth analysis and Country Memoranda would have given no signal of constraints related to human capital in labour markets in Uganda. Aggregate levels and dynamics of returns to education in Uganda do not present deviant behaviour and an analyst would be unable to extract any type of growth constraint in the country. Important inclusive growth constraints are only unveiled in the analysis models subnational heterogeneity explicitly.

The analysis of subnational labour market data such as for the example presented above, which is an essential step in inclusive growth analysis, is however potentially plagued with problems of spatial autocorrelation which require the use of methods to account for geographical spillovers. These methods, which have not hitherto been used by the existing inclusive growth diagnostics, can reveal key information for regional policy analysis. In the following section we deal in detail with available tools which approach spatial spillovers explicitly and that should become standard in the framework of inclusive growth analysis.

### 4. Spatial spillovers and policy analysis in inclusive growth analytics

The ultimate goal of inclusive growth analysis is the design of policies that reduce poverty through productive employment. As already discussed in the preceding sections, differences across a country’s regions are an important indicator to assess constraints to inclusive growth with respect to the metric defined by geographical divisions that constitute administrative subnational units.

Figure 1 presents a map of poverty rates for county-level data in Kenya, which serves as an example in this section to illustrate some of the problems related to the development of econometric tools for inclusive growth analysis using subnational data. The data refer
to the years 2005/06 and have been estimated by the World Bank based on figures sourced from the Kenya Integrated Household Budget Survey (KIHBS). Understanding the determinants of poverty at the subnational level implies building up models based on data such as those depicted in Figure 1.

![Figure 1: Poverty rates at the county level, Kenya](image)

It is obvious from Figure 1 that the levels of poverty do not appear to be randomly distributed across regions. Poverty rates appear to be clustered in space the same way as positively autocorrelated time series data are in time, due at least partly to within-country migration and economic linkages between nearby regions. Regions with relatively low levels of poverty tend to be surrounded by regions whose poverty rates are also relatively low, and vice versa. This phenomenon is known as spatial autocorrelation and needs to be assessed explicitly in models of regional data to avoid biases in estimates of statistical models for subnational data. If the assumption of independence across regions is not fulfilled, tools which do not account for spatial linkages may provide misleading conclusions concerning inclusive growth constraints.

Spatial autocorrelation in this framework implies that the level of poverty of a given region is influenced by the poverty rates of the rest of the regions of the country, and that this influence is modulated by the distance between subnational divisions. The

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5 The data are freely available at http://opendata.go.ke.
6 The recent book by LeSage and Pace (2009) presents an excellent account of spatial econometric models.
simplest specification for data that present spatial autocorrelation is the spatial autoregressive (SAR) model, where the variable of interest is assumed to depend on a weighted average of the value of the variable in the other regions. The weights, in turn, depend on the distance between the respective divisions,

$$y = \lambda W(d) y + u,$$

where $y$ is a vector containing in our case the poverty rates for the counties of Kenya, $u$ is a vector of random shocks and $W(d)$ is a matrix whose diagonal elements are zero and their off-diagonal elements refer to the relative weight of the poverty rate of each other region. This spatial link matrix depends, in turn, on the distance between regions. Standard spatial link matrices include the inverse distance matrix, whose typical element is given by the inverse of the distance between the corresponding regions, or $k$-th order Queen contiguity matrices, which assign positive weights to neighbouring regions up to $k$-th order neighbours and zero weight otherwise. If the estimate of $\lambda$ is positive and significant, positive spatial autocorrelation is present in the data and policy analysis would need to take into account that policy actions in a given location have effects in nearby regions which could be sizable. Using the poverty data for counties in Kenya, we estimate a simple spatial autoregressive model using an inverse distance matrix, as well as a first order Queen contiguity matrix. The results are presented in the first two columns of Table 4 and give strong evidence of positive spatial autocorrelation in poverty rates for Kenya independently of the spatial weighting matrix used.

Empirical studies about the effect of human capital variables as a determinant of poverty reduction are an important input for inclusive growth analysis and generally rely on models where the relationship between poverty rates and selected covariates is estimated, usually in the framework of linear regression specifications. Spatial spillovers can be included explicitly in the model by adding a spatial autoregressive term as an extra regressor in these specifications. We estimate a simple model to explain differences in poverty across Kenyan counties including, in addition to the spatial autoregressive term measures of human capital accumulation (percentage of population with primary education and percentage of population with secondary education) and infrastructure (percentage of households with access to electricity). The estimates of the model are presented in the third column of Table 4. For comparison reasons, column 4 in Table 4 presents the estimates of the same model without the spatial autoregressive term.

The estimated model in column (3) indicates that even after controlling for human capital and infrastructure, spatial autocorrelation is present in the poverty data, as reflected by the significant positive estimate of $\lambda$. The differences in the estimated parameters between the model with spatial autocorrelation (column 3) and the model which does not account for it (column 4) are large. The model without spatial autocorrelation obtains larger elasticity estimates of poverty reduction to improvements in educational attainment. The SAR model, on the other hand, interprets the reaction of poverty to improvements in education partly as a direct effect (of smaller

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7 Admittedly, endogeneity of the covariates of the model may be a further source of bias in the estimates. Since our methodological discussion is concentrated exclusively in the problem of spatial spillovers, we abstract from the endogeneity discussion here.
magnitude than that estimated by the model without spatial effects) and partly as a reaction to poverty changes in surrounding regions.

<table>
<thead>
<tr>
<th>Model</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda )</td>
<td>0.711***</td>
<td>0.687***</td>
<td>0.485***</td>
<td>(0.142)</td>
</tr>
<tr>
<td>Primary education</td>
<td>-0.823</td>
<td>-1.339**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Secondary education</td>
<td>-1.098*</td>
<td>-2.125***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electricity access</td>
<td>-63.150***</td>
<td>-75.310***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial weight matrix</td>
<td>Inverse distance</td>
<td>1st order contiguity</td>
<td>1st order contiguity</td>
<td>None</td>
</tr>
<tr>
<td>Observations</td>
<td>47</td>
<td>47</td>
<td>47</td>
<td>47</td>
</tr>
</tbody>
</table>

**Table 4: Models for subnational differences in poverty rates, Kenyan counties 2005/06**

The use of models with spatial spillovers adds a dimension of realism to inclusive growth diagnostics, in particular when it comes to analyzing potential labour market or education policies at the regional level. Should a constraint to inclusive growth be discovered in a given region that would require improving attainment rates in secondary education, the assessment of the quantitative effect that this policy would have on poverty in the country would be fundamentally different depending on whether models with spatial spillovers are used.

The model without spatial autoregressive term would predict that the increase will materialize in the corresponding decrease in poverty in the affected region, without changing poverty rates elsewhere. The inclusion of spatial spillovers, on the other hand, would allow us to track the geographical spillovers of this policy by estimating the effects that the change in attainment rates causes in the rest of the counties and the feedback that these changes create in the region of interest. Using the estimated models, we obtain two policy simulations in order to measure the role of spatial spillovers in policy analysis. In particular, we assume that, ceteris paribus, the secondary school attainment rate in Nairobi increases by 5 percentage points and estimate the poverty rates in the country as fitted values of the corresponding model after the change. Figure 2 presents the corresponding maps for the fitted poverty rates of the models with and without spatial spillovers after the increase in educational attainment. Figure 3 depicts the differences in simulated poverty rates between the models with and without spatial spillovers. As can be seen in these Figures, the estimated effects of the policy can be very different depending on the underlying specification, in particular for peripheral counties.
when building statistical models and comparing policy scenarios for subnational datasets should become part of the standard toolbox for inclusive growth analysis, a status that they have not yet achieved judging by the existing studies.

5. Conclusions

Several promising methodological improvements have been proposed for the analysis of labour markets in inclusive growth diagnostic studies. First, we propose using models of transition to the labour market as a useful tool to pinpoint differential employability characteristics among population subgroups. We also propose making use of more detailed heterogeneity metrics when studying demographic dynamics and returns to education.

We also put forward the use of standard spatial econometric specifications in order to build more realistic models at the regional level which can be used for policy simulations. The differences in access to productive employment and thus in poverty reduction across subnational units, which has received a lot of interest in the inclusive growth literature, may be better understood by explicitly allowing for spatial spillovers in the specifications used for the analysis.

For many economies, the utilization of the type of models proposed in our study implies that further resources should be put in expanding existing data collection efforts and complementing them with new datasets at the microeconomic level.
References


