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Convergence analysis for hierarchical longitudinal data[☆]

Giorgio Fazio[a,b,*], Davide Piacentino[b]

[a] Newcastle University Business School, Newcastle University, 5 Barrack Road, NE1 4SE, Newcastle upon Tyne, UK
[b] SEAS, University of Palermo, Edificio 13, Palermo, ITA-90128, Italy

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ABSTRACT

Convergence analysis is typically envisaged either from a macro or a micro perspective. However, empirical tests tend to ignore that the two levels are often "nested" in a hierarchy. Building on hierarchical growth curve modelling, we propose an approach to convergence analysis that allows contemporaneous inference on macro and micro-convergence. Compared to the classic linear convergence analysis, the suggested methodology provides a more flexible alternative to model heterogeneity and validate the results for possible Galton's fallacy. We illustrate the approach in two empirical examples, one considering convergence across European regions and countries and the other across Italian firms and regions. In the European case, we find that the evidence of convergence depends on the choice of cross-sectional sample. Evidence on convergence in Italy applies only to part of the temporal sample and, therefore, is not robust to Galton's fallacy. Our analysis returns more robust results on the convergence process and allows better inference for policy intervention. We can envisage that this approach will find increasing applications in the future, as disaggregated data becomes available and heterogeneity becomes an increasingly prominent feature in economic modelling.

1. Introduction

Understanding economic convergence is of critical importance in order to formulate growth policies at the national, regional and local level. It is not surprising, then, that convergence analysis has become one of the most important objectives of empirical macroeconomic modelling. In this direction, traditional empirical growth studies typically consider a reference level of analysis, e.g. countries or regions, and perform tests of convergence using aggregate data from national or international statistical sources.[1] Following Solow (1956), the classic linear convergence approach relies on the assumption that economies share similar preferences and technologies and, therefore, have similar aggregate production functions. However, as discussed in detail by Durlauf and Johnson (1995) and Durlauf et al. (2001, 2005), the data generating process underlying the Solow parameters may be substantially different across countries (or regions) leading to incorrect conclusions on the convergence process. This issue has prompted a number of contributions in the macroeconometric literature that try to model parameter heterogeneity in the convergence analysis (see, among the others, Durlauf et al., 2001, Phillips and Sul, 2007, Haupt et al., 2017). Another issue emerging from the use of the aggregate production function is related to its ability to represent the underlying economy and, therefore, the convergence process. Actually, the very existence of aggregate production functions is part of a long-standing controversy, as illustrated by Cohen and Harcourt (2003) and more recently by Felipe and McCombie (2014). Indeed, considerable heterogeneity may exist among the underlying micro units that are part of the macro aggregate of interest (Altomonte and Colantone, 2008; Fazio and Piacentino, 2010). As such, empirical growth analysis is bound to miss the underlying microeconomic processes, such as technological diffusion/catching-up and concentration/dispersion occurring at the micro level (regional, firm or industry), that according to economic theory are critical to observe economic convergence or divergence at the

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* Corresponding author. Newcastle University Business School, Newcastle University, 5 Barrack Road, NE1 4SE, Newcastle upon Tyne, UK.
E-mail addresses: giorgio.fazio@ncl.ac.uk (G. Fazio), davide.piacentino@unipa.it (D. Piacentino).

[1] See Islam (2003) for an extensive survey on the convergence debate and Martin and Sunley (1998), Rey and Janikas (2005), Le Gallo and Fingleton (2014) and Gennaioli et al. (2014) for a more specific regional perspective.

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macro-level.[2]

For the above reasons, a number of papers have shifted the focus from the macro to the micro level, looking for example at firms or industries (see, among the others, Hausmann et al., 2007; Bartelsman et al., 2008; Egger and Pfaffermayr, 2009; Huber and Pfaffermayr, 2010; Chevalier et al., 2012). This literature tends to find stronger evidence of convergence at the micro rather than the macro-level.[3] Yet, also a purely disaggregated and micro-level perspective has its pitfalls. First, from the policy perspective it is typically the macro level of interest - usually a certain administrative unit - that matters in order to formulate policies to boost growth and reduce inequality. Second, observational units are clearly clustered in space, a concept given particular attention in regional science and economics (e.g. Arbia et al., 2010, 2012), where Garretsen and Martin (2011) and Ottaviano (2011) further highlight the need to more explicitly consider how micro-level heterogeneity and micro-level interactions among people and firms affect macro-level heterogeneity.[4] In this context, the spatial economics literature emphasises how the choice of the appropriate level of interest and the relative statistical inference may be affected by the well-known *ecological fallacy* or *aggregation bias* problems first discussed by Robinson (1950).[5]

Both the purely macro and the purely micro approaches, however, tend to ignore that often the economic processes under consideration, and the relative data measurements, are hierarchically nested. The importance of such hierarchical nature is evident if one considers, for example, how firms dynamics are influenced by their "ecology" or how national convergence is shaped by both within and between country forces. Acknowledging such hierarchical nature can help tackling some of the above limitations.

Moving in this direction, this paper illustrates how the estimation of growth curves in hierarchical longitudinal data, traditionally used in the literature on education (e.g. Steele, 2008; Kremer et al., 2016), can be used as an additional alternative approach to model parameter heterogeneity and overcome some of the limitations of the classic convergence analysis. The suggested methodology presents some notable advantages. First, it allows inference on convergence at the macro level of interest by exploiting the underlying information on micro-convergence.[6] As such, it takes into account macro and micro growth heterogeneity by looking at the underlying disaggregated growth processes. Second, it obtains at the same time convergence tests at the macro and the micro levels, while accounting for interactions both within and between the levels of the hierarchy. In the process, it allows controlling for various sources of heterogeneity at both levels and their interactions. A further important advantage of the proposed approach is to allow cross-checking the convergence result for potential Galton's fallacy, one of the main problems of the classic convergence approach.

The rest of the paper is organized as follows. The next section illustrates the proposed approach to testing for convergence over hierarchical longitudinal data. Section 3 applies the approach to two empirical examples investigating convergence among regions and countries in Europe and convergence among firms and regions in Italy. Section 4 concludes and discusses the implications from the analysis.

2. Hierarchical growth curves and convergence

2.1. Cross-sectional β- convergence analysis

The proposed approach is best understood in relation to the traditional β convergence analysis due to Barro and Sala-i-Martin (1991, 1992), who estimate a reduced-form equation of the neoclassical growth model due to Solow (1956, 1957). Assuming the same steady state for all economies, absolute or unconditional convergence is measured by considering the following regression equation:

$$\frac{1}{T}\left(y_{nT} - y_{n0}\right) = g_n = \beta_0 + \beta_1 y_{n0} + \varepsilon_n \,, \tag{1}$$

where y_{n0} and y_{nT} represent the natural log of per capita income of economy n in the initial and final period, so that g_n is the average growth of unit n over the observed period T, and ε_n is the usual error term. Equation (1) is estimated in a purely cross-sectional setting, where convergence requires economies with lower initial levels of per capita income to grow faster than economies with higher initial levels of per capital income, i.e.

$$\hat{\beta}_1 = \frac{cov(g_n, y_{n0})}{var(y_{n0})} < 0 \,. \tag{2}$$

As mentioned in the introduction, an important drawback of equation (1) pertains to the fact that it is based on the assumption of common production functions (parameters) across all economies under consideration. Durlauf et al. (2001, 2005) highlight how this assumption can be particularly stringent and lead to misleading conclusions, as different economies are likely to have different underlying production functions and corresponding growth processes.

Some of this heterogeneity can be captured in a multi-level version of equation (1). Chasco and Lopez (2009), for example, capture country-level variability in a regional growth regression by fitting the following model, where i regions are nested within n countries and z is a vector of control variables:

$$\begin{aligned} g_{in} &= \beta_{0n} + \beta_1 y_{0in} + \theta' z_{in} + \varepsilon_{in} \\ \beta_{0n} &= \beta_0 + v_{0n} \end{aligned} \tag{3}$$

The heterogeneity in growth across countries is captured by the random intercept terms $v_{0n} \sim N(0, \sigma_{v_0})$. The authors find that the inclusion of random intercepts. i.e. cross-country differences, affects the speed of convergence across European regions.

Dapena et al. (2017a, 2017b) further extend equation (3) to allow not only intercepts, but also slopes β_1 to vary across the n economies. By capturing the heterogeneity in the relationship between the growth rate and the initial income, they obtain a decomposition of the overall convergence process into the national and regional parts.

[2] For example, Bartelsman et al. (2008) argue for the importance to consider firm-level dynamics and allow for micro-level heterogeneity in order to properly account for the role of technological diffusion. They exploit international firm-level data to construct national and global productivity frontiers and find that UK firms tend to display greater convergence towards the national frontier rather than the global one.

[3] Rodrik (2013) identifies international unconditional convergence when disaggregated sectoral data is used in place of aggregate national data. According to the Author, aggregate macro studies tend to ignore intra-sectoral heterogeneity, particularly evident in lagging countries where few industries may be close - and many others far away - from the frontier. He argues that even though strong convergence is found within manufacturing, the limited extent of manufacturing in developing and low income countries explains the failure of aggregate convergence.

[4] For example, in this literature, a number of authors consider the role of firm heterogeneity (Ottaviano, 2011; von Ehrlich and Seidel, 2013; Fazio and Maltese, 2015) or work heterogeneity (Groot et al., 2014) with respect to agglomeration economies. Venables (2011) discusses the connection between heterogeneity across workers and heterogeneity across cities. Altomonte and Colantone (2008) perform a microfounded analysis of the sources of regional economic disparities and find that such disparities are endogenous to the interaction between firm-level dynamics and the initial market conditions. Rizov and Zhang (2014) investigate regional productivity disparities in China from firm-level data, Basile et al. (2014) exploit firm-level data to explore the regional business cycles differentials. Campbell et al. (2016) discuss the role of firm heterogeneity for aggregate convergence. They construct regional indicators of firm performance and identify an important role of best performers for regional convergence within an aggregate analysis. In the opposite direction, Magrini et al. (2015) consider the role of aggregate fluctuations, such as business cycle synchronization, in the analysis of regional convergence in the USA.

[5] See Paelinck (2000) for a more extensive discussion.

[6] Indeed, Goldstein (2011) highlights the usefulness of a hierarchical approach even when the aggregate level is the main level of interest.