Testing for Convergence from the Micro-Level

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Empirical convergence analysis is typically envisaged from a macro aggregate perspective. However, researchers have recently highlighted how investigating convergence at the disaggregate level may yield interesting insights into the convergence debate. In this paper, we suggest an approach that allows exploiting large micro panels to test for convergence. Compared to the traditional convergence analysis, this approach allows obtaining β and σ like convergence parameters for both the micro and the macro level of interest. We provide a practical example that analyses productivity convergence across firms and provinces using a large sample of Italian firms.

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1 Introduction

Convergence analysis is typically envisaged from a macroeconomic standpoint where tests are performed at the desired aggregate level of interest, such as countries or regions.[1] However, to the extent that macro dynamics result from the underlying microeconomic activity, further information on macro convergence may also be hidden in the micro-level. Indeed, convergence at the disaggregate industrial and firm level is attracting increasing interest in empirical economic growth (see, among the others, Egger and Pfaffermayr, 2009; Hausmann *et al.*, 2007; Huber and Pfaffermayr, 2010). Further, the evidence of convergence seems to be stronger at the disaggregate level, as recently highlighted by Rodrik (2011).

Choosing the appropriate level for the analysis of convergence is important from both the theoretical and empirical standpoint. On one hand, aggregate analysis can be problematic. Relationships estimated at the aggregate level cannot always be interpreted as representative of micro-level relationships.[2] Also, in the determination of the appropriate aggregate level of analysis, problems of *ecological fallacy* or *aggregation bias* may emerge.[3] Disaggregate analysis, on the other hand, does not allow drawing inference about convergence at the macro level, often the main level of interest, and it may yield biased estimates under the likely violation of the assumption of within cluster independence. Finally, and importantly, the separate analysis of each level does not consider the interactions between levels.

In this direction, multilevel analysis can provide a useful reference methodology, providing a toolbox that allows the estimation of convergence at both the micro and macro levels, without ignoring their interaction.[4]

Hence, in this paper, we propose an approach that, based on multilevel growth models, allows looking at the same time at the growth trajectories and their convergence for both the micro-level and the macro aggregates of interest. Our approach is directly comparable to the traditional parametric β and σ convergence analysis. However, it allows obtaining two β like convergence parameters for both the micro, i, and macro s, level considered. We call these parameters μ_i and μ_s and name this approach μ convergence analysis. Similarly, this approach returns a σ like convergence parameter for each level. Further, while in the traditional analysis tests of β and σ convergence are performed separately, in this approach it is possible to perform them in one estimation procedure.

Compared to the traditional analysis, this methodology presents a number of benefits. First, it allows exploiting the increasing availability and greater statistical power of large microeconomic datasets. Second,

[1]See Islam (2003) for a survey.

[2]For example, the use of aggregate production functions is actually the subject of a long standing controversy (see Cohen and Harcourt, 2003, for a retrospective).

[3]See Robinson (1950).

[4]As discussed by Goldstein (2003), a multilevel approach can be useful even when the aggregate level is the main level of interest.

while traditional approaches test for convergence only at the desired macro level, our approach allows the contemporaneous testing of convergence at more levels, e.g. micro and macro. Third, it allows conditioning the growth regressions on control variables observed at both the micro and macro level, while controlling for unobserved micro and macro effects.

The next section discusses the proposed approach in relation to the traditional β and σ convergence. Section 3 provides an empirical example that tests for convergence in labour productivity using Italian data. Section 4 concludes.

2 Methodology

β and σ convergence.

Both parametric and non-parametric methods are used to analyse convergence.[5] Within the parametric framework adopted here, the most commonly employed approach is, probably, the β convergence approach proposed by Barro and Sala-i-Martin (BSM, 1991, 1992), who estimate a reduced form equation of the neoclassical growth model due to Solow (1956, 1957). Briefly, after assuming the same steady state for all economies, BSM measure absolute convergence looking at the estimate of β from the following regression:

$$(y_{it} - y_{it-1}) = \alpha + \beta \cdot y_{it-1} + u_{it} \ , \tag{1}$$

where y_{it} is the natural log of per capita income, α and β are parameters and u_{it} is a disturbance term. The BSM equation is then usually estimated in the purely cross-sectional framework:

$$\frac{1}{T} \cdot (y_{iT} - y_{i0}) = \Delta \bar{y}_i = \alpha + \beta \cdot y_{i0} + u_i \ , \tag{2}$$

where y_{iT} and y_{i0} represent the natural log of per capita income of unit i in the final and initial period of the interval $t = [0, ..., T]$, respectively. Clearly, 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.

$$\hat{\beta} = \frac{cov(\Delta \bar{y}_i, y_{i0})}{var(y_{i0})} < 0 \ .$$

The σ convergence approach, instead, looks at the variance of per capita incomes over time, with a reduction of dispersion denoting convergence. β and σ convergence are clearly related, and, as shown by

[5]The most popular non-parametric alternative is the distributional approach due to Quah (1993).

Sala-i-Martin (1996), β convergence is a necessary, albeit not sufficient, condition for σ convergence. Under no β convergence, there cannot be σ convergence, but under β convergence, σ convergence further requires the initial level of σ^2 to lie above its steady state and diminish over time. Hence, it is in principle possible to conclude for β convergence, while the dispersion actually increases over time. In this case, concluding for convergence would lead to committing Galton's fallacy (see Egger and Pfaffermayr, 2009, and Huber and Pfaffermayr, 2010, for a recent discussion).

Multilevel μ convergence

Convergence at the micro level

Our μ convergence approach recognizes that data can be hierarchically structured in more levels, e.g. micro and macro, and that convergence can occur differently over the two levels. Hence, it allows different growth trajectories for the levels in the hierarchy. In order to illustrate this approach, consider, as standard in growth empirics, the simple compound growth process:

$$Y_t = Y_0(1+g)^t \ , \tag{3}$$

where Y_t and Y_0 are, respectively, per capita income at time t and 0. Taking natural logs, we obtain a standard log-linear growth process:[6]

$$ln(Y_t) = ln(Y_0) + t \cdot ln(1+g). \tag{4}$$

We can define $ln(Y_t) = y_t$, $ln(Y_0) = \gamma_0$ and $ln(1+g) = \gamma_1$, and recognize in the above equation the familiar linear-trend model:

$$y_t = \gamma_0 + \gamma_1 t + u_t \ , \tag{5}$$

where

$$\gamma_1 = \frac{dy}{dt} = \frac{d\ln(Y)}{dt} = \frac{1}{Y}\frac{dY}{dt} = \frac{dY/Y}{dt} \ .$$

and u_t is the usual disturbance term. The estimate of γ_1, $\hat{\gamma}_1$, can be interpreted as the estimated growth of y over the period $t_T - t_0$, and can be compared to the average growth rate considered by BSM, i.e. $\hat{\gamma}_1 \simeq \Delta\bar{y}_t$.

In order to obtain different growth trajectories for each individual, equation (5) can be estimated in a

[6] Here, a simple log-linear growth process is assumed, but the approach is easily extended to the non-linear case.

multilevel framework. To this end, given N units observed over period T, we can denote by y_{ti} the realization of the variable of interest for unit i ($i = 1, \ldots, N$) at time t ($t = 1, \ldots, T$) and by t_{ti} the point in time when y_{ti} is recorded. In multilevel growth models, this is a simple hierarchical structure, where the recording time represents the first level and the realization of y for unit i is the second level. In our case, responses are recorded continuously and contemporaneously, i.e. $t_{ti} = t_t$. Then, following Steele (2008), a linear trajectory can be fitted for each individual unit estimating the following system of equations:

$$
\begin{aligned}
y_{ti} &= \gamma_{0i} + \gamma_{1i} t_t + \epsilon_{ti} \\
\gamma_{0i} &= \gamma_0 + \eta_{0i} \\
\gamma_{1i} &= \gamma_1 + \eta_{1i}
\end{aligned}
\tag{6}
$$

The above can be expressed in reduced form, as follows:

$$
y_{ti} = \underbrace{\gamma_0 + \gamma_1 t_t}_{determimistic} + \underbrace{\eta_{0i} + \eta_{1i} t_t + \epsilon_{ti}}_{stochastic}, \tag{7}
$$

where γ_{0i} is an individual-specific intercept composed by a fixed part, γ_0, and a random part, η_{0i}. γ_{1i} is an individual-specific slope with respect to time, again composed by the fixed part γ_1 and the random part η_{1i} . The final term ϵ_{ti} is the random component related to time. While the term $\gamma_0 + \gamma_1 t_t$ represents the common initial level and trend in the relationship between y and t, η_{0i} and η_{1i} are the individual departures, respectively, in terms of intercept and slope, i.e. the growth rate. Residuals are assumed to be normally distributed, i.e. $\epsilon_{ti} \sim N(0, \sigma^2_\epsilon)$, and may be level-correlated.[7] The following variance/covariance matrix can be obtained:

$$
\Omega_\eta = \begin{pmatrix} \sigma^2_{\eta_0} & \\ \sigma_{\eta_{01}} & \sigma^2_{\eta_1} \end{pmatrix},
$$

where $\sigma^2_{\eta_0}$ and $\sigma^2_{\eta_1}$ are respectively the variance of individual intercepts and slopes (growth rates). Here, t is centered around the first observed year so that the intercept will represent the initial period and $\sigma^2_{\eta_0}$ the variance of per capita income between-individuals at the initial period.[8]

[7] Within multilevel growth models it is also possible to allow for AR(1) residuals. Here, we have considered a general structure for the correlation for the level residuals, because it is the one more directly comparable to the traditional cross-sectional analysis of convergence.

[8] In the multilevel literature, the time variable t is usually centered around the mid-point, so that $\sigma^2_{\eta_0}$ is interpreted as the between-individual variance in y at the mid-point.

The covariance between intercepts and slopes, $\sigma_{\eta_{01}}$, provides a measure of convergence in the β convergence sense. A statistically significant negative (positive) covariance will imply convergence (divergence): individual units with lower (higher) values of y at the initial period experience higher (lower) growth rates over the observed period.

Since $\sigma_{\eta_{01}} = cov(\hat{\gamma}_{0i}, \hat{\gamma}_{1i}) \simeq cov(y_{i0}, \Delta\bar{y}_i)$, μ convergence can be compared to β convergence if we take the covariance between intercepts and slopes as a share of the variance of the intercepts, i.e. for level i:

$$\hat{\beta} = \frac{cov(y_{i0}, \Delta\bar{y}_i)}{var(y_{i0})} \simeq \frac{cov(\hat{\gamma}_{0i}, \hat{\gamma}_{1i})}{var(\hat{\gamma}_{0i})} = \hat{\mu}$$

Convergence at the micro and macro level

This approach allows testing for convergence also for higher levels in the hierarchy, such as a macro level, s, that is added to equation (7). In multilevel terms, the new representation becomes a three level model, as follows:

$$\begin{aligned} y_{tis} &= \gamma_{0is} + \gamma_{1is} t_t + \epsilon_{tis} \\ \gamma_{0is} &= \gamma_0 + \nu_{0s} + \eta_{0is} \\ \gamma_{1is} &= \gamma_1 + \nu_{1s} + \eta_{1is} \end{aligned} \tag{8}$$

or in reduced form:

$$y_{tis} = \gamma_0 + \gamma_1 t_t + \eta_{0is} + \nu_{0s} + \eta_{1is} t_t + \nu_{1s} t_t + \epsilon_{tis} \ . \tag{9}$$

In equation (9), the growth rate is now allowed to vary both across micro-level units, i, and across macro-level units, s. Estimation of equation (9) yields two variance-covariance matrices:

$$\Omega_\eta = \begin{pmatrix} \sigma^2_{\eta_0} & \\ \sigma_{\eta_{01}} & \sigma^2_{\eta_1} \end{pmatrix}; \qquad \Omega_\nu = \begin{pmatrix} \sigma^2_{\nu_0} & \\ \sigma_{\nu_{01}} & \sigma^2_{\nu_1} \end{pmatrix}$$

where $\sigma_{\eta_{01}}$ can be interpreted, as before, as a measure of convergence among micro-level units and $\sigma_{\nu_{01}}$ now represents a measure of convergence among macro-level units. While in the β convergence framework, we would have run separate regressions on different data levels to obtain β_i and β_s, in μ convergence we simultaneously obtain two $\mu_{i,s}$ parameters, corresponding to the two levels:

$$\mu_i = \frac{\sigma_{\eta_{01}}}{\sigma^2_{\eta_0}};\ \mu_s = \frac{\sigma_{\nu_{01}}}{\sigma^2_{\nu_0}}.$$

This can be particularly important as it allows the researcher to disentangle at which level of the hierarchy convergence really occurs.

A σ type convergence can also be obtained looking at the dispersion of the data for both the intercepts of the individual units, $\sigma^2_{\eta_0}$, and the macro units, $\sigma^2_{\upsilon_0}$, over time. Recursively centering the model around each t in the sample, we can look at the dispersion of per capita income at each point in time and for each level. Confidence intervals can be constructed to look at the statistical significance of the σ convergence process, i.e. whether we observe a statistically significant reduction of the level variance over the observed period. Such σ convergence analysis can be useful in order to validate the μ convergence approach in terms of the above mentioned Galton's fallacy.

Conditioning on exogenous variables.

Since multilevel analysis uses random effects estimation, it can easily accommodate, similarly to the conventional conditional convergence analysis, for the starting values of growth determinants at both the micro and the macro level.[9] This allows conditioning the initial level γ_{0is} to growth determinants at both the i and the s levels.

We can, then, easily incorporate starting values of growth determinants:

$$\begin{aligned} y_{tis} &= \gamma_{0is} + \gamma_{1is} t_t + \epsilon_{tis} \\ \gamma_{0is} &= \gamma_0 + \nu_{0s} + \alpha_i X_{0i} + \alpha_s X_{0s} + \eta_{0is} \\ \gamma_{1is} &= \gamma_1 + \nu_{1s} + \eta_{1is} \end{aligned} \tag{10}$$

or in reduced form:

$$y_{tis} = \gamma_0 + \gamma_1 t_t + \alpha_i X_{0i} + \alpha_s X_{0s} + \eta_{0is} + \nu_{0s} + \eta_{1is} t_t + \nu_{1s} t_t + \epsilon_{tis}, \tag{11}$$

where X_{0i} and X_{0s} are set of first and second level variables at the beginning of period. This allows interpreting the estimated variances and covariances as conditional on growth determinants.

[9] The inclusion of micro and macro level fixed effects also allows overcoming potential mispecification issues in the random effects estimator under non-random cross-sectional differences.

3 Convergence of labour productivity in Italy

Next, we propose an empirical investigation based on the estimation of labour productivity convergence in Italy. Given the well known spatial disparities in Italy (see, among the others, Byrne *et al.*, 2009; Fazio and Piacentino, 2010), we believe this a suitable case study to illustrate our method. Specifically, we investigate labour productivity convergence over the period 1999-2005 across a sample of Italian firms in the manufacturing and services sectors (public utilities and state monopolies excluded). Labour productivity at the firm level is calculated as the ratio between the series of value added and the number of employees,[10] both drawn from the Italian section of the Bureau Van Dijk Database (AIDA), which reports balance sheet data covering more than 90 percent of Italian companies with a value of production above 100.000 Euros.

However, the reported balance sheets may be consolidated accounts, which means that in those instances when the company has subsidiaries and plants in more locations, we would be incorrectly considering their value added as generated in one unique location. The best way to limit this issue is not to consider large firms, which are the most likely to have a multi-plant organization. Hence, we concentrate on Small and Medium Enterprises (SMEs), here selected using standard criteria (more than 10 and less than 250 employees; more than 2 and less than 43 million Euros of Total Asset Value). This choice seems also more in line with the need to capture the underlying characteristics of the Italian productive system. After some data mining, the data query returns 9,284 observations, our individual units, i, distributed across the national territory. As a macro-level, s, we consider the 103 Italian provinces. This level of disaggregation is mostly dictated by the need to ensure sufficient degrees of freedom to estimate the macro level in our multilevel structure (see Appendix A for the relevant summary statistics).

We can now turn our attention to the estimation stage. Following the discussion in the previous section, in figure 1 we present the results of the traditional β convergence analysis. Since we have chosen the provinces as our macro level of interest, we can estimate BSM type regressions using aggregate data for provincial labour productivity. This could be obtained from the national accounting data of the Italian National Statistics Office (ISTAT). The upper left quadrant of figure 1 plots the period average growth, $\Delta\bar{y}$, against the initial level of productivity in 1999 and reports the estimated β regression. Results show a negative relationship between initial levels and average productivity growth, i.e. province-level convergence.

In order to see the agreement between the national accounting and our micro data, we have aggregated, summing or averaging, the micro-level data from AIDA. The β convergence analysis on these aggregations shown in the upper right and lower left diagrams, respectively, of figure 1, highlight stronger β convergence

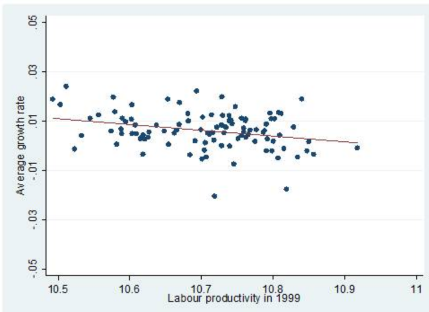
[10] Value added has been deflated using sectoral prices from the OECD.

compared to the ISTAT data (2 percent against 5 and 8 respectively). These results seems in line with the stylised evidence highlighted by Rodrik (2011).[11]

FIGURE 1

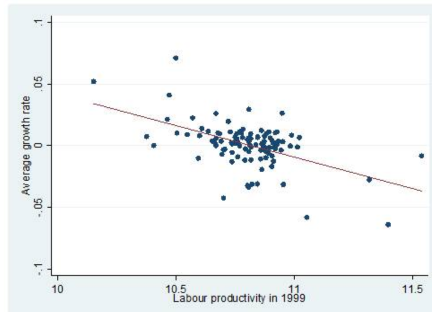
β convergence (Labour Productivity)

a) Province-level - ISTAT data



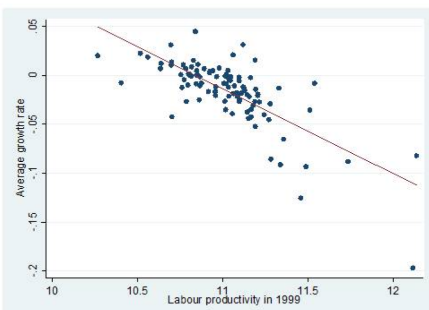
β = -0.023***; $Adj-R^2$ = 0.07

b) Province-level - AIDA aggregate data 1



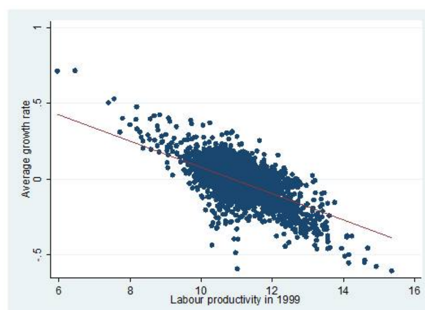
β= -0.051***; $Adj-R^2$= 0.26

c) Province-level - AIDA aggregate data 2



β = -0.086***; $Adj-R^2$= 0.54

d) Firm-level data - AIDA



β= -0.087***; $Adj-R^2$ = 0.38

Notes: These figures plot the period average growth, $\Delta\bar{y}$, against the beginning of period productivity, y_{1999}, and report the estimated β convergence*;* Panel a) uses national accounting data from ISTAT-SITIS database at the provincial level. Panel b) uses firm level data from AIDA aggregated at the provincial level by sum. Panel c) uses firm level data from AIDA averaged at the provincial level. Panel d) uses disaggregated firm level data. ***denotes statistical significance at the 1% level

Alternatively, if we were interested in the convergence among firms, we could estimate β convergence at the firm level. The lower right quadrant of figure 1 shows the presence of convergence also at this level of analysis. Overall these results seem to indicate that the convergence we observe at the micro firm level in panel d) of figure 1 is reflected in the convergence at the macro province level of panels a) to c), and viceversa. However, the β convergence tests at the macro and micro levels are performed separately.

[11]A possible explanation for this results may be that while AIDA data only includes the productivity of the private sector, ISTAT data will also include the productivity of the public sector, so that a more proper mix of industries is probably present in our sample.

TABLE 1

μ convergence (Labour Productivity)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
γ_0	10.861	10.862	10.861	10.830	10.830	10.838	10.838
	(0.004)	(0.005)	(0.005)	(0.008)	(0.008)	(0.007)	(0.007)
γ_1	-0.008	-0.008	-0.008	-0.008	-0.007	-0.010	-0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
σ^2_ϵ	0.298	0.186	0.176	0.186	0.176	0.186	0.176
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma^2_{\eta 0}$		0.112	0.141	0.109	0.139	0.109	0.139
		(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
$\sigma_{\eta 01}$			-0.008		-0.008		-0.008
			(0.001)		(0.001)		(0.001)
$\sigma^2_{\eta 1}$			0.002		0.002		0.002
			(0.000)		(0.000)		(0.000)
σ^2_{v0}				0.003	0.003	0.002	0.001
				(0.001)	(0.001)	(0.001)	(0.001)
σ_{v01}						0.000	0.000
						(0.000)	(0.000)
σ^2_{v1}						0.000	0.000
						(0.000)	(0.000)
$-2Log(L)$	105209.6	90048.0	89716.4	89909.3	89572.6	89884.2	89553.5

Notes: Estimation by Restricted Iterative Generalized Least Squares; Standard Errors in parentheses. All variables are in logs

Next, we apply the μ convergence approach described above.[12] Table 1, in particular, presents results for alternative specifications of $\mu-$convergence in columns (1) to (7), where we first estimate the simplest linear trend model and then start adding random effects at the micro (firm) and macro (province) levels both in the intercepts and trends.

Some results are worth mentioning. First, a significant negative trend in labour productivity emerges quite clearly from all models, indicating that Italian firms in general have experienced a productivity decrease. Secondly, for the firm-level our approach, just like the BSM regression, returns evidence of convergence, i.e. $\mu_i = -0.072$ (=-0.008/0.141) in column 3 and $\mu = -0.057$ (=-0.008/0.139) in column 7, where the most flexible specification is adopted. However, and most importantly, contrary to the BSM regression, no evidence of macro (province) level convergence can be found, i.e. $\mu_s = 0$ in columns 6 and 7.

As discussed above, convergence can also be tested after adding beginning-of-period determinants of growth at the micro or macro level. Hence, in table 2 we have added both firm and province level controls at the initial year. These include firm-level capital intensity (from AIDA) and province-level labour productivity, employment rate and degree of openness (from ISTAT). These are the most "comprehensive" variables we

[12]This part of the analysis is performed with MlwiN 2.23 (see Rasbash *et al.*, 2009).

could find in the general scarcity of firm-level and province level data. Province level variables are introduced one at the time in order to avoid multicollinearity issues. Further, we include a set of dummies to control for sectoral effects (2 digits of the ATECO 2002 classification).

TABLE 2

μ convergence with controls (Labour Productivity)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
γ_0	9.969	10.015	8.812	10.545	9.509	10.911	10.011
	(0.039)	(0.267)	(0.288)	(0.171)	(0.187)	(0.019)	(0.040)
γ_1	-0.010	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capital Intensity	0.081		0.081		0.081		0.081
(firm level)	(0.003)		(0.003)		(0.003)		(0.002)
Labour Productivity		0.226	0.303				
		(0.070)	(0.074)				
(province level)							
Employment				0.087	0.121		
(province level)				(0.045)	(0.048)		
Openness						0.033	0.040
(province level)						(0.010)	(0.010)
Sectoral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
σ^2_ϵ	0.176	0.176	0.176	0.176	0.176	0.176	0.176
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma^2_{\eta 0}$	0.113	0.131	0.113	0.131	0.113	0.131	0.113
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$\sigma_{\eta 01}$	-0.006	-0.008	-0.006	-0.008	-0.006	-0.008	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma^2_{\eta 1}$	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ^2_{v0}	0.002	0.001	0.002	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
σ_{v01}	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ^2_{v1}	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$-2Log(L)$	87845.5	88843.4	87831.9	88848.5	87839.4	88841.0	87830.7

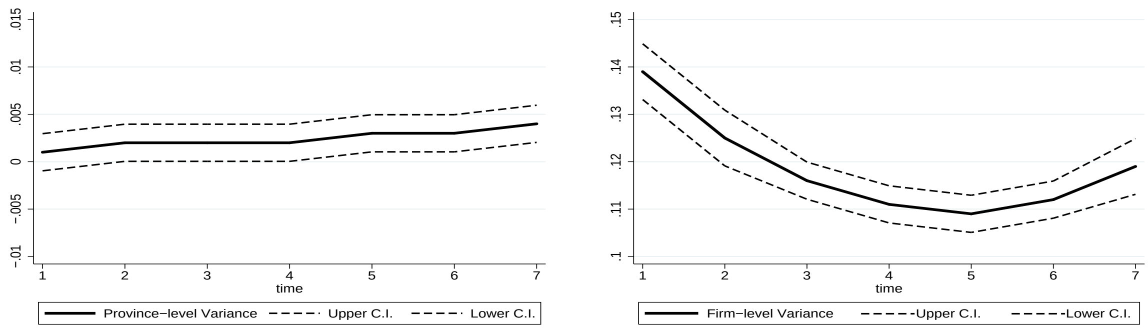
Notes: Estimation by Restricted Iterative Generalized Least Squares; Standard Errors in parentheses; Firm-level Capital Intensity is Capital Stock over Employees for the initial year in 1999 from AIDA, Province-Level labour productivity, Employment Rate and Openness Rate are for the initial year in 1999 from the ISTAT-SITIS database. All variables are in logs.

Results show that all the conditioning variables enter the regressions significantly and with the expected positive sign. At the micro level, conditional convergence now ranges from 0.045 and 0.061, depending on the specification. Conditioning on micro and macro-level variables and on sectoral dummies does not modify the results in terms of province-level convergence, i.e. no conditional macro-level convergence can be found.

FIGURE 2

σ convergence at the province level (panel a) and firm level (panel b).

a) *b)*



In figure 2 we further show the σ like convergence test discussed in the previous section. By centering the model around each successive year, the estimated variance of the intercepts represents the dispersion of labour productivity at each point in time. The figure also reports the 95% confidence interval for the σ^2 estimates. Panel a) of the figure shows that the province level dispersion does not statistically changes over time. Hence, the lack of μ convergence at the macro provincial level is confirmed by the lack of σ like convergence. For the firm-level, where evidence of μ convergence was found, panel b) shows a statistically significant decrease in the estimated variance from the beginning to the end of the period,[13] as indicated by the non-overlapping confidence intervals of the estimated variance for the first and the last year in the analysis.

4 Conclusions

The traditional analysis of convergence typically concentrates on the aggregate macro-level of interest, such as countries or regions. Recently, however, researchers have highlighted the importance to investigate convergence also at the disaggregate level. In this paper, we have drawn from the multilevel growth literature to propose a methodology that exploits data disaggregated at the micro-level to test for convergence at both the micro and macro level, obtaining β and σ like convergence parameters simultaneously for both levels of interest.

We have provided an empirical example based on Italian firm-level data, where convergence in labour productivity is tested at the same time among firms and provinces. Our results indicate convergence at

[13]The estimated variance decreases from the beginning until the fifth year of the sample and then shows a moderate, but statistically insignificant, increase for the last two years.

the micro-level, but not at the macro provincial level. Interestingly, this is in contrast to what is obtained in a standard β regression framework, where convergence is identified at both levels. Our results confirm that further examination of the growth dynamics at the micro-level and the relationship between the micro and macro levels may yield important insights into the convergence debate. Further, they highlight the importance to correctly choose the level to analyse the convergence process and, more generally, call for a deeper investigation into the implications of aggregation for convergence analysis.

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APPENDIX A: Summary statistics

TABLE A1

a) Value Added (Y)

Year	*Obs*	*Mean*	*Std. Dev.*
1999	9284	2955602	2707294
2000	9284	3214667	2821090
2001	9284	3269919	2797542
2002	9284	3325462	2679049
2003	9284	3335659	2669504
2004	9284	3479666	2636435
2005	9284	3549202	2658073

b) Number of Employees (L)

Year	*Obs*	*Mean*	*Std. Dev.*
1999	9278	56	52
2000	9280	61	56
2001	9284	71	60
2002	9284	75	61
2003	9284	75	59
2004	9284	66	50
2005	9284	66	49

c) Labour Productivity (Y/L)

Year	*Obs*	*Mean*	*Std. Dev.*
1999	9278	68592.21	98681.92
2000	9280	78061.76	176282.5
2001	9284	53135.63	45377.92
2002	9284	52081.57	69064.48
2003	9284	50999.01	43545.35
2004	9284	61528.31	64356.65
2005	9284	61157.15	39373.16