Testing for Convergence from the Micro-Level

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May 6, 2011

Abstract

In the growth literature, researchers are typically concerned with macro convergence. However, to the extent that macro dynamics result from the underlying microeconomic relations, convergence should also be investigated at the micro-level. 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, at the same time, β and σ like convergence parameters for both the micro and the macro level of interest. We provide a practical example that analyzes productivity convergence in Italy across firms and provinces using a large sample of Italian firms.

Keywords: Convergence, Multilevel Models, Italian firms.

JEL Classification: C33, D20, O47.

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1 Introduction

Growth convergence 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 be hidden in the micro-level.[2] Yet, very little empirical effort has been devoted to analyze convergence at the micro-level and the relationship between convergence at the micro and macro levels.

In this paper, we propose a novel approach that allows looking at growth trajectories and their convergence for both the micro-level and the macro aggregates of interest. We refer to this as μ-convergence analysis.

Compared to traditional alternatives, this methodology presents a number of benefits. First, it allows exploiting the increasing availability and greater statistical power of large microeconomic datasets. Second, 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. Finally, it allows estimating convergence in both the β and σ sense at the same time.

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

2 Methodology

2.1 β and σ convergence.

The most commonly employed approach to measure for cross-sectional convergence 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:

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

where y_{it} is the natural log of per capita income, α and β are parameters and u_{it} is a disturbance term.

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

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

The BSM equation is then usually estimated in the purely cross-sectional framework:

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

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 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.

2.2 Multilevel convergence

2.2.1 Absolute μ convergence

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:

$$Y_t = Y_0 (1 + g)^t \ ,$$

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:[3]

$$ln(Y_t) = ln(Y_0) + t \cdot ln(1 + g).$$

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:

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

$$y_t = \gamma_0 + \gamma_1 t + u_t \ , \tag{1}$$

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 (1) can be estimated in a 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 two-level 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:

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

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

$$y_{ti} = \underbrace{\gamma_0 + \gamma_1 t_t}_{determimistic} + \underbrace{\eta_{0i} + \eta_{1i} t_t + \epsilon_{ti}}_{stochastic}, \tag{2}$$

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, i.e.:

$$\Omega_\eta = \begin{pmatrix} \sigma^2_{\eta0} & \\ \sigma_{\eta01} & \sigma^2_{\eta1} \end{pmatrix}.$$

$\sigma^2_{\eta0}$ and $\sigma^2_{\eta1}$ 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 $\sigma^2_{\eta0}$ the variance of per capita income between-individuals at the initial period.[4]

The covariance between intercepts and slopes, $\sigma_{\eta01}$, provides a measure of convergence in the β-convergence sense. A statistically significant negative (positive) covariance will imply first-level convergence (divergence): individual units with lower (higher) values of y at the initial period experience higher (lower) growth rates over the observed period.

Since $\sigma_{\eta01} = cov(\hat{\gamma}_{0i}, \hat{\gamma}_{1i}) \simeq cov(y_{i0}, \Delta\bar{y}_i)$, 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:

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

This approach allows testing for convergence also for higher levels in the hierarchy, such as a macro level, s, that is added to equation (2). In multilevel terms, the new representation becomes a three level model, as follows:

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

or in reduced form:

$$y_{tis} = \gamma_0 + \gamma_1 t_t + \eta_{0is} + \nu_{0s} + \eta_{1is} t_t + \nu_{1s} t_t + \epsilon_{tis} \ . \quad (3)$$

In equation (3), the growth rate is now allowed to vary both across micro-level units, i, and across macro-level units, s. Estimation of equation (3) yields two variance-covariance matrices:

[4]In the multilevel literature, the time variable t is usually centered around the mid-point, so that $\sigma^2_{\eta0}$ is interpreted as the between-individual variance in y at the mid-point.

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

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 to 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 second-level units, $\sigma^2_{\eta_0}$, over time. Recursively centering the model around each t in the sample, we can look at the dispersion of each level per capita income at each point in time. 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.

2.2.2 Conditional μ-convergence

Since multilevel analysis uses random effects estimation, it can easily accommodate fixed effects at both the micro and the macro-level of the hierarchy.[5] This allows conditioning the initial level γ_{0is} to growth determinants at both the i and the s levels.

We can, then, easily accommodate μ-convergence to the conditional growth case:

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

or in reduced form:

$$y_{tis} = \gamma_0 + \gamma_1 t_t + \alpha_i X_{0i} + \alpha_s X_{0s} + \eta_{0is} + \nu_{0s} + \eta_{1is} t_t + \nu_{1s} t_t + \epsilon_{tis}, \tag{4}$$

[5] 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.

where X_{0i} and X_{0s} are set of first and second level variables at the beginning of period. This allows estimating conditional variances and covariances.

3 Convergence in Labor Productivity in Italy

Next, we propose an empirical investigation based on the estimation of labor productivity convergence in Italy. Given the well known spatial disparities in Italy (see, among the others, Byrne et al. (2009)), we believe this can represent a suitable case study to illustrate our method. Specifically, we investigate convergence over the period 1999-2005 across a sample of Italian firms drawn from the Italian section of the Bureau Van Dijk Database (AIDA). AIDA reports balance sheet data covering more than 90 percent of Italian companies with a value of production above 100.000 Euros. After some data mining, this query returns 9,284 observations distributed across the national territory, which will represent our individual units, i. We consider as macro level, s, the 103 Italian provinces. This ensures sufficient degrees of freedom to estimate the macro level (see Appendix 1 for the relevant summary statistics).

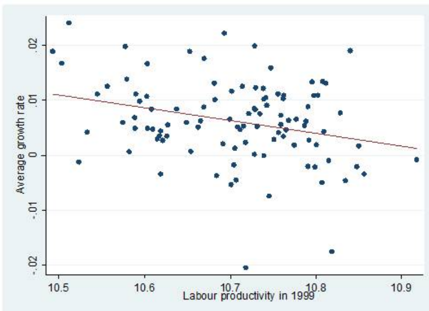
For comparison, we first perform the traditional β-convergence analysis using aggregate provincial labor productivity from the National Accounting data of the Italian National Statistics Office (ISTAT). The upper left quadrant of figure 1 plots the period average growth, $\Delta\bar{y}$, against the 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 the 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 compared to the ISTAT data (2 percent against 5 and 8 respectively).[6]

[6] 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.

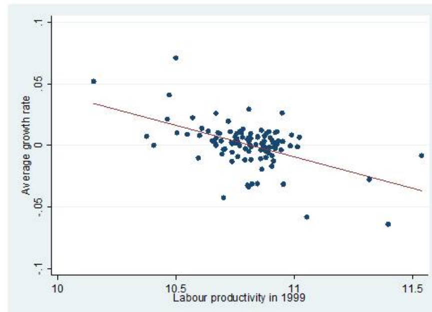
Figure 1: β- Convergence (Labor Productivity)

a) Province-level - ISTAT data



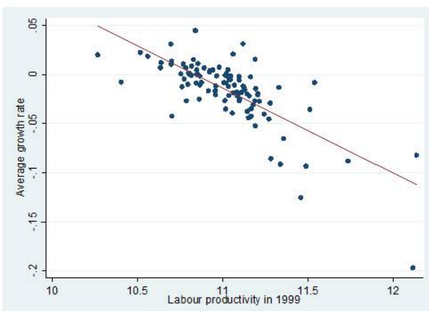
β = -0.023***; $Adj - R^2$ = 0.07

b) Province-level - AIDA aggregate data 1



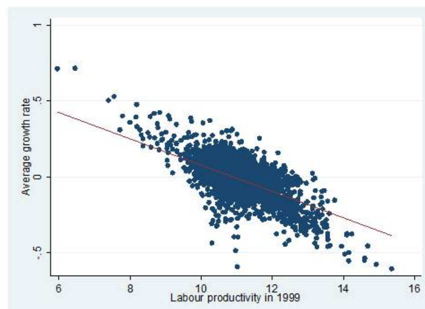
β= -0.051***; $Adj - R^2$= 0.26

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

Finally, the lower right quadrant of figure 1 shows the presence of convergence also at the firm level. These results indicate that Italian firms productivities have converged over the period. Overall these results seem to indicate that the convergence we observe at the micro firm level is reflected in the convergence at the macro province level. However, these β-convergence tests are still performed separately for the two levels in the hierarchy.

Table 1: Absolute μ-convergence (Labor Productivity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ_0	10.8612	10.862	10.861	10.8301	10.830	10.8378	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

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. Table 1, in particular, presents results for alternative specifications of absolute $\mu-$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 labor productivity emerges quite clearly from all models. Secondly, a degree of convergence similar to what estimated by the BSM regression emerges at the firm-level (-0.008/0.141=-0.072). Finally, and most importantly, contrary to the BSM regression, no evidence of macro (province) level convergence can be found.

Conditional convergence can also be tested by adding beginning-of-period determinants of growth at the micro or macro level to obtain conditional variances and covariances. In order to illustrate this, in table 2 we have added both firm and province level controls at the initial year, i.e. firm-level capital intensity (from AIDA) and province-level labor productivity, employment rate and the degree of openness (from ISTAT). These were the most "comprehensive" variables we could find in the general scarcity of firm-level and province level data.

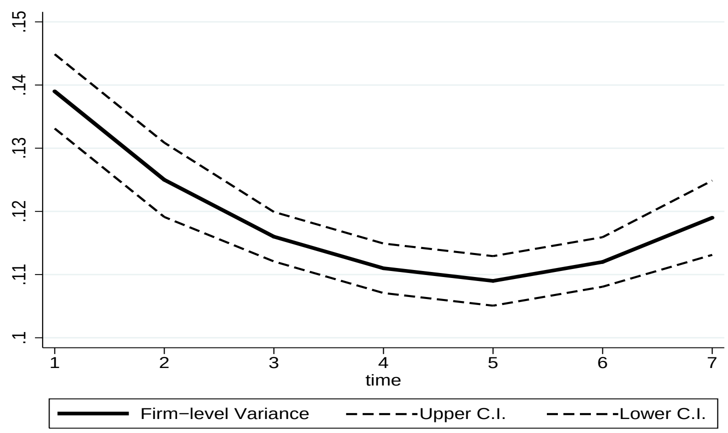
Table 2: Conditional μ-convergence (Labor Productivity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ_0	7.662	9.694	4.786	10.507	6.712	10.871	7.739
	(0.026)	(0.279)	(0.450)	(0.184)	(0.293)	(0.012)	(0.031)
γ_1	-0.007	-0.009	-0.006	-0.010	-0.006	-0.010	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capital Intensity	0.309		0.309		0.309		0.309
(firm level)	(0.002)		(0.002)		(0.002)		(0.002)
Labor		0.299	0.755				
Productivity		(0.073)	(0.118)				
(province level)							
Employment				0.087	0.251		
(province level)				(0.048)	(0.077)		
Openness						0.033	0.070
(province level)						(0.010)	(0.016)
σ^2_ϵ	0.120	0.176	0.121	0.176	0.120	0.176	0.120
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma^2_{\eta 0}$	0.194	0.139	0.193	0.139	0.193	0.139	0.193
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
$\sigma_{\eta 01}$	-0.011	-0.008	-0.011	-0.008	-0.011	-0.008	-0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma^2_{\eta 1}$	0.004	0.002	0.004	0.002	0.004	0.002	0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ^2_{v0}	0.009	0.001	0.006	0.001	0.008	0.001	0.007
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)
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)
$-2Log(L)$	74677.6	89540.1	74649.0	89540.4	74668.1	89543.6	74660.2

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 Labor 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 sign. The firm-level intercepts variance, $\sigma^2_{\eta 0}$, increases slightly and so the covariance between the starting levels of productivity and productivity growth, i.e. convergence, when capital intensity is introduced. However, conditioning on macro-level variables does not modify the results in terms of province-level convergence, i.e. no conditional macro-level convergence can be found.

Figure 2: Firm-Level σ convergence



For the firm-level, where evidence of convergence has been found, the recursive σ convergence is also considered in figure 2. By centering the model around each successive year, the estimated variance of the intercepts represents the dispersion of firm-level labor productivity at each point in time. The figure also reports the 95% confidence interval for the σ^2 estimates. As it can be seen, the estimated variance decreases from the beginning until the fifth year of the sample and then shows a very moderate, and statistically insignificant, increase for the last two years. Importantly, a statistically significant reduction in dispersion can be identified for the period as a whole, as indicated by the non-overlapping confidence intervals of the variance for the first and the last year in the analysis.

4 Conclusions

Convergence tests typically ignore micro-level relationships and look directly at the macro-level of interest. In this paper, we have proposed a methodology that exploits micro-level data to test for convergence. Considering data hierarchically structured in micro and macro levels, this method allows obtaining β and σ like convergence parameters simultaneously for both levels of the hierarchy, i.e. the micro-level and the macro-level of interest.

We have provided an empirical example based on Italian firm-level data, where convergence in labor productivity is tested at the same time among firms and provinces. Our results indicate convergence at the micro-level, but not at the macro province level. Interestingly, this result is in contrast to what would be obtained by a β regression. This result suggests that further investigation of growth dynamics at the micro-level and the relationship between the micro and macro level may yield important insights into the convergence debate.

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APPENDIX 1: SUMMARY STATISTICS

A1 a) Value Added (Y)

Variable	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

A1 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

A1 c) Labor 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