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Distortions in Cross-Sectional Convergence Analysis when the Aggregate Business Cycle is Incomplete

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Abstract

Existing literature on convergence largely ignores the effect of aggregate fluctuations on the evolution of income disparities. However, if regional income disparities follow a distinct pro- or counter-cyclical pattern in the short-run, the period of analysis should be chosen with great care. Failing to do so might distort results towards convergence or divergence, depending on the type of short-run cyclical pattern and the phases that are over-represented. Using the distribution dynamics approach it is shown that the distortion could be quite sizeable; then convergence among 48 conterminous US states is analysed over an appropriately chosen period (1989-2007) that includes only complete cycles..

Keywords

Convergence, Regional disparities, Business cycle, Distribution dynamics

JEL Codes

O40, R10, E32, C14

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1 Introduction

The vast majority of studies on convergence among national and sub-national economic systems implicitly adopts a long-run perspective as it relates empirical findings from the analysed period to the long-run predictions of a variety of theoretical models. Very few studies have instead adopted a different viewpoint and analysed the evolution of income disparities among a set of economies in relation to the aggregate business cycle. In most cases, regional disparities are found to move in a pro-cyclical fashion, therefore increasing during expansion periods and diminishing during slowdowns. Some examples are AZZONI (2001), who analyses per capita GDP growth and disparities across Brazilian states between 1939 and 1995, DEWHURST (1998), who analyses regional household income disparities among 63 UK counties between 1984 and 1993, CHATTERJI and DEWHURST (1996) who study per capita GDP disparities across English and Welsh counties and Scottish regions between 1977 and 1991, PETRAKOS and SARATSI (2000), who analyse per capita GDP inequalities among Greek prefectures between 1970 and 1995, TERRASI (1999), who studies convergence in per capita GDP among 20 Italian regions between 1953 and 1993, PETRAKOS *et al.* (2005), who analyse per capita GDP disparities across 8 EU countries between 1960 and 2000, and PIKE *et al.* (2010), who study the evolution of disparities in per capita disposable household income across UK NUTS1 regions between 1984 and 2007. In fewer instances authors instead report the presence of counter-cyclical disparities. This is the case of PEKKALA (2000) and KANGASHARJU and PEKKALA (2004), who investigate per capita GDP disparities across small scale Finnish subregions respectively in the 1988-1995 and in the 1988-2000 periods, and of BOUVET (2010), who studies the evolution of per capita GDP inequalities among 197 NUTS2 regions belonging to 13 EU countries between 1977 and 2003. Furthermore, QUAH (1996) reports some evidence of counter-cyclical

behaviour of per capita personal income disparities while analyzing US states between 1982 and 1990. Finally, DURAN (forthcoming), applying time series techniques on per capita personal income data for the 48 coterminous US states between 1969 and 2008, finds that disparities move either pro or counter-cyclically depending on the period of analysis. In particular, the analysis shows that the switch from counter to pro-cyclicality occurred since the beginning of the 1990s is largely a consequence of differences in the timing with which the business cycle is felt across US states.

From a theoretical point of view, several interpretations have been offered for the pro-cyclical behaviour of regional disparities. PETRAKOS *et al.* (2005) and PETRAKOS and SARATSIS (2000) explain this behaviour by referring to BERRY (1988) who, sharing Myrdal's view (MYRDAL, 1957) on the spatially cumulative nature of growth, suggests that leading regions are in a better position to take advantage of the opportunities generated by an economic boom. In particular, according to this view, expansion phases begin in more developed and metropolitan areas where agglomeration and market size create a lead over other regions, thus leading to an increase in regional disparities (PETRAKOS *et al.*, 2005). The opposite applies in downturns, during which more developed and metropolitan areas tend to suffer more (PETRAKOS and SARATSIS, 2000). A somewhat different perspective is offered by RODRÍQUEZ-POSE and FRATESI (2007) who concentrate on the concept of sheltered regions, i.e. isolated economies which are mostly dependent on the agriculture sector, government transfers and public employment. Based on this view, sheltered regions do not keep up with the rest of the aggregate economy and do not use their potential for convergence during the expansion periods. By contrast, during downturns they do not suffer as much as other regions and, therefore, tend to reduce their gap with respect to richer ones. In the same vein, AZZONI (2001) states that richer regions are better prepared to face growing demand

during expansions due to the presence of more dynamic sectors in their production structure, a claim that is fully consistent with the explanation of different timing and amplitudes of cyclical waves provided by AIROV (1963) and van DUIJN (1973). On the opposite side, PEKKALA (2000) and KANGASHARJU and PEKKALA (2004) explanation of counter-cyclical disparities in Finland hinges upon the equilibrating role played by labour mobility and the effectiveness of regional policies. In particular, the authors note that during expansions there is a higher degree of mobility and that these workers tend to migrate mainly towards developed subregions, thus contributing to reduce per capita income disparities. Conversely, inequalities increase during slowdowns as workers' migration stagnates. In addition, regional policies have had a more cohesive effect during the upswing years of the economic cycle due to a relatively more abundant amount of resources devoted to pursuing regional equality with respect to slowdown periods.

Shedding light on this issue is of crucial importance for empirical convergence analysis. To the extent that regional income disparities follow a distinct cyclical pattern in the short-run, moving either pro- or counter-cyclically, the choice of the period of analysis becomes a delicate matter: when the chosen period includes an unequal number of expansions and downturns, the over-represented dynamics might introduce a bias in the results. For instance, suppose regional disparities follow a pro-cyclical pattern. Then, if the period of analysis contains less (more) contraction phases than expansions, results might be misleading as they would derive from an over-representation of dynamics towards divergence (convergence). It is only when the period of analysis contains an equal number of expansions and downturns that the analyst might be able to understand whether convergence or divergence is occurring.

The fact that the choice of the period of analysis might spuriously affect the empirical results

has already been suggested by a few authors (MAGRINI, 1999; PEKKALA, 2000; PETRAKOS *et al.*, 2005); none of them, however, has ever attempted to show explicitly how large the introduced distortion could actually be. This paper is precisely aimed at shedding light on this issue. At the same time, given that misleading results can arise unless cyclical effects on convergence are taken into consideration, convergence in per capita personal income among 48 US States is analysed over a specifically chosen period (1989-2007) that stretches between two peaks of the aggregate business cycle.

From a methodological point of view, the continuous state-space distribution dynamics approach first introduced by QUAH (1997) is opted for. Following the work of BAUMOL (1986), BARRO and SALA-I-MARTIN (1991 and 1995), MANKIW *et al.* (1992) and SALA-I-MARTIN (1996), most empirical research on convergence has adopted the so-called regression approach to investigate whether β -convergence occurs, where β is the generic notion for the coefficient on the initial income variable in the growth-initial level regressions and relates to the speed with which a representative economy approaches its steady state growth path within the neoclassical growth model. This approach, however, has stimulated the critical attention of many scholars who have emphasized its limitations and proposed alternatives (for an account of this literature see, among others DURLAUF and QUAH, 1999; TEMPLE, 1999; ISLAM, 2003; MAGRINI, 2004 and 2009; ABREU *et al.* 2005; DURLAUF *et al.*, 2005). Sharing the view that the regression approach presents several critical inadequacies, this study therefore follows the distribution dynamics approach, a nonparametric approach that, rather than focussing on the representative economy, concentrates on the evolution of the entire cross-sectional distribution and describes both the change in its external shape and the intra-distribution dynamics through the estimate of a stochastic kernel.

Previous applications of the distribution dynamics approach to US data provide ambiguous results. On the one hand, a few studies report evidence of income convergence across US states. For instance, QUAH (1997) depicts a pattern of convergence in per capita personal income among the states between 1948 and 1989 and notes that the ergodic distribution is unimodal, in sharp contrast with the club convergence result found while analyzing income distribution among world countries. Similar findings are also obtained by JOHNSON (2000), who concentrates on the slightly more extended period 1948-1993 and finds again a unimodal ergodic distribution, and by HAMMOND and THOMPSON (2002) who, resorting to the discrete state-space distribution dynamics approach, report the presence of a strong tendency towards convergence in per capita personal income of the states during the 1929-1999 period. In addition, YAMAMOTO (2008) studies convergence dynamics in per capita personal income across both states and counties between 1957 and 2005. For both sets of spatial units a convergence result is reported as the corresponding ergodic distributions are unimodal; however, this tendency towards convergence appears to be stronger across counties. WANG (2004) studies disparities in per capita personal income across 59 provinces and states in Canada and the US and shows that they strongly decreased in the 1950-1970 period, kept almost unchanged in the 1971-1990 period while exhibiting a clear increase in the 1991-2000 period. TSIONAS (2000), analyses the evolution of the distribution of per capita Gross State Product between 1977 and 1996 by fitting finite normal mixtures by maximum likelihood methods and reports the existence of strong persistence in regional differences as mixture means and standard deviations tend to move together. Finally, DICECIO and GASCON (2010) report evidence of polarization. More specifically, the authors analyse per capita personal income convergence across states, metropolitan and non metropolitan portions of the states between 1969 and 2005 and find bimodal ergodic distributions for all sets. Moreover,

they show that while the metropolitan portions of the states converge towards the national average, non-metropolitan portions converge to lower incomes.

The organization of the paper is as follows. In Section 2, the US business cycle is estimated using Hodrick-Prescott (HP) filtering and then the timing of the phases is established using the Bry-Boschan algorithm. Section 3 provides a description of the distribution dynamics approach adopted here while the convergence analysis is implemented in Section 4. Section 5 concludes the study.

2 US business cycle and regional disparities

Our analysis starts with an estimate of the US business cycle as well as of the turning points within this cycle. Preliminarily, two decisions must be made: the income variable to be employed and the time period to be examined. With reference to the income variable, it must be considered that, generally speaking, two options are available at a regional level in the US: Gross Domestic Product and personal income. As is common practice among studies focussing on the US, the latter has been chosen here for two main reasons. On the one hand, in order to correctly identify the phases of the cycle and produce a meaningful analysis, a relatively high frequency of data (at least quarterly) is needed and this is only available for personal income. On the other hand, due to the SIC-NAICS switch, only few observations on Gross State Product are actually available for recent years.

It must however be stressed that studies focussing on other countries generally employ per capita GDP. For this reason it is worth spelling out the main differences between these two variables in order to understand whether they should exhibit different patterns in regional disparities along the cycle. In short, personal income is equal to Gross Domestic Product, less:

capital depreciation, corporate profits with inventory valuation and capital consumption adjustments, contributions for government social insurance, domestic net interest and miscellaneous payments on assets, net business current transfer payments, current surplus of government enterprises, and undistributed wage accruals; plus: net income from assets abroad, personal income receipts on assets, and personal current transfer receipts. Among these, the entry that more evidently moves in relation to the cycle is “personal current transfer receipts”, which act in such a way to smooth out cyclical waves with respect to GDP during downturns. Essentially for this reason, the present study adopts personal income per capita net of personal current transfer receipts. Consequently, this entry should play no role in explaining the differences between GDP and personal income series and any remaining difference should then be attributed to: globalization patterns; indirect and corporate taxes, capital depreciation and undistributed corporate profits; differences in the price indexes employed for deflating the series (LABONTE, 2006). All in all, the role that these elements should play in explaining different patterns in disparities along the cycle is rather uncertain and the variable employed here is therefore not expected to bias the results in any particular direction.

As far as the time period is concerned, DURAN (forthcoming) finds that income disparities across US states switch from counter to pro-cyclical between the end the 1980’s and the beginning of the 1990s and ascribes this to a combination of a process of structural transformation towards a knowledge based “new economy” and a change in the direction of factor flows. For the purpose of our analysis it is essential to focus on a period in which disparities move unambiguously either pro or counter-cyclically; hence, it is a rather natural choice for us to select the period stretching between 1989:Q1 and 2007:Q4 since inequalities follow clearly a pro-cyclical evolution.

Moving now to the business cycle, it must be emphasized that the attention is concentrated here on deviation cycles, i.e. fluctuations of the economy around its deterministic trend. As suggested by several authors, (e.g., ZARNOWITZ and OZYILDIRIM, 2006; HODRICK and PRESCOTT, 1997) due to a decreased output volatility after WWII in the US, deviation cycles are more useful in recent periods than classical cycles as the former include more fluctuations with adequate duration and amplitude. From a technical point of view, the Hodrick-Prescott filter (HODRICK and PRESCOTT, 1997) is therefore used to de-trend US per capita real personal income net of current transfer receipts¹ and the Bry-Boschan algorithm (BRY and BOSCHAN, 1971), as re-organized by HARDING and PAGAN (1992) for quarterly data, to detect turning points.² Table 1 summarizes the identified turning points for the US economy between 1989 and 2007 while Figure 1 presents expansions and slowdowns. Specifically, it is possible to identify 4 peaks and 3 troughs which, as anticipated, will be used for choosing the time span of the periods in the analysis of convergence.

(Table 1 and Figure 1 About Here)

It should be pointed out that several alternative methods to indentify the cycle and its turning points are available in the literature. Here the HP filter has been opted for due to its simplicity and widespread use and the Bry-Boschan algorithm also for its nonparametric nature; at the same time, in order to evaluate the sensitivity of the results, a few alternatives have also been employed. As far as the identification of the cycle is concerned, DURAN (forthcoming) finds very similar results by applying both the HP filter and the one proposed by CHRISTIANO and FITZGERALD (2003) to US states data over a comparable period. Hence, to add further evidence on this issue, a third well-known technique is employed in this paper, the Baxter-

King filter (BAXTER and KING, 1999). A second set of turning points has therefore been obtained by applying the Bry-Boschan algorithm to the Baxter-King filtered data. Finally, also the official turning points set declared by the NBER³ has been considered. These two alternative sets of turning points are reported in Table 2 while corresponding results from the distribution dynamics analysis are reported in Appendices 1 and 2.

(Table 2 About Here)

Figure 2 displays the evolution of some inequality measures calculated using per capita personal income data for the 48 coterminous states in relation to the timing of the US business cycle phases. A wide variety of inequality measures exist in the literature and it is known that the choice of instrument may affect the results (see COWELL, 2008; FIREBAUGH, 2003; PORTNOV and FELSENSTEIN, 2010). For this reason, attention is focussed on three among the most commonly adopted measures, namely, the Coefficient of Variation, the population weighted Coefficient of Variation and the Theil Index. All these measures appear to suggest that income disparities tend to move in a pro-cyclical fashion, with the only exception of a period of four years stretching from 1992:Q1 to 1995:Q4. In other words, pro-cyclical disparities appear to dominate the period of analysis as they can be recognized over more than 75% of the period of analysis.

(Figure 2 About Here)

Having estimated the turning points in the US cycle and noted that cross-sectional disparities in per capita income tend to move in a pro-cyclical way, it is now possible to turn the attention to the analysis of convergence providing, first of all, a few technical details on the adopted

methodology.

3 Distribution Dynamics Approach

As motivated in Section 1, convergence is analysed adopting the distribution dynamics approach whose distinctive feature is to examine directly the evolution of the cross-sectional distribution of per capita income.

Let the random variables X and Y represent per capita income (relative to group average) of a group of n economies at time t and $t+s$ respectively. Now, let $F(X)$ and $F(Y)$ represent the corresponding distributions and assume that each of them admits a density denoted respectively with $f(X)$ and $f(Y)$. Next, assuming that the dynamics of $f(\bullet)$ can be modelled as a first order process, the density at time $t+s$ is given by:

$$f(Y) = \int_{-\infty}^{\infty} f(Y|X)f(X)dX \quad (1)$$

in which $F(Y|X)$ is the stochastic kernel, effectively a conditional density function, mapping the density at time t into the density at time $t+s$. The stochastic kernel is essentially the element that allows to perform the analysis of convergence within this approach: it provides information both on the evolution of the external shape of the income distribution and on intra-distributional dynamics, i.e. on the movement of the economies from one part of the distribution to another between time t and time $t+s$. Convergence can hence be analysed directly from the shape of a plot of the stochastic kernel estimate or, assuming that the process behind (1) follows a time homogenous markov process, by comparing the shape of the initial distribution to the stationary (or ergodic) distribution which is the limit of $f(Y)$ as $s \rightarrow \infty$.

One possible way to do this is through the discretization of the income space whereby the

density estimates in equation (1) can be obtained via a very simple nonparametric density estimator, the histogram. As a consequence of discretization, the cross-sectional distributions become probability vectors; for the same reason, the stochastic kernel simplifies into a transition probability matrix. Despite its simplicity, the histogram is rather statistically inefficient compared to other nonparametric density estimators. Moreover, as commonly recognised in the literature, discretising a continuous process can distort dynamics in important ways (MAGRINI, 1999; REICHLIN, 1999; BULLI, 2001).

Given these critical remarks, a radical alternative is to eschew discretisation and retain a continuous income space.⁴ In this case, a common way to obtain an estimate of the stochastic kernel in equation (1) is through the kernel density estimator. In particular, denote by $\{(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)\}$ the sample of size n , and by $\{(x_{11}, y_1), (x_{21}, y_2), \dots, (x_{n1}, y_n)\}$ our observations. The kernel density estimator of Y conditional on $X = x$ is as follows:

$$\hat{f}(y | x) = \sum_{j=1}^n w_j(x) K_b(y - Y_j) \quad (2)$$

where

$$w_j(x) = \frac{K_a(x - X_j)}{\sum_{j=1}^n K_a(x - X_j)}$$

a and b are bandwidth parameters which control for the smoothness in the dimensions of X and Y respectively and

$$K_b(u) = b^{-1} K\left(\frac{u}{b}\right)$$

is a scaled kernel function.⁵

Despite its widespread use, however, HYNDMAN *et al.* (1996) argue that the estimator in

equation (2) might have poor bias properties. To clarify this, denote the conditional mean with

$$m(x) = E(Y | X = x)$$

so that:

$$Y_j = (X_j = x_j) = m(x_j) + \varepsilon_j$$

where $j=1, \dots, n$ and ε is zero mean, independent but not necessarily identically distributed.

An estimate of the conditional mean function $m(x)$ is provided by the mean of the conditional density estimator in (2):

$$\hat{m}(x) = \int Y \hat{f}(y | x) dy = \sum_{j=1}^n w_j(x) Y_j$$

This estimate has been shown by HYNDMAN *et al.* (1996) to be equivalent to the Nadaraya-Watson (NADARAYA, 1964; WATSON, 1964), or Local Constant, regression estimator which is known to be biased on the boundary of the X space and also in the interior. This bias has often be referred to as the mean-bias.

To overcome the mean-bias problem, HYNDMAN *et al.* (1996) develop a new class of conditional density estimators:

$$\hat{f}^*(y | x) = \sum_{j=1}^n w_j(x) K_b(y - Y_j^*(x))$$

where

$$Y_j^*(x) = \hat{m}(x) + e_j - \sum_{i=1}^n w_i(x) e_i$$

with $i = 1, \dots, n$.

According to these authors, a lower mean-bias can be obtained using an estimator of $m(x)$

with better properties than the Nadaraya-Watson regression estimator. One possibility is to use a local linear estimator (LOADER, 1999):

$$\hat{m}(x) = \frac{\sum_{j=1}^n K_a(x - X_j) Y_j}{\sum_{j=1}^n K_a(x - X_j)} + (x - \bar{X}_w) \frac{\sum_{j=1}^n K_a(x - X_j) (X_j - \bar{X}_w) Y_j}{\sum_{j=1}^n K_a(x - X_j) (X_j - \bar{X}_w)^2}$$

where

$$\bar{X}_w = \frac{\sum_{j=1}^n K_a(x - X_j) X_j}{\sum_{j=1}^n K_a(x - X_j)}$$

The mean-bias adjustment proposed by HYNDMAN *et al.* (1996) is therefore applied in the present analysis and the local linear estimator is used to obtain an estimate of the mean function.

4 Empirical Results

In this section, results of the empirical analysis of convergence across US States over the entire period spanning from 1989 to 2007 are reported.

Initially, coherently with what previously explained, convergence dynamics between corresponding turning points along the business cycle are analysed. Specifically, focussing on the turning points identified through the Bry-Boschan algorithm on HP filtered personal income quarterly data, the entire period of the analysis is defined as the period running from the peak of 1989:1Q to the peak of 2007:2Q.⁶ Convergence, therefore, is studied both using a single transition between the just mentioned peaks and using three transitions thus making use of two additional intermediate peaks (1994:4Q and 2000:1Q). Hereafter, this type of analysis

is referred to as the analysis “in phase”.

Subsequently, it is shown how short run dynamics can alter the picture by distorting the outcome of the convergence analysis. In order to do so, the results found in the “in phase” analysis are compared with those arising from an “out of phase” one. In particular, the “out of phase” analysis is defined as the one based on one or more transitions running from opposite turning points, i.e. either from peak to trough or from trough to peak. Assume that, as previously suggested, disparities follow a pro-cyclical behaviour. Then, when the “out of phase” transition is derived by removing an expansion (slowdown) from a larger “in phase” transition, results are then expected to be biased towards (against) convergence.

4.1 Convergence analysis

The results of the convergence analysis among US States over the period 1989-2007 are reported in Figures 3 and 4. Each figure shows the estimate of the stochastic kernel (both the 3-D plot and the contour plot), an estimate of the cross-sectional distribution at the beginning of the considered transitions and the estimate of the ergodic distribution.

(Figures 3 and 4 About Here)

Focussing on a single transition between the peak of 1989:Q1 and the peak of 2007:Q2 (Figure 3), the estimate of the stochastic kernel shows a weak tendency toward convergence only for the States belonging to the very end of the left tail of the cross-sectional distribution. In contrast, there seems to be a clock-wise rotation of the probability mass, suggesting the presence of diverging dynamics, in a neighbourhood of the sample mean. Consistently, compared with the initial, the ergodic distribution indicates a tendency towards divergence

due to the emergence of a second mode in correspondence to a value of 20% in excess of the sample mean. Fundamentally, the same type of conclusions can be drawn also from Figure 4 where the estimates obtained using three peak-to-peak transitions⁷ are reported. In sum, it appears that over the period stretching across approximately two decades, US States have been characterized by a process of divergence in terms of personal income per capita.

4.2 Influence of the period of analysis

Now that the dynamics characterizing the recent experience of the distribution of personal income per capita across US States have been established, it is possible to move to the second purpose of the study and show if, and how, short-run distribution dynamics along the business cycle affect the results.

As anticipated, to do so a set of comparisons between two ergodic distributions are carried out: an “in phase” distribution and an “out of phase” one. The “in phase” distribution is estimated on transition periods running between different peaks of the business cycle and effectively corresponds to the ergodic distribution estimates reported in Section 4.1. Then, for each peak-to-peak transition characterizing the “in phase” estimate, two types of “out of phase” estimates can be considered. The first one is obtained by concentrating on the transition between an in-between trough and the final peak, thereby removing the slowdown period running from the initial peak and the intermediate trough; the second type of estimate is instead obtained by considering the transition between the initial peak and the intermediate trough, in which case the expansion period running from the intermediate trough and the final peak has been removed. If distribution dynamics effectively move in a pro-cyclical fashion, the first type of “out of phase” ergodic estimate is therefore expected to display a more pronounced tendency towards divergence in comparison to the “in phase” estimate. In

contrast, the second type of “out of phase” ergodic estimate should exhibit a more marked tendency towards convergence.

To draw conclusions, attention can be primarily focussed on the visual inspection of differences in the shape of the estimated ergodic distributions. In each of the considered cases, however, the evidence provided by the graph is supported by adding a comparison between dispersion indexes such as the standard deviation and the interquartile range.

The first of these comparisons is reported in Figures 5-8. In particular, Figures 5 and 6 report the results, respectively based on one and three transition periods, when “out of phase” definition is of the first type and hence excludes slowdown periods. In this case, the introduction of a bias towards divergence is quite evident from the shape of the ergodic distributions: in both figures, the “out of phase” ergodic distribution estimate is markedly bimodal and characterized by higher values for the dispersion indexes.

(Figures 5-8 About Here)

Analogously, Figures 7 and 8 provide an account of the consequences of defining the “out of phase” transition by excluding expansion periods. As expected, the ergodic distribution corresponding to the “out of phase” transitions is showing substantial convergence if compared to the “in phase” distribution. In addition, this implication is clearly confirmed by the reported values of the standard deviation and interquartile range. Finally, as reported in Appendix 2, the same type of conclusions can be drawn when the analysis is replicated using the turning points based on Baxter-King filtered data or as defined by NBER.

A final aspect that is worth considering relates to the common practice of dividing the period of analysis into a number of sub-period of the same length. As a result, the detected dynamics still characterize the entire period, but with reference to transitions of length equal to the sub-periods' length. The main reason behind this operation is that it allows to make use of a richer set of information and thus improve the quality of the estimates. Given the results reported so far, however, it is plausible that this commonly adopted practice is not harmless since the extension of the sub-period is unlikely to coincide with the length of the cycle phases.

The period of analysis selected in this study stretches between the first quarter of 1989 and the second quarter of 2007. If this is divided into three transitions of approximately the same length the resulting sub-periods overlap almost completely with those based on the phases of the US cycle. In particular, a mechanical split of the time span leads to transition of 24 or 25 quarters, which means that the first sub-period would end in 1994:Q4 and the second in 2001:1. In other words, by pure chance the analysis based on a mechanical split of the period is likely to coincide with the one reported in Figure 4. Indeed, this is clearly the message conveyed by the comparison represented in Figure 9.

So, in order to show that the problem just emphasized is not just a theoretical possibility, the period is sub-divided in a somewhat different way but still retaining the ability to allow for the cyclical behaviour of the cross-sectional disparities. The 1994:Q4 peak is therefore ignored and two sub-periods separated by the 2000:Q1 peak are identified. In such a way, the first sub-period runs between 1989:Q1 and 2000:Q1 (approximately 11 years), and the second between 2000:Q1 and 2007:Q2 (approximately 7 years). The analysis carried out over the transition periods thus identified is compared to an analysis conducted using two mechanically determined sub-period of identical length (hence separated by 1998:Q1).

(Figures 9 and 10 About Here)

As clearly shown in Figure 10, in this case the results arising from the mechanical split are affected by a severe distortion: the corresponding ergodic distribution is substantially different from the one obtained through a cycle-based split and markedly bimodal.

Two final remarks are in order here. First, it must be emphasized that, despite the fact the overall period is the same and defined according to the aggregate cycle, profoundly different results emerge. This is simply because the sub-periods have been defined differently. Second, even knowing whether disparities were pro- or anti-cyclical, still it would be impossible to predict the direction of the distortion introduced via the mechanical splitting. Intuitively, the overall level of distortion is a somewhat net effect of the distortions present in each sub-period whose size and direction depend on where mechanically defined boundaries are located with respect to the cycle turning points.

5 Conclusions

This paper assessed the importance of the choice of the period of analysis in relation to the cyclical behaviour of cross-sectional income disparities while investigating convergence dynamics.

First of all, the business cycle for the US economy has been identified using the Hodrick-Prescott filter and then the turning points of the cycle have been detected with the Bry-Boschan algorithm. The overall period of analysis that is consequently selected starts with the peak identified in the first quarter of 1989 and ends with the peak detected in the second

quarter of 2007. Over this period, it appears that per capita personal income disparities across 48 coterminous US states follow a cyclical pattern. In particular, the visual inspection of the evolution of the coefficient of variation in relation to the timing of the US business cycle phases suggests that disparities move in a pro-cyclical fashion.

Second, assuming that the just reported cyclical behaviour might actually affect dynamics, convergence across the states of the US is studied over periods that allow for the cyclical movement of the aggregate economy. Through a comparison between the initial and the ergodic distribution, a tendency towards divergence due to the emergence of a second mode in correspondence to a value of 20% in excess of the sample mean is identified. This finding is then confirmed using three peak-to-peak transitions.

Then, it is demonstrated that the definition of the period of analysis without allowing for the cyclical movements of the aggregate economy might indeed seriously affect the dynamics and lead to misrepresented results.

Finally, it is also shown that the commonly adopted practice of dividing the period of analysis into a number of sub-period of the same length might also bear important consequences. A mechanical sub-division of a correctly identified overall period of analysis might indeed introduce a distortion of a similar size to the one detected when the period of analysis is incorrectly identified.

To sum up, an incorrect choice of a period of analysis (i.e., a period that does not contain entirely both phases of the cycle), as well as a mechanical sub-division of a correctly identified period into transitions of the same length, is likely to produce misleading results. It

is only when the analysed time period includes exactly one (or more) entire business cycles that the researcher may be able to recover the true underlying dynamics of cross-sectional income disparities.

These considerations are not only interesting *per se*, but they also have far reaching consequences for regional policy. From a policy maker viewpoint it is indeed important to recognize whether regional disparities move along the business cycle and hence to discriminate between a short-run component of the disparities, possibly bound to vanish, and the long-run one. While the type of intervention required by an increase in disparities due to the short-run component might possibly be limited to temporarily sustaining income in less favoured regions (for instance through direct and indirect income transfers), in case of a long-run increase in disparities quite different structural interventions might be called for (for instance, policies aimed at fostering infrastructure upgrading in strategic sectors, sustaining the development of human capital and improving the environment for both innovation and firm creation). In addition, also the sign of the association between regional disparities and cyclical swings matters. In particular, it is important to emphasize that in case of a counter-cyclical behaviour, disparities tend to enlarge during slowdowns i.e. during periods in which it is reasonable to expect that fewer resources could be devoted to short term policies aimed at tackling them.

Finally, it is important to keep a clear distinction between short-run and long-run implications of the results reported here. It has been shown that, during the 1989-2007 period, regional disparities display a pro-cyclical behaviour and that the underlying long-run tendency is towards divergence. However, it must be stressed that the second result cannot be inferred from the first. More explicitly, pro-cyclical disparities do not necessarily imply that disparities

increase in the long-run when the aggregate economy is growing nor that policies aimed at fostering growth of the aggregate economy in the long-run necessarily lead to a steady increase in regional disparities. Indeed, the determinants of short-run and long-run dynamics in regional disparities could differ significantly so that the increase in regional disparities detected during an expansion phase might be more than compensated during the slowdown thus leading to a net reduction over the entire cycle.

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Table 1 **US turning points (Hodrick-Prescott Cycle)**

Dates	Peak or Trough
1989-Q1	Peak
1991-Q4	Trough
1994-Q4	Peak
1995-Q4	Trough
2000-Q1	Peak
2003-Q1	Trough
2007-Q2	Peak

Table 2 Alternative US turning points

Baxter-King Cycle		NBER Announcements	
Dates	Peak or Trough	Dates	Peak or Trough
1991-Q3	Trough	1990-Q3	Peak
1992-Q3	Peak	1991-Q1	Trough
1993-Q3	Trough	2001-Q1	Peak
1994-Q3	Peak	2001-Q4	Trough
1997-Q2	Trough	2007-Q4	Peak
1998-Q3	Peak		
1999-Q2	Trough		
2000-Q3	Peak		
2002-Q1	Trough		
2004-Q3	Peak		
2005-Q2	Trough		
2007-Q3	Peak		

Figure 1 **US Personal income and cycle phases, 1989-2007**

Note: Gray-shaded areas represent slowdowns identified using the Bry-Boschan algorithm on HP filtered data.

Figure 2 US business cycle and regional disparities, 1989-2007

Note: Gray-shaded areas represent slowdowns identified using the Bry-Boschan algorithm on HP filtered data.

Figure 3 **Distribution Dynamics**
peak-to-peak: 1989:Q1- 2007:Q2

stochastic kernel

initial (t_1)

ergodic

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel.
A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).
In the plots, t_1 refers to the initial moment(s) of the transition period(s).

Figure 4 **Distribution Dynamics**
peak-to-peak: 1989:Q1-1994:Q4; 1994:Q4- 2000:Q1; 2000:Q1-2007:Q2

stochastic kernel

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996). In the plots, t_1 refers to the initial moment(s) of the transition period(s).

Figure 5 Comparison between Distribution Dynamics

peak-to-peak: 1989:Q1-2007:Q2
trough-to-peak: 1991:Q4-2007:Q2

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2028	0.3288
OUT (trough-to-peak)	0.2530	0.4597

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure 6 Comparison between Distribution Dynamics
peak-to-peak: 1989:Q1-1994:Q4; 1994:Q4-2000:Q1; 2000:Q1-2007:Q2
trough-to-peak: 1991:Q4-1994:Q4; 1995:Q4-2000:Q1; 2003:Q1-2007:Q2

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2572	0.3877
OUT (trough-to-peak)	0.3380	0.6246

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure 7 Comparison between Distribution Dynamics

peak-to-peak: 1989:Q1-2007:Q2

peak-to-trough: 1989:Q1-2003:Q1

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2028	0.3288
OUT (peak-to-trough)	0.1650	0.2213

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure 8 Comparison between Distribution Dynamics
peak-to-peak: 1989:Q1-1994:Q4; 1994:Q4-2000:Q1; 2000:Q1-2007:Q2
peak-to-trough: 1989:Q1-1991:Q4; 1994:Q4-1995:Q4; 2000:Q1-2003:Q1

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2572	0.3877
OUT (peak-to-trough)	0.2133	0.3106

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure 9 Comparison between Distribution Dynamics

peak-to-peak: 1989:Q1-1994:Q4; 1994:Q4-2000:Q1; 2000:Q1-2007:Q2
 mechanical: 1989:Q1-1995:Q1; 1995:Q1-2001:Q2; 2001:Q2-2007:Q2

	Standard deviation	Interquartile range
peak-to-peak	0.2572	0.3877
mechanical	0.2602	0.3886

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure 10 Comparison between Distribution Dynamics

peak-to-peak: 1989:Q1-2000:Q1; 2000:Q1-2007:Q2
mechanical: 1989:Q1-1998:Q1; 1998:Q1-2007:Q2

	Standard deviation	Interquartile range
peak-to-peak	0.1902	0.2612
mechanical	0.2753	0.4649

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Appendix 1 Convergence Dynamics Using Alternative Cycle Datings

Figure A1.1 Convergence Dynamics (dating based on Baxter-King filtered data)

peak-to-peak: 1988:Q4-2007:Q3

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).
In the plots, t_1 refers to the initial moment(s) of the transition period(s).

Figure A1.2 Convergence Dynamics (dating based on Baxter-King filtered data)

peak-to-peak: 1988:Q4-1992:Q3; 1992:Q3-1994:Q3; 1994:Q3-1998:Q3;
1998:Q3-2000:Q3; 2000:Q3-2004:Q3; 2004:Q3-2007:Q3

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel.

A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

In the plots, t_1 refers to the initial moment(s) of the transition period(s).

Figure A1.3 Convergence Dynamics (NBER dating)
peak-to-peak: 1990:Q3-2007:Q4

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel.
A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).
In the plots, t_1 refers to the initial moment(s) of the transition period(s).

Appendix 2 Comparison between Distribution Dynamics Using Alternative Cycle Datings

Figure A2.1 Comparison between Distribution Dynamics (dating based on Baxter-King Filtered data)

peak-to-peak: 1988:Q4-2007:Q3

trough-to-peak: 1991:Q3-2007:Q3

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.1882	0.2964
OUT (trough-to-peak)	0.2517	0.4468

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure A2.2 Comparison between Distribution Dynamics (dating based on Baxter-King Filtered data)

peak-to-peak: 1988:Q4-1992:Q3; 1992:Q3-1994:Q3; 1994:Q3-1998:Q3;
1998:Q3-2000:Q3; 2000:Q3-2004:Q3; 2004:Q3-2007:Q3
trough-to-peak: 1991:Q3-1992:Q3; 1993:Q3-1994:Q3; 1997:Q2-1998:Q3;
1999:Q2-2000:Q3; 2002:Q1-2004:Q3; 2005:Q2-2007:Q3

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure A2.3 Comparison between Distribution Dynamics (dating based on Baxter-King filtered data)

peak-to-peak: 1988:Q4-2007:Q3

peak-to-trough: 1988:Q4-2005:Q

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.1882	0.2964
OUT (peak-to-trough)	0.1661	0.2426

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure A2.4 Comparison between Distribution Dynamics (dating based on Baxter-King Filtered data)

peak-to-peak: 1988:Q4-1992:Q3; 1992:Q3-1994:Q3; 1994:Q3-1998:Q3;
1998:Q3-2000:Q3; 2000:Q3-2004:Q3; 2004:Q3-2007:Q3
peak-to-trough: 1988:Q4-1991:Q3; 1992:Q3-1993:Q3; 1994:Q3-1997:Q2;
1998:Q3-1999:Q2; 2000:Q3-2002:Q1; 2004:Q3-2005:Q2

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2766	0.4112
OUT (peak-to-trough)	0.2297	0.3385

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure A2.5 Comparison between Distribution Dynamics (NBER dating)

peak-to-peak: 1990:Q3-2007:Q4
trough-to-peak: 1991:Q1-2007:Q4

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2274	0.3769
OUT (trough-to-peak)	0.2517	0.4412

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Figure A2.6 Comparison between Distribution Dynamics (NBER dating)

peak-to-peak: 1990:Q3-2007:Q4
peak-to-trough: 1990:Q3-2001:Q4

	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2274	0.3769
OUT (peak-to-trough)	0.2145	0.3257

Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

Notes

¹ Denoting income at time t with y_t , the HP filter minimizes in τ_t the following expression

$$\min \sum_{t=1}^T (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$$

where λ is a penalty parameter which captures the smoothness of the trend τ_t . Specifically, the first term represents the deviations of income from the trend while the second term is the product of λ and the sum of the squares of the second differences of the trend component which penalizes variations in the growth rate of the trend. Penalty increases with λ , producing smoother estimates, and as suggested by the authors in case of quarterly data, we set $\lambda=1600$.

² The Bry-Boschan algorithm is designed to detect, initially, the set of local minima and maxima in the income series and it then imposes several restrictions on the duration of the phases and cycles in order to ensure their persistence. In the present analysis we set the minimum phase and cycle length as 2 and 5 quarters respectively.

³ It should be noted that we do not primarily concentrate on NBER turning points because NBER detects the turning points referring directly to classical cycles while we instead use deviation cycles; besides, NBER uses many aggregate variables when detecting the turning points while we use only personal income data.

⁴ A further possibly critical issue concerns the effects of spatial dependence on the kernel density estimates. While in the parametric literature, and in particular in the literature on convergence within the regression approach, there is a full awareness that neglecting spatial dependence may lead to biased and inefficient estimates, this issue has been almost ignored so far within the nonparametric literature. So, for example, REY and JANIKAS (2005) in their discussion of the properties of kernel density estimators note that “the properties of these estimators in the presence of spatial dependence are unknown” (page 165).

⁵ The kernel $K(\bullet)$ is assumed to be a real valued, integrable, non-negative, even function.

⁶ In the Appendix, we also report results obtained using the turning points dated on Baxter-King filtered data (BAXTER and KING, 1999) and the official turning points provided by NBER. As explained earlier in the text, it must be emphasized that NBER turning points are not fully compatible with our framework since NBER dating is based on a wide set of indicators (rather than just personal income) and refers to classical cycles (rather than deviation cycles). For this reason, when using NBER turning points we only carry out estimates over a single transition period.

⁷ The same results are also obtained using the turning points based on Baxter-King filtered data, either considering just one peak-to-peak transition (Figure A1.1) or all possible ones (Figure A1.2), and using official NBER turning points (Figure A1.3).