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Short-run dynamics of income disparities and cycle synchronization across regions

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The undersigned Hasan Engin Duran, in his quality of doctoral candidate for a Ph.D. degree in Economics granted by the Università Ca' Foscari Venezia attests that the research exposed in this dissertation is original and that it has not been and it will not be used to pursue or attain any other academic degree of any level at any other academic institution, be it foreign or Italian.

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Dedicated to my fiancée
"Gizem"

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PREFACE

Since the 1990s, the issue of regional income convergence and its long term tendencies has been thoroughly and heatedly discussed. Far less attention, however, has been devoted to the short-run dynamics of regional convergence. The present thesis is devoted to studying explicitly the short-run dynamics of regional income disparities; in particular, to the interconnections between regional income inequalities and the aggregate business cycle as well as to the interactions among disaggregate and aggregate economic fluctuations in the U.S. To shed light on these issues, we use data for the 48 coterminous US states in three empirical studies adopting different but complementary perspectives.

In the first chapter, we characterize the short-run behavior of income disparities across states by assessing whether regional disparities manifest a tendency to move systematically along the national cycle and investigate the mechanisms behind such behaviour. Our results indicate that income disparities do not move randomly in the short-run but follow a distinct cyclical pattern, moving either anti-cyclically, i.e. decreasing during expansions and increasing during recessions, or pro-cyclically, i.e. increasing during expansions and decreasing during recessions, depending on the analyzed period. As for the underlying mechanism, it appears that the short-run evolution of the disparities in recent years is largely a consequence of differences in the timing with which the business cycle is felt across states rather than the outcome of amplitude differences across local cyclical swings.

In Chapter 2, we investigate whether and why some economies might be systematically ahead of others along the swings of the business cycle. The analysis of such a lead/lag structure is carried out in two steps using data for US states over the period 1979-2010. First, we show that leading (or lagging behind) is a feature that does not occur at random across the states. Second, we investigate the economic drivers that could explain such a behavior. Our results suggest the existence of increasingly evident timing differences across state cycles as well as of a lead/lag structure whereby some states are systematically ahead of others along the swings of the business cycle. The Three-Stage Least-Squares estimate of a 4-equation model reveals that the lead/lag structure is significantly explained by the degree of synchronization among cycles and, indirectly, by trade flows and financial integration. In addition, specialization, and particularly specialization in the high-tech sector, plays an important role in predicting whether a state leads or lags behind another.

To the extent that regional income disparities follow a distinct cyclical pattern in the short-run, moving either pro- or counter-cyclically, the period of analysis should be chosen with great care. Failing to do so might in fact lead to an overestimation of the tendency towards either convergence or divergence. In Chapter 3, we explicitly show that an incorrect choice of a period of analysis (i.e., a period that does not contain entirely both phases of the cycle) might indeed seriously affect the convergence dynamics and hence lead to misrepresented results. It is only when the analyzed 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.

CHAPTER 1

Short-run dynamics of income disparities and regional cycle synchronization

Hasan Engin Duran

1.1 Introduction

In the literature on economic convergence, much attention has been devoted to the analysis of the evolution of regional disparities. In almost all cases, these studies have implicitly adopted a long-run perspective. This is probably motivated by the fact that the most commonly adopted empirical tools are derived, more or less directly, from the traditional neoclassical model that, as is well known, describes a monotone path along which, under certain assumptions on production, technology and preferences, each economic system converges towards a stable long-run dynamic equilibrium. The short-term dynamics and, in particular, the interconnections between the disparities across economic systems (e.g. between regions) and the aggregate economic cycle have received very limited attention.

In spite of this, the few studies which have been confronted with this topic seem to suggest that regional disparities can vary significantly along the aggregate economic cycle. This result, if confirmed, has extremely important implications both for the empirical analysis of convergence and for regional economic policy. On the one hand, because time series on income are usually quite short at the regional level, if regional disparities are shown to move significantly along the business cycle, then the period of analysis should be chosen with great care so to avoid it could affect the results (Magrini, 1999; Pekkala, 2000). Indeed, if regional disparities move, say, in an anti-cyclical fashion, i.e., increasing during the economic downturn and decreasing during the expansion phase, the choice of a period of analysis that does not contain entirely both phases of the cycle is likely to produce misleading results due to an overestimation of the tendency towards convergence (divergence) when the period of analysis excludes a part of the contraction (expansion) phase.

With regard to the implications for regional economic policy, it is important to emphasize that the recognition and quantification of a short-term component in the dynamics of regional disparities, as well as the causes of this component, would help understanding the extend to which policy interventions are needed in order to absorb structural and long-run regional differences. In a European perspective, in particular, assuming that regional disparities move in an anti-cyclical fashion, if the widening of the disparities during a recession is such to undermine the overall objective of social and territorial cohesion within the Union, it may be appropriate to put in place additional resources explicitly targeted to the containment of these dynamics. Conversely, if regional disparities demonstrate a pro-cyclical component, the reduction of disparities that take place during an economic downturn can be considered rather positively as it eases the pressure on resources to be devoted to the objective of territorial cohesion during the contraction phases.

Most of the papers dealing with the short-term regional disparities report evidence in favor of a pro-cyclical behavior. This finding implies that regional disparities move in the same direction as the national economic cycle and, therefore, tend to increase during expansion periods and diminish in times of recession. Some examples are Dewhurst (1998), who analyzes income disparities among 63 UK counties between 1984 and 1993, Petrakos and Saratsis (2000), who study inequalities among Greek prefectures between 1970 and 1995 and Petrakos *et al*. (2005), who focus on the disparities across EU countries between 1960 and 2000. In terms of methodology, most of the studies adopt a time series regression approach and regress a measure of regional disparities (i.e. the coefficient of variation) on the growth rate of the aggregate economy.

From a theoretical point of view, the studies try to interpret the pro-cyclical disparities by referring to Berry's (1988) explanations which are in line with the spatially cumulative nature of growth (Myrdal, 1957). According to this view, expansion phases begin in more developed regions where agglomeration and market size create a lead over other regions. As a consequence, regional inequalities increase during expansions since economic growth does not spread to the rest of the country automatically (Petrakos *et al*., 2005). By contrast, developed areas suffer more than other regions during recessions and therefore income inequalities decrease (Petrakos and Saratsis, 2000).

An alternative explanation is provided by Rodriquez-Pose and Fratesi (2007). They show that most Southern European countries exhibit pro-cyclical regional disparities between 1980 and 2005. These countries leave sheltered regions in their rural areas. Sheltered regions are isolated economies which are mostly dependent on the agriculture sector, government transfers and public employment. Therefore, they are not fit enough to compete with the rest of the economy and cannot use their potential for convergence which is generally available during the expansion periods. By contrast, in recessions they do not suffer as much as other regions and, therefore, tend to converge to richer regions. Consequently, in these countries, regional disparities follow a pro-cyclical pattern and increase during the national booms and decrease in the times of recession.

Apart from these pro-cyclical findings, there are some other studies which find evidence of anti-cyclical regional disparities. Pekkala (2000) investigates inequalities across 88 Finnish regions between 1988 and 1995 by using distribution dynamics approach. She finds evidence of anti-cyclical regional disparities and mentions that mobility of regions within the cross sectional distribution is high (low) during boom (recession) times and thus regional disparities tend to decrease (increase). Finally, Quah (1996) finds no evidence on the impact of business cycles on the income distribution of the US economy between 1948 and 1990.

The present paper extends the literature in several directions. First, the relationship between regional disparities and business cycle might not be constant over time. Despite this, with the only exception of Rodriquez-Pose and Fratesi (2007), none of the existing studies have attempted to analyze the change in this relationship over time. Here, we try to fill the gap and investigate the evolution of this relationship[1].

Second, to our knowledge all existing studies define the national business cycle by referring directly to the growth rate of the aggregate economy. Therefore, positive growth years are interpreted as expansion periods and negative growth years are interpreted as recession periods. However, we prefer to define the business cycle in a wider sense and, therefore, use deviation cycles, i.e. the fluctuations of the aggregate economy around its deterministic trend, so that for an economy to experience a

[1] For instance, Rodriguez-Pose and Fratesi (2007) found that most Southern European countries exhibit increasingly pro-cyclical regional disparities over time.

recession it is sufficient that its actual growth rate is smaller than its trend growth.

Third, as far as we know, none of the studies on the short-run behavior of regional disparities have attempted to investigate the dynamics behind it. However, recognizing these dynamics might help us understanding the short-run behavior of disparities. In particular, we consider two short-run mechanisms behind the evolution of the disparities: disparities might evolve as a consequence of differences in the timing with which the business cycle is felt across regional economies; alternatively, the evolution of disparities might be motivated by amplitude differences across local cyclical swings.
In this paper, we intend to contribute to this literature by characterizing the short-run behavior of income disparities across US states in relation to the national business cycle. Below, we briefly summarize our set of research questions:

i. Is there a relationship between the US business cycle and income disparities across states? If so, do income disparities move pro-cyclically or anti-cyclically? Does this relationship change over time?
ii. Are there meaningful state specific cycles? Are there important differences in the timing and amplitudes of the cycles of the states? How do the differences in timing and amplitudes change over time?
iii. What are the short-run driving forces behind the evolution of income disparities? Do the differences in amplitudes or timing across state cycles drive the evolution of income disparities? Which mechanism is more important?

The organization of the paper is as follows. In Section 1.2 we implement a regression analysis in order to characterize the short-run behavior of income disparities. In Section 1.3 we show how sizable are differences in amplitudes and timing across state cycles by using information obtained from the turning points of state cycles. In Section 1.4, using Cholesky variance decompositions, we analyze whether amplitude or timing differences across states tend to be the major short-run driver of income disparities. Finally, Section 1.5 concludes the paper.

1.2 Characterizing the short-run behavior of regional disparities

One of the main objectives of this study is to characterize the short-run behavior of income disparities among states. Therefore, in this part, we try to understand whether income disparities change in response to aggregate fluctuations of the economy. To do so, we use data on per capita real personal income net of current transfer receipts (quarterly) series for US states over the period between 1969:1 and 2008:4 provided by the Bureau of Economic Analysis.

As a measure of cross-sectional income disparities, we use the coefficient of variation:

$$CV_t = \frac{\sqrt{\sum_{i=1}^{n}(RPI_{i,t} - R\overline{P}I_t)^2/(n-1)}}{R\overline{P}I}$$

where $RPI_{i,t}$ is the level of per capita real personal income excluding transfers of state i at time t, $R\overline{P}I_t$ its cross-sectional mean at time t, while n is the number of states. As commonly done in the literature, we exclude Alaska, Hawaii and the District of Columbia and focus on the 48 contiguous states. Moreover, all the series used in this study are deflated using the 1982-1984 US city average national consumer price index. The seasonality is adjusted using a multiplicative ratio to moving average technique. The evolution of CV_t is shown in Figure (1.1); it can easily be seen that income disparities across US states have a clear upward trend after the mid-70s.

(Figure 1.1 About Here)

In order to study the relationship between cross-sectional income disparities and business cycle we consider the following model:

$$CV_t = \alpha + \beta CYC_t + \varepsilon_t \tag{1.1}$$

Specifically, CYC_t is derived by using a Hodrick-Prescott filtering to de-trend US per capita real personal income net of current transfer receipts between 1969:1 and 2008:4.[2] Clearly, a positive and significant estimate for β would indicate that income disparities move in the same direction as the aggregate cycle, i.e., pro-cyclically. By contrast, a negative and significant β implies that income inequalities move in the opposite direction to the aggregate cycle, i.e., anti-cyclically, or counter-cyclically.

Before effectively obtaining the estimates, however, a couple of crucial issues must be

[2] In what follows, *CYC* denotes the national business cycle while CYC_i denotes the cycle of state *i*.

addressed. First, a number of filtering techniques are available in the literature, among many others those proposed by Hodrick and Prescott (1997), HP, and by Christiano and Fitzgerald (2003), CF. In Table 1.1, we compare the CF and HP cycles for the aggregate economy and check their ability to match the official timing provided by the National Bureau of Economic Research (NBER).

(Table 1.1 About Here)

Although the two filters give similar results, in what follows we adopt the HP filter due to its simplicity and widespread use in the literature. Denoting income at time t with y_t, the HP filter minimizes in τ_t the following expression:

$$\min \sum_{t=1}^{T} \left(y_t - \tau_t\right)^2 + \lambda \sum_{t=2}^{T-1} \left[\left(\tau_{t+1} - \tau_t\right) - \left(\tau_t - \tau_{t-1}\right)\right]^2 \qquad (1.2)$$

where λ is a penalty parameter which captures the smoothness of the trend τ_t. Specifically, the first term of equation (1.2) 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. As recommended by Hodrick and Prescott (1997) for quarterly data, we set λ=1600. The evolution of US personal income and the estimated trend via HP filtering is shown in Figure 1.2 while the corresponding deviation cycle is depicted in Figure 1.3.

(Figure 1.2 and Figure 1.3 About Here)

A second important issue in time series analysis concerns the stationarity properties of the variables that guarantee valid regression inference. In order to check this out, we implement the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979) for each variable. We determine the optimal lag length for the ADF regressions by choosing the number of lags which minimizes the Akaike Information Criterion (AIC) while the maximum number of lags has been determined by using the rule of thumb provided by Schwert (1989):

$$p\max = 12 \times \left(\frac{T}{100}\right)^{1/4}$$

where T is the number of observations and p max is the maximum number of lags. Table 1.2 summarizes the results. We observe that the time series of cross-sectional income disparities (CV_t) follow a non stationary, I(1), process. So, in order to introduce this variable in the regression model (1.1), we make it stationary by applying the HP filter; de-trending the disparities enables us to observe the increase/decrease in disparities, not in absolute terms, but relative to its trend. The de-trended disparities variable (which we label $CVHP_t$) follows an I(0) process over the whole period as well as over two sub periods (before and after 1987).[3] As far as the business cycle variable, CYC_t, it exhibits a mean reversion over the whole period (and over the two sub periods) and it follows an I(0) process.

(Table 1.2 About Here)

We can now turn to the regression estimates, using $CVHP_t$ as dependent variable, whose results are reported in Table 1.3. It should be observed, however, that OLS estimates suffer from a serial correlation problem. In order to address this, we allow for first order autoregressive errors and, in this way, get rid of the serial correlation. Doing this, no more evidence of serial correlation is found via Breusch-Godfrey Lagrange Multiplier test (Breusch, 1978; Godfrey, 1978) using up to 8 quarters lag length. In actual facts, the estimated model is

$$\begin{cases} CVHP_t = \alpha + \beta CYC_t + \varepsilon_t \\ \varepsilon_t = \rho\varepsilon_{t-1} + u_t \end{cases}$$

That yields the transformed model:

$$CVHP_t = \alpha(1-\rho) + \rho CVHP_{t-1} + \beta(CYC_t - \rho CYC_{t-1}) + u_t$$

The serial correlation parameter ρ and the coefficient β are simultaneously estimated using the Levenberg-Marquardt Nonlinear Least Squares algorithm (Levenberg, 1944; Marquardt, 1963).[4]

(Table 1.3 About Here)

[3] The motivation for this subdivision will be clarified shortly.

[4] We also run a Prais-Winsten regression (Prais and Winsten, 1954) to address autocorrelation. The results are very similar. Therefore, we do not report them here but they are included in Table 1.12.

The regression results are summarized in the first column of Table 1.3 from which it is immediate to note that the estimate of β is not significantly different from zero. This result might be due to a change in the relationship between the business cycle and income disparities over the time period of the analysis brought in by political and socio-economic transformations. For instance, the late 1980s are known to be the initial period of the "new economy", i.e. period of a transition from an industrial/manufacturing to a knowledge/technology based economy accompanied with sustained growth, low unemployment and immunity to boom-bust economic cycles during 1990s. Moreover, from an international perspective, the late 1980s has witnessed acceleration in trade and financial liberalization. Empirical evidence in the literature on US economy supports this break period as well (DeVol *et al.*, 1999). For these reasons, we split the period of analysis in two sub-periods: the first runs from 1969:1 to 1986:4, the second from 1987:1 to 2008:4. Columns 2 and 3 of Table 1.3 therefore report the corresponding estimates of the parameter β in the two sub-periods, respectively β_1 and β_2. As expected, both estimates are now significantly different from zero. In particular, the coefficient for the first sub-period, β_1, is negative, thereby suggesting the existence of an anti-cyclical behavior for the cross-sectional disparities. In other words, before 1987 income disparities across states tend to diminish (relative to the trend) during periods of national expansion and increase during recessions. By contrast, there exists strong evidence for pro-cyclical disparities after 1987 since β_2 is strongly significant and positive. Hence, it appears that income disparities have turned from being anti-cyclical to pro-cyclical in last two decades and now tend to co-move with the cycle of the aggregate economy. As for the size of the impact, the estimated values imply that, before 1987, over a typical expansion (that lasts, on average, about 13 quarters) the coefficient of variation declines by -3.42% whilst, over a typical recession (lasting, on average, about 9 quarters) the coefficient of variation increases by 3.02%. Moving to the second sub-period, the coefficient of variation increases by 4.54% over an expansion and decreases by -4.24% over a recession.

To support also from an inferential point of view our choice of splitting the time period, we carry out a Chow test for the existence of a significant break in the relationship between the business cycle and income disparities. According to the F-statistics and the log-likelihood ratio, we found a significant (at 1% level) break at the 1986:4.

In addition to the model (1.1), we consider an alternative regression specification to check the robustness of our results. Specifically, we regress the first differences of our measure of cross-sectional income disparities (ΔCV) on the growth rate of the aggregate economy. Both variables clearly follow a stationary process.

(Table 1.4 About Here)

Table 1.4, which reports the regression estimates, confirms the picture drawn above. No significant relationship between the growth rate of the economy and income disparities is found over the entire period, while the sign of the relationship between business cycle and income disparities moves from negative, before 1987, to positive, afterwards. Once more, this change in the relationship has been verified using the Chow breakpoint test which recognizes a significant break at 1% level.

To sum up, using two alternative specifications, we find that income disparities across US states follow an anti-cyclical pattern until the late 1980s, declining during times of national expansion and increasing during recessions. After the 1987, there is a significant change in the short-run behavior of the disparities as they become pro-cyclical, thereby increasing during expansions and declining during recessions.

1.3 Are there meaningful state-level cycles?

After having characterized the short-run behavior of cross-sectional income disparities, we investigate the short-run dynamics underneath their evolution and try to establish whether it could be explained by differences in the timing with which the business cycle is felt across states or it could instead be motivated by amplitude differences across local cyclical swings. Before doing so, it is however useful to understand whether there exist meaningful state-level cycles with different characteristics in timing and amplitudes. Clearly, if there were no sizable differences in timing or amplitudes across state cycles, it would be unlikely that the two mechanisms could actually play any important role in the evolution of the disparities.

To investigate the differences in timing and amplitudes, we first detect the turning points in state-level cycles and then evaluate the size of such differences using several measures commonly adopted in the literature.

1.3.1 Turning points detection

Several methodologies for detecting turning points have been put forward in the literature. Before going a step further, we therefore need to provide a brief account of the main technical advancements in this field.

Burns and Mitchell (1946) established the methods which became the main principles of business cycle dating procedure adopted by NBER. Since 1980, the NBER has been officially responsible for detecting and declaring the chronology of US turning points. NBER's Business Cycle Dating Committee declares a turning point when its members reach a consensus. The decision is taken using many variables and techniques. The use of multiple series is largely due to the fact that there exists no single variable which perfectly represents the aggregate economic activity. However, this procedure has recently been criticized. Since each committee member follows different techniques, the turning point detection seems rather subjective, neither transparent nor reproducible (Chauvet and Piger, 2003). Furthermore, the NBER announces the turning points not immediately but well after the fact (Chauvet and Piger, 2003). Therefore, the literature on this issue has tried to develop and formalize the dating rules by using transparent and simple methodologies in order to reproduce NBER's chronology accurately and in a timely manner.

The early literature focused on how to accurately replicate the NBER's dates using single series. Bry and Boschan (1971) first documented the formal algorithm which aims at finding specific phases and cycles in the economic series. The basic principle of this non-parametric technique is to find the set of local maxima and minima in the economic series and ensure that any detected cycle shows persistence. Harding and Pagan (2002) re-organized the algorithm and modified it for quarterly data.

On the other hand, a parametric autoregressive Markov-Switching (MSVAR) model has been developed by Hamilton (1989) to identify regime shifts in the economic activity. This model, that has become a commonly used tool in the business cycle literature, defines the shifts in the business cycle phases as the shifts in the mean growth rate of the economy which follows an autoregressive process and switches between two regimes: expansion and recession (Hamilton, 1989; Owyang *et al*., 2005).

It must be emphasized that although much effort has been put on dating business cycles at the national level, little work has been done at the regional or state level (e.g. Owyang *et al*., 2005; Hall and Dermott, 2004). So, apart from representing the first step in our investigation on the short-run dynamics underneath the evolution of income disparities, dating the state-level cycles represents an interesting issue *per se*. To do so, we employ the Bry-Boschan Quarterly algorithm to detect turning points for the US aggregate cycle as well as for 48 state-level cycles using HP de-trended (logarithm of) per capita real personal income (excluding transfers) between 1969 and 2008.

The main principles of the Bry-Boschan algorithm require that any selected cycle, expansion and recession are characterized by an adequate duration. The algorithm is therefore designed to, first, detect the local minima and maxima in the series and, second, impose restrictions to ensure the duration of the phases. For instance, equations (1.3) show an example of local minimum and maximum given a 5-quarter window length:

$$\begin{aligned}\text{local maximum} &= \left\{\left(y_{t-2}, y_{t-1}\right) < y_t > \left(y_{t+2}, y_{t+1}\right)\right\} \\ \text{local minimum} &= \left\{\left(y_{t-2}, y_{t-1}\right) > y_t < \left(y_{t+2}, y_{t+1}\right)\right\}\end{aligned} \tag{1.3}$$

where y_t represents income. Once local minima and maxima have been detected in the time series, minimum duration restrictions are imposed ensuring that every cycle, from peak to peak (from trough to trough), has a length of at least 5 quarters and every phase, from peak to trough (from trough to peak) has a length of at least 2 quarters. The algorithm checks also whether detected turning points orderly alternate. [5]

Results from the application of the Bry-Boschan algorithm to the US States data are presented in Table 1.5. At a first glance, it can be observed that while until late 1980s, state-level turning points are concentrated around the national turning points, after 1987, these turning points are rather dispersed. This implies a tendency for state cycles to become less synchronized with respect to the US cycle. In the next sub-section, we

[5] Besides these main principles, the Bry-Boschan algorithm includes several intermediate, a detailed description of which is reported in Appendix 1.1

deepen these findings by quantifying the level of synchronization using several measures commonly adopted in the literature.

(Table 1.5 About Here)

1.3.2 Cycle synchronization among states

A growing body of literature investigates whether national, or regional, cycles tend to synchronize with each other and the economic factors behind the observed patterns. A first strand of this literature concentrates on the co-movement of the cycles. For instance, Fatas (1997) studies the co-movement among European countries, Artis and Zhang (1999) among OECD countries, Montoya and Haan (2007) among European regions and Carlino and Sill (2001) among US regions. However, in only a small proportion of cases the authors detected the cycle turning points and subsequently used this piece of information when assessing the level of synchronization among cycles (Owyang *et al.*, 2005; Hall and Dermott, 2004). In line with these fewer works, we think that the (dis)similarities in the timing of the turning points may provide useful information about the synchronization of the cycles. In this section, therefore, we employ several descriptive statistics to explore the variation in timing across the cycles of US states.

Recently, two popular measures of synchronization have been developed. These are the concordance index and the diffusion index. Owyang *et al.* (2005) relied on the first index to evaluate the degree of synchronization between US states and the aggregate economy. Similarly, Hall and Dermott (2004) used the same index to analyze the degree of synchronization among regions of New Zealand. Artis *et al.* (2003) instead used both indexes to evaluate synchronization within the Euro area.

Specifically, the concordance index measures the percentage of time in which two economies are in the same business cycle phase. In equation (1.4), I measures the concordance between the cycles of economies i and j over a period of T instants:

$$I = \frac{1}{T}\sum_{t=1}^{T}\left[S_{i,t}S_{j,t} + \left(1 - S_{i,t}\right)\left(1 - S_{j,t}\right)\right] \tag{1.4}$$

where $S_{\bullet,t}$ is a binary variable which takes on value 1 when an economy is in recession and value 0 when it is in an expansion. The index thus ranges between 1 and 0; when *I* is equal to 1 there is perfect synchronization between economies, i.e. *i* and *j* are in the same cycle phase 100% of the time. By contrast, when *I* is equal to 0 there is no synchronization between the two economies.

The diffusion index in equation (1.5) instead measures, at any point in time, the percentage of cross-sectional units which are experiencing a recession (or expansion). Consequently, the diffusion index of recessions is equal to 1 if all of the units are in recession and, by contrast, is equal to 0 if they are all experiencing an expansion

$$D_t = \frac{1}{n}\sum_{i=1}^{n} S_{i,t} \tag{1.5}$$

We summarize the concordance between the US states' business cycles the national economy in Table 1.6, for the period 1969-1986, and in Table 1.7, for the period 1987-2008.

(Table 1.6 and Table 1.7 About Here)

Before 1987 (Table 1.6), the US state that shows the highest level of synchronization with the national economy is Ohio (during 99% of the time span they share the same phase of the cycle), followed by South Carolina (94%) and Alabama (94%). The least synchronized states are Kansas (64%), Oklahoma (56%) and North Dakota (57%). On average, the concordance of the 48 states with the national economy is 82%. This value is consistent with Owyang *et al.* (2005)'s findings, who report, between 1979 and 2002, an average concordance around 80%.

After 1987 (Table 1.7), we observe a lower degree of synchronization as the average concordance index decreases to 0.75. The most synchronized states are North Carolina, Virginia and South Carolina with 92%, 90% and 89% concordance rates respectively, while the least synchronized states are Montana, South Dakota and North Dakota whose concordance indexes are 52%, 49% and 47% respectively. This decrease in the level of synchronization is consistent with the findings and theoretical explanations put forward by Krugman (1991), according to whom economic and financial integration among states favors a process of concentration of industries and sectoral specialization, thus leading to asymmetric shocks and time-diverging business cycles.

A decreasing level of synchronization in the US has also been found by Partridge and Rickman (2005) while analyzing regional cycle asymmetries between 1971 and 1998. Their conclusion is that synchronization declines after the late 1980s. Quite interestingly, they argue that while the US is commonly considered as a benchmark for the feasibility of the optimal common currency area (OCCA), the observed time-diverging pattern of states' cycles does not support this idea. A similar result is also reported by Artis *et al*. (2009) who found no evidence of convergence across states' business cycles in the US.

(Figure 1.4 and Figure 1.5 About Here)

Figures 1.4 and 1.5 illustrate the diffusion index of recessions and expansions. At a glance, we observe that recessions are more homogeneously diffused across states than expansions. On average, 75% of the states (38 states) are in expansion when the national economy is expanding, while, during national recessions, 80% of the states (40 states) are also in recession. Moreover, the diffusion index shows that after the late 1980s, both expansions and recessions are weakly diffused in comparison to the 1970s and early 1980s. Weaker diffusion of economic phases implies declining synchronization and increasing timing differences across states over time, a result which is clearly in line with the findings from the concordance index analysis.

1.3.3 Amplitude differences across state cycles

An important feature of the state cycles that might play a critical role in shaping the evolution of income disparities across states is represented by their different amplitudes. The evaluation of the extent to which there are differences in amplitude is therefore the object of the present sub-section. Following Harding and Pagan (2002), we measure the amplitude of a phase calculating the cumulative growth rate of a state, excluding trend growth, during that specific phase. Tables 1.8 and 1.9 summarize, for each state, the average amplitude of recessions and expansions.

(Table 1.8 and Table 1.9 About Here)

Before 1987 (Table 1.8), we notice a wide variation of amplitudes across states. The state with the most volatile business cycle is North Dakota characterized by an amplitude equal to 0.14 for expansions and -0.12 for recessions. The mean amplitude across all states is 0.04 during expansions and -0.037 during recessions. This means that, on average, a state grows by 3.7-4% during an expansion and declines by a similar percentage during a recession, net of the effect of the trend growth.

In order to provide a measure of dispersion in amplitudes across states, we report the coefficient of variation, separately for expansions and recessions, in the last row of Tables 1.8 and 1.9. The values of 0.44 for expansion periods and -0.45 for recessions (over the 1969-1986 period) indicate the existence of wide amplitude differences across states, a result in line with Carlino and Sill (2001) who found considerable differences in the amplitudes of US regions. However, after 1987 (Table 1.9), the picture changes as the coefficient of variation now becomes 0.31 for expansions and -0.29 for recessions; i.e., compared to the previous period, amplitude differences across states have declined considerably both during expansions and recessions.

Overall, a very interesting feature appears to emerge from the analysis of timing and amplitude characteristics of the state cycles: after 1987, the states become less similar with respect to the timing of their cycles but more similar with respect to their amplitudes. This feature has some important implications about the short-run mechanisms of income disparities. Before 1987, the large variation in cycle amplitudes appears to be an important determinant of disparities in the short-run, but the role played by this factor tends to decline as the variation in amplitudes declines. Indeed, from 1987 onwards, it seems that the main driver behind the short-run dynamics of cross-sectional income disparities is now represented by the differences in the timing of the cycles.

In the next section, we will concentrate on this specific issue and try to disentangle more formally the role played by amplitude and timing differences across states on the short-run evolution of the cross-sectional disparities.

1.4 Short-run dynamics of income disparities: Does timing or amplitude matter?

In order to analyze the evolution of income disparities in the short-run, the object of the analysis carried out in this section is de-trended income as de-trending obviously enables us to focus exclusively on the type of dynamics we aim to study, having got rid of those dynamics which are instead related to the long-run.

As anticipated, we consider two possible short-run factors which might drive the evolution of income disparities across states: differences in amplitudes and differences in timing of states' business cycles. In the literature, a number of studies have analyzed the tendency of amplitude and timing of cycles to converge (or diverge). In particular, differences in cycle amplitudes across US regions have been documented by Carlino and Sill (2001) and Owyang *et al*. (2005) who also suggest a number of economic explanations for the observed cross-sectional variation. According to these authors, the cyclical response of a region depends primarily on its industrial structure and, in particular, on the share of employment in the manufacturing sector. In addition, regional differences in the responsiveness to changes in monetary policy or in oil price as well as differences in the demographical structure have also been indicated as possible influencing factors. As for timing differences, as already seen in Section 1.3, much attention has been devoted in the literature to the analysis of synchronization among state cycles. However, to our knowledge, no study has ever investigated the role of amplitude and timing differences as short-run drivers of cross-sectional income disparities.

From a mechanical point of view, the two drivers might operate as follows. Let us consider de-trended income over time for two states and assume that, at the initial time, de-trended income is the same in the two states. Now, as shown in Figure 1.6, suppose the cycles of the two states are perfectly synchronized with each other while they differ in terms of amplitude. In such an extremely simplified instance, therefore, any (de-trended) income difference between the two states must be exclusively due to differences in the size of their cyclical swings. Specifically, disparities increase until t_1, then decrease until t_2, increase once more until t_3 and finally decrease until t_4. Alternatively, as in Figure 1.7, suppose the cycles of the two states differ only in terms of timing while the amplitude of the swings is identical. As before, (de-trended) income disparities move in cyclical fashion, alternating periods of divergence to periods of convergence.

(Figure 1.6 and Figure 1.7 About Here)

In reality, not only the two figures represent extreme simplifications of the evolution of the disparities due to each of the factors, but the two factors obviously co-exist, making the short-run dynamics of income disparities quite a complex phenomenon. In order to try to disentangle these dynamics and assess the relative importance of timing and amplitude differences, we consider a Vector Autoregression (VAR) system and, using Cholesky variance decomposition, we evaluate the amount of shocks to disparities explained by timing differences across state cycles.

Operatively, to calculate disparities we de-trend the personal income series (in logs) of the 48 US states and calculate the cross sectional variance over time:

$$DIS_t = \frac{\sum_{i=1}^{n}\left(CYC_{i,t} - \overline{CYC}_t\right)^2}{n-1}$$

where $CYC_{i,t}$ is the HP de-trended income of state i at time t. In Figure 1.8, we present the evolution of DIS_t in the analyzed period. We clearly observe that the pattern of disparities changes after late 1980s: while before this period disparities fluctuate greatly, afterwards the evolution becomes smoother

(Figure 1.8 About Here)

In order to neutralize the differences in cycle amplitude and thus isolate the effect of timing differences, we follow Carlino and Sill (2001) as well as the OECD's procedure for amplitude standardization of the cycles: in each of the two sub-periods, we divide each state’s de-trended income series by its standard deviation thereby homogenize the amplitudes of the cycles:

$$NCYC_{i,t} = \frac{CYC_{i,t}}{\sigma_i}$$

where σ_i is the standard deviation of the de-trended income series of state i. Having standardized the cycles with respect to their amplitudes, we then calculate the cross-sectional variance, at any point in time, using *NCYC*. The resulting variable, $NDIS_t$, therefore represents the amount of disparities mostly due to timing differences across states, having removed away amplitude and trend growth differences:

$$NDIS_t = \frac{\sum_{i=1}^{n}\left(NCYC_{i,t} - NC\overline{Y}C_t\right)^2}{n-1}$$

Figures 1.9 and 1.10 report the evolution of cross-sectional disparities in de-trended and amplitude adjusted incomes in the two sub-periods.

(Figures 1.9 and 1.10 About Here)

Hence, the bivariate VAR system we consider is the following:

$$DIS_t = c + \vartheta_1 DIS_{t-1} + \theta_1 NDIS_{t-1} + \ldots + \vartheta_p DIS_{t-p} + \theta_p NDIS_{t-p} + \varsigma_t$$

$$NDIS_t = d + \gamma_1 DIS_{t-1} + \phi_1 NDIS_{t-1} + \ldots + \gamma_p DIS_{t-p} + \phi_p NDIS_{t-p} + \eta_t$$

which we estimate for each of the two sub-periods, using a lag length of 1 for both sub-periods determined using the Akaike Information Criterion.

Finally, we move to the last step and apply Cholesky variance decomposition, i.e. a tool that specifically allows to determine the proportion of the variance of a variable caused by shocks to a second variable. Carlino and Sill (2001), for example, use Cholesky variance decomposition to estimate, for each BEA region, the proportion of variation in per capita income attributed to cyclical and trend shocks. Our target is to find out the proportion in cross-sectional variance (*DIS*) which could be attributed to the component of disparities ascribed exclusively to timing (*NDIS*). The decomposition is implemented for a 10-period time horizon; this means that we evaluate not only the simultaneous impact of timing differences on disparities, but also the impact of up to 10-quarter lagged shocks to timing differences on the evolution of disparities.

Decomposition results are presented in Tables 1.10 and 1.11 and in Figures 1.11 and 1.12.[6] It is evident that, before 1987, only about 32-35% of the disparities can be attributed to timing differences across states; in contrast, about 88% of the disparities is due to timing differences across states after this date. Therefore, we can argue that timing differences across states' business cycles become an increasingly important factor in the evolution of regional disparities in the US after 1987. This result is

[6] In Cholesky variance decomposition one needs to assume which variable propagates the other. Here we assume that timing differences propagates the interactions among two variables.

consistent with the main message conveyed in section 1.3, i.e. amplitude differences across states tend to fade out while timing differences get more important since late 1980s.

(Table 1.10 and Table 1.11 About Here)

(Figure 1.11 and Figure 1.12 About Here)

1.5 Conclusions

In this paper, we studied explicitly the short-run nature of income disparities across 48 conterminous States between 1969 and 2008. First, we found that disparities follow a non stationary process, with an upward trend which implies that income inequalities across states have recently become a more relevant issue. Second, by estimating the relationship between cross-sectional income disparities and a measure of the business cycle we characterized the short-run behavior of the disparities across states. In particular, we found that disparities move counter-cyclically before 1987 but tend to move pro-cyclically afterwards, a change in the relationship that has been confirmed by a Chow structural break test. Third, we demonstrated that there exist sizable differences in the timing and amplitudes of the cycles of the states. Furthermore, we noted that differences in timing were particularly evident after 1987, parallel to a decline in amplitude differences. Finally, through bivariate VARs and Cholesky variance decomposition, we confirmed that, as a mechanism, differences in timing of the cycles across states tend to be the major driver of the disparities after 1987 while the impact of amplitude differences tends to fade away.

To sum up, income disparities do not move randomly in the short-run but tend to have a distinct pattern. Inequalities follow a cyclical pattern in the short-run, moving either anti-cyclically or pro-cyclically depending on the analyzed period. In addition, the differences in timing across states cycles tend to be the main short-run mechanism behind the evolution of the disparities in recent decades.

These findings on short-run regional disparities have important implications both for analysts and policy makers. When income disparities follow a distinct cyclical pattern in the short-run, the choice of the period of analysis becomes of great importance. If the aim of the researchers is to recover the long-run dynamics of income disparities, the analyzed time period must include exactly one (or more) entire business cycles. Failing to do so, runs the risk of introducing a bias towards convergence or divergence depending on the pro- or counter-cyclical nature of disparities and on which phases are over-represented. From the perspective of the policy maker it is important to discriminate between the short-run component of the disparities, possibly bound to vanish, and the long-run one. Clearly, the type of intervention which might be called upon by an increase in disparities due to the short-run component is likely to be quite different from those policies aimed at tackling a long-run, structural increase in the cross-sectional disparities.

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Tables

Table 1.1 NBER Cycles and Turning Points implied by different Filters

	NBER	HP	CF
peak	1969-4	1969-3	1969-3
trough	1970-4	1970-4	1971-1
peak	1973-4	1973-4	1973-3
trough	1975-1	1975-2	1975-3
peak	1980-1	1979-1	1979-1
trough	1980-3		
peak	1981-3		
trough	1982-4	1982-4	1982-4
peak		1984-3	1984-3
trough		1986-4	1987-4
peak	1990-3	1989-1	1990-2
trough	1991-1	1991-4	1991-3
peak		1994-4	1994-3
trough		1995-4	1997-2
peak	2001-1	2000-1	2000-3
trough	2001-4	2003-1	2003-2
peak	2007-4	2007-2	2007-3

Notes: HP denotes Hodrick-Prescott filter
CF denotes Christiano-Fitzgerald band-pass filter

Table 1.2 ADF Test Results

Variables	McKinnon ADF Statistics	Optimal lag length	Process
CV	0.75	1	I(1)
CVHP	-4.21***	1	I(0)
CVHP (1969-1986)	-3.56***	1	I(0)
CVHP (1987-2008)	-2.82***	1	I(0)
CYC	-5.10***	4	I(0)
CYC (1969-1986)	-4.16***	3	I(0)
CYC (1987-2008)	-3.22***	2	I(0)

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%
Optimal lag length is chosen using Akaike Information Criterion

Table 1.3 Regression Results

Coefficients	1969-2008	1969-1986	1987-2008	Chow test
α	-1.36E-05 (0.000816)	-0.000586 (0.00112)	0.000361 (0.000902)	
β	9.11E-07 (2.33E-06)	-	-	
β1	-	-5.94E-06** (2.91E-06)	-	
β2	-	-	6.15E-06*** (2.13E-06)	
autoregressive error	0.73*** (0.072594)	0.69*** (0.088376)	0.71*** (0.078555)	
R-squared	0.55	0.44	0.67	
White	7.36**	3.01	9.15***	
Breusch-Godfrey	0.12	0.01	0.38	
F-stat				4.17***
Log-likelihood				12.48***

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%
Autocorrelation corrected parameter estimates are performed using Marquardt Nonlinear Least Squares. White is the White Heteroskedasticity test; Breusch-Godfrey is the Breusch-Godfrey LM test for serial correlation In case of heteroskedasticity, White heteroskedasticity robust standard errors are used. Standard errors of the coefficients are reported in parenthesis.

Table 1.4 Alternative Regression Results

Coefficients	1969-2008	1969-1986	1987-2008	Chow test
α	4.81E-05 (0.000275)	0.000289 (0.000419)	-0.000128 (0.000301)	
β	-0.004567 (0.079027)	-	-	
β1	-	-0.19** (0.089346)	-	
β2	-	-	0.18*** (0.072074)	
R-squared	0.000039	0.06	0.07	
White	14.00***	2.17	4.05	
Breusch-Godfrey	0.08	0.004	0.84	
F-stat				5.87***
Log-likelihood				11.61***

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%
White is the White Heteroskedasticity test; Breusch-Godfrey is the Breusch-Godfrey LM test for serial correlation In case of heteroskedasticity, White heteroskedasticity robust standard errors are used. Standard errors of the coefficients are reported in parenthesis.

Table 1.5 Turning points in state-level cycles

Quarters	AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
1969-1			x		x		x			x					x							x							x											x					x			x
1969-2			x		x		x			x					x							x							x											x					x			x
1969-3			x		x		x			x					x							x							x											x					x			x
1969-4	x		x	x	x		x		x	x	x	x	x	x	x	x		x	x	x		x	x	x	x		x		x		x	x	x	x	x	x		x	x	x	x			x	x		x	x
1970-1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x		x	x
1970-2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x
1970-3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x
1970-4	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x
1971-1		x	x	x		x		x		x	x		x	x	x	x	x	x	x		x	x	x	x		x	x	x	x		x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1971-2			x	x		x				x			x	x	x	x	x		x		x	x	x	x		x		x				x		x		x	x		x		x				x	x		x
1971-3						x				x			x	x	x	x	x				x		x	x		x						x		x		x			x		x				x	x		
1971-4						x								x	x	x	x				x		x			x						x		x		x			x		x					x		
1972-1																x										x						x							x									
1972-2																																x																
1972-3																																																
1972-4																																																
1973-1																													x													x				x		
1973-2						x												x										x	x	x												x				x		
1973-3				x		x												x	x	x								x	x	x							x					x	x			x		
1973-4				x		x												x	x	x								x	x	x							x					x	x			x		
1974-1	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1974-2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1974-3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1974-4	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1975-1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1975-2	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x
1975-3					x	x		x			x		x	x		x			x		x			x		x		x		x		x	x	x			x		x						x	x		x
1975-4					x	x		x			x		x	x							x			x	x					x		x		x					x						x			x
1976-1					x								x	x							x			x	x							x		x					x									x
1976-2					x								x	x							x			x	x							x		x					x									x
1976-3					x									x										x	x							x		x					x									
1976-4					x									x										x								x		x														
1977-1					x									x										x								x		x														
1977-2																																x		x														
1977-3																																																
1977-4																																																
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1978-2																																																
1978-3													x																																			
1978-4	x		x				x	x					x			x													x												x							
1979-1	x		x		x		x	x		x			x			x					x				x	x			x			x						x	x		x	x		x		x		x
1979-2	x	x	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x	x	x		x		x
1979-3	x	x	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x	x	x		x	x	x
1979-4	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x	x	x	x	x	x	x
1980-1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x
1980-2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x
1980-3	x	x		x	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x		x		x	x	x	x	x	x	x
1980-4	x	x		x		x	x	x	x	x	x	x			x		x	x	x	x	x		x			x	x	x	x	x	x		x		x	x	x	x		x		x	x	x	x	x	x	x
1981-1	x	x		x		x	x	x	x	x	x	x			x		x	x	x	x	x		x			x	x	x	x	x	x		x		x	x	x	x		x		x	x	x	x	x	x	x
1981-2	x	x		x		x	x	x	x	x	x	x			x		x	x	x	x	x		x			x	x	x		x	x		x		x	x	x	x		x		x	x	x	x	x	x	x
1981-3	x	x		x		x	x	x	x	x	x	x			x		x	x	x	x	x		x			x	x	x		x	x		x		x	x	x	x		x		x	x	x	x	x	x	x
1981-4	x	x	x	x		x	x	x	x	x	x	x	x		x		x	x	x	x	x	x	x		x	x	x	x		x	x		x		x	x	x	x	x	x		x	x	x	x	x	x	x
1982-1	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x		x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x
1982-2	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x		x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x
1982-3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x
1982-4	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x			x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x
1983-1			x			x					x		x	x	x	x		x			x	x			x				x	x		x		x		x			x		x	x				x	x	x
1983-2						x					x		x		x	x																x		x		x										x		x
1983-3													x																			x		x														
1983-4																																x																
1984-1																																																
1984-2																																																
1984-3								x					x									x																										
1984-4				x	x	x		x	x		x		x	x	x	x			x		x	x	x	x				x		x	x	x	x				x	x	x	x		x		x	x	x	x	
1985-1				x	x	x		x	x		x		x	x	x	x			x		x	x	x	x				x		x	x	x	x				x	x	x	x		x		x	x	x	x	
1985-2	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	
1985-3	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	
1985-4	x		x	x	x	x	x	x		x	x	x	x	x	x	x	x	x			x	x	x	x	x	x		x	x	x		x	x		x	x		x	x		x	x	x	x	x	x	x	
1986-1	x		x	x	x	x	x	x		x	x				x	x		x		x		x	x		x			x	x			x	x			x		x			x	x		x		x		
1986-2	x		x		x		x	x		x					x	x				x		x	x						x				x	x				x			x	x				x		x
1986-3	x		x		x			x		x					x	x				x		x							x				x	x				x			x	x				x		x
1986-4	x		x		x			x		x					x	x				x		x							x				x	x					x		x	x				x		x

Note: Grey shaded areas represent national recessions and "x" sign represents state recessions

Table 1.5 (Continued)

Quarters	AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
1987-1	x		x																	x													x	x					x			x			x	x		x
1987-2	x		x																	x	x		x	x									x	x					x			x			x	x		x
1987-3			x										x	x						x	x		x	x								x		x					x			x			x	x		x
1987-4													x	x							x		x	x								x		x					x			x			x			x
1988-1													x	x							x		x	x								x							x			x			x			x
1988-2													x	x							x			x								x							x									
1988-3													x	x							x			x								x							x									
1988-4													x	x										x	x	x						x							x									
1989-1													x	x					x					x	x	x																						
1989-2	x	x	x		x	x		x	x	x	x	x	x	x	x		x	x	x	x		x	x	x	x	x	x	x	x		x		x			x		x		x			x	x			x	
1989-3	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x		x	x	x	x	x	x	x	x		x		x		x	x	x	x		x			x	x			x	
1989-4	x	x	x		x	x	x	x	x	x	x	x	x	x	x		x	x	x	x		x	x	x	x	x	x	x	x		x		x		x	x	x	x		x			x	x			x	
1990-1	x	x	x		x	x	x	x	x	x	x	x	x		x		x	x	x	x		x	x	x	x	x	x	x	x		x		x		x	x	x	x		x			x	x			x	
1990-2	x	x	x		x	x	x	x	x	x	x	x	x		x		x	x	x	x		x	x	x	x	x	x	x	x		x		x		x	x	x	x		x		x	x	x			x	
1990-3	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	x
1990-4	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1991-1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1991-2	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x		x	x		x	x	x	x	x			x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x
1991-3	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x			x			x	x	x	x	x			x		x	x	x	x	x		x	x	x	x	x	x	x	x	x
1991-4	x	x		x	x	x	x	x			x		x			x		x						x	x	x	x	x	x			x		x	x						x	x		x	x	x		x
1992-1	x	x		x			x	x								x		x						x					x						x							x						x
1992-2	x	x		x			x									x		x						x					x						x							x						x
1992-3	x	x		x			x									x		x						x					x						x							x						x
1992-4	x	x		x			x									x		x						x					x			x			x				x			x						x
1993-1	x	x		x		x	x									x		x						x		x		x	x			x		x	x				x		x	x			x	x		x
1993-2						x	x																	x		x		x				x		x					x		x				x	x		x
1993-3						x	x																	x		x		x				x		x					x		x				x	x		x
1993-4						x	x																	x		x		x				x		x					x		x				x			x
1994-1						x	x			x														x		x		x				x		x					x		x				x			x
1994-2						x				x														x		x						x		x					x		x				x			
1994-3			x			x			x	x			x	x	x				x					x		x	x					x		x					x		x		x	x	x			
1994-4			x		x	x			x	x	x	x	x	x	x			x	x			x	x	x		x	x					x		x					x		x		x	x	x	x		
1995-1		x	x		x	x			x	x	x	x	x	x	x		x	x	x	x		x	x	x		x	x		x		x	x	x	x	x				x	x	x	x	x	x	x	x	x	x
1995-2	x	x	x	x	x	x		x	x	x	x	x	x	x	x		x	x	x	x		x	x	x		x			x		x	x	x	x	x			x	x	x	x	x	x	x	x	x	x	x
1995-3	x	x	x	x	x	x		x		x	x	x		x	x		x	x	x	x		x	x	x		x			x		x	x	x	x	x			x		x	x	x	x	x	x	x	x	x
1995-4	x	x	x	x	x	x		x		x	x	x		x		x	x	x	x	x		x	x	x		x			x		x	x	x	x	x		x	x		x	x	x	x	x	x	x	x	x
1996-1	x	x	x	x	x	x		x		x	x	x				x	x	x	x	x		x		x					x		x	x	x		x		x			x	x	x	x	x		x	x	
1996-2	x	x	x	x	x			x		x	x	x				x	x	x		x		x		x					x			x			x		x			x	x	x	x			x	x	
1996-3	x	x	x	x	x		x	x	x	x	x	x	x			x	x	x		x		x		x	x		x		x			x			x		x		x	x	x	x	x			x	x	
1996-4	x	x	x	x	x		x	x	x	x	x	x	x			x	x	x		x		x		x	x	x	x		x			x			x		x	x	x	x	x	x	x			x	x	
1997-1	x		x	x	x		x	x	x	x	x	x	x				x	x	x	x		x		x	x	x	x		x			x			x		x	x	x	x		x	x				x	
1997-2	x		x	x	x			x	x	x		x	x				x	x	x	x		x		x	x	x	x		x			x			x		x	x	x	x		x	x				x	
1997-3			x						x	x		x					x		x	x		x			x	x	x		x			x					x	x	x	x		x	x					
1997-4										x										x					x	x	x		x			x							x			x						
1998-1																													x																			
1998-2																													x																			
1998-3							x									x					x								x					x	x													
1998-4		x					x	x			x		x	x	x	x					x		x	x				x	x					x	x							x				x	x	
1999-1		x					x	x			x	x	x	x	x	x					x	x	x	x				x	x					x	x	x						x				x	x	
1999-2	x	x	x				x	x			x	x	x	x	x	x					x	x	x	x				x	x					x	x	x						x				x	x	
1999-3	x	x	x				x	x			x	x	x	x	x	x					x	x	x	x					x					x	x	x										x	x	
1999-4	x	x	x					x				x				x	x					x													x	x											x	
2000-1	x	x						x				x				x	x					x													x	x											x	
2000-2	x	x						x	x			x				x	x	x		x		x					x						x		x	x					x				x		x	x
2000-3	x	x						x	x	x		x	x		x	x	x	x		x		x	x			x	x				x		x		x	x		x	x		x		x		x		x	x
2000-4	x	x		x				x	x	x	x	x	x	x	x	x	x	x		x	x	x	x			x	x				x	x	x		x	x		x	x	x	x		x		x		x	x
2001-1	x	x		x				x	x	x	x	x	x	x	x	x	x	x		x	x	x	x			x	x	x			x	x	x		x	x		x	x	x	x		x		x		x	x
2001-2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2001-3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2001-4	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2002-1	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x		x		x	x	x	x	x	x	x	x	x		x		x		x	x	x	x	x	x	x	x	x		x
2002-2	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x			x		x	x	x	x	x	x	x	x	x		x		x		x	x	x	x	x	x	x	x	x		x
2002-3	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x			x		x	x	x	x	x	x	x	x	x		x		x		x	x	x	x	x	x	x	x	x		x
2002-4	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x			x		x	x	x	x	x	x	x	x	x		x		x		x	x	x	x	x	x	x	x	x		x
2003-1	x	x		x	x	x	x	x		x	x				x	x	x	x	x								x	x	x	x	x			x		x		x			x	x	x		x	x		
2003-2	x	x			x		x	x		x					x	x	x		x								x		x		x			x		x		x				x	x		x	x		
2003-3	x	x			x		x								x	x											x		x					x		x		x				x	x		x	x		
2003-4					x											x																x												x			
2004-1												x				x				x												x															
2004-2												x				x				x												x															x
2004-3												x				x				x				x								x			x				x				x					x
2004-4												x		x		x				x				x								x			x		x		x				x					x
2005-1											x	x	x	x		x	x			x	x			x	x		x					x			x		x		x				x			x	x	
2005-2											x		x	x		x	x			x	x				x		x					x			x		x		x				x			x	x	
2005-3											x		x	x		x	x			x	x				x	x	x					x					x		x				x			x	x	
2005-4											x		x	x		x				x	x				x	x	x					x					x		x				x				x	
2006-1							x						x												x	x						x							x									
2006-2		x					x																			x						x		x														
2006-3		x					x	x		x																x						x		x														
2006-4		x					x	x		x																						x		x														x
2007-1		x					x	x		x																								x	x						x							x
2007-2		x				x	x	x		x							x	x	x									x		x	x		x	x	x	x	x					x		x	x			x	x
2007-3		x		x		x	x	x	x	x				x	x	x	x	x	x		x						x	x		x	x		x	x	x	x	x					x	x	x	x		x	x	x
2007-4	x	x		x		x	x	x	x	x				x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x		x	x	x	x	x	x			x	x	x	x	x	x	x	x
2008-1	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x	x	x	x	x
2008-2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2008-3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2008-4	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Table 1.6 Concordance of states with US cycle, 1969-1986

State	Concordance	State	Concordance
Alabama	0.94	Nebraska	0.76
Arizona	0.85	Nevada	0.79
Arkansas	0.79	New Hampshire	0.86
California	0.9	New Jersey	0.86
Colorado	0.76	New Mexico	0.78
Connecticut	0.79	New York	0.85
Delaware	0.88	North Carolina	0.9
Florida	0.9	North Dakota	0.57
Georgia	0.93	Ohio	0.99
Idaho	0.85	Oklahoma	0.56
Illinois	0.86	Oregon	0.86
Indiana	0.92	Pennsylvania	0.85
Iowa	0.68	Rhode Island	0.85
Kansas	0.64	South Carolina	0.94
Kentucky	0.88	South Dakota	0.72
Louisiana	0.78	Tennessee	0.88
Maine	0.78	Texas	0.78
Maryland	0.86	Utah	0.88
Massachusetts	0.86	Vermont	0.86
Michigan	0.9	Virginia	0.88
Minnesota	0.79	Washington	0.81
Mississippi	0.83	West Virginia	0.76
Missouri	0.9	Wisconsin	0.9
Montana	0.68	Wyoming	0.75
Mean	0.82		

Table 1.7 Concordance of states with US cycle, 1987-2008

State	Concordance	State	Concordance
Alabama	0.76	Nebraska	0.73
Arizona	0.75	Nevada	0.73
Arkansas	0.74	New Hampshire	0.8
California	0.78	New Jersey	0.82
Colorado	0.82	New Mexico	0.69
Connecticut	0.84	New York	0.81
Delaware	0.61	North Carolina	0.92
Florida	0.78	North Dakota	0.47
Georgia	0.88	Ohio	0.88
Idaho	0.78	Oklahoma	0.61
Illinois	0.8	Oregon	0.66
Indiana	0.69	Pennsylvania	0.85
Iowa	0.63	Rhode Island	0.69
Kansas	0.7	South Carolina	0.89
Kentucky	0.85	South Dakota	0.49
Louisiana	0.6	Tennessee	0.85
Maine	0.83	Texas	0.77
Maryland	0.85	Utah	0.65
Massachusetts	0.84	Vermont	0.77
Michigan	0.7	Virginia	0.9
Minnesota	0.61	Washington	0.75
Mississippi	0.82	West Virginia	0.67
Missouri	0.8	Wisconsin	0.74
Montana	0.52	Wyoming	0.7
Mean	0.75		

Table 1.8 Amplitude of cycle phases, 1969-1986

State	Recessions	Expansions	State	Recessions	Expansions
Alabama	-0.038	0.038	Nebraska	-0.037	0.042
Arizona	-0.043	0.046	Nevada	-0.034	0.041
Arkansas	-0.049	0.044	New Hampshire	-0.039	0.043
California	-0.026	0.031	New Jersey	-0.024	0.028
Colorado	-0.022	0.026	New Mexico	-0.023	0.025
Connecticut	-0.022	0.032	New York	-0.022	0.026
Delaware	-0.030	0.034	North Carolina	-0.034	0.043
Florida	-0.031	0.039	North Dakota	-0.118	0.139
Georgia	-0.031	0.040	Ohio	-0.042	0.042
Idaho	-0.040	0.043	Oklahoma	-0.036	0.037
Illinois	-0.028	0.033	Oregon	-0.031	0.037
Indiana	-0.043	0.050	Pennsylvania	-0.025	0.030
Iowa	-0.059	0.053	Rhode Island	-0.029	0.035
Kansas	-0.036	0.040	South Carolina	-0.032	0.040
Kentucky	-0.041	0.043	South Dakota	-0.077	0.077
Louisiana	-0.032	0.025	Tennessee	-0.037	0.041
Maine	-0.031	0.037	Texas	-0.032	0.027
Maryland	-0.020	0.025	Utah	-0.028	0.030
Massachusetts	-0.025	0.031	Vermont	-0.028	0.035
Michigan	-0.064	0.064	Virginia	-0.025	0.030
Minnesota	-0.038	0.047	Washington	-0.026	0.026
Mississippi	-0.035	0.035	West Virginia	-0.035	0.037
Missouri	-0.026	0.034	Wisconsin	-0.031	0.037
Montana	-0.047	0.054	Wyoming	-0.060	0.049
Mean	-0.03671	0.04043			
Std. Dev.	0.01665	0.01773			
Coeff. of Variation	-0.45	0.44			

Table 1.9 Amplitude of cycle phases, 1987-2008

State	Recessions	Expansions	State	Recessions	Expansions
Alabama	-0.017	0.014	Nebraska	-0.018	0.018
Arizona	-0.021	0.022	Nevada	-0.021	0.021
Arkansas	-0.014	0.015	New Hampshire	-0.022	0.020
California	-0.023	0.023	New Jersey	-0.024	0.023
Colorado	-0.024	0.022	New Mexico	-0.018	0.016
Connecticut	-0.030	0.028	New York	-0.036	0.035
Delaware	-0.012	0.015	North Carolina	-0.026	0.024
Florida	-0.020	0.020	North Dakota	-0.045	0.046
Georgia	-0.016	0.015	Ohio	-0.021	0.019
Idaho	-0.027	0.027	Oklahoma	-0.020	0.021
Illinois	-0.014	0.013	Oregon	-0.013	0.012
Indiana	-0.019	0.016	Pennsylvania	-0.020	0.016
Iowa	-0.018	0.018	Rhode Island	-0.019	0.015
Kansas	-0.014	0.014	South Carolina	-0.017	0.015
Kentucky	-0.017	0.016	South Dakota	-0.025	0.026
Louisiana	-0.019	0.025	Tennessee	-0.019	0.018
Maine	-0.021	0.016	Texas	-0.021	0.021
Maryland	-0.019	0.016	Utah	-0.021	0.017
Massachusetts	-0.021	0.019	Vermont	-0.019	0.019
Michigan	-0.024	0.020	Virginia	-0.019	0.017
Minnesota	-0.013	0.015	Washington	-0.023	0.019
Mississippi	-0.020	0.021	West Virginia	-0.013	0.013
Missouri	-0.014	0.013	Wisconsin	-0.017	0.015
Montana	-0.014	0.015	Wyoming	-0.020	0.024
Mean	-0.02017	0.01933			
Std. Dev.	0.005887	0.006065			
Coeff. of Variation	-0.29	0.31			

Table 1.10 Cholesky variance decomposition
Percentage of shocks to disparities due to timing differences, 1969-1986

Period	% of shocks	s.e.
1	35.76	7.38E-05
2	33.33	8.17E-05
3	32.42	8.35E-05
4	32.12	8.40E-05
5	32.02	8.42E-05
6	31.99	8.42E-05
7	31.98	8.42E-05
8	31.98	8.42E-05
9	31.98	8.42E-05
10	31.98	8.42E-05

Note: The s.e. column reports the forecast error of the *NDIS* variable for each forecast horizon

Table 1.11 Cholesky variance decomposition
Percentage of shocks to disparities due to timing differences, 1987-2008

Period	% of shocks	s.e.
1	86.42	1.77E-05
2	88.64	1.94E-05
3	88.89	2.00E-05
4	88.89	2.02E-05
5	88.89	2.02E-05
6	88.88	2.03E-05
7	88.88	2.03E-05
8	88.88	2.03E-05
9	88.88	2.03E-05
10	88.88	2.03E-05

Note: The s.e. column reports the forecast error of the *NDIS* variable for each forecast horizon

Table 1.12 Preis-Winsten Regression

Coefficients	1969-2008	1969-1986	1987-2008
α	-5.68E-05	-0.0004782	-0.0003572
	(0.0007934)	(0.010545)	(0.0008922)
β	9.19E-07	-	-
	(1.80E-06)		
β_1	-	-5.87E-06**	-
		(2.87E-06)	
β_2	-	-	6.18E-06***
			(2.03E-06)
autoregressive error	0.73	0.69	0.72

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%
Standard errors of the coefficients are reported in parentheses.

Figures

Figure 1.1 Evolution of income disparities across states

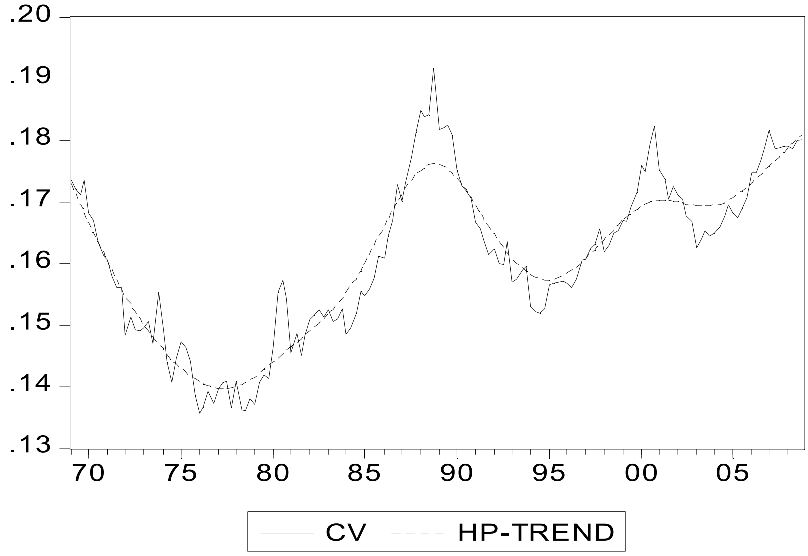


Figure 1.2 US Personal Income

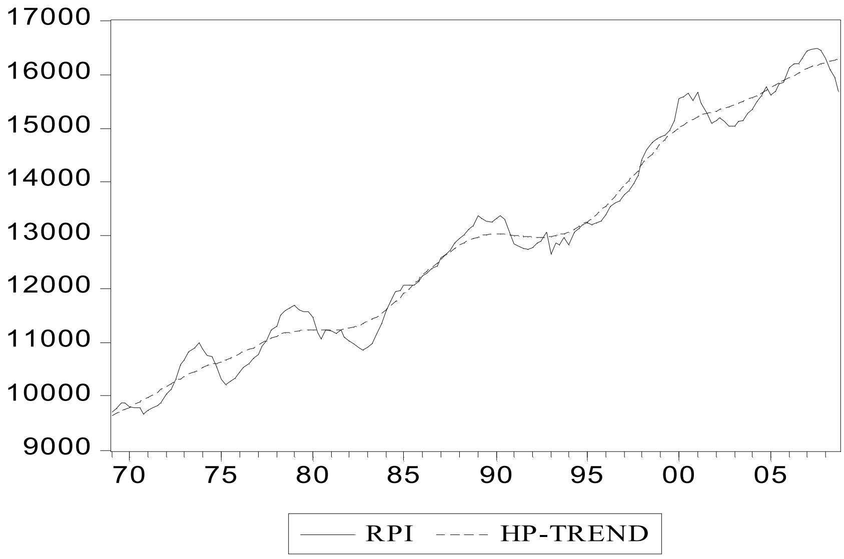


Figure 1.3 US deviation cycle

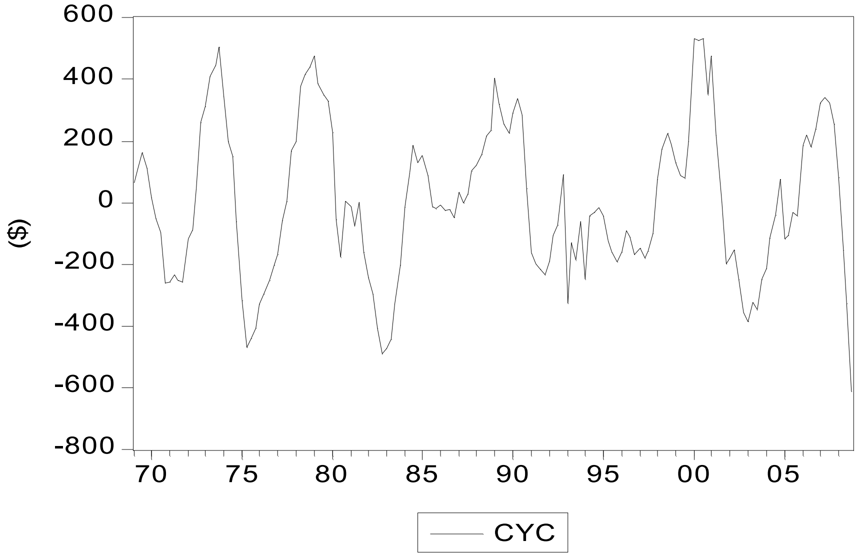
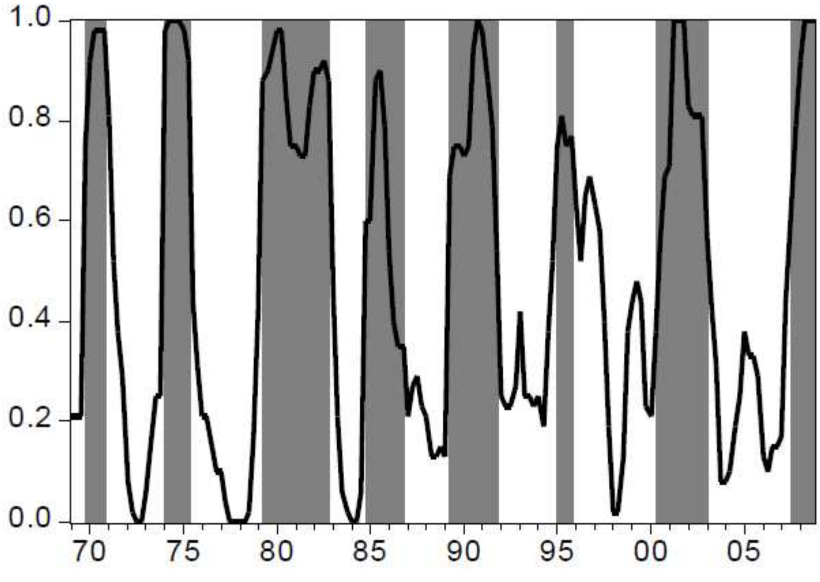
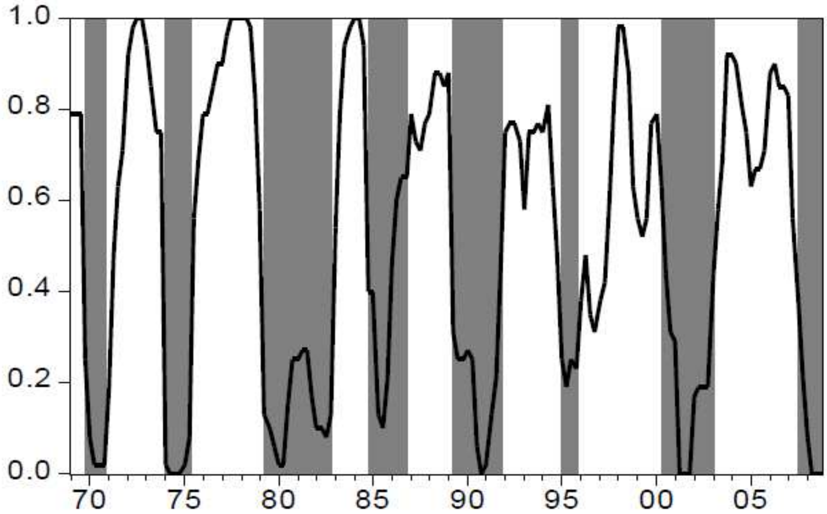


Figure 1.4 Diffusion of Recessions



Note: grey shaded areas represent the national recessions

Figure 1.5 Diffusion of Expansions



Note: grey shaded areas represent the national recessions

Figure 1.6 Amplitude differences

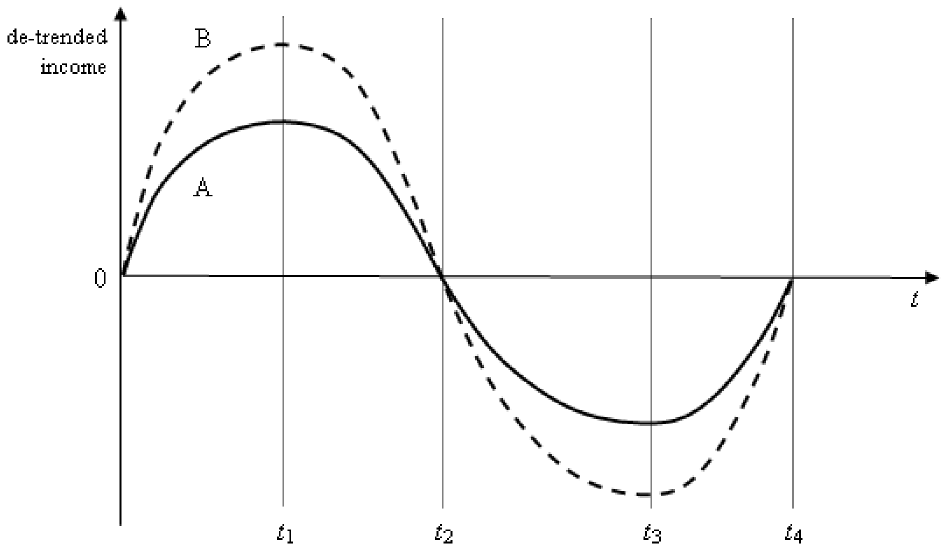


Figure 1.7 Timing differences

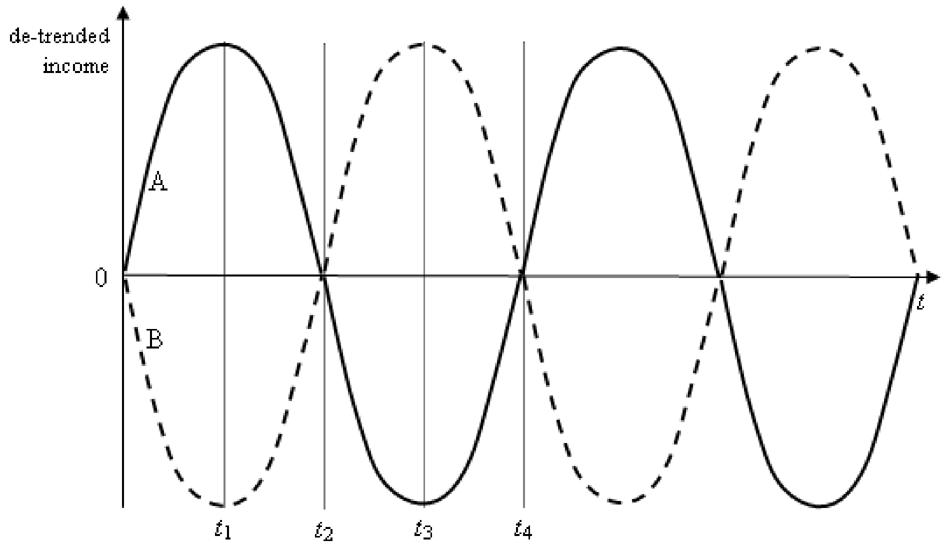


Figure 1.8 Evolution of cross sectional disparities in de-trended personal incomes

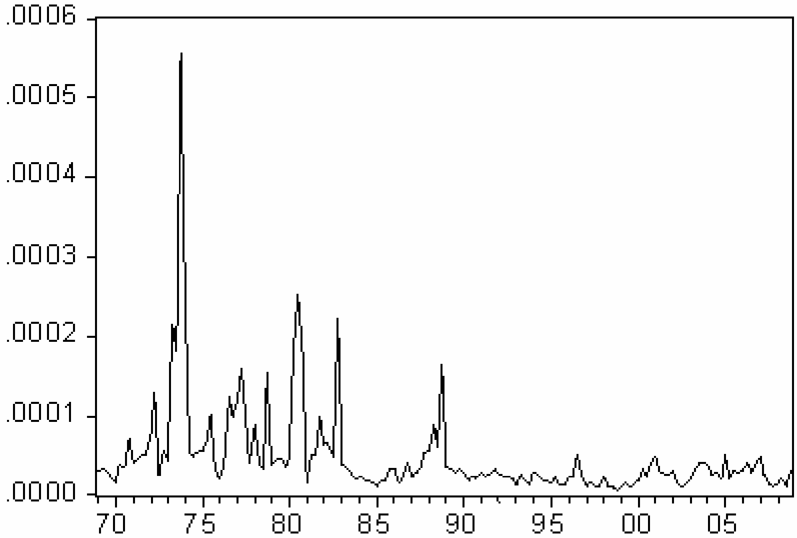


Figure 1.9 Evolution of cross sectional disparities in de-trended and amplitudes adjusted incomes, 1969-1986

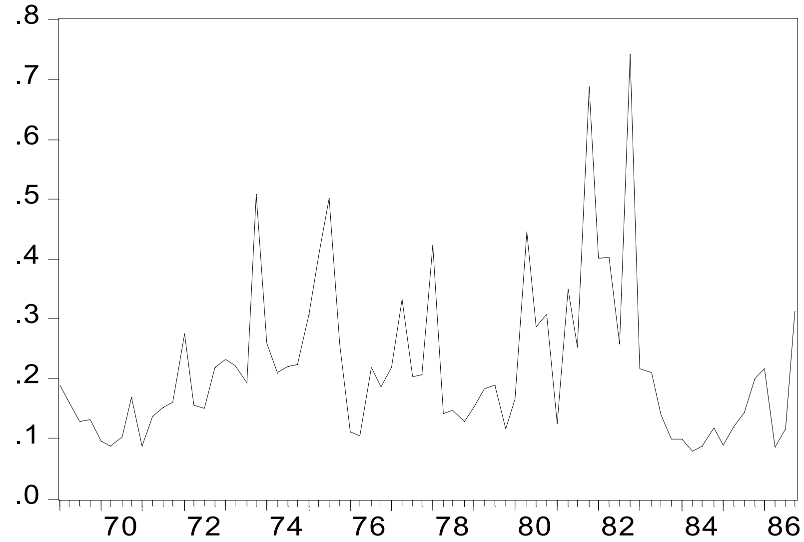


Figure 1.10 Evolution of cross-sectional disparities in de-trended and amplitudes adjusted incomes, 1987-2008

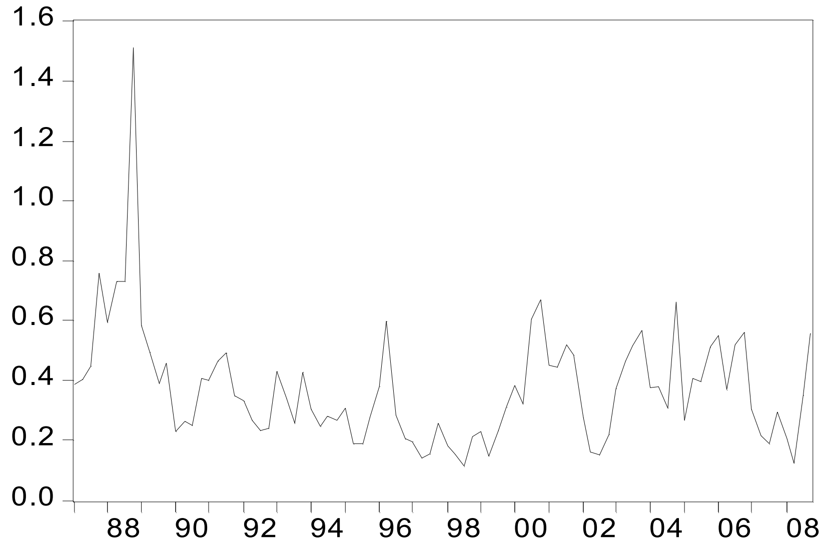


Figure 1.11 VAR Cholesky decomposition: contribute to disparities from timing differences, 1969-1986

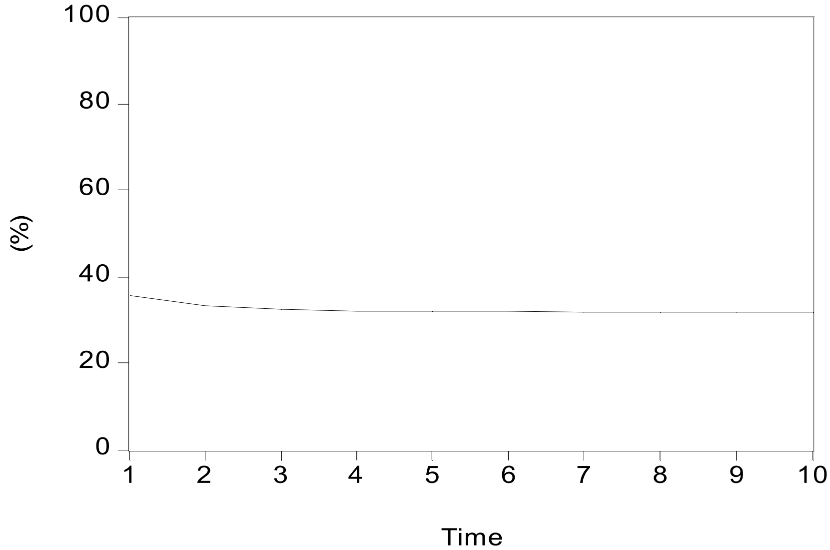
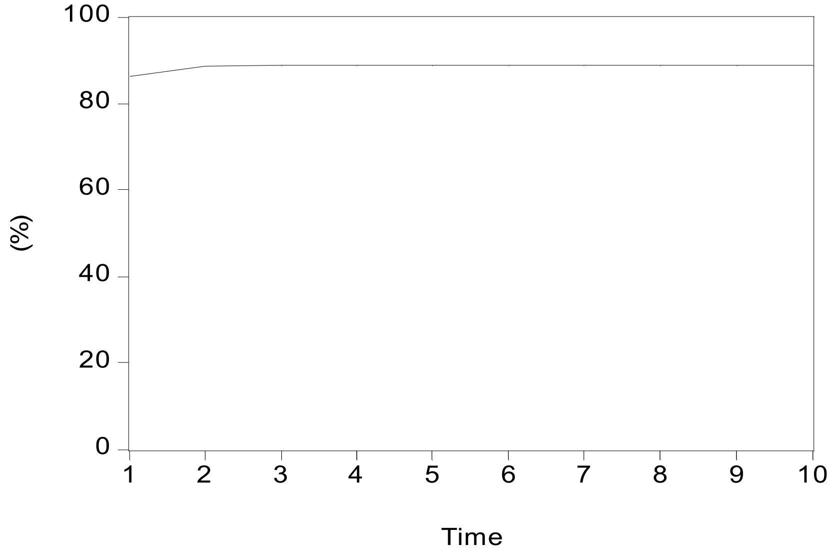


Figure 1.12 VAR Cholesky decomposition: contribute to disparities from timing differences, 1987-2008



APPENDIX 1.1 Bry-Boschan (1971) Quarterly Algorithm

I. On the HP de-trended series, a Spencer moving average is applied in order to obtain the Spencer Curve.[7]

II. HP de-trended series are corrected for outliers. Outliers are the observations which are at least 3.5 standard deviations away from the mean. We replace outliers by their equivalent value on the Spencer Curve. Applying a Spencer moving average on the outlier corrected series creates an outlier-corrected Spencer curve.

III. A 2x4 centered Moving Average (MA) is applied on the outlier-corrected data to obtain the "first cycle" curve. 2x4 centered moving average means that a 4-term centered moving average is applied on a 2-term centered moving average cycle.

IV. A first set of turning points is searched within the first cycle curve and then these turning points have been used to look for the corresponding turning points on the Spencer Curve. The local minima/maxima have been searched in every 5 quarters. Therefore, the window length is 5 quarters.

V. A minimum cycle length restriction is imposed so that any cycle from peak (trough) to peak (trough) has at least a duration of 5 quarters. It is checked whether the peaks and troughs orderly alternate, i.e. peak-trough-peak, and the alternation is imposed if necessary.

VI. The Months for Cyclical Dominance (MCD), “the minimum month-delay for which the average of absolute deviations of growth in Spencer cycle is larger than that in the irregular component” is computed. After that, a moving average of length MCD is applied on the previously outlier-corrected series. A new set of turning points is searched on the basis of the complementary turning points that were found on the Spencer curve. Again, a minimum cycle length restriction is imposed (5 quarters) and orderly alternation of the turning points is imposed.

VII. This last set of turning points is cleaned by discarding the points corresponding to the first and last two observations. A minimum phase length restriction of 2 quarters is imposed. Thus, the final set of turning points is obtained.

[7] The details of the algorithm are obtained from manual of BUSY 4.1 software.

APPENDIX 1.2 Variables and data sources

Variable	Definition
RPI	Per capita real personal income net of current transfers receipts. All income series are deflated using the 1982-1984 US city average national consumer price index.
CYC	Hodrick Prescott de-trended per capita real personal income net of transfers series. It denotes national cycle unless sub-script *i* exists.
CV	Coefficient of variation as a measure of cross sectional dispersion of income across states calculated using per capita real personal income net of transfers.
CVHP	Hodrick Prescott de-trended coefficient of variation.
NCYC	Hodrick Prescott de-trended and amplitude adjusted per capita real personal income net of transfers series.
DIS	Cross sectional variance of income calculated using de-trended personal income series of states.
NDIS	Cross sectional variance of income calculated using de-trended and amplitude standardized personal income series of states.

Data Sources: Personal income and current transfer receipts series are obtained from U.S. Bureau of Economic Analysis (BEA). U.S. city average consumer price index is obtained from U.S. Bureau of Labor Statistics (BLS).

Software: The analysis in this paper has been implemented using EVIEWS 4.0, R 2.12 and BUSY 4.1.

CHAPTER 2

Understanding the lead/lag structure among regional business cycles

Stefano Magrini, Margherita Gerolimetto and Hasan Engin Duran

2.1 Introduction

It is rather well-known that business cycles across the US states are not synchronized with the national cycle and hence with each other (among others, Beckworth, 2010; Crone, 2005; Owyang *et* al., 2005; Partridge and Rickman, 2005; Carlino and DeFina, 2004; Carlino and Sill, 2001). If this feature was due to a random mechanism, such that states on some occasions tend to anticipate and on some others tend to follow the national business cycle, the important aspect to be studied would merely be the degree of synchronization. However, if business cycles of some states persistently anticipate (follow) the national cycle, then systematic leading (lagging behind) behaviors emerge and the mechanism is no more random. If that were the case, examining the degree of synchronization would fall short from providing an adequate account of the observed feature and the analysis would also need to explain why some regions do tend to start the business cycle before others. The aim of this paper is to explore whether such a persistent pattern can be found among the US states and, in case, to understand the reasons behind it.

Differently from synchronization, there is no commonly adopted measure for the lead/lag phenomenon in the literature. Therefore, for the sake of clarity, we think it might be useful to spell out right from the introductory section the type of variable we are going to use in the analysis. Let us suppose there are m turning points indexed in z ($z = 1,\ldots, m$) which characterize the national business cycle over a certain period of analysis. For each state i, we define a measure of its lead or lag behind behavior with respect to the nation as the average along z of the time (in months) with which i anticipates or follows the turning points of the national business cycle ($t_{i,z}$):

$$LL_i = \frac{\sum_{z=1}^{m} t_{i,z}}{m}$$

where, in particular, $t_{i,z} > 0$ when i anticipates the national economy and $t_{i,z} < 0$ when i follows. When the attention is shifted to the relationship between any two states i and j then the corresponding measure is

$$LL_{ij} = LL_i - LL_j \tag{2.1}$$

Intuitively, given that the national cycle is obviously the same, a positive (negative) value of LL_{ij} implies that i leads (lags behind) j by the corresponding number of months. It is important to note that the information conveyed by the measure in (2.1) is actually twofold. On the one hand the absolute value of this measure tells us how much two states are far from being synchronized; on the other hand the sign of (2.1) tells us which of the two states leads and which instead lags behind. In fact, the first component of LL_{ij} conceptually coincides with the measure commonly employed in the empirical studies on the degree of synchronization among business cycles of different economic systems. In relation to this, a particularly well-known model has been proposed by Imbs (2004). This model allows to analyze the degree of synchronization by means of trade openness, financial integration and industrial specialization and their respective links. More specifically, in its cross-country application (Imbs, 2004; Xing and Abbott, 2007), and focusing only on its main variables, the model consists of a system of four simultaneous equations in which: bilateral business cycle correlation is explained by differences in industrial specialization, bilateral financial integration and trade flows; differences in specialization patterns depend on trade flows and financial integration; trade flows are explained by differences in specialization (and gravity-type variables); financial integration is simply proxied via measures of existing restrictions to financial flows. In a companion working paper (Imbs, 2003), the model is also employed within an intra-national framework using data on US states. In such a case, however, its structure is somewhat simplified: bilateral financial integration is calculated from an estimate of the state-specific index of risk-sharing proposed by Kalemli-Ozcan *et al.* (2003) and, given the lack of data on inter-state trade, trade flows are estimated via a gravity model. As a result, only two equations have to be estimated simultaneously.

One element that characterizes the model put forward by Imbs is the relationship between the dissimilarities in industry specialization and the lack of correlation between business cycles. Quite naturally, if two economies are differentiated in terms of the type of goods they produce, they will react differently to sector-specific shocks and their business cycles will become less correlated. A reduction in the correlation might also be observed in relation to an unanticipated monetary policy as different sectors will respond differently to this common shock. Evidence in support of these argumentations is indeed reported in a number of papers that analyze whether the US fits the criteria for being considered an optimal currency area by examining the way in which the states react to monetary policy shocks (Beckworth, 2010, Carlino and DeFina, 1998, 1999a, 1999b and 2004; Crone, 2006 and 2007; Kouparitsas, 2001; Owyang and Wall, 2004 and 2009).

The relationship between specialization and synchronization assumed in most of these studies is in fact a one-way relationship: i.e., from the degree of similarity in production patterns to the level of correlation between cycles. There is however recent evidence suggesting the possibility of a circular mechanism. More specifically, Beckworth (2010) observes that the smaller the correlation between a state's business cycle and the national one, the more asymmetric the state's response to a common monetary shock is likely to be. The interpretation of this result offered by the author is that monetary policy exacerbates states cycles that are not synchronized with the national economy in case there are no economic shock absorbers such as flexible wages and prices, factor mobility fiscal transfers and an adequate level of diversification in the production structure. Put it differently, if states differ in terms of their industrial structure their business cycles will not be synchronized. Then, any monetary policy action will lead the states to react differently according to their specific industrial structure. These reactions, in turn, take the form of asymmetric changes in the states' structures so to further decrease the level of synchronization of their cycles. To sum up, therefore, it seems plausible to suppose the existence of a circular mechanism that leads to a cumulative decline in the level of synchronization through a progressive differentiation of specialization patterns. Consequently, the first main difference between the analysis carried out in this paper and the one proposed by Imbs (2004) is indeed represented by the fact that we explicitly allow for a possible circular relationship between industry specialization and the degree of synchronization between states business cycles.

Still, we are not yet able to explain the second component of our target variable LL_{ij}, i.e. its sign, or, in other words, why do some states lead the national cycle and others lag behind. In order to explain this component we must again turn our attention to the differences in industry mix that characterize the economic structure of the states. However, what matters here is not a general measure of dissimilarities in specialization but, rather, the sectors in which specialization actually takes form. There are several indications in the literature about which sectors appear to be more responsive and thus have cycles that tend to lead the others. Among others, while Crone (2006) reports that states with a higher share of output in agriculture and construction lead the growth in the nation, Sill (1997) and Park and Hewings (2003) point to the manufacturing sector. According to the last two authors, this is due to the high sensitivity of manufacturing to changes in monetary policy and to technology developments. A similar point is made by Carlino and DeFina (2004) and by Irvine and Shuh (2005) who focus, in particular, on the durable goods industry. From a practical point of view, it is clearly impossible to consider explicitly the evolution of each of the possibly relevant sectors. Hence, a decision must be taken on which sector to focus upon. The broad indication arising from the just mentioned literature leads to think that the manufacturing sector could be an appropriate choice. However, this sector could be excessively heterogeneous in our view and we have therefore decided to focus our attention on the high-tech industries. A first motivation of this choice is that high-tech manufacturing products are purchased for investment by firms or consumers as durable goods which implies that purchasing decisions should be highly affected by general economic conditions (DeVol *et al.*, 1999) and, in particular, by changes in the interest rate. In addition, Bernanke and Kuttner (2005) show that stock market values of high-tech industries tend to be relatively more sensitive to unanticipated changes in monetary policies. Finally, from a different perspective, Moretti (2010) documents that the high-tech sector is characterized by a much larger local multiplier than manufacturing; this implies that, in case a shock hits, the effect on the local economy induced by the response of the high-tech sector is much stronger than the effect arising from manufacturing.

The relationships among the main variables of the model just outlined are shown in Figure 2.1. In this figure, in addition to the direction of the relationships we also report their expected signs, more details on which will be provided in Section 2.4. Given the simultaneity characterizing the evolution of several variables, following Imbs (2004) and Xing and Abbott (2007) the model will be estimated via the Three-Stage Least Squares Estimator.

(Figure 2.1 About Here)

The structure of the paper is as follows. Section 2.2 studies the degree of synchronization characterizing the US states in recent decades. Section 2.3 is first devoted to the identification of the states who lead and those who lag behind and then it analyses whether the observed pattern is persistent over a set of sub-periods. The economic explanation of the lead/lag structure among the states' cycles over the period 1990-2009 is then provided in Section 2.4 where the just outlined model is estimated. Section 2.5 concludes.

2.2 Synchronization among state business cycles

First of all, we estimate the business cycles for the US and its 48 contiguous states using the monthly coincident index between 1979:7 and 2010:10. The coincident index is a macroeconomic indicator that summarizes the current economic conditions of a state in a single variable. It includes four main elements: non-farm payroll employment, average hours worked in manufacturing, unemployment rate and wage and salary disbursements.[8]

To each series we apply a Baxter-King (Baxter and King, 1999) filter that allows to extract directly the cyclical movements in the economic series whose periodicity is within a certain range. In particular, Baxter and King propose a band-pass filter, based on Burns and Mitchell's (1946) definition of a business-cycle, designed to remove low and high frequencies from the data. As recommended by Baxter and King, the filter passes through components of time series with fluctuations between 18 and 96 months while removing higher and lower frequencies.

In addition, to identify the cycle we also use the Hodrick-Prescott (Hodrick and Prescott, 1997) de-trended (quarterly) per capita real personal income net of transfers

[8] Coincident indexes are obtained from Federal Reserve Bank of Philadelphia.

between 1969:1 and 2008:4 (from Chapter 1) for US and 48 States.[9]

The outcome of the two filtering procedures is shown respectively in Figures 2.2 and 2.3. Allowing for a different degree of smoothing characterizing the two techniques, the cyclical movements identified appear highly consistent.

(Figure 2.2 and 2.3 About Here)

In order to evaluate the degree of synchronization at each point in time, we compute the rolling window cross-correlations between each state and US cycle and then take the average of these correlations for each window which gives an average value of synchronization within the US for the time instant corresponding to the mid-point of the window. We set the window length of 120 months which is a period long enough to capture the complete business cycles (peak-to-peak or trough-to-trough).

(Figures 2.4 and 2.5 About Here)

Figure 2.4 and 2.5 report the evolution of synchronization respectively for coincident index and personal income cycles. We firstly concentrate on the latter as the covered time-span is broader. We note that the degree of synchronization among US states cycles clearly decreases from the 1970s (0.92 on average) until 1990 (reaching a value as low as 0.74) and, after a rebound, appears to be rather stationary (around a value of 0.80). As a consequence, timing differences across states' business cycles have become more relevant in recent years compared to the 1970s.

The implications from the evolution of synchronization for coincident index cycles (Figure 2.4) are consistent with those just highlighted as far as the overlapping period (approximately, 1985-2003) is concerned. After 2003, we observe a sudden jump in

[9] The term below explains the Hodrick-Prescott deviation cycle estimation procedure. Let y_t represent income at time t and λ a trend smoothness parameter. Given a properly chosen λ, there is a trend τ_t minimising

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

the first component of which represents deviations of income from trend while the second determines the smoothness of the trend. The trend gets smoother trend as λ increases; here, following what is commonly done in the literature we set λ=1600.

synchronization which is obviously not observable in Figure 2.5.

2.3 Identifying who leads and who lags behind

In the previous Section we concluded that timing differences across state cycles appear to have increased in recent years with respect to the '70s and '80s. Now, we investigate whether there are states that permanently lead others along the swings of the business cycle. To do so, we first need to identify which states lead and which instead lag behind, as well as their geographical distribution within the US. This will be done using two alternative approaches, one based on dynamic cross-correlations, the second on turning points. Finally, we will evaluate whether the observed pattern is actually persistent over the time period under analysis.

2.3.1 Dynamic Cross-Correlation Approach

The first approach we employ is a widely used methodology that allows to identify the economies that lead or lag behind by calculating the dynamic cross-correlations among the cycles of the economic units (Park and Hewings, 2003).

In details, for each state i we calculate the dynamic correlations between its cycle and the US national cycle:

$$\rho_{i,\tau} = corr\left(C_{US,t}, C_{i,t-\tau}\right) \tag{2.2}$$

where $C_{\bullet,t}$ stands for the cycle component obtained via filtering and τ ranges between –8 and +8 (months). Then, we identify the value of τ such that $\rho_{i,\tau}$ is maximized. So, for instance, if the correlation in (2.2) is maximized when τ = 2 (τ = –2) this means the cycle of state i leads (lags behind) the US cycle by 2 months. Table 2.1 summarizes the results obtained applying this methodology to the Baxter-King filtered coincident index cycles of the 48 coterminous states between 1979:7 and 2010:10.

(Table 2.1 About Here)

The state that most clearly leads the US cycle is Montana (3 months ahead of the US cycle), followed by Rhode Island, South Carolina, Oregon, Florida, Idaho, Michigan

Indiana and Maine (2 months ahead of the US cycle). The states which are instead lagging behind most substantially are Wyoming (4 months behind the US cycle), and Texas, Oklahoma and Louisiana (3 months behind the US cycle).

(Figure 2.6 About Here)

Figure 2.6 displays the geographical distribution of leading and lagging behind states. Areas with the brightest color represent the states that lead the most while darkest areas represent the states that lag behind most substantially. We can easily observe that the states that most consistently lag behind are located in the West South Central Census Division (Louisiana, Oklahoma and Texas) and in part of the Mountain Division (Colorado, New Mexico and Wyoming). On the other hand, a large part of the leading states are located in the Pacific (Oregon, Washington), in the Midwest (Indiana, Michigan), in the Mountain Division (Montana, Idaho) and in the South Atlantic (Florida, South Carolina) Divisions.

2.3.2 Turning Points Approach

Another possible approach for the identification of leading and lagging behind states is through a comparison between the timing of the turning points of the US cycle and those characterizing the cycle of each state.

Operatively, first of all we detect the turning points in each business cycle applying the Bry-Boschan (Bry and Boschan, 1971) algorithm to the Baxter-King filtered monthly coincident index series. The algorithm detects a set of local minima and maxima in the series and then imposes several restrictions on the phase and cycle lengths to ensure an adequate duration.[10] It also makes sure that detected peaks and troughs orderly alternate. In particular, since our data is monthly, we impose that a phase must be at least 5 months long and a cycle must last at least 15 months. Table 2.2 summarizes, for each state and for each turning point of the US business cycle, the number of months by which a state leads or lags behind due to differences in timing of cycle swings.

[10] Details on the Bry-Boschan algorithm can be found in Appendix 2.1.

(Table 2.2 About Here)

Then, state by state, we calculate the median lead or lag with respect to the US turning points. These values are reported in Table 2.3. Similarly to the results obtained with the previous approach, the most leading state is Montana (3 months ahead of the US cycle); then, we find Maine, Rhode Island, Massachusetts, Washington, Idaho and Nevada (2 months ahead of the US cycle). Yet again, the most lagging states are Louisiana, Texas and Wyoming (3 months behind the US cycle) and Oklahoma (2 months behind the US cycle).

(Table 2.3 About Here)

Figure 2.7 reports the geographical distribution of leads and lags. In general, lagging states are located in the Southwest Central Census Division (Texas, Oklahoma, Louisiana) while leading ones can be found in the New England (Maine, Rhode Island, Massachusetts), Mountain (Montana, Idaho) and Pacific Divisions (Washington, Nevada).

(Figure 2.7 About Here)

Overall, the geographical positioning of leads and lags is consistent across the two approaches since the darkest and brightest areas of Figures 2.6 and 2.7 mostly overlap.

2.3.3 Persistence of leads and lags

Having seen that over the entire period of analysis some states tend to anticipate the national business cycle and some others to follow it, we now want to understand whether the pattern is actually persistent over different sub-periods.

In details, we divide the overall time-span into the following five, non-overlapping sub-periods: 1979:7-1985:9; 1985:10-1991:12; 1992:1-1998:3; 1998:4-2004:6; 2004:7-2010:10. Then, for each of these sub-periods we repeat the analysis carried out in the previous Sections; results are shown in Tables 2.4 and 2.5.

(Tables 2.4 and 2.5 About Here)

For each sub-periods, we also display the geographical distribution of leads and lags calculated using both the dynamic cross-correlations approach (Figure 2.8) and the turning points approach (Figure 2.9).

(Figures 2.8 and 2.9 About Here)

Similarly to what previously seen, areas with the brightest color represent states that lead the most while darkest areas represent the states that lag behind most substantially. We can therefore observe that the geographical location of leads and lags does not change much over time, with the only exception of the 1992-1998 period in Figure 2.9. Overall, these maps suggest that location of leads and lags is not purely random but possibly displays a systematic behavior.

To investigate this issue further, in Table 2.6 we count the number of states that switch from leading (+) to lagging (–) (or *vice versa*) across consecutive periods. Based on the cross-correlations approach, on average, only about 6 states out of 48 switch their behavior across each couple of consecutive periods. This figure increases to 12-13 when we resort to the turning points approach. The difference in the results coming from the two approaches is most probably due to the fact that, in calculating leads and lags, the cross-correlations approach makes reference to a time window; consequently, its outcome is characterized by a lower degree of variability with respect to that obtained through the turning point approach which, instead, works turning point-by-turning point.

(Table 2.6 About Here)

Anyway, only about 6 to 13 states switch their lead/lag behavior across consecutive periods, which correspond to about 13% to 27 % of the considered states. Put it differently, we can conclude that between 73 %-87% of the states tend to exhibit a time-consistent leading/lagging behavior. One may therefore argue that state business cycles in the US tend to display a hierarchical nature so that fluctuations in the aggregate economy are in actual facts propagated by leading states and then spread out to the others as a wave that sweeps along the nation. Trying to understand the economic reasons behind this behavior is the focus of the next Section.

2.4 Why do some states lead others?

2.4.1 The Estimated Model

Following the discussion in the introductory section, the model we estimate consists of four simultaneous equations:

$$\begin{cases} LL_{ij} = \alpha_0 + \alpha_1 \rho_{ij} + \alpha_2 DL_{ij} + \alpha_3 \left(\rho_{ij} \cdot DL_{ij} \right) + \alpha_4 HT_{ij} + \varepsilon_{ij} \\ \rho_{ij} = \delta_0 + \delta_1 S_{ij} + \delta_2 \hat{T}_{ij} + \delta_3 \hat{F}_{ij} + \boldsymbol{\delta} \mathbf{V}^{\rho}_{ij} + \eta_{ij} \\ S_{ij} = \gamma_0 + \gamma_1 \rho_{ij} + \gamma_2 \hat{T}_{ij} + \gamma_3 \hat{F}_{ij} + \boldsymbol{\gamma} \mathbf{V}^{S}_{ij} + \upsilon_{ij} \\ HT_{ij} = \beta_0 + \boldsymbol{\beta} \mathbf{V}^{HT}_{ij} + \xi_{ij} \end{cases} \tag{2.3}$$

The first equation explains the lead/lag relationship between the cycles of states *i* and *j* (LL_{ij}) in terms of its two fundamental components. The first component, the time that separates the cycles of state *i* and *j*, is introduced directly by means of the degree of synchronization between the business cycles of *i* and *j* (ρ_{ij}). The second component, i.e. which cycle leads the other, is captured by the bilateral differences in employment shares in high-tech industries. We must recall that LL_{ij} actually takes on both positive and negative values and, in principle, as depicted in Figure 2.10, the relationship between this variable and the degree of synchronization should be negative when LL_{ij} is positive (implying that the time that separates the cycles decreases as their degree of synchronization increases) and positive in the opposite case. In order to capture this, the first equation also includes a dummy variable for the leading state (DL_{ij}), taking value 1 when *i* leads *j*, and an interaction term between this dummy and the synchronization variable.[11]

The second equation in (2.3) models the determinants of the degree of synchronization. In particular, synchronization depends on the differential level of sectoral specialization (S_{ij}), on a measure of bilateral trade intensity ($\hat{T}_{ij}$) and on the level of financial

[11] We do not impose any restriction on these coefficients in the estimation and then check that the estimated values are compatible with the signs implied by Figure 2.1.

integration ($\hat{F}_{ij}$) between the states. The explanation of the relationships between these variables and synchronization borrows from Imbs (2004). In particular, S_{ij} is likely to affect synchronization of the cycles directly in a negative fashion: the degree of synchronization between the cycles of i and j should increase as the discrepancies in their economic structures decrease given that they should react in a more similar fashion to any shock. Following the implications coming from a variety of theoretical models (see Imbs, 2001 for an account of the related literature), intense bilateral trade flows tend to be associated with higher synchronization levels. Finally, financial integration should weaken the degree of synchronization among business cycles according to standard international macroeconomic theories (Obstfeld, 1994; Heathcote and Perri, 2006; Kalemli-Ozcan *et al.*, 2009).

Through the third equation the circularity between synchronization levels and differences in specialization patterns takes form. Here, based on the dynamics explained in the introductory section, we expect a negative relationship between these two variables. In addition, in line with Imbs (2004), also trade flows and financial integration are considered as possible determinants of the correlation among cycles: while the sign of the first relationship is expected to be positive, the sign of the second is ambiguous.[12]

The intensity with which state economies specialize in high-tech industries is explained in the fourth equation through a set of exogenous variables that act as instruments ($\mathbf{V}^{HT}$). The rationale for this is that the level of specialization in high-tech is quite likely to be endogenous in the first equation.

Given the simultaneity characterizing the evolution of these variables, the model is estimated via the Three-Stage Least Squares Estimator. The identification of the system is guaranteed by the three vectors of instruments $\mathbf{V}^{\rho}$, $\mathbf{V}^{S}$ and $\mathbf{V}^{HT}$ a detailed account of which will be offered in the following section.

[12] See Imbs (2004) for details on the sign of these relationships.

2.4.2 Data

As shown in Section 2.2, timing differences across state business cycles appear to have increased significantly after 1990. For this reason, and given the well-known difficulties that the move from the Standard Industrial Classification (SIC) to the North American Industrial Classification System (NAICS) poses for the construction of many of our variables, we concentrate our analysis on the period that follows 1990.

The main dependent variable, $LL_{ij,}$ is calculated for all pairs of 48 coterminous states according to equation (2.1). In particular, in order to identify the cycle we applied the Baxter-King band-pass filter on the monthly coincident index for the national economy. The set of turning points, z, is derived using the Bry-Boschan algorithm on the filtered coincident index data. For each state i, the indicator $t_{i,z}$ is calculated as the average along z of the time (in months) with which i anticipates or follows the turning points of the national business cycle ($t_{i,z}$).

The degree of synchronization among state business cycles, ρ_{ij}, is simply the bilateral correlation among the Baxter-King cycles of states i and j. The industrial dissimilarity index is computed in the following way:

$$S_{ij} = \frac{1}{T}\sum_{t}\sum_{n=1}^{N}\left|s_{n,i,t} - s_{n,j,t}\right|$$

where $s_{n,i,t}$ is the employment share of industry n in total employment, in state i at time t, and S_{ij} is the time average of the discrepancies in the two states' industrial structures.[13] This variable increases as industrial structures of two states become different and takes value of 0 when structures are identical.

As we anticipated, given the lack of data on inter-state trade, trade flows $\hat{T}$ are obtained via a gravity model along the lines of Imbs (2003).[14] In addition, bilateral financial

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[13] The N industries that have been used are: agriculture, mining, utilities, construction, manufacturing, wholesale trade, retail trade, transportation, information, finance and insurance, real estate, rental and leasing, professional, scientific and technical services, management of companies and services, administrative services, educational services, health care and social assistance, arts, entertainment, recreation services, accommodation and food services, other services except government and government sector.

[14] Here we adopt the original coefficients estimated by Imbs (2003) so that inter-state trade between i and j is:

integration is calculated from an estimate of the state-specific index of risk-sharing proposed by Kalemli-Ozcan *et al*. (2002). Specifically, the state-specific index of risk sharing θ_i is obtained by estimating

$$\ln \mathrm{GSP}_{i,t} - \ln \mathrm{DY}_{i,t} = c + \theta_i \, \mathrm{GSP}_{i,t} + e_{i,t}$$

where GSP stands for the per capita gross state product while DY is the disposable income per capita (both detrended using the Hodrick-Prescott filter). Then, the measure of cross-state financial integration between *i* and *j* is

$$\hat{F}_{ij} = \hat{\theta}_i + \hat{\theta}_j$$

Bilateral differences in the degree of specialization in high-tech production are calculated as the time average of yearly bilateral differences across states in the relevance of the high-tech sector:

$$HT_{ij} = \frac{1}{T}\sum_t \left(HT_{i,t} - HT_{j,t}\right)$$

where $HT_{i,t}$ is the share of employment in high-tech industries in state *i* at time *t*.

As already mentioned, to guarantee the identification of the system three instrument sets, $\mathbf{V}^{\rho}$, $\mathbf{V}^{S}$ and $\mathbf{V}^{HT}$, enter the model. The variables featuring in the first two sets are in line with what previously done in the literature adopting this framework. The first set, $\mathbf{V}^{\rho}$, includes the pairwise product of GSP per capita and difference in crude oil productions (expressed in absolute value); the second set, $\mathbf{V}^{S}$, employed in the explanation of the differences in specialization, includes the natural logarithm of distance between state capitals, the pairwise difference (expressed in absolute value) and product of GSP per capita.

Due to its novelty, the last set, $\mathbf{V}^{HT}$, deserves a few words of motivation. Here, the general aim is to introduce variables which are as exogenous as possible and, at the same time, able to provide an explanation to the differential development of high-tech sectors across states. A possible set of candidates stems from the literature on amenity migration within the US. Since (natural) amenities are considered a normal or superior good (Graves, 1979 and 1980) and high-skill workers tend to have a relatively higher average income it might be plausible to think that high-tech jobs tend to move towards areas characterized by a relatively higher supply of the type of amenities. Evidence in

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$$\hat{T}_{ij} = -1.355\ln\left(\mathrm{distance}_{ij}\right) + 1.057\ln\left(\mathrm{GDP}_i \cdot \mathrm{GDP}_j\right) - 0.635\ln\left(\mathrm{Pop}_i \cdot \mathrm{Pop}_j\right) - 29.834$$

support to this link between amenities and high-tech employment is reported by Partridge *et al*. (2008). However, the work by Dorfman *et al*. (2008) seems to suggest that this link should be qualified better as they find little evidence that high-skill workers drive amenity migration towards rural areas. To try to accommodate both suggestions we introduce two variables: the first measures the bilateral differences in natural amenities using the natural amenity index for each state provided by the Economic Research Service of the United States Department of Agriculture; the second is the pairwise differences in the states' share of employment in agriculture. Based on the suggestions from the just cited works, our expectation is that the first variable should be positively associated with high-tech employment, while the opposite should hold for the second. Then we include a further variable related to old resource-based industries, in the form of pairwise differences in the states' share of employment in mining activities; given the impact of these activities on landscape, skills and on the availability of land, we expect this variable to have a negative influence on the ability of the region to attract high-tech jobs. Finally, as in the explanation of the discrepancies in the two states' industrial structures, we include the pairwise difference of GSP per capita.

2.4.3 Results

Table 2.7 reports the results from the Three-Stage Least-Squares (TSLS) estimation of the system in equation (2.3) from which we can immediately notice that, with the only exception of the constant term in the *HT* equation, all coefficients are significant at the 1% level or better.

(Table 2.7 About Here)

As expected, the coefficient of high-tech is positive. To evaluate the impact of this variable on *LL* we consider the "representative leading" state and calculate the corresponding predicted lead (approximately 42 days); similarly, we calculate the predicted lag (approximately 56 days) for the "representative lagging behind" state. [15]

[15] By "representative leading" state we mean the hypothetical state for which all independent variables take on their sample mean value conditional on the dummy *DL* being equal to 1. A similar concept applies for the "representative lagging behind" state with the only difference that the dummy *DL* is equal to 0.

Then, we consider an increase of one standard deviation in the mean value of *HT* of the "representative leading" state and, analogously, a decrease of one standard deviation in the mean value of *HT* for the "representative lagging behind" state. As a result, we obtain that the "representative leading" state increases its lead by approximately 7.5 days while the lag of the "representative lagging behind" state grows by 8.1 days.
Also the estimated relationship between LL_{ij} and ρ_{ij} is in accordance with expectations and, in particular, with the representation in Figure 2.10. More in detail, the relationship is negative ($\alpha_1+\alpha_3=-5.36$) when LL_{ij} is positive, which implies that the lead decreases as the degree of synchronization increases, and becomes positive ($\alpha_1=4.63$) when LL_{ij} is negative. With the same logic described above, we can calculate the impact of a change in the degree of synchronization: a one standard deviation increase in the degree of synchronization for a "representative leading" state determines a reduction of about 1 day in the predicted lead; a one standard deviation reduction in the degree of synchronization for a "representative lagging behind" state determines an increase of about 1 day in the predicted lag.

All signs in the second equation are in accordance to the theoretical predictions summarized in Sections 2.4.1-2.4.2. The effect of specialization on ρ has a negative sign, implying that more dissimilar industrial structures result in lower levels of synchronization. In addition, the level of synchronization is affected positively by trade flows and negatively by financial integration. Finally, couples of states with higher GSP and lower differences in crude oil production tend to display more synchronized business cycles.

Estimates for the third equation confirm the possibility of a circular relationship between synchronization levels and differences in specialization patterns. The coefficient of ρ is significant and its negative sign is clearly in line with the negative sign on the link between *S* and ρ in the second equation. Specifically, the smaller the correlation between state business cycles, the more asymmetric their industrial structures. Trade flows induce differentiation in industrial specialization while financial integration has the opposite effect. In addition, pairs of richer states as well as pairs of states with lower GSP gaps and lower physical distance tend to have more similar economic structures.

Finally, estimates for the *HT* equation suggest that natural amenities play a positive role in favoring the relative concentration of high-tech jobs while, as expected, all other variables tend to discourage it.

Table 2.8 reports equation-by-equation estimates using Ordinary Least-Squares (OLS). Similarly to the TSLS estimation, all coefficients are significant at the 1% level with, again, the only exception of the constant term in the *HT* equation.

(Table 2.8 About Here)

However, two important remarks must be made. First, the sign of coefficient of *HT*, α_4, in the first equation is reversed with respect to the TSLS estimate and is thus in contrast with the theoretical predictions. Second, concentrating now on the second and third equations of the system and, in particular, on the potential circularity between ρ and S, we observe that, compared to TSLS, OLS clearly diminish the absolute value of the estimated coefficients possibly due to a bias arising from neglected endogeneity. Moreover, it should be noted that the strong significance levels of δ_1 and γ_1 in the OLS estimates was also found in the TSLS estimates where the possible circularity between ρ and S was allowed for. Intuitively, this result appears to support the appropriateness of the specification introduced in this analysis.

2.5 Conclusions

This paper analyzes the possibility that some economies might be systematically ahead of others along the swings of the business cycle and tries to find out the economic reasons why this may happen. To do so we concentrate on the business cycle fluctuations of the 48 coterminous US states between 1979 and 2010.

First of all, we have observed that timing differences across state cycles have recently become more evident. Furthermore, we have reported evidence suggesting the existence of a lead/lag structure whereby some states are systematically ahead of others (and, clearly, others are systematically behind) along the swings of the business cycle.

The core of our analysis is the development of a multiple equation econometric model to explain not only the degree of synchronization that might exist among regional cycles but also the economic reasons why some state cycles do anticipate others. In particular, due to the presence of simultaneous relationships among featured variables the model is estimated via Three-Stage Least-Squares. This strategy also allows us to accommodate an hypothesized circular mechanism between the degree of synchronization and the dissimilarities in industrial structures. Our estimates show that the lead/lag structure is significantly explained by the degree of synchronization and, indirectly, by trade flows and financial integration. In addition, specialization, and particularly specialization in the high-tech sector, plays an important role in predicting whether a state leads or lags behind another.

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Tables

Table 2.1 Lead/lag of the states with respect to the US cycle
Dynamic Cross-Correlations Approach, 1979-2010

States	Lead (+)/Lag(–)	States	Lead (+)/Lag(–)
Alabama	1	Nebraska	–1
Arizona	1	Nevada	1
Arkansas	0	New Hampshire	1
California	0	New Jersey	1
Colorado	–1	New Mexico	–1
Connecticut	0	New York	–1
Delaware	1	North Carolina	1
Florida	2	North Dakota	0
Georgia	0	Ohio	1
Idaho	2	Oklahoma	–3
Illinois	–1	Oregon	2
Indiana	2	Pennsylvania	0
Iowa	0	Rhode Island	2
Kansas	0	South Carolina	2
Kentucky	1	South Dakota	1
Louisiana	–3	Tennessee	1
Maine	2	Texas	–3
Maryland	0	Utah	0
Massachusetts	1	Vermont	1
Michigan	2	Virginia	1
Minnesota	–1	Washington	1
Mississippi	1	West Virginia	0
Missouri	0	Wisconsin	–2
Montana	3	Wyoming	–4

Table 2.2 Lead/Lag of state turning points with respect to US turning points

US turning points (T)/(P)	80-08 (T)	81-09 (P)	83-02 (T)	84-09 (P)	86-12 (T)	90-05 (P)	91-10 (T)	94-12 (P)	96-03 (T)	98-02 (P)	99-02 (T)	00-11 (P)	03-09 (T)	08-04 (P)	09-07 (T)
Alabama	0	2	2	5	1	1	1	-2	-11	-4	-1	4	-2	0	0
Arizona	1	2	2	-12	0	-1	-16	0	-11	0	1	0	1	2	0
Arkansas	0	3	3	3	-2	1	3	-3	-10	0	3	3	2	-1	-1
California	1	2	1	-2	2	-2	-23	-10	-8	-4	-5	-1	-1	-1	0
Colorado	-2	-3	-2	-1	-2	-1	0	-1	-7	1	-4	-1	1	-1	-1
Connecticut	0	1	0	1	14	16	-2	1	-12	-6	-4	3	3	0	0
Delaware	2	7	-2	-6	7	3	1	-2	-7	12	6	1	0	-2	
Florida		2	1	1	6	0	-2	1	-4	-5	-5	0	0	5	1
Georgia	2	4	1	1	1	0	0	1	7	0	1	1	0	-1	
Idaho	1	3	5	-5	0	0	3	3	-6	6	2	2	-1	6	0
Illinois	-3	-1	0	-1	9	-3	-3	-3	-12	-6	-4	0	0	-1	-1
Indiana	1	2	2	4	1	15	2	-2	0	16	6	1	0	1	-2
Iowa	0	2	2	3	3	14	-19	-1	-12	3	3	-1	-1	1	
Kansas	0	1	2	2	14	2	5	-1	-6	-4	-5	-2	1	-1	-1
Kentucky	-1	0	-1	-1	3	2	4	0	-10	-2	2	4	1	1	1
Louisiana	2	-2	-3	-1	-1	-2	-19	-4	-9	-3	-4	8	9	-4	-3
Maine	1	3	1	1	11	15	4	-2	-2	14	2	5	2	0	-2
Maryland		6	1	-2	2	3	-3	0	-1	11	12	1	5	1	-1
Massachusetts	5	6	2	0	5	15	3	15	6	-3	-3	0	2	1	-1
Michigan	0	2	3	6	-12	1	1	0	-9	2	1	6	2	0	1
Minnesota	1	1	1	-1	6	0	1	-11	-11	0	0	0	-2	-2	-1
Mississippi	0	1	2	6	-1	0	3	4	-12	10	3	0	0	-4	
Missouri	0	1	-1	0	-3	2	4	2	-3	7	8	9	-5	-1	0
Montana	1	3	6	3	-7	18	7	2	5	-5	-2	5	-1	5	1
Nebraska	0	2	1	-2	-2	-3	-19	3	-10	-5	-1	-8	4	0	-1
Nevada	2	1	1	3	8	0	-18	4	6	13	11	-2	16	1	0
New Hampshire	1	2	3	5	18	16	4	-1	-8	-2	-3	-1	12	0	-1
New Jersey	0	1	1	2	10	4	-1	0	0	-3	-2	3	7	0	0
New Mexico	0	1	0	-13	-4	-1	0	-3	-6	2	-2	-4	1	-1	-1
New York	0	0	0	1	10	0	-1	-1	-10	0	0	-1	-1	-1	
North Carolina	0	2	3	4	5	2	3	-1	-1	1	0	1	0	-1	
North Dakota	-2	-2	2	7	6	0	-20	2	5	1	1	-6	14	0	1
Ohio	0	1	2	3	-3	0	3	-1	-3	-1	0	4	1	0	0
Oklahoma	-1	-5	-3	-9	-1	0	0	1	6	-3	-8	-4	2	-3	-2
Oregon	1	4	5	4	7	0	-1	-1	0	5	0	1	0	1	1
Pennsylvania	0	1	1	3	8	2	0	0	2	-3	-1	2	2	-1	-1
Rhode Island	2	4	2	0	-2	15	1	14	-9	-5	-3	2	15	10	-1
South Carolina	2	3	3	4	14	-1	1	-4	-8	-5	-1	4	0	2	1
South Dakota	0	2	3	3	-9	-1	5	-4	-7	5	4	9	1	0	0
Tennessee	0	1	1	3	3	4	3	-3	-8	-3	-1	3	1	0	0
Texas	-1	-3	-3	-10	-2	-3	-8	-2	-4	-3	-6	-2	1	-3	-2
Utah	-2	-2	-1	1	-8	-4	-11	8	-1	-1	2	2	0	0	
Vermont	0	2	3	6	2	13	4	-4	-11	-1	0	1	6	0	0
Virginia		7	3	-4	7	2	0	1	1	-9	-6	1	3	0	-1
Washington	2	4	4	4	2	0	2	2	2	0	1	3	1	0	0
West Virginia	-1	0	1	2	10	-1	2	-2	-7	1	4	3	1	-2	-1
Wisconsin	-2	-2	-1	3	-3	0	1	0	1	-2	-2	5	4	-4	-2
Wyoming	1	-3	-3	-15	-3	-3	-14	2	-2	3	2	-12	7	-4	-3

Note: Empty values represent a non-corresponding turning point of a state with respect to national cycle.

Table 2.3 Median Lead/lag of the states with respect to the US cycle
Turning Points Approach, 1979-2010

States	Lead (+)/Lag(–)	States	Lead (+)/Lag(–)
Alabama	0	Nebraska	–1
Arizona	0	Nevada	2
Arkansas	1	New Hampshire	1
California	–1	New Jersey	0
Colorado	–1	New Mexico	–1
Connecticut	0	New York	0
Delaware	1	North Carolina	1
Florida	0.5	North Dakota	1
Georgia	1	Ohio	0
Idaho	2	Oklahoma	–2
Illinois	–1	Oregon	1
Indiana	1	Pennsylvania	1
Iowa	1.5	Rhode Island	2
Kansas	0	South Carolina	1
Kentucky	1	South Dakota	1
Louisiana	–3	Tennessee	1
Maine	2	Texas	–3
Maryland	1	Utah	–1
Massachusetts	2	Vermont	1
Michigan	1	Virginia	1
Minnesota	0	Washington	2
Mississippi	0.5	West Virginia	1
Missouri	0	Wisconsin	–1
Montana	3	Wyoming	–3

Table 2.4 Lead /lag of states with respect to US cycle during sub-periods Dynamic Cross-Correlations Approach

lead/lag	1979-1985	1985-1991	1992-1998	1998-2004	2004-2010
Alabama	2	0	0	2	0
Arizona	1	0	0	0	1
Arkansas	3	1	-3	3	-1
California	1	-2	-8	-1	0
Colorado	-2	-1	0	-1	-1
Connecticut	1	2	0	1	0
Delaware	2	2	-1	4	0
Florida	1	0	0	-1	2
Georgia	1	0	0	0	0
Idaho	3	0	1	0	2
Illinois	-1	0	0	0	-1
Indiana	2	1	0	5	1
Iowa	2	3	-3	4	-1
Kansas	1	3	-2	-3	-1
Kentucky	-1	2	0	4	1
Louisiana	-3	-3	-4	-5	-5
Maine	2	4	0	3	1
Maryland	-2	0	0	1	0
Massachusetts	3	5	0	-1	0
Michigan	2	0	0	5	1
Minnesota	1	0	0	0	-1
Mississippi	1	0	3	8	0
Missouri	0	2	1	5	0
Montana	4	4	2	5	2
Nebraska	0	-2	0	-3	-1
Nevada	1	-2	4	1	1
New Hampshire	2	6	0	0	0
New Jersey	1	2	0	0	0
New Mexico	0	-1	-1	-6	-1
New York	0	0	0	0	-1
North Carolina	2	1	0	1	1
North Dakota	0	1	0	-2	0
Ohio	1	1	0	3	0
Oklahoma	-4	-2	-1	-6	-2
Oregon	4	0	0	1	1
Pennsylvania	1	1	1	1	-1
Rhode Island	2	1	2	3	1
South Carolina	3	0	-1	4	1
South Dakota	3	2	-4	5	0
Tennessee	1	2	0	3	0
Texas	-4	-4	-1	-3	-2
Utah	-2	-4	0	-1	1
Vermont	1	4	0	1	0
Virginia	3	1	2	0	0
Washington	3	0	3	2	0
West Virginia	1	0	0	3	-1
Wisconsin	-1	0	0	1	-3
Wyoming	-4	-5	2	-8	-3

Table 2.5 Lead /lag of states with respect to US cycle during sub-periods Turning Points Approach

lead/lag	1979-1985	1985-1991	1992-1998	1998-2004	2004-2010
Alabama	2	1	-4	-1	0
Arizona	1.5	-1	0	1	1
Arkansas	3	1	-3	3	-1
California	1	-2	-8	-1	-0.5
Colorado	-2	-1	-1	-1	-1
Connecticut	0.5	14	-6	3	0
Delaware	0	3	-2	1	-2
Florida	1	0	-4	0	3
Georgia	1.5	0	1	1	-1
Idaho	2	0	3	2	3
Illinois	-1	-3	-6	0	-1
Indiana	2	2	0	1	-0.5
Iowa	2	3	-1	-1	1
Kansas	1.5	5	-4	-2	-1
Kentucky	-1	3	-2	2	1
Louisiana	-1.5	-2	-4	8	-3.5
Maine	1	11	-2	2	-1
Maryland	1	2	0	5	0
Massachusetts	3.5	5	6	0	0
Michigan	2.5	1	0	2	0.5
Minnesota	1	1	-11	0	-1.5
Mississippi	1.5	0	4	0	-4
Missouri	0	2	2	8	-0.5
Montana	3	7	2	-1	3
Nebraska	0.5	-3	-5	-1	-0.5
Nevada	1.5	0	6	11	0.5
New Hampshire	2.5	16	-2	-1	-0.5
New Jersey	1	4	0	3	0
New Mexico	0	-1	-3	-2	-1
New York	0	0	-1	-1	-1
North Carolina	2.5	3	-1	0	-1
North Dakota	0	0	2	1	0.5
Ohio	1.5	0	-1	1	0
Oklahoma	-4	0	1	-4	-2.5
Oregon	4	0	0	0	1
Pennsylvania	1	2	0	2	-1
Rhode Island	2	1	-5	2	4.5
South Carolina	3	1	-5	0	1.5
South Dakota	2.5	-1	-4	4	0
Tennessee	1	3	-3	1	0
Texas	-3	-3	-3	-2	-2.5
Utah	-1.5	-8	-1	2	0
Vermont	2.5	4	-4	1	0
Virginia	3	2	1	1	-0.5
Washington	4	2	2	1	0
West Virginia	0.5	2	-2	3	-1.5
Wisconsin	-1.5	0	0	4	-3
Wyoming	-3	-3	2	2	-3.5

Table 2.6 Number of states that switch from leading (lagging) to lagging (leading) behavior across consecutive sub-periods

		Number of switching states	
Initial period	Following period	Cross-Correlations Approach	Turning Points Approach
1979-1985	1985-1991	3	5
1985-1991	1992-1998	7	17
1992-1998	1998-2004	6	15
1998-2004	2004-2010	7	14
	Mean	5.75	12.75

Table 2.7 Three-Stage Least-Squares regression results

	Variables	Coefficients	s.e.
Dependent Variable: *LL*	constant	–5.3403***	0.8172
	HT	38.0828***	11.4080
	DL	10.9556***	1.3599
	ρ	4.6319***	1.0501
	ρ·*DL*	–9.9860***	1.7366
	R-squared	0.6065	
Dependent Variable: ρ	constant	1.0121***	0.0614
	S	–0.6578***	0.1044
	$\hat{T}$	0.0121***	0.0043
	$\hat{F}$	–0.0855***	0.0161
	GSP product	0.0039***	0.0015
	Oil	–0.0002***	0.0000
	R-squared	0.1119	
Dependent Variable: *S*	constant	0.4883***	0.0796
	ρ	–0.2760***	0.0813
	$\hat{T}$	0.1123***	0.0153
	$\hat{F}$	–0.0469***	0.0106
	Distance	0.1689***	0.0215
	GSP product	–0.0275***	0.0034
	GSP difference	0.0149***	0.0060
	R-squared	0.1785	
Dependent Variable: *HT*	constant	0.0001	0.0003
	Amenity	0.0022***	0.0002
	Mining	–0.1970***	0.0170
	Agriculture	–0.0478***	0.0107
	GSP difference	–0.0041***	0.0004
	R-squared	0.1827	

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%
Endogenous variables: *LL*, *HT*, *S*, ρ·*DL*, ρ

Table 2.8 Equation-by-equation Ordinary Least-Squares regression results

	Variables	Coefficients	s.e.
Dependent Variable: *LL*	constant	-5.0341^{***}	0.3079
	HT	-19.4412^{***}	3.6183
	DL	10.1466^{***}	0.4265
	ρ	4.0543^{***}	0.3895
	ρ·*DL*	-8.7373^{***}	0.5342
	R-squared	0.6905	
Dependent Variable: ρ	constant	0.8633^{***}	0.0532
	S	-0.2692^{***}	0.0458
	$\hat{T}$	0.0184^{***}	0.0039
	$\hat{F}$	-0.0609^{***}	0.0149
	GSP product	0.0059^{***}	0.0015
	Oil	-0.0003^{***}	0.0000
	R-squared	0.1674	
Dependent Variable: *S*	constant	0.3072^{***}	0.0355
	ρ	-0.0880^{***}	0.0177
	$\hat{T}$	0.1277^{***}	0.0158
	$\hat{F}$	-0.0337^{***}	0.0095
	Distance	0.1971^{***}	0.0215
	GSP product	-0.0322^{***}	0.0033
	GSP difference	0.0217^{***}	0.0062
	R-squared	0.2539	
Dependent Variable: *HT*	constant	0.0003	0.0003
	Amenity	0.0023^{***}	0.0002
	Mining	-0.1950^{***}	0.0172
	Agriculture	-0.0427^{***}	0.0117
	GSP difference	-0.0022^{***}	0.0005
	R-squared	0.1974	

Notes: Significance levels: * = 10%, ** = 5% , *** = 1%

Figures

Figure 2.1 Relationships between the main variables of the model

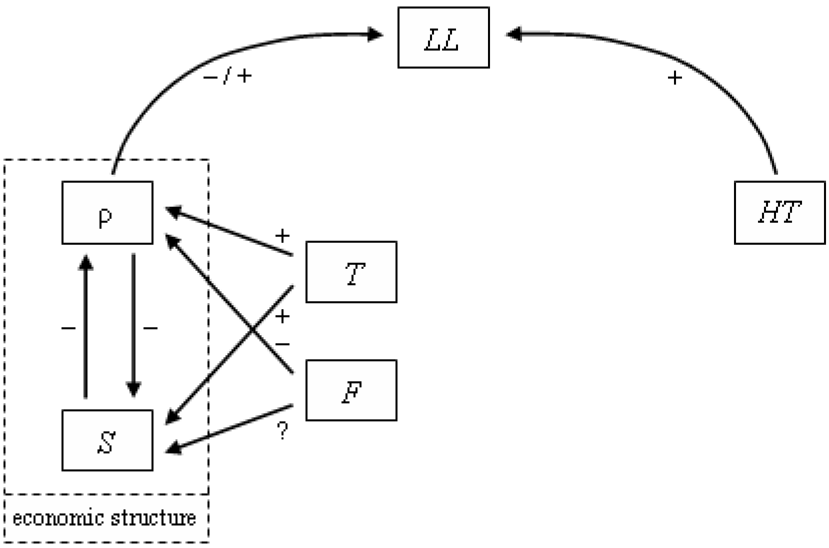


Figure 2.2 US Business Cycle (1979:7-2010:10)
Baxter-King filtered coincident index

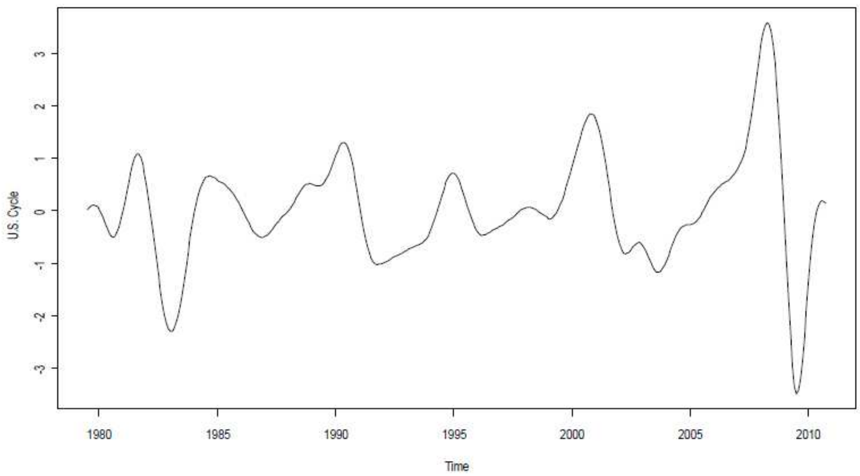


Figure 2.3 US Business Cycle (1969:Q1-2008:Q4)
Hodrick-Prescott filtered personal income

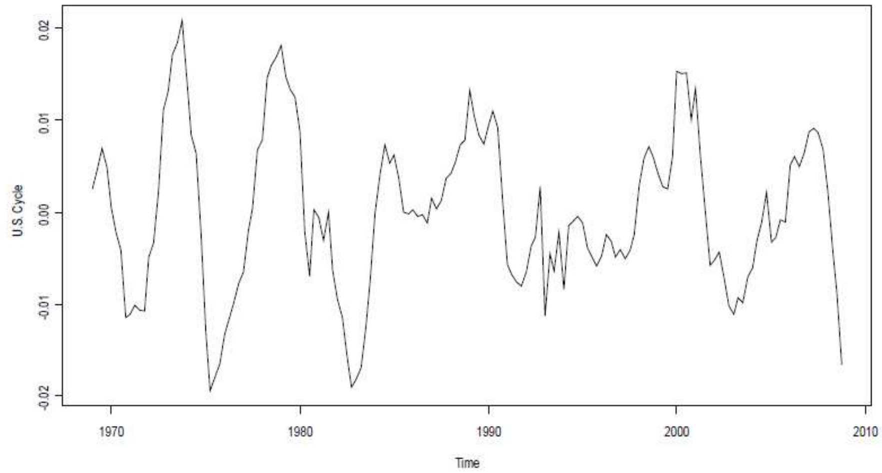


Figure 2.4 Degree of Synchronization within the US (coincident index cycles)

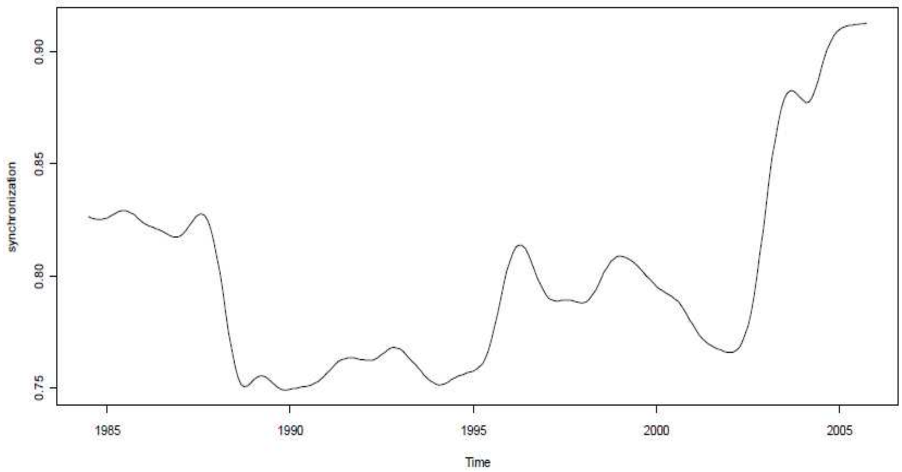


Figure 2.5 Degree of Synchronization within the US (personal income cycles)

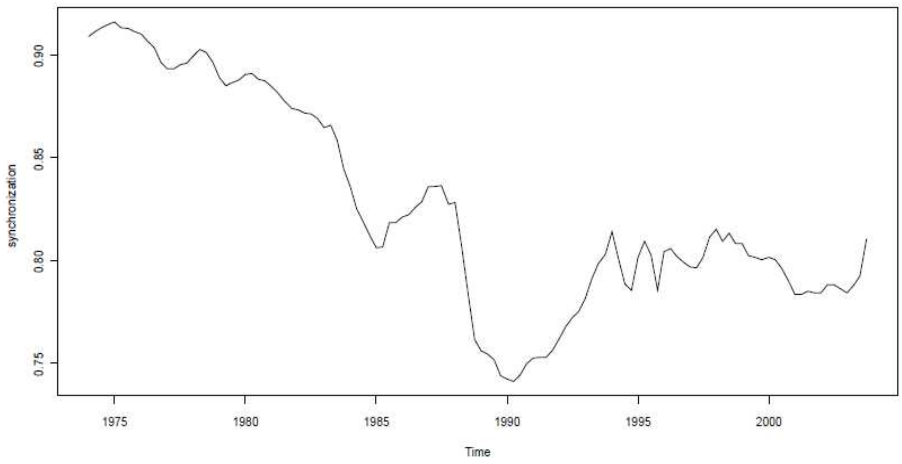
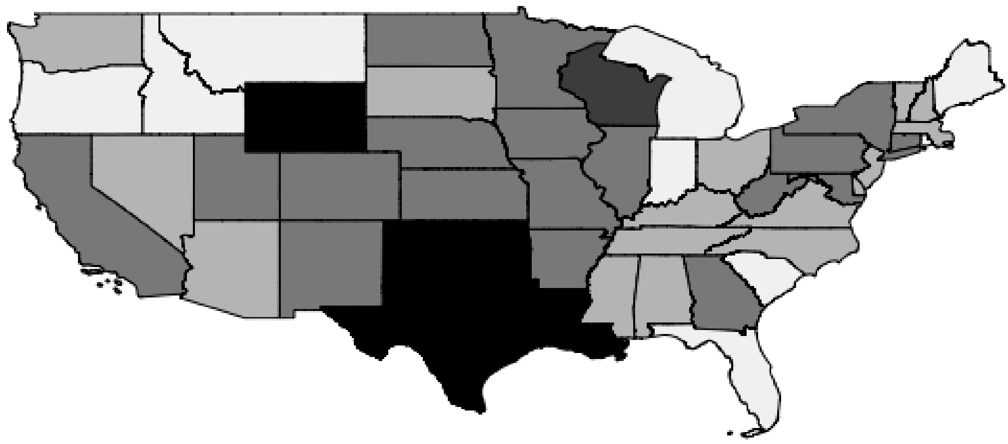


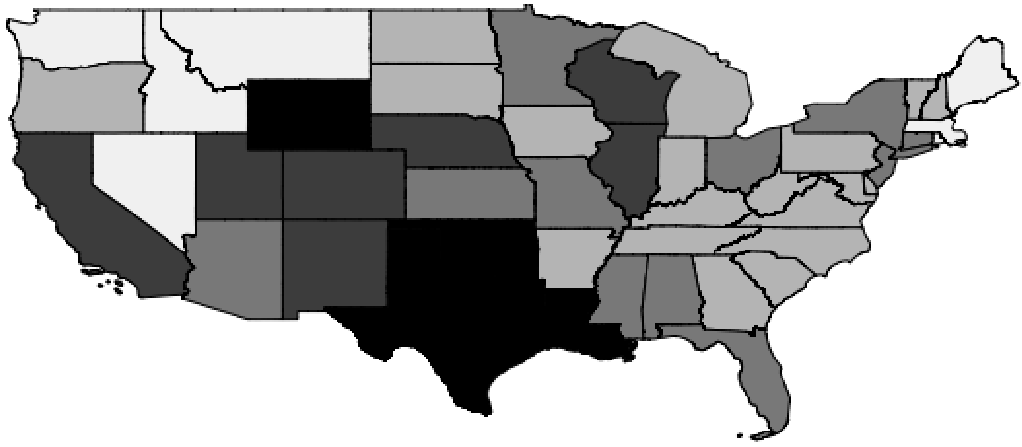
Figure 2.6 Geographical distribution of leads and lags, 1979-2010
Cross-Correlation Approach



min	-4
max	3

Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads
Each color represents a class were the classes are created by dividing the range of the lead/lags above into 5 equal intervals

Figure 2.7 Geographical distribution of leads and lags, 1979-2010
Turning Points Approach

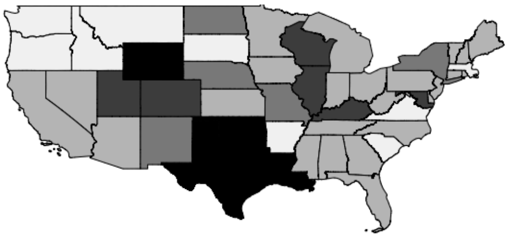


min	-3
max	3

Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads
Each color represents a class were the classes are created by dividing the range of the lead/lags above into 5 equal intervals

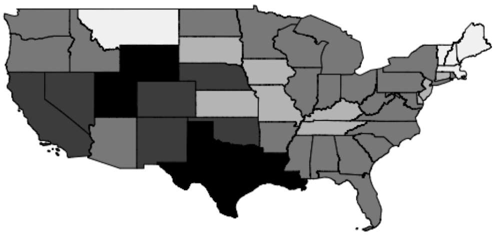
Figure 2.8 Geographical distribution of leads/lags during sub-periods (Cross-Correlation Approach)

1979-1985



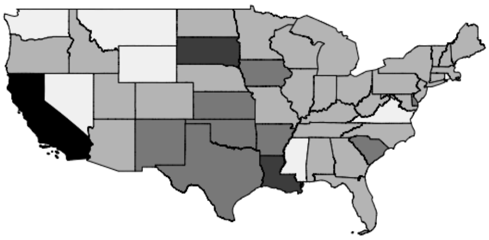
min	-4
max	4

1985-1991



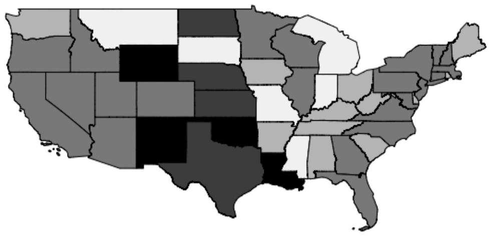
min	-5
max	6

1992-1998



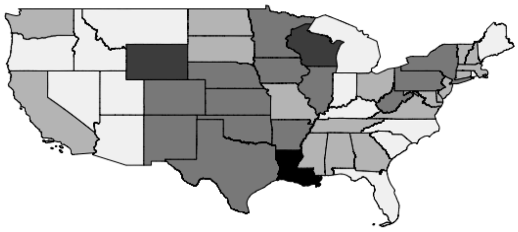
min	-8
max	4

1998-2004



min	-8
max	8

2004-2010

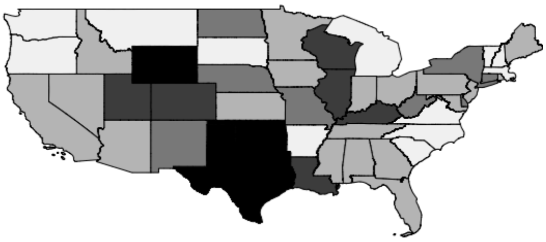


min	-5
max	2

Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads
Each color represents a class were the classes are created by dividing the range of the lead/lags above into 5 equal intervals

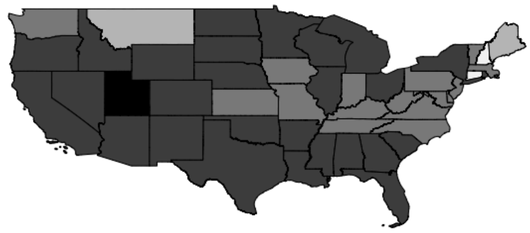
Figure 2.9 Geographical distribution of leads/lags during sub-periods (Turning points Approach)

1979-1985



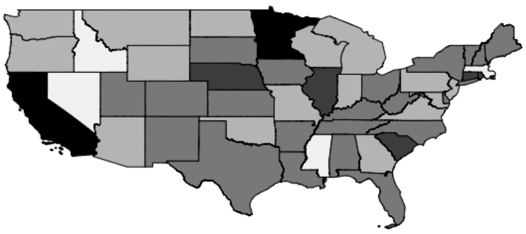
min	-4
max	4

1985-1991



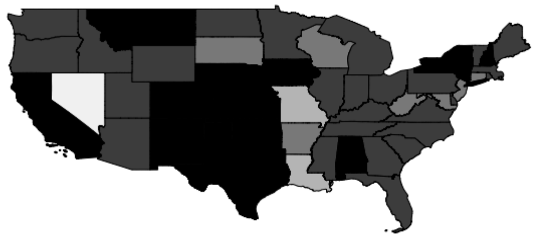
min	-8
max	16

1992-1998



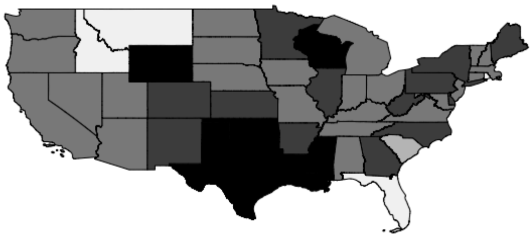
min	-11
max	6

1998-2004



min	-4
max	11

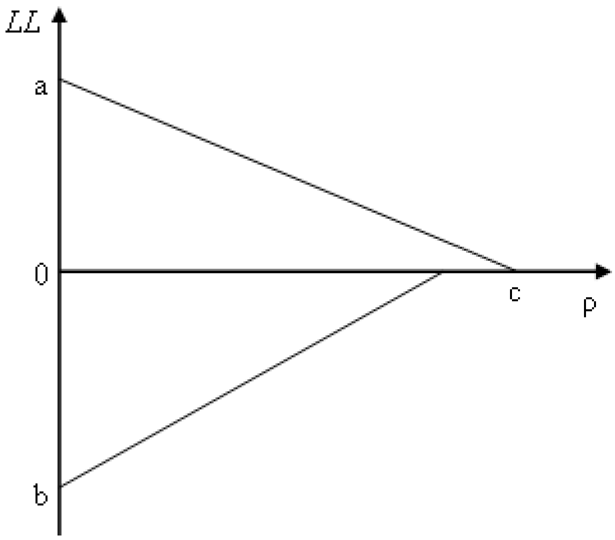
2004-2010



min	-4
max	4.5

Notes: Grey represents coincidence with the US cycle
Colors from grey to black represent an increasing number of lags
Colors from grey to white represent an increasing number of leads
Each color represents a class were the classes are created by dividing the range of the lead/lags above into 5 equal intervals

Figure 2.10 Relationship between *LL* and ρ



Notes: Based on the coefficients reported in the first equation of the system, the slope is α_1+α_3 (<0) in the positive section of the codomain and α_1 (>0) in the negative one. In addition:

$a = \alpha_0 + \alpha_2 (> 0)$, $b = \alpha_0 (< 0)$, $c = -\frac{\alpha_0 + \alpha_2}{\alpha_1 + \alpha_3} (> 0)$.

APPENDIX 2.1 Bry-Boschan Algorithm

I. On the Baxter-King de-trended series, a Spencer moving average is applied in order to obtain the Spencer Curve.[16]

II. Baxter-King de-trended series are corrected for outliers. Outliers are the observations which are at least 3.5 standard deviations away from the mean. We replace outliers by their equivalent value on the Spencer Curve. Applying a Spencer moving average on the outlier corrected series creates an outlier-corrected Spencer curve.

III. A 2x12 centered Moving Average (MA) is applied on the outlier-corrected data to obtain the "first cycle" curve.

IV. A first set of turning points are searched within the first cycle curve and then these turning points have been used to look for the corresponding turning points on the Spencer Curve. The local minima/maxima have been searched in every 11 months. Therefore, the window length is 11 months.

V. A minimum cycle length restriction is imposed. So that any cycle has at least a duration of 15 months. It is checked whether the peaks and troughs orderly alternate, i.e. peak-trough-peak, and the alternation is imposed if necessary.

VI. The Months for Cyclical Dominance (MCD), “the minimum month-delay for which the average of absolute deviations of growth in Spencer cycle is larger than that in the irregular component is computed.” Then, a moving average of length MCD is applied on the previously outlier-corrected series. A new set of turning points is searched next to the complementary turning points that were found on the Spencer curve. Again, a minimum cycle length restriction is imposed (15 months) and orderly alternation of the turning points is imposed.

VII. This last set of turning points is cleaned by discarding the turning points corresponding to the first and last six observations. A minimum phase length restriction of 5 months is imposed. Thus, the final set of turning points is obtained.

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[16] The details of the algorithm are obtained from manual of BUSY 4.1 program.

APPENDIX 2.2 Variables and data sources

Variables	Definition	Data Source
LL	Average (along national turning points) of the number of months by which a state's business cycle anticipates or follows the national business cycle	
ρ	bilateral correlation among states' cycles. Cycles have been identified using the Baxter-King band-pass filter	
S	Time average of yearly pairwise differences across states in the industry mix: $S_{ij} = \frac{1}{T}\sum_{t}\sum_{n=1}^{N}\left\|s_{n,i,t} - s_{n,j,t}\right\|$ where $s_{n,i,t}$ is the employment share of industry *n* in total employment for state *i* at time *t*	US Bureau of Economic Analysis
HT	Time average of yearly pairwise differences across states in the share of high technology sector employment over total employment; high-tech sector is proxied by NAICS 340000 "computer and electronic product manufacturing"	US Bureau of Economic Analysis
DL	Dummy variable which takes on a value of 1 if the first state of the pair is leading the second in terms of business cycle, 0 otherwise	
T	Bilateral trade intensity	Estimated as described in the text
F	Cross-state financial integration	Estimated as described in the text
Amenity	Pairwise differences across states in the natural amenity index	Economic Research Service; US Department of Agriculture
Agriculture	Time average of yearly pairwise differences across states in the share of agriculture employment over total employment	US Bureau of Economic Analysis
Mining	Time average of yearly pairwise differences across states in the share of mining employment over total employment	US Bureau of Economic Analysis
Oil	Pairwise differences across states in 2010 oil production (in million barrels)	US Energy Information Administration
Distance	Logarithm of Euclidean distance across states' capitals	
GSP difference	Time average of yearly pairwise differences across states in Gross State Product	US Bureau of Economic Analysis
GSP product	Time average of yearly pairwise products across states in Gross State Product	US Bureau of Economic Analysis

CHAPTER 3

Distortions in cross-sectional convergence analysis when the aggregate business cycle is incomplete

Stefano Magrini, Margherita Gerolimetto, Hasan Engin Duran

3.1 Introduction

The vast majority of studies on convergence among national and sub-national economic systems implicitly adopt a long-run perspective as it relates empirical findings from the analyzed period to the long-run predictions of a variety of theoretical models. A few studies have instead adopted a different viewpoint and analyzed the evolution of income disparities among a set of economies in relation to the aggregate business cycle. Among these, Dewhurst (1998), Petrakos and Saratsis (2000) and Petrakos *et al*. (2005) investigate regional disparities within European countries and find evidence of a pro-cyclical evolution of the disparities, i.e. disparities across regions that move in the same direction as the national economic cycle and hence increase during expansion periods and diminish in times of recession. By contrast, Pekkala (2000) reports evidence of counter-cyclical disparities among Finnish regions while Quah (1996) finds no relation between the evolution of convergence dynamics among US states and aggregate fluctuations.

Shedding light on this issue is however 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 recessions, 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 recessions 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. In this paper we do precisely that. At the same time, given that misleading results can arise unless cyclical effects on convergence are taken into consideration, we analyze convergence in per capita personal income among 48 US States over a specifically chosen period (1989-2007) that stretches between two peaks of the aggregate business cycle.

From a methodological point of view, we opt for the continuous state-space distribution dynamics approach first introduced by Quah (1997). 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; Fotopoulos, 2008; Abreu *et al*. 2005; Durlauf *et al*., 2005). Sharing the view that the regression approach presents several critical inadequacies, in this study we therefore follow the distribution dynamics approach, a nonparametric approach that, rather than focusing 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 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. In addition, Yamamoto (2008) studies convergence dynamics 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.

In contrast to the above findings, DiCecio and Gascon (2010) report evidence of polarization. More specifically, the authors analyze 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 3.2, we estimate the US business cycle using Hodrick-Prescott filtering and then the timing of the phases using the Bry-Boschan algorithm. In Section 3.3, we provide a description of the distribution dynamics approach adopted here and, in Section 3.4, we implement the convergence analysis and present the results. Section 3.5 concludes the study.

3.2 US business cycle and regional disparities

A necessary first step in our analysis is to produce an estimate of the US business cycle as well as of the turning points within this cycle.

The cycle is identified using a Hodrick-Prescott filter (Hodrick and Prescott, 1997) to de-trend US per capita real personal income net of current transfer receipts.[17] Denoting income at time t with y_t, the HP filter minimizes in τ_t the following expression

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

[17] Here we borrow from the analysis carried out in the first chapter of this thesis in which the cycle is identified using data between 1969:Q1 and 2008:Q4.

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 λ=1600.

Turning points are detected using the Bry-Boschan algorithm (Bry and Boschan, 1971) and Hodrick-Prescott de-trended income series of US over the period between 1989 and 2007. The Bry-Boschan algorithm is designed to detect, initially, the set of local minima and maxima in the (de-trended) income series and it then imposes several restrictions on the duration of the phases and cycles in order to ensure their persistence. It also checks whether detected turning points orderly alternate. The following equation shows an example of a local minimum and maximum:

$$\text{local maximum} = \{(y_{t-2}, y_{t-1}) < y_t > (y_{t+2}, y_{t+1})\}$$
$$\text{local minimum} = \{(y_{t-2}, y_{t-1}) < y_t > (y_{t+2}, y_{t+1})\}$$

Let y be an income series. There exists a local maximum at time t when the value of y at time t is the highest among the five observations. By contrast, there exists a local minimum at time t when the value of y is the lowest. In this example, the window length is 5 where the local minimum or maximum is searched in every 5 periods. In our case, we use a window length of 5 quarters, as commonly done in the literature. Having detected the local minima and maxima in the series, we impose restrictions on the minimum duration of phases and cycles. We set the minimum phase and cycle length as 2 and 5 quarters respectively. Further details of the Bry-Boschan program can be found in Appendix 3.3

Table 3.1 summarizes the identified turning points for the US economy between 1989 and 2007 while Figure 3.1 presents expansion and recession periods. Specifically, we detected 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 3.1 and Figure 3.1 About Here)

In order to evaluate the sensitivity of the results we considered two alternative sets of turning points for the 1989-2007 period (Table 3.2). On the one hand, we detected turning points from Baxter-King filtered data (Baxter and King, 1999)[18]. On the other hand, we also considered the turning points declared by the NBER.

(Table 3.2 About Here)

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

Figure 3.2 displays the evolution of the coefficient of variation calculated using per capita personal income data for the 48 coterminous states in relation to the timing of the US business cycle phases. This plot suggests 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 3.2 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, we can now turn to the analysis of convergence providing, first of all, a few technical details on the methodology we adopt.

3.3 Distribution Dynamics Approach

As motivated in Section 3.1, in order to analyze convergence we adopt the distribution dynamics approach whose distinctive feature is to examine directly the evolution of the cross-sectional distribution of per capita income.

[18] Similarly to what we did before, the Baxter-King cycle has been identified over the period 1969:Q1-2008:Q4, and turning points for the 1989-2007 period have been detected with the Bry-Boschan algorithm.

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 which we denote respectively with $f(X)$ and $f(Y)$. Next, assuming that the dynamics of $f(\bullet)$ can be modeled as a first order process, the density at time $t+s$ is given by:

$$f(Y)=\int_{-\infty}^{\infty} f(Y \mid X) f(X) dX \tag{3.1}$$

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 analyzed directly from the shape of a plot of the stochastic kernel estimate or, assuming that the process behind (3.1) 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 $s \rightarrow \infty$.

A common way to obtain an estimate of the stochastic kernel in equation (3.1) is through the kernel density estimator. In particular, denote by $\{(X_1,Y_1), (X_2,Y_2), \ldots, (X_n,Y_n)\}$ the sample of size n, and by $\{(x_1,y_1), (x_2,y_2), \ldots, (x_n,y_n)\}$ our observations. The kernel density estimator of Y conditional on $X = x$ is as follows:

$$\hat{f}(y \mid x)=\sum_{j=1}^{n} w_j(x) K_b(y-Y_j) \tag{3.2}$$

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.[19]

Despite its widespread use, however, Hyndman *et al*. (1996) argue that the estimator in equation (3.2) might have poor bias properties. To clarify this, denote the conditional mean with

$$m(x) = E(Y \mid X = x)$$

so that:

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

where j=1,…,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 (3.2):

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

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 been referred to as the mean-bias.

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

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

where

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

with i =1,…,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):

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

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

where

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

In what follows we therefore apply the mean-bias adjustment proposed by Hyndman *et al*. (1996) and use the local linear estimator to obtain an estimate of the mean function.

3.4 Empirical Results

In this section we describe the results of the empirical analysis of convergence across U.S. States over the entire period spanning from 1989 to 2007.

Initially, coherently with what previously explained, we analyze convergence dynamics between corresponding turning points along the business cycle. Specifically, focusing on the turning points identified through the Bry-Boschan algorithm on Hodrick-Prescott filtered personal income quarterly data, we define the entire period of the analysis as the period running from the peak of 1989:1Q to the peak of 2007:2Q.[20] Convergence, therefore, is analyzed 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, we refer to this type of analysis as the analysis "in phase".

Subsequently, we show how short run dynamics can alter the picture by distorting the outcome of the convergence analysis. In order to do so, we compare the results found in

[20] 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 emphasised 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.

the “in phase” analysis with those arising from an “out of phase” one. In particular, we define as “out of phase” an analysis based on one or more transitions running from opposite turning points, i.e. either from peak to trough or from trough to peak. Let us assume that, as previously suggested, disparities follow a pro-cyclical behavior. Then, when the “out of phase” transition is derived by removing an expansion (recession) from a larger “in phase” transition, then we expect the results to be biased towards (against) convergence.

3.4.1 Convergence analysis

The results of the convergence analysis among U.S. States over the period 1989-2007 are reported in Figures 3.3 and 3.4. 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 3.3 and 3.4 About Here)

Focusing on a single transition between the peak of 1989:Q1 and the peak of 2007:Q2 (Figure 3.3), 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 neighborhood 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 3.4 where we show the estimates obtained using three peak-to-peak transitions.[21] In sum, it appears that over the period stretching across approximately two decades, U.S. States have been characterized by a process of divergence in terms of personal income per capita.

[21] 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 A3.1.1) or all possible ones (Figure A3.1.2), and using official NBER turning points (Figure A3.1.3).

3.4.2 Influence of the period of analysis

Now that we have established the dynamics characterizing the recent experience of the distribution of personal income per capita across U.S. States, we can move to the second purpose of our study and show if, and how, short-run distribution dynamics along the business cycle affect the results.

As anticipated, to do so we perform a set of comparisons between two ergodic distributions: 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 3.4.1. 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 recession 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 we are removing the expansion period running from the intermediate trough and the final peak. If distribution dynamics effectively move in a pro-cyclical fashion, we therefore expect the first type of "out of phase" ergodic estimate 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 our conclusions, we primarily focus on the visual inspection of differences in the shape of the estimated ergodic distributions. In each of the considered cases, however, we support the evidence provided by the graph though a comparison between dispersion indexes such as the standard deviation and the interquartile range.

The first of these comparisons is reported in Figures 3.5-3.8. In particular, Figures 3.5 and 3.6 report the results, respectively based on one and three transition periods, when "out of phase" definition is of the first type and hence excludes recession 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 3.5-3.8 About Here)

Analogously, Figures 3.7 and 3.8 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 3.2, 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-periods 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.

Our period of analysis stretches between the first quarter of 1989 and the second quarter of 2007. If we divide it into three transitions of approximately the same length we actually end up with sub-periods which overlap almost completely with those base 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 3.4. Indeed, this is clearly the message conveyed by the comparison represented in Figure 3.9.

So, in order to show that the problem just emphasized is not just a theoretical possibility, we must sub-divide the period in a somewhat different way but still able to allow for the cyclical behavior of the cross-sectional disparities. We therefore ignore the 1994:Q4 peak and end up with two sub-periods separated by the 2000:Q1 peak. 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 3.9 and 3.10 About Here)

As clearly shown in Figure 3.10, 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, we must emphasize that, despite the fact the overall period is the same and defined according to the aggregate cycle, we obtain profoundly different results. This is simply because the sub-periods have been defined differently. Second, even if we knew whether the disparities move pro- or anti-cyclically, 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.

3.5 Conclusions

In this paper, we assessed the importance of the choice of the period of analysis in relation to the cyclical behavior of cross-sectional income disparities while investigating convergence dynamics.

First of all, we identified the business cycle for the US economy using the Hodrick-Prescott filter and then detected the turning points of the cycle with the Bry-Boschan algorithm. In particular, the overall period of analysis starts with the peak identified in the first quarter of 1989 and ends with the peak detected in the second quarter of 2007. It appears that per capita personal income disparities across 48 coterminous US states follow a cyclical pattern over this period. 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 behavior might actually affect dynamics, we studied convergence across the states of the US over periods that allow for the cyclical movement of the aggregate economy. Through a comparison between the initial and the ergodic distribution, we observed 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. We then confirmed this finding using three peak-to-peak transitions.

Then, we actually demonstrated that the definition of the period of analysis without allowing for the cyclical movements of the aggregate economy, i.e. from peak to trough or vice versa, might indeed seriously affect the dynamics and lead to misrepresented results.

Finally, we also showed that the commonly adopted practice of dividing the period of analysis into a number of sub-periods 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 analyzed 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 being able 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 favored regions, in case of a long-run increase in disparities quite different structural interventions might be called for.

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Tables

Table 3.1 US turning points (Hodrick-Prescott Cycle)

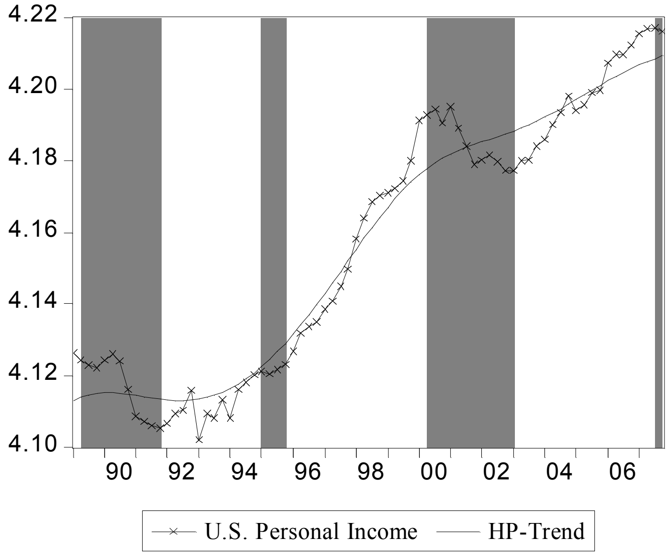
Dates	Peak or Trough
1989-Q1	Peak
1991-Q4	Trough
1994-Q4	Peak
1995-Q4	Trough
2000-Q1	Peak
2003-Q1	Trough
2007-Q2	Peak

Table 3.2 Alternative US turning points

Baxter-King Cycle		NBER Announcements	
Dates	Peak or Trough	Dates	Peak or Trough
1988-Q4	Peak		
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		

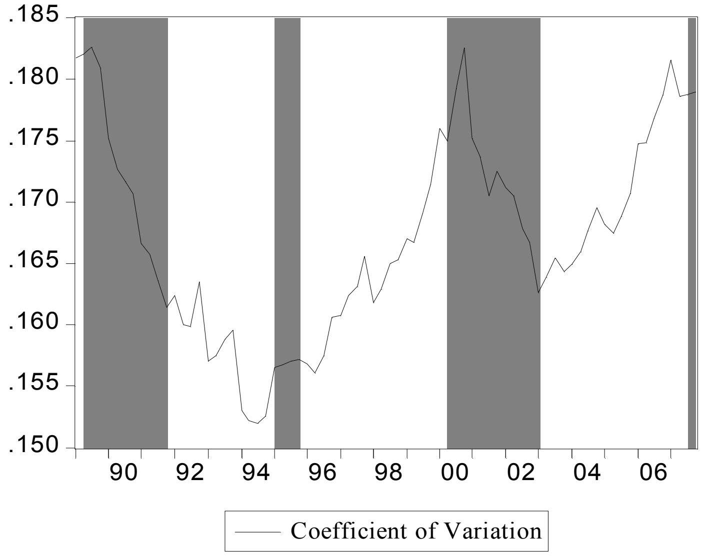
Figures

Figure 3.1 US Personal income and cycle phases, 1989-2007



Note: Gray-shaded areas represent recession periods.

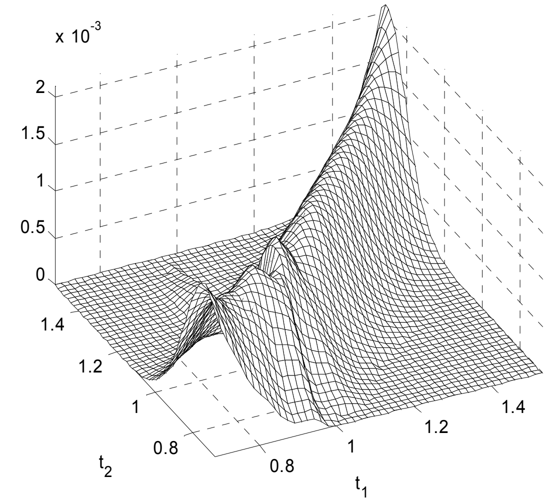
Figure 3.2 US business cycle and regional disparities, 1989-2007

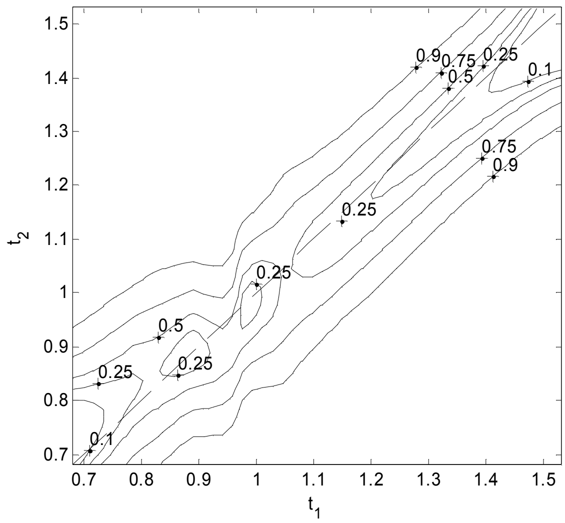


Note: Gray-shaded areas represent recession periods.

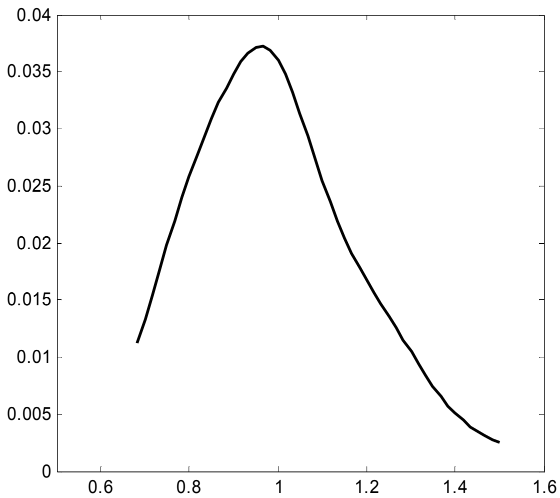
Figure 3.3 Distribution Dynamics
Peak 1989:Q1 – Peak 2007:Q2

stochastic kernel

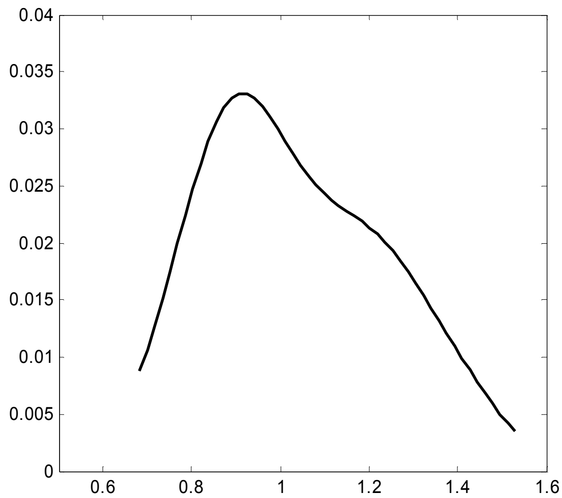




initial (t_1)



ergodic

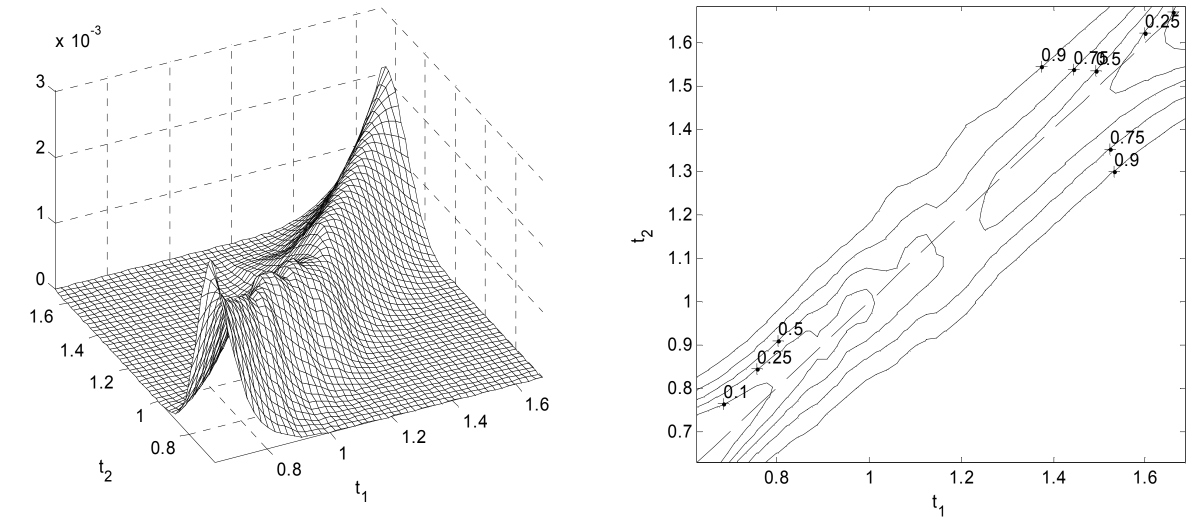


Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al*., 1996). In the plots, t_1 refers to the initial moment(s) of the transition period(s).

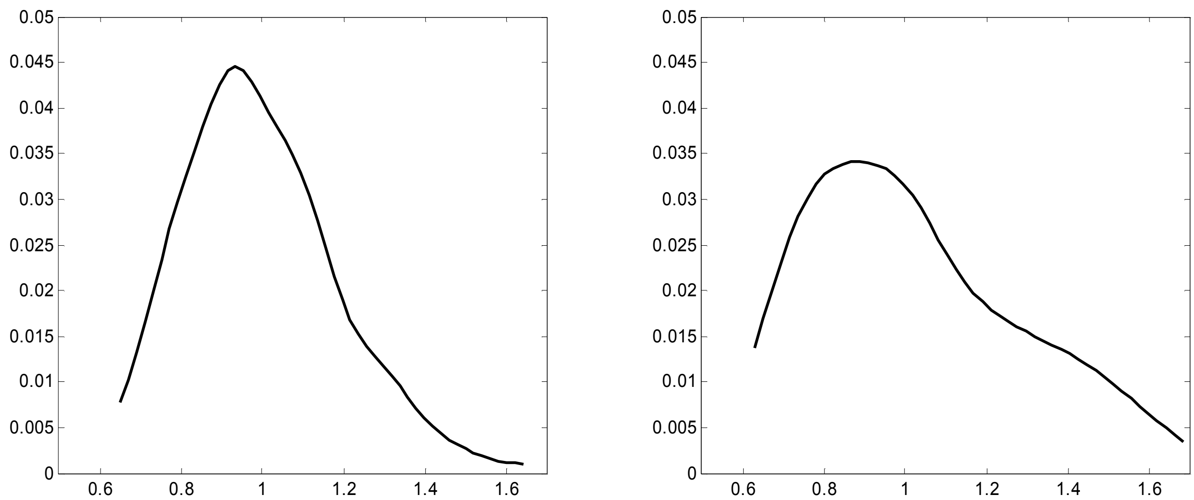
Figure 3.4 Distribution Dynamics

Peak 1989:Q1 – Peak 1994:Q4; Peak 1994:Q4 – Peak 2000:Q1; Peak 2000:Q1 – Peak 2007:Q2

stochastic kernel

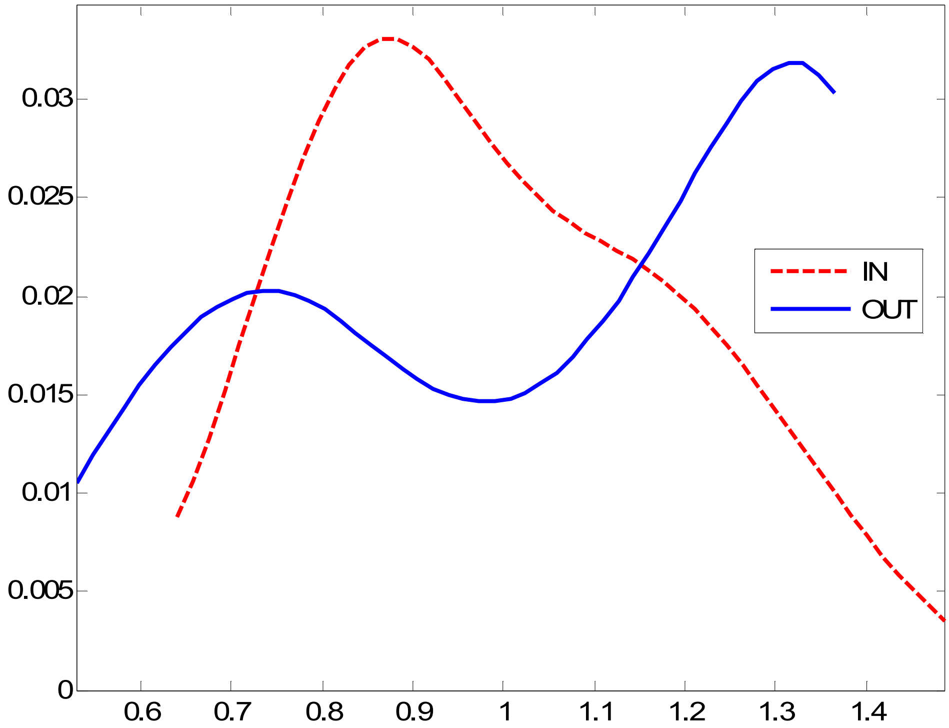


initial (t_1) ergodic



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 3.5 Comparison between Distribution Dynamics
IN (peak-to-peak): 1989:Q1 – 2007:Q2
OUT (trough-to-peak): 1991:Q4 – 2007:Q2



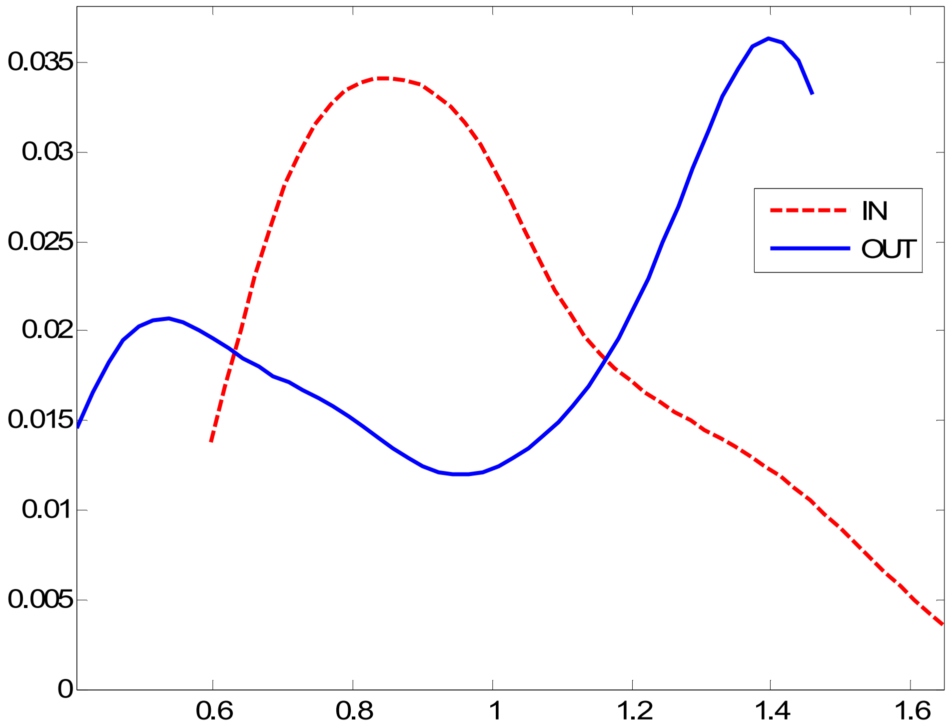
	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2028	0.3288
OUT (trough-to-peak)	0.2530	0.4597

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 3.6 Comparison between Distribution Dynamics

IN (peak-to-peak): 1989:Q1–1994:Q4; 1994:Q4–2000:Q1; 2000:Q1–2007:Q2

OUT (trough-to-peak): 1991:Q4–1994:Q4; 1995:Q4–2000:Q1; 2003:Q1–2007:Q2



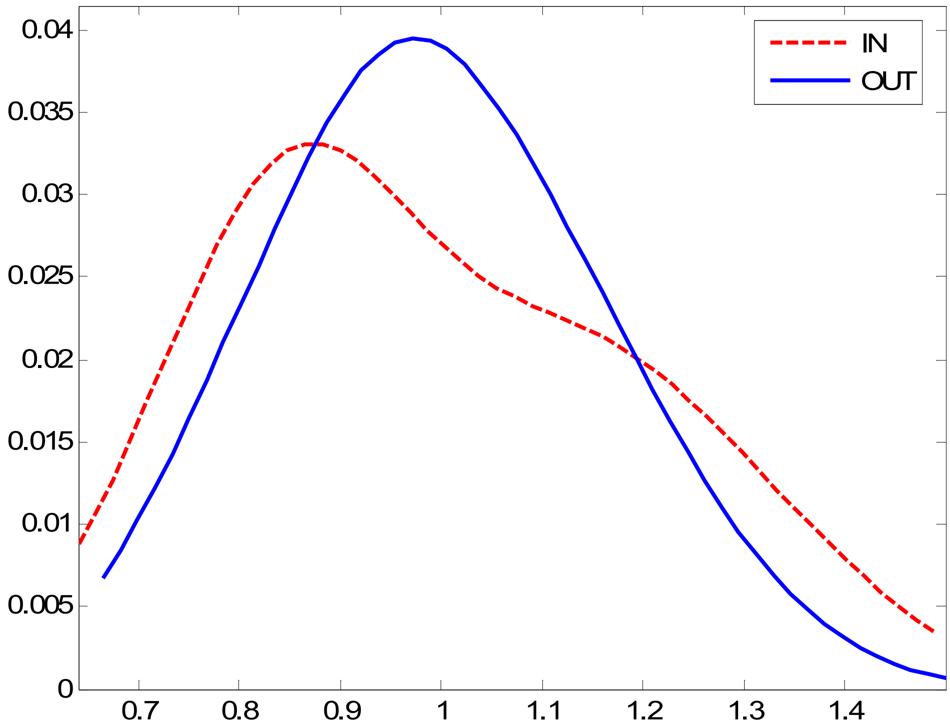
	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2572	0.3877
OUT (trough-to-peak)	0.3380	0.6246

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 3.7 Comparison between Distribution Dynamics

IN (peak-to-peak): 1989:Q1–2007:Q2

OUT (peak-to-trough): 1989:Q1–2003:Q1



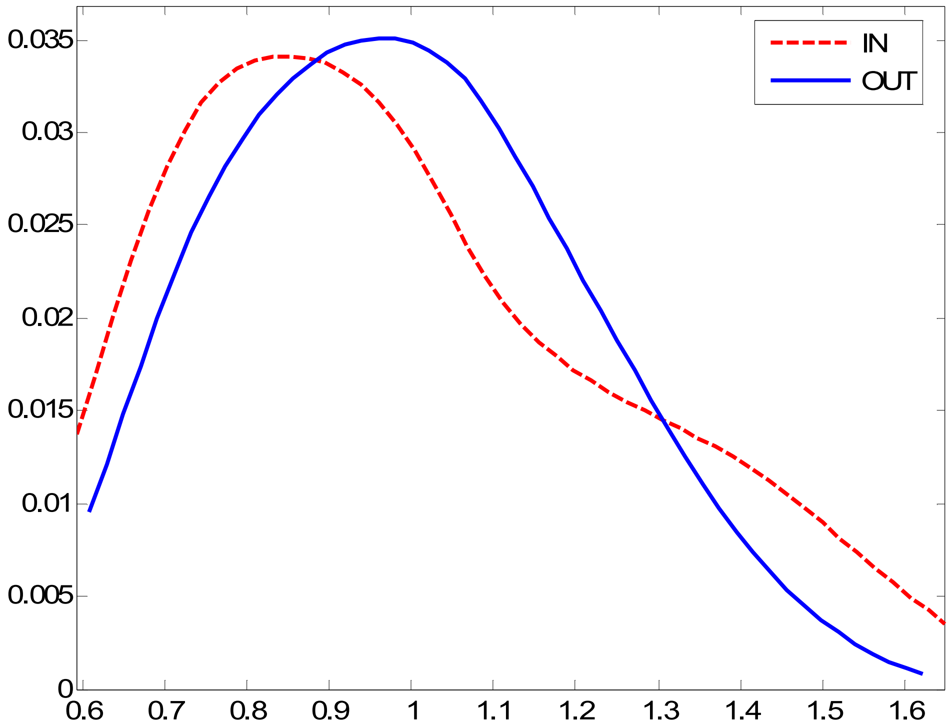
	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2028	0.3288
OUT (peak-to-trough)	0.1650	0.2213

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 3.8 Comparison between Distribution Dynamics

IN (peak-to-peak): 1989:Q1–1994:Q4; 1994:Q4–2000:Q1; 2000:Q1–2007:Q2

OUT (peak-to-trough): 1989:Q1–1991:Q4; 1994:Q4–1995:Q4; 2000:Q1–2003:Q1



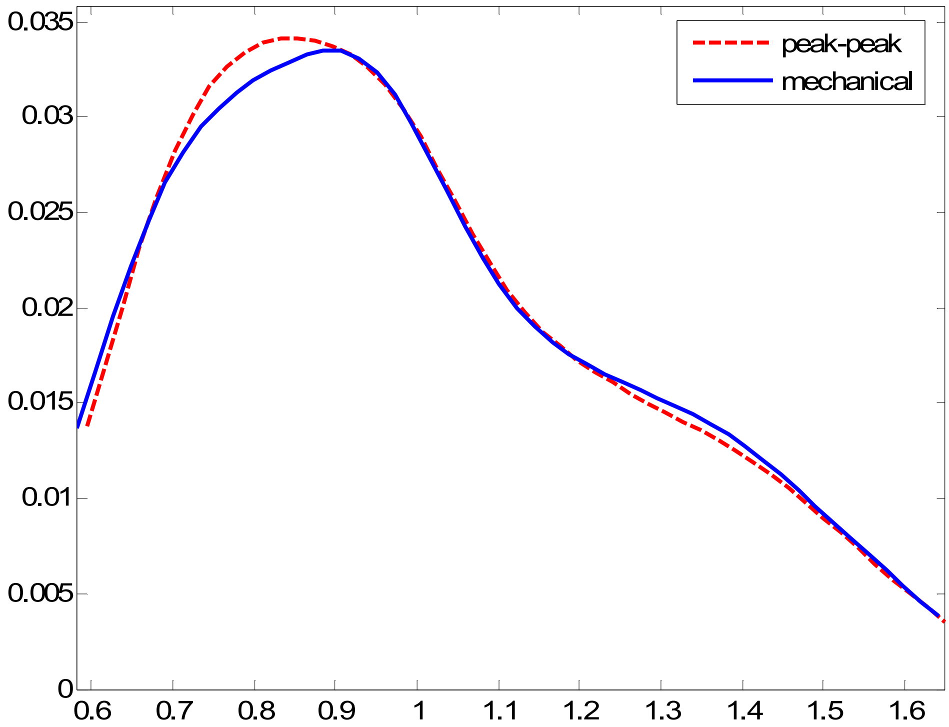
	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2572	0.3877
OUT (peak-to-trough)	0.2133	0.3106

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 3.9 Comparison between Distribution Dynamics

peak-to-peak: 1989:Q1 – 1994:Q4; 1994:Q4 – 2000:Q1; 2000:Q1 – 2007:Q2

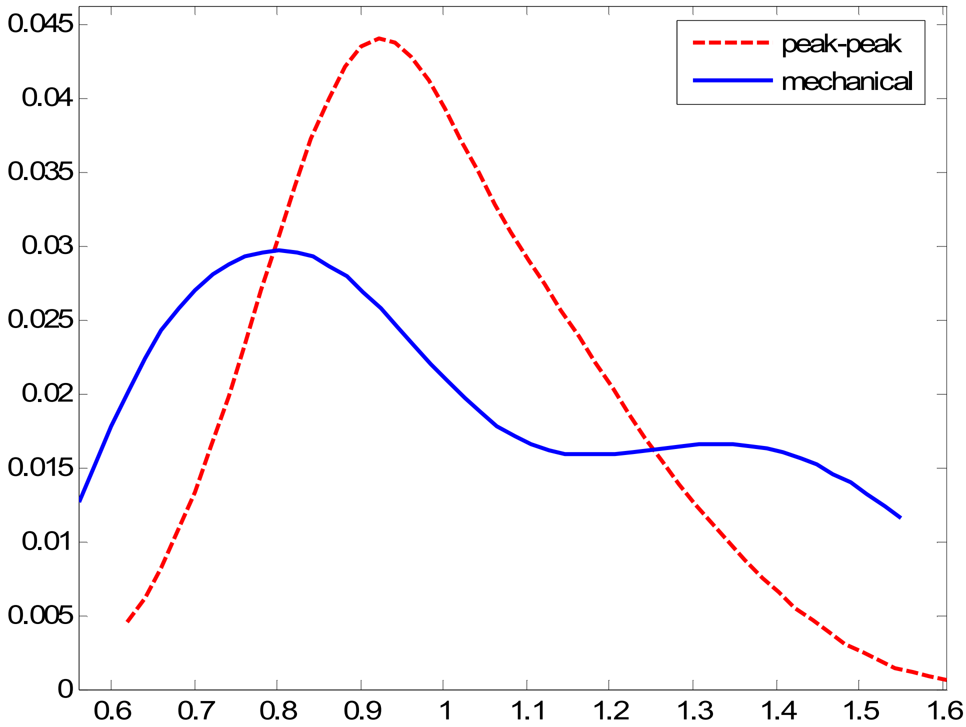
mechanical: 1989:Q1 – 1995:Q1; 1995:Q1 – 2001:Q2; 2001:Q2 – 2007:Q2



	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 3.10 Comparison between Distribution Dynamics
peak-to-peak: 1989:Q1 – 2000:Q1; 2000:Q1 – 2007:Q2
mechanical: 1989:Q1 – 1998:Q1; 1998:Q1 – 2007:Q2



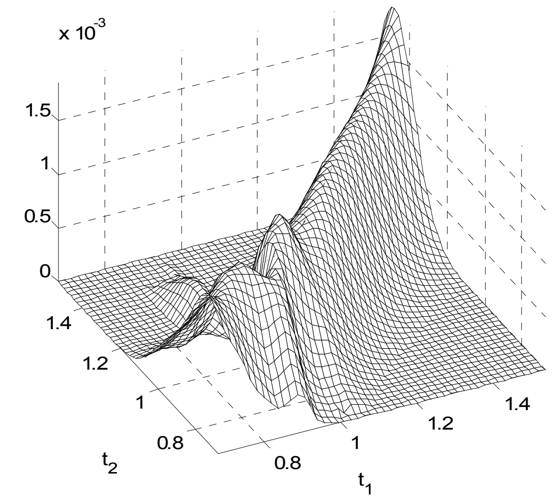
	Standard deviation	Interquartile range
peak-to-peak	0.1902	0.2612
mechanical	0.2753	0.4649

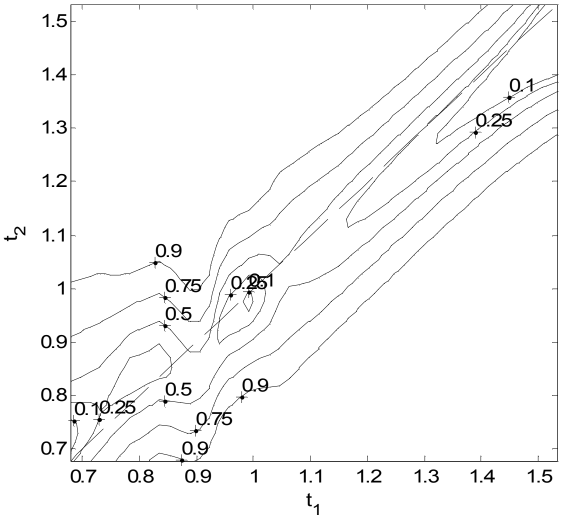
Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al.*, 1996).

APPENDIX 3.1

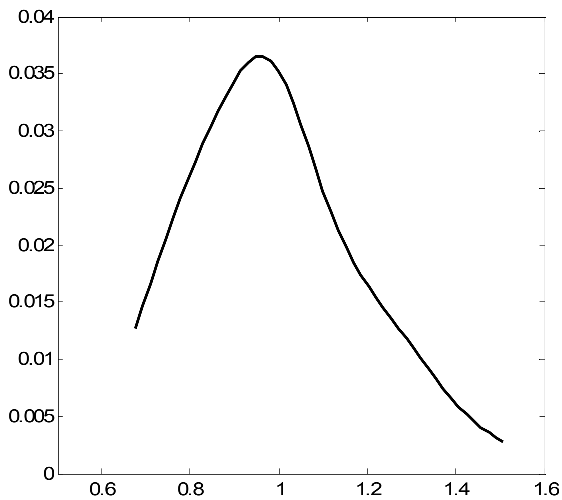
Figure A3.1.1 Convergence Dynamics (dating based on Baxter-King filtered data)
Peak 1988:Q4 – Peak 2007:Q3

stochastic kernel

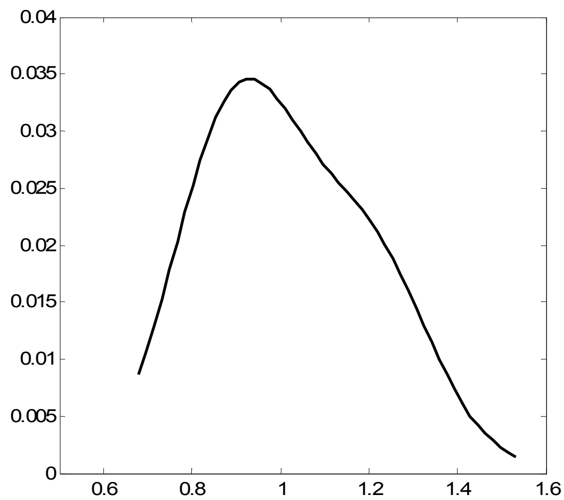




initial (t_1)



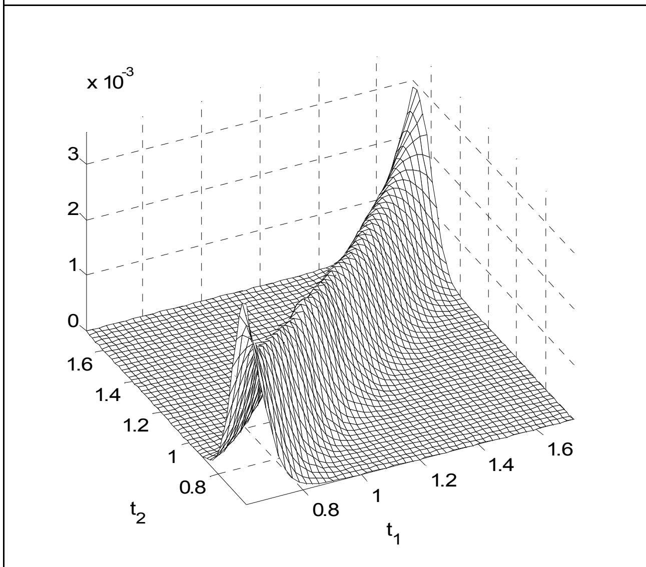
ergodic

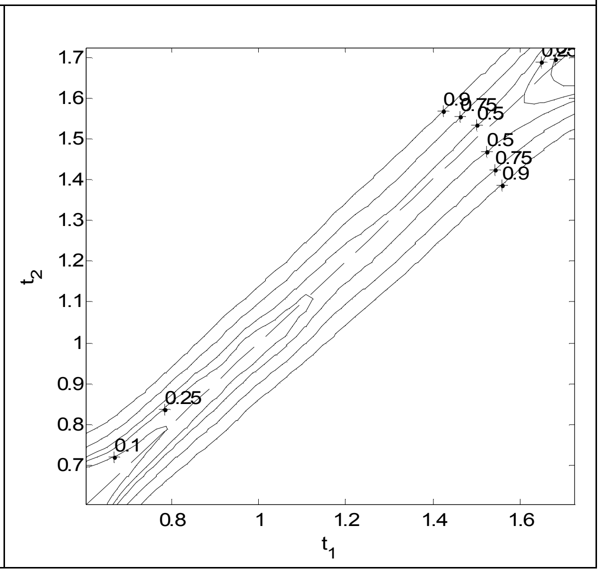


Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al*., 1996). In the plots, t_1 refers to the initial moment(s) of the transition period(s).

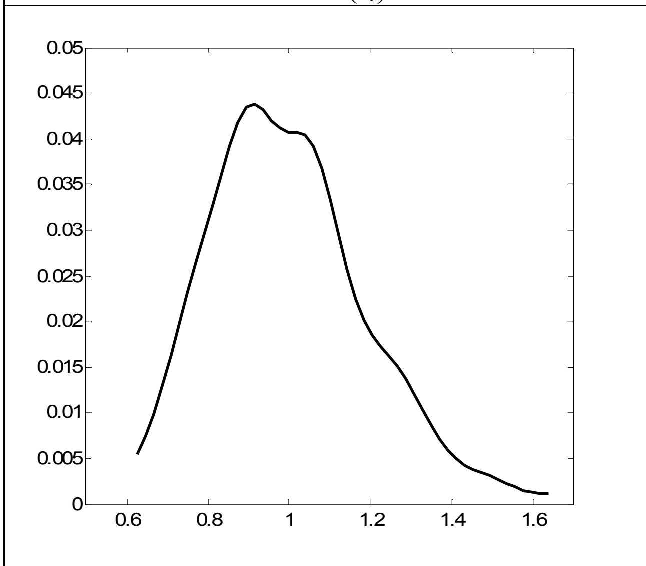
Figure A3.1.2 Convergence Dynamics (dating based on Baxter-King filtered data)
Peak 1988:Q4 – Peak 1992:Q3; Peak 1992:Q3 – Peak 1994:Q3; Peak 1994:Q3 – Peak 1998:Q3;
Peak 1998:Q3 – Peak 2000:Q3; Peak 2000:Q3 – Peak 2004:Q3; Peak 2004:Q3 – Peak 2007:Q3

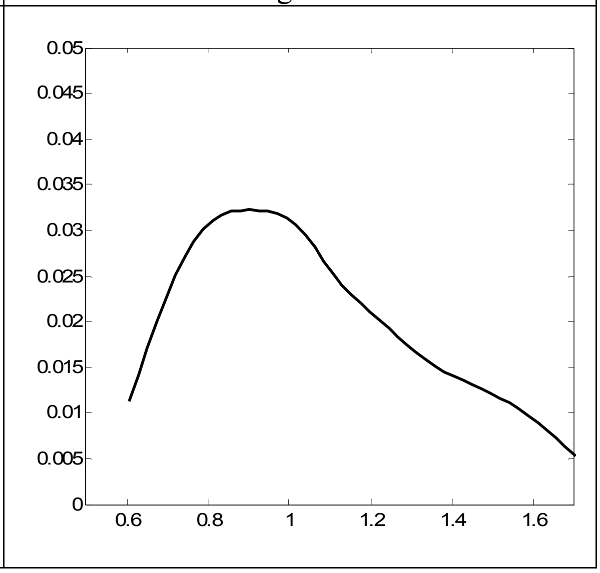
stochastic kernel





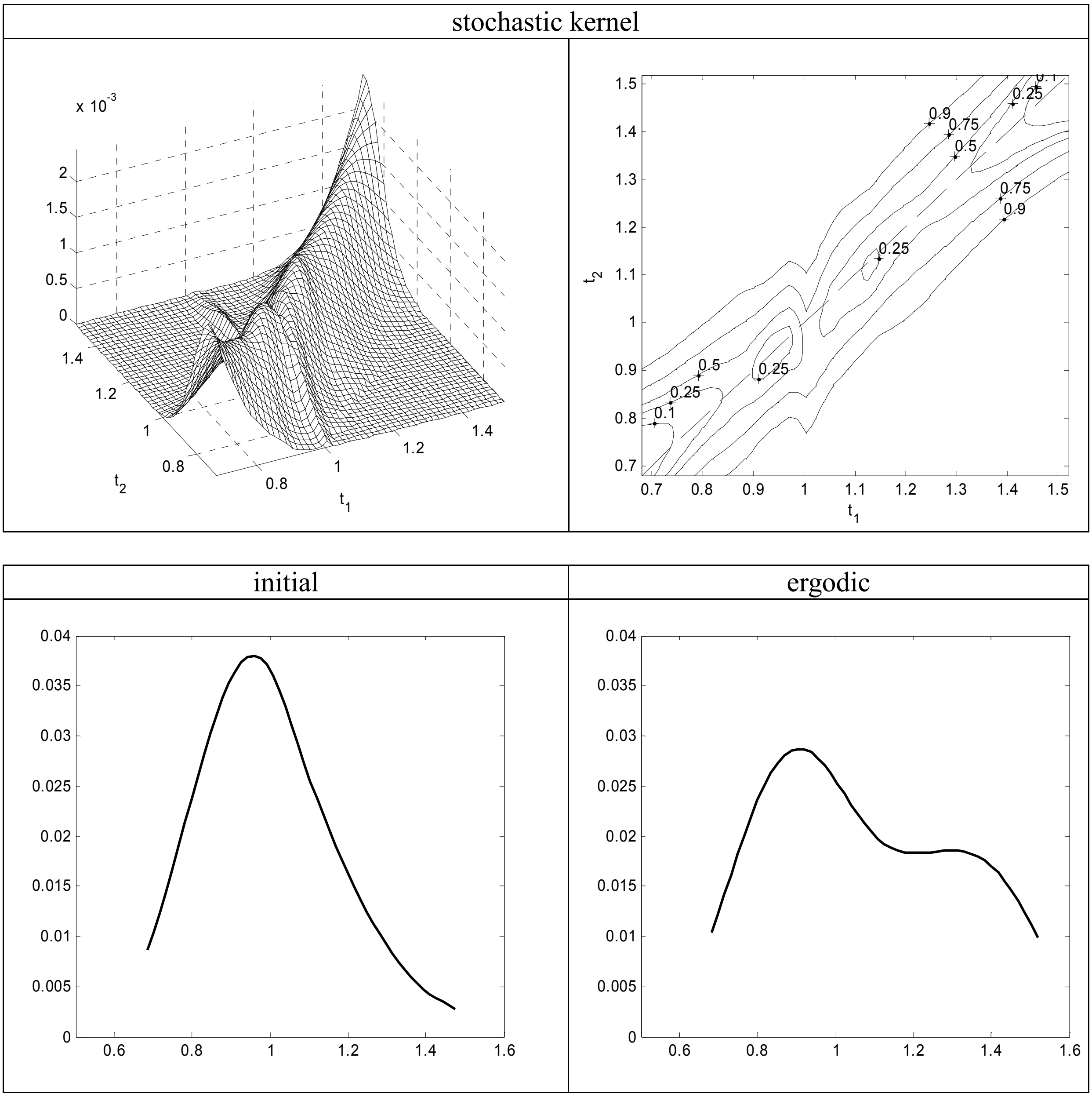
initial (t_1) | ergodic





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 A3.1.3 Convergence Dynamics (NBER dating)
Peak 1990:Q3 – Peak 2007:Q4

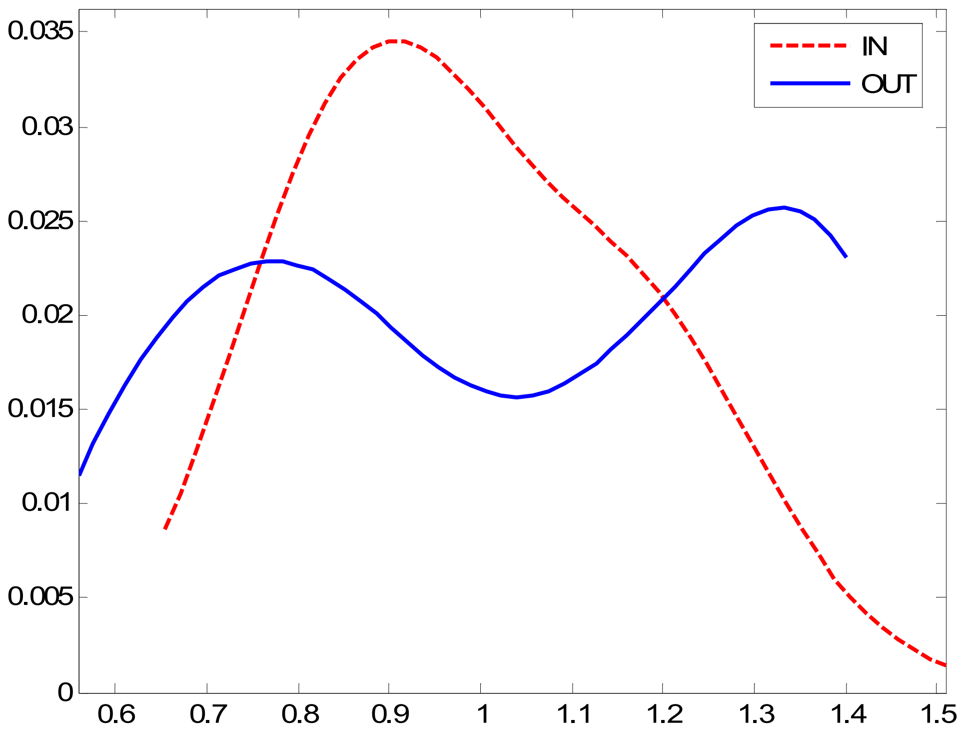


Notes: Estimates are obtained using Normal Scale bandwidths (Silverman, 1986) and a Gaussian kernel. A local linear estimate of the mean function is employed for the mean bias adjustment (Hyndman *et al*., 1996). In the plots, t_1 refers to the initial moment(s) of the transition period(s).

APPENDIX 3.2

Figure A3.2.1 Comparison between Distribution Dynamics (dating based on Baxter-King Filtered data)

IN (peak-to-peak): 1988:Q4–2007:Q3
OUT (trough-to-peak): 1991:Q3–2007:Q3



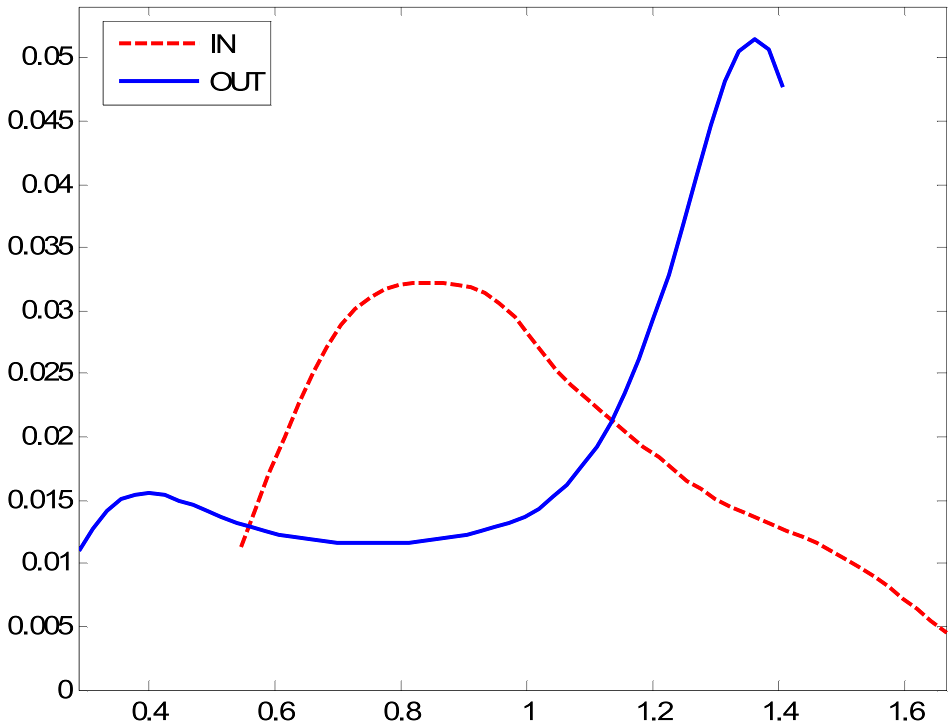
	Standard deviation	Interquartile range
IN (peak-to-peak)	0.1882	0.2964
OUT (trough-to-peak)	0.2517	0.4468

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 A3.2.2 Comparison between Distribution Dynamics (dating based on Baxter-King Filtered data)

IN (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

OUT (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

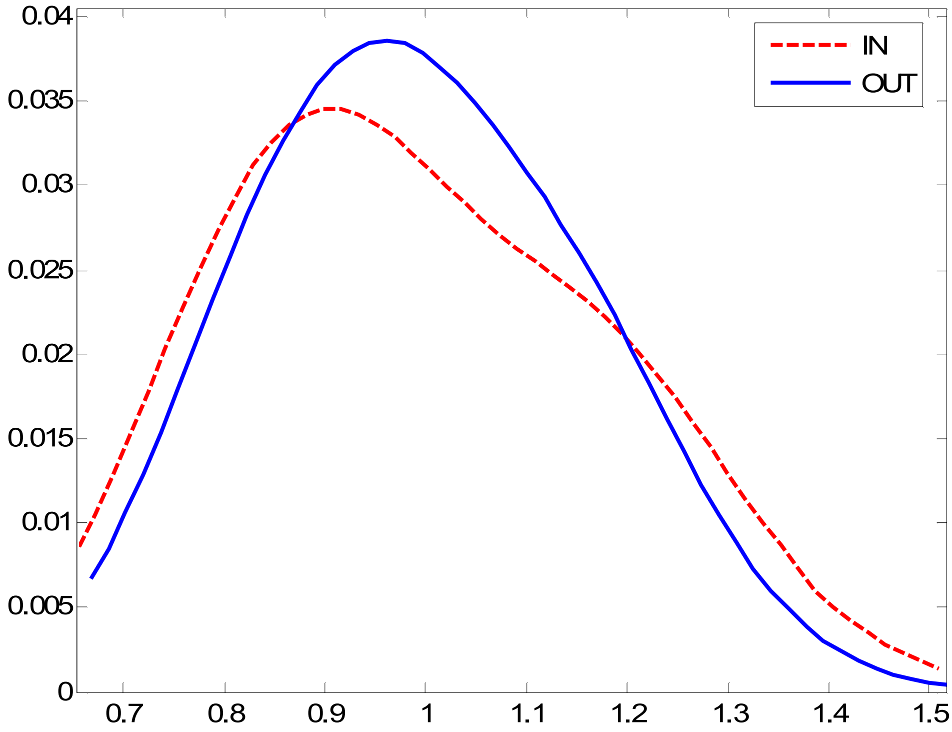


	Standard deviation	Interquartile range
IN (peak-to-peak)	0.2766	0.4112
OUT (trough-to-peak)	0.3494	0.5939

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 A3.2.3 Comparison between Distribution Dynamics (dating based on Baxter-King filtered data)

IN (peak-to-peak): 1988:Q4–2007:Q3
OUT (peak-to-trough): 1988:Q4–2005:Q2



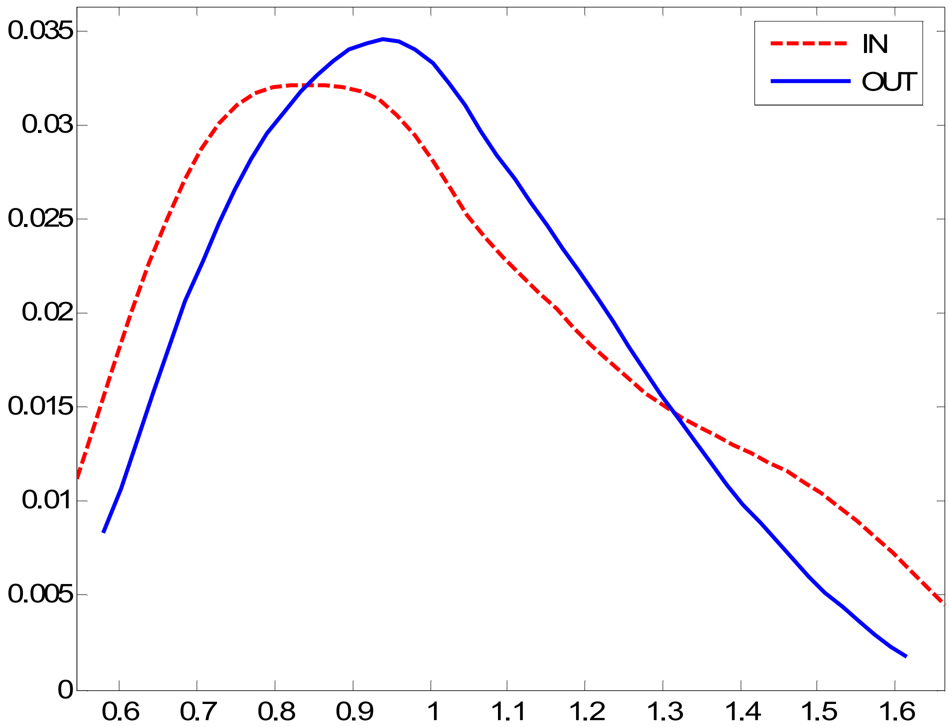
	Standard deviation	Interquartile range
IN (peak-to-peak)	0.1882	0.2964
OUT (peak-to-trough)	0.1661	0.2426

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 A3.2.4 Comparison between Distribution Dynamics (dating based on Baxter-King Filtered data)

IN (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

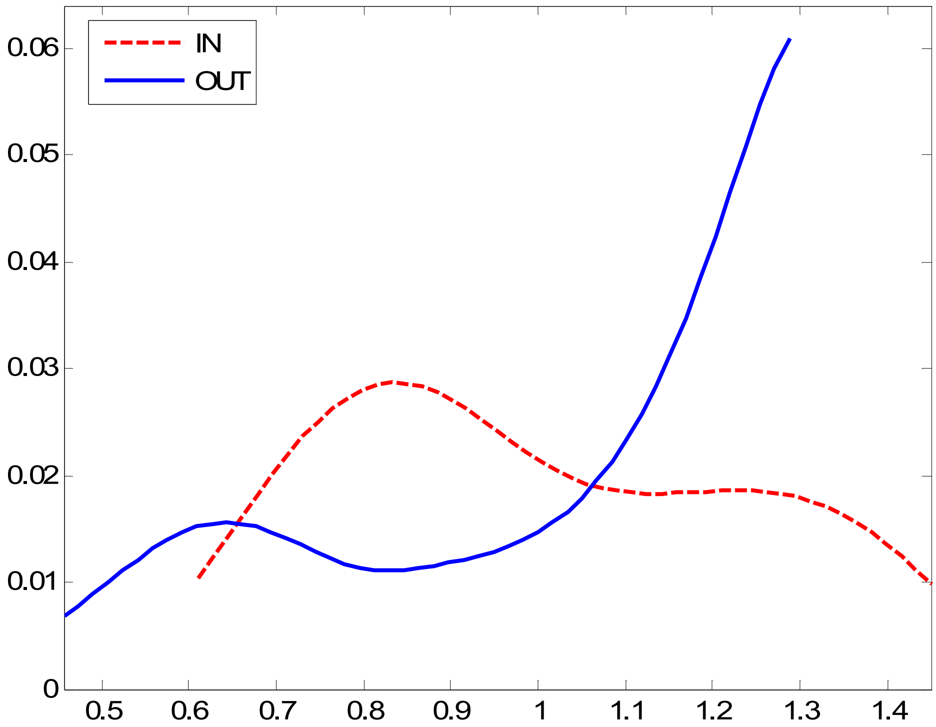
OUT (peak-to-trough): 1988:Q4–1991:Q3; 1992:Q3–1993:Q3; 1994:Q3–1997:Q2; 1998:Q3–1999:Q2; 2000:Q3–2002:Q1; 2004:Q3–2005:Q2



	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).

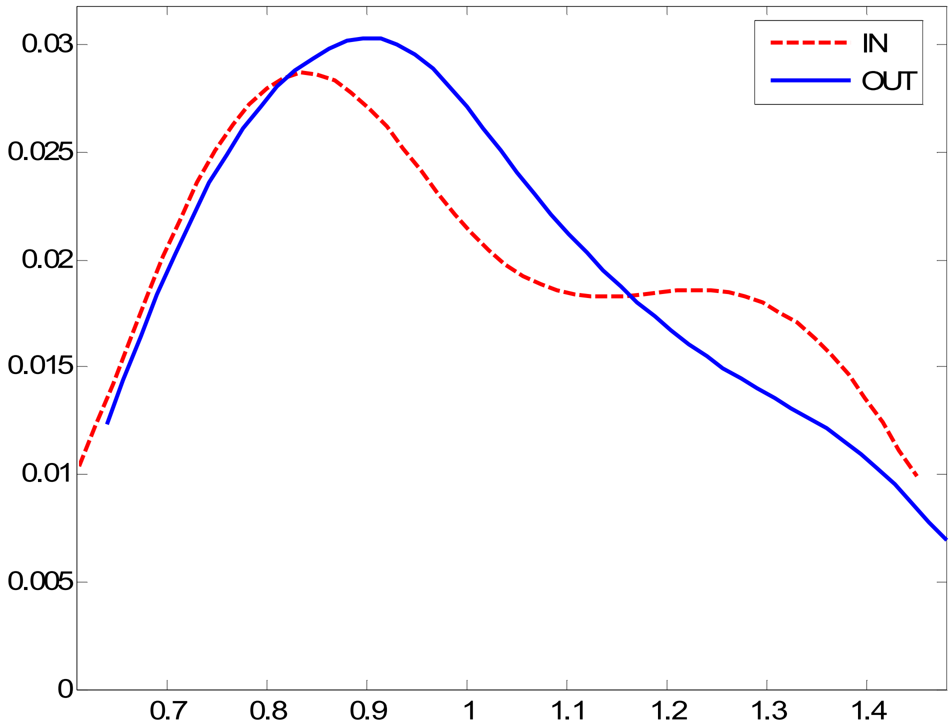
Figure A3.2.5 Comparison between Distribution Dynamics (NBER dating)
IN (peak-to-peak): 1990:Q3–2007:Q4
OUT (trough-to-peak): 1991:Q1–2007:Q4



	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 A3.2.6 Comparison between Distribution Dynamics (NBER dating)
IN (peak-to-peak): 1990:Q3–2007:Q4
OUT (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).

APPENDIX 3.3 Bry Boschan (1971) Quarterly Algorithm

I. On the HP de-trended series, a Spencer moving average is applied in order to obtain the Spencer Curve.[22]

II. HP de-trended series are corrected for outliers. Outliers are the observations which are at least 3.5 standard deviations away from the mean. We replace outliers by their equivalent value on the Spencer Curve. Applying a Spencer moving average on the outlier corrected series creates an outlier-corrected Spencer curve.

III. A 2x4 centered Moving Average (MA) is applied on the outlier-corrected data to obtain the "first cycle" curve. 2x4 centered moving average means that a 4-term centered moving average is applied on a 2-term centered moving average cycle.

IV. A first set of turning points is searched within the first cycle curve and then these turning points have been used to look for the corresponding turning points on the Spencer Curve. The local minima/maxima have been searched in every 5 quarters. Therefore, the window length is 5 quarters.

V. A minimum cycle length restriction is imposed so that any cycle from peak (trough) to peak (trough) has at least a duration of 5 quarters. It is checked whether the peaks and troughs orderly alternate, i.e. peak-trough-peak, and the alternation is imposed if necessary.

VI. The Months for Cyclical Dominance (MCD), “the minimum month-delay for which the average of absolute deviations of growth in Spencer cycle is larger than that in the irregular component” is computed. After that, a moving average of length MCD is applied on the previously outlier-corrected series. A new set of turning points is searched on the basis of the complementary turning points that were found on the Spencer curve. Again, a minimum cycle length restriction is imposed (5 quarters) and orderly alternation of the turning points is imposed.

VII. This last set of turning points is cleaned by discarding the points corresponding to the first and last two observations. A minimum phase length restriction of 2 quarters is imposed. Thus, the final set of turning points is obtained.

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[22] The details of the algorithm are obtained from manual of BUSY 4.1 software.

Estratto per riassunto della tesi di dottorato

Studente: Hasan Engin Duran
Matricola: 955291
Dottorato: Economia
Ciclo: 22

Titolo della tesi : *Short-run dynamics of income disparities and cycle synchronization across regions*

Abstract:

Since the 1990s, the issue of regional income convergence and its long term tendencies has been thoroughly and heatedly discussed. Far less attention, however, has been devoted to the short-run dynamics of regional convergence. The present thesis is devoted to explicitly studying the short-run dynamics of regional income disparities; in particular to the interconnections between regional income inequalities and the aggregate business cycle as well as to the interactions among disaggregate and aggregate economic fluctuations in the US. In the first chapter, we characterize the short-run behavior of income inequalities across states and investigate the mechanisms behind such behavior. In Chapter 2, we investigate whether and why some economies might be systematically ahead of others along the swings of the business cycle. Chapter 3 aims at evaluating the distortion introduced in the cross-sectional analysis of economic convergence when the period under study contains incomplete business cycles.

Estratto:

Dal 1990, il tema della convergenza del reddito regionale e le sue tendenze di lungo termine è stato notevolmente approfondito e discusso. Minore attenzione, tuttavia, è stata dedicata alla dinamiche di breve periodo delle convergenze regionali. La presente tesi analizza esplicitamente le dinamiche delle disparità regionali di reddito di breve periodo; in particolare, le interconnessioni tra le disuguaglianze di reddito regionale e il ciclo economico aggregato, nonché le interazioni tra le fluttuazioni economiche negli Stati Uniti sia a livello disaggregato e aggregato. Nel primo capitolo, si caratterizza il comportamento delle disparità di reddito nel breve periodo degli stati e si studiano i meccanismi dietro tale comportamento. Nel capitolo 2, vengono indagate le ragioni per cui alcune economie sistematicamente guidano le oscillazioni dei cicli economoci ed altre le seguono con dei ritardi. Il capitolo 3 è dedicato esplicitamente alle distorsioni che possono sorgere nell'analisi cross-section della convergenza quando il periodo di analisi include cicli aggregati incompleti.