

CONVERGENCE ACROSS THE U.S. STATES BETWEEN 1987 AND 2013

By

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ABSTRACT

This study aims to answer the question, whether recent convergence trends between 1987 and 2013 can be identified in the U.S., and whether these trends yield any implications for long run policy targets. The thesis reviews the relevant literature, introducing important concepts of convergence in order to place the study in context. Subsequently, the build-up of the analytical framework is presented in detail. The empirical analysis presents the results, identifying threats of polarization, leading to a core-periphery structure on the long run. The results suggest that non-coastal states are experiencing a slow process of desertification, with signs of full agglomeration in coastal states. In other words, economic activity and population is slowly relocating to the coastal areas. With the help of New Economic Geography theories, the thesis identifies important policy targets in order to slow these trends down, or even reverse them in the future. Concluding the study, several policy recommendations are presented in order to formulate a long run strategy, which could mitigate the threats of polarization.

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1. Introduction

Convergence studies are rarely used as the backbone for active policy planning. Instead, they are applied to formulate and validate various growth and convergence theories, and to explain historical events or identify trends in growth patterns across economies. Many researchers are often engulfed in the continuous debate over the perfect methodology which can define convergence in theory and is also able to capture it across real life economies. While finding the best model for measuring convergence is truly important, only a small part of the abundant literature apply convergence theories for policy assessment and even less to shed light to areas for policy targeting and planning.

A larger part of the literature, often using these theories on data sets spanning fifty, eighty or even several hundreds of years, focuses on the perennial question whether inequality is decreasing across economies of the World. This question is of utmost importance indeed, but these theories can also be applied to study more recent, shorter periods, from which plausible trends can be derived about growth behavior. Such trends can identify key opportunities or threats, which could provide sound foundation for long run policy targets. Of course, such an analysis require high quality data, which often proves to be the most hard to get ingredient, with only a few exceptions. This thesis is an attempt to answer the question, whether recent growth trends in the U.S. can pinpoint areas of interest for policy makers.

1.1. Thesis Statement

This thesis provides an analysis of convergence of per capita output across the U.S. states between 1987 and 2013, and reveals the long run threats of polarization among coastal and non-coastal states.

The analysis extends not only to the period of 1987-2013, but also to three sub-periods, in order to study convergence dynamics – that is, how the rate of convergence changed within the covered twenty-seven years. In particular, my study identifies the rate at which poorer states tended to catch up with richer ones, and also derives trends that are reasonably expected to continue in the future. This paper argues that identified trends of separation across groups of states should be recognized as a threat to cohesion, and be among the governing factors for long run policy planning.

1.2. Methodology

In order to determine the rate of convergence and study its dynamics, two well-known methods are applied in the thesis. One is the well-debated neoclassical approach, identifying β -convergence through cross-sectional regressions; and the other is the more commonly endorsed dispersion approach, identifying σ -convergence. Both methods are applied to the whole period in focus, and its sub-periods as well to study convergence dynamics. This thesis incorporates different concepts of convergence into an analytical framework, explained in detail in the third chapter.

1.3. Contribution to the field

While one can find both regional and country level studies in the abundant literature, the absence of work on more recent periods provides gaps to be filled. Barro, Sala-i-Martin, Blanchard and Hall (1991) and Sala-i-Martin (1996) studied state level convergence of per capita output across the U.S. until 1988 and 1992 respectively.¹ More recent work on U.S.

¹The authors have extended their previous work in (Barro & Sala-i-Martin, Economic Growth, 2004), measuring convergence across U.S. states until 2000, however, they study only income per capita convergence, and not state level output.

convergence considered county level data with no aggregation at the state level. Thus the U.S. between 1987 and 2013 was not studied at the state level before.

Another aspect of contribution, is studying U.S. state level convergence during the crisis of 2007-09, and see how the two different methods capture this far-reaching economic shock. The use of high quality, recent datasets (e.g. data constructed in 2012) might also be considered yet another type of contribution.

Finally, this research relates convergence analysis to policy planning by evaluating growth patterns from a policy perspective.

1.4. Structure of the thesis

The thesis is structured so that it provides an easy and logical read. Following the Introduction, the second chapter introduces different concepts of convergence that will be used later, while reviews the relevant literature for the models applied in the thesis. Subsequently, the third chapter reiterates previously defined concepts, molding them into models, and also explains the scope and quality of data in detail. The fourth chapter presents the Empirical Analysis with its main results, and also identifies policy targets. The final chapter concludes all findings and formulates final policy implications.

2. Concepts of Convergence and Relevant Literature

This chapter introduces the concepts of β -convergence and σ -convergence, which provide the basis for the analysis, and reviews the most important literature for those concepts. Convergence studies have a vast literature with several hundreds of papers, thus any selected set of papers can easily be reflecting an ad-hoc and/or partial choice by the author. In order to overcome this key issue, an authoritative survey on growth econometrics is used for guidance in the selection. Durlauf, Johnson and Temple (2004) conducted this exhaustive survey and synthesis, where they presented and critically analyzed well above 300 relevant papers in the field. The review follows their logic but in my presents my own evaluation, highlighting important aspects for the analysis in this thesis.

An important goal of this review is to give the reader a feel of the dynamics of the debate in the field of convergence studies. Moreover, this chapter establish a firm foundation for the different concepts and methods that the thesis builds upon. This review is structured around analytical frameworks, while efforts are also taken to keep a chronological order as well. With different concepts of convergence introduced in this chapter, it is vital to make the review easier to follow. These essential concepts are introduced in a gradual fashion, timed to appear along their corresponding literature. In order to highlight and keep track of the concepts, they are introduced in boxes, separated from the main body of text.

Convergence studies root back to the neoclassical growth theory by Ramsey in 1928 and later by Solow (1956). The most relevant parts of the Solow model – its elements used for

convergence studies – are presented here without sketching up the entire model itself.² One of the key assumptions of the neoclassical growth model is that capital is subject to diminishing returns. The model predicts that through capital accumulation, an economy will converge to its steady state. Steady state is defined by $sk(t)^\alpha = (n + g + \delta) * k(t)$. Where $sk(t)$ is the fraction of output per unit of effective labor that is saved and invested, and $(n + g + \delta) * k(t)$ is the amount of investment that is required to keep the economy at the steady state level in each period t . δ is the depreciation rate, n is the rate of population growth, g is the rate of technology growth, t denotes time, s is the savings rate, k is capital per effective unit of labor and α is the elasticity of output w.r.t. capital. The Solow model predicts that an economy will converge to its own steady state level of output – defined by n , g and δ – at a diminishing rate. In other words, the closer an economy is to the steady state level, the slower its growth will be.

BOX 1: Concept of β -convergence

Considering the Solow model, if two economies have the same steady state, and capital accumulation is subject to diminishing returns, the poorer economy will converge to that steady state at a faster rate than the richer one in a given period. By default, this means that the economies will converge to each other as well, with the poorer economy catching up to the richer one. This attribute enables to study convergence based on the neoclassical growth model with cross-sectional OLS regressions. In the regression, growth rate of output is regressed on the initial level of output, with β being the coefficient of the latter; hence the name: β -Convergence.

Box 1 – Concept of β -convergence

² All the important derivations can be found in Solow (1956) for the base-; and in Mankiw, Romer and Weil (1992) for the augmented model. The most important equations, however, are presented in the third chapter of the thesis.

Baumol (1986) examined convergence of productivity across 72 countries through 110 years. With no primary data collection, he used Maddison's data,³ covering the period 1870-1979 and used Solow's neoclassical growth model as a basic framework for his regressions. Potential issues could have arisen for Maddison's data since for the early years, it was estimated by reverse extrapolation, which could have caused spurious regression when checking for convergence. Baumol argued that this problem dissolved, since when looking at the scatterplot of the 72 countries' growth rates in the analyzed period, it showed an almost zero R^2 , which means that the data was not showing signs of convergence across all countries. However, he found high rates of convergence within separate groups of countries. Baumol introduced the "convergence club" notation, referring to his finding, showing that convergence is present across the industrialized market economies and across some central planned command-economies (each group converging to their own "club") but not across developing countries.

BOX 2: Concept of Convergence Clubs

According to the Convergence Club hypothesis, certain groups of regions or economies which are similar in a way, will converge to a similar steady state value. This assumes that convergence can be identified within groups of similar economies, but is not necessarily present across economies of different groups.

Box 2 – Concept of Convergence Clubs

Barro and Sala-i-Martin (1990)⁴ presented a similar, Solow model based convergence analysis, estimating β -convergence. The authors extensively analyzed state level convergence in the U.S. They investigated whether poorer states tended to catch up to richer ones, and introduced

³ Data estimated by Angus Maddison, in (Maddison, 1983).

⁴ (Barro & Sala-i-Martin, 1990) is the working paper version of (Barro, Sala-i-Martin, Blanchard, & Hall, 1991), it is included separately due to the fact that it spurred vehement criticism, which was addressed in their final paper in 1991.

another important concept of convergence, σ -convergence. They demonstrated clear evidence of β -convergence across U.S. states, in both personal income per capita (2.2% average annual rate of convergence in the period 1880-1988), and state level output per capita (2.1% average annual rate of convergence between 1963 and 1986). In their preliminary tests for other countries and regions – with various periods for each set of economies – they found very similar rates of β -convergence across all datasets: about 2% of average annual convergence.

BOX 3: Concept of σ -convergence

σ -convergence can be identified if the dispersion of the standard deviation of output across economies is decreasing through time. There are no possible theoretical errors in this approach, since it is more of an observatory study. Hence, leaving little room for debate, this is the most widely accepted method of measuring convergence.

Box 3 – Concept of σ -convergence

In (Barro & Sala-i-Martin (1990)), the authors also tried to establish a deterministic relationship between β -convergence and σ -convergence, arguing that the first necessarily implies the second. While the relationship seems easy to accept at first,⁵ it was heavily criticized. Among others, Quah (1990) and Quah (1993)⁶ presented a theoretical criticism towards neoclassical model based convergence studies. In both works, Quah argued that cross-section regressions used to analyze average growth rate dynamics are inherently inappropriate. He further argued that these regressions are exposed to Galton's fallacy,⁷ and catch and interpret the natural

⁵ This is discussed in detail in the third chapter of the thesis.

⁶ Quah (1990) is the working paper version of Quah (1993), it is included separately due to the fact that Barro and Sala-i-Martin reflected to this working paper in 1991.

⁷ Galton's Fallacy refers to the findings and eventually wrong conclusions of Sir Francis Galton in the 19th century. Galton found that fathers with extreme heights (compared to the mean height) tend to have sons with heights closer to the mean (mean height of the population). He concluded that this phenomenon will ultimately lead to heights of people getting closer to the mean value, thus "regressing to the mean", reaching a point when everybody will have the same heights. The conclusions of Galton are known to be incorrect, since closer to average height people can have children with more extreme heights. On the long run, ratios of people with different heights

phenomenon of regression towards the mean as convergence. Thus stating that β -convergence would imply σ -convergence is a conceptual error, and the two types of convergence have no relationship. He claimed that more direct empirics – introducing a distributional approach – uncover a tendency for divergence of per capita income levels across countries. Quah concluded that countries are becoming either very rich or very poor on the long run, with the middle income group ultimately vanishing. It has to be noted though, that Quah's analysis was volatile even to the smallest changes in model specification and yielded ambiguous results across different datasets.

Barro, Sala-I-Martin, Blanchard and Hall (1991) extended their analysis of convergence using their previously established framework, and also made a detour to reflect to Quah's criticism. In this paper they applied their convergence models to compare Africa, South Asia, and Latin America to developed countries. They also improved their analysis on the U.S. by taking net migration into account, and constructed several regional classifications and a by-sector approach as well. The paper again, found strong evidence for convergence across all datasets. They extended the scope of their analysis to 73 western European regions, which yielded similar results, identifying a 2% annual convergence rate in economic growth. However, these results show up only when checking for conditional β -convergence – that is, controlling for the steady-state. The authors also took note of the threat of Galton's fallacy, raised in Quah (1990), and also agreed that a relationship between the two concepts of convergence should not be established. However, they argued that on one hand, if the problem of Galton's fallacy is real, the rate at which countries converge to the "mean" is still of great interest; on the other hand the big threat of this fallacy – with regression towards the mean – is possible overestimation of convergence rates, but it's not existent in a model with first differentials and linear log-

are reproducing themselves to some extent in the population. Thus it may seem that heights are converging to the mean but in reality this is not true when the whole population is considered over a long period.

differenced variables. Due to this final argument it makes perfect sense to use unconditional β -convergence estimates to measure convergence, and to use conditional estimates to see theoretical convergence.

A similar research was presented in Mankiw, Romer and Weil (1992), with an augmented, Solow based model on per capita real income across 3 groups of countries. The authors introduced an augmented Solow model with human capital accumulation (proxy for human capital being the percentage of secondary school students among the working-age population), which they found to result in a model with better explanatory power ($R^2 = 80\%$) for the variation of income per capita in cross-country data. Their empirical study confirmed the Solow model's prediction for the influence of physical (and human-) capital accumulation and population growth. They also found evidence on the model's implications about convergence if population growth (n) and capital accumulation is held constant. The authors controlled for these two variables, and assumed technology growth (g) to be constant in order to control for the steady state. Their model predicted that initially poorer countries should tend to have a higher rate of returns to both human- and physical capitals, compared to an initially richer country, if controlled for the steady state.

BOX 4: Concepts of conditional and unconditional (absolute) β -Convergence

Unconditional β -Convergence is estimated by regressing growth rates on initial levels of output or per capita income, with the assumption that economies are same in their long run steady states. Conditional β -Convergence is similar to the unconditional one, but when estimated, the model includes control variables that aim to rule out the differences in the steady state. This way convergence can be estimated, as if the steady state would be the same across economies (since it is controlled for). While these control variables vary a lot in the literature, common choices usually include population growth, savings rate, and various proxies for human capital and technology growth (steady state determinants in the Solow model).

Box 4 – Concepts of conditional and unconditional β -convergence

Sala-i-Martin (1996) further argued that the two types of convergence are very useful for drawing conclusions about the behavior of growth of an economy, and extended his earlier study to Japanese regions and regions of five European nations. He again, found similar results of roughly 2% annual convergence across the new data, and identified σ -convergence in the decreasing interregional dispersion of income per capita. He further explained his findings with increasing technology diffusion and capital mobility.

Among other critics and model variations to the neoclassical approach, I find Bernard and Durlauf (1996) particularly interesting. First they focused on the framework, with which the convergence hypothesis was tested by Barro et al. (1991). The authors provide two definitions of convergence: as “catching up” with decreasing output per capita across countries; and “convergence as equality of long-term forecasts at a fixed time”. They introduced the neoclassical model, relating output in the base period to output growth in the coming periods, and compared this convergence model to another one, with a time series approach. They found

that the two different approaches were based on different assumptions about convergence and properties of the countries, with the cross-sectional test being less restrictive on the behavior of growth; and the time series approach requiring countries under study to have very similar long-run equilibria. They concluded that the two methods can lead to very different results and that the best choice for a framework to test convergence is highly dependent on the type of data available and the hypotheses under study. They envisioned a more general method superior to both, encompassing transition in the neoclassic model and integrating steady state data in the time series.

Obviously, this review did not cover all potential methods for studying convergence, but reviewed the most important and basic papers relevant for β -convergence and σ -convergence. It has to be noted that there are several instances when authors apply the same model to estimate β -convergence for the same economies and periods but with different controls for the steady state and often find different results. Different results often appeared when economists diverge from the mainstream proxies, identified in the Solow model. In general, while the neoclassical based model is the most debated approach, it is the most applied model as well. The convergence concepts introduced in this chapter will be crucial throughout the whole thesis, as my analysis is based on these.

3. Methodologies and Data

The empirical analysis aims to present and apply two different methodologies derived from the literature, and show how these interpret and measure convergence and what conclusions they yield for the U.S. states. More importantly, I'm interested whether those conclusions can be related to historical events, or periods of interest. This chapter presents each framework separately, with their application to the U.S. states. The applied models are 1) the well-debated cross-sectional approach based on the neoclassical growth theories with an augmented model including human capital, estimating unconditional- and conditional β -convergence; and 2) the analysis of dispersion⁸ of state level log GDP per capita, identifying σ -convergence.

Both models are applied to the U.S. states in the period 1987 – 2013. The choice for this period is driven by three factors. One is that high quality, granular data is available at the state level starting from 1987; second, it should be interesting to see if, and how the crisis of 2007-09 affected convergence of the states; and third, convergence of the U.S. states have not been analyzed⁹ in this period with a focus on convergence dynamics and assumptions stemming from it.

⁸ Following Barro et al. (1991) and Sala-i-Martin (1996), dispersion is measured as the cross-sectional dispersion of the standard deviation of state level log output per capita.

⁹ This period was not studied at the state level before. The early years were included in Barro et al. (1991) and Sala-i-Martin (1996), but more recent years (starting from 1991) have not been analyzed at the state level.

3.1. Applied Methodologies

3.1.1. Estimating β -Convergence with Cross-Sectional Data

As noted in the literature review, the Solow model has very important implications which provide the basis for convergence studies. In the basic model, output in period t is assumed to be given by a Cobb-Douglas production function in the form of:

$$(1) \quad Y(t) = K(t)^\alpha (A(t)L(t))^{1-\alpha} \quad 0 < \alpha < 1.$$

Equation (1) – Production Function in the Basic Solow Model

Where t denotes the given time period, Y is the output, K is capital, A is the level of technology (or TFP), L is labor, and α is the output elasticity w.r.t. capital, and $(1 - \alpha)$ is the output elasticity w.r.t. effective labor. Since both capital and labor are paid their marginal products, and the production function has constant returns to scale, α and $(1 - \alpha)$ represent capital's and labor's share of the output. By assumption, labor and the level of technology grow at the rate of n and g respectively, so that unit of effective labor grows at a rate of $n + g$. The model also assumes full employment, thus n represents population growth.

The model predicts that an economy will converge to its steady state level of output through accumulation of k , the stock of capital per effective unit of labor (calculated as K/LA). Accumulation of k is driven by the rate of savings s (which is a constant fraction of output being reinvested); n , the growth rate of population (growth of labor); g , the growth rate of technology (TFP); and δ , the depreciation rate (the fraction of capital that needs to be replaced in each period). Capital accumulation will grow with diminishing returns until the steady state level of k , k^* is reached. The steady state marks the maximum output w.r.t. its determinants. k^* is defined as:

$$(2) \quad k^* = (s/(n + g + \delta))^{1/(1-\alpha)}$$

Equation (2) – Determinants of the Steady State in the Basic Solow Model

In the Solow model, s is constant and n and g are exogenous, and capital accumulation is subject of diminishing returns. As previously shown,¹⁰ the Solow model predicts that – given their steady states are the same – poorer economies will grow at a faster rate than richer economies. This is the attribute of the model that can be utilized in order to analyze convergence between economies. In this thesis both unconditional and conditional estimates are presented.

3.1.1.1. *Unconditional β -convergence*

Neoclassical convergence studies capitalize on the Solow model and try to estimate convergence as the β coefficient in a simplified OLS regression, in the following form:

$$(3) \quad (1/T) * (\log Y_{i,t+T} - \log Y_{i,t}) = \alpha + \beta * (\log Y_{i,t}) + \varepsilon_{i,t}$$

Equation (3) – Cross-Sectional Regression for Estimating Unconditional Convergence

Where T is the length of the period in years, t is the base year of the period, i is index for economies (countries, regions or states), $Y_{i,t+T}$ is per capita output at the end of period, $Y_{i,t}$ is per capita output in the base year of the period, $\varepsilon_{i,t}$ is the error term, α is the constant and the rate of convergence is β . Rate of average annual convergence is identified in this model as the value of β , if it has a negative sign (with positive sign it would show the rate of divergence).

This equation in its current form can shed light to plausible convergence rates if, and only if the economies in question have the same steady state. This means that economies should have the same values for n , g , δ and s , which is highly unlikely in reality. The U.S. states might be

¹⁰ See the literature review, Box 1 – Concept of β -convergence.

an exception though, due to their high level of “economic proximity”. The U.S. states are exposed to the same monetary environment, behaving similar in many aspects and their economic activities are measured by the same standards and same methodologies, providing the best subjects for estimating convergence rates with an equation in the form of (3). The analysis is done for the whole period of 1987 – 2013 pooled, and also for smaller periods where the initial period is divided into three sub-periods: 1987 – 1996; 1997 – 2006; and 2007 – 2013. This partitioning is done in order to see the change of dynamics of convergence – if there is any; that is, letting the slope of the fitted linear approximation change within the base period. This is done with particular interest in the last sub-period, covering the years of the crisis.

3.1.1.2. *Conditional β -convergence*

Since all economies do not have the same steady state in reality, many economists dwelling on convergence studies use an extended version of (3), estimating conditional β -convergence and trying to find the best proxies in order to control for the steady state. Conditional β -convergence is approximated by the following equation in this analysis:

$$(4) \quad (1/T) * (\log Y_{i,t+T} - \log Y_{i,t}) = \alpha + \beta * (\log Y_{i,t}) + \Psi(X_{i,t}) + \varepsilon_{i,t}$$

Equation (4) – Cross-Sectional Regression for Estimating Conditional Convergence

Where T is the length of the period in years, t is the base year of the period, i is index for economies (states), $Y_{i,t+T}$ is per capita output at the end of period, $Y_{i,t}$ is per capita output in the base year of the period, $X_{i,t}$ is a vector of all the control variables, $\varepsilon_{i,t}$ is the error term, α is the constant, Ψ is the coefficient of the vector for all controls and β is the rate of convergence. Average annual rate of conditional convergence is identified under this model as the value of β , if it has a negative sign (with positive sign it would show the rate of divergence).

For estimating conditional β -convergence I used an augmented Solow model, based on the work of Mankiw, Romer and Weil (1992). This augmented model also accounts for human capital, resulting in an augmented production function:

$$(5) \quad Y(t) = K(t)^\alpha H(t)^\beta (A(t)L(t))^{1-\alpha-\beta} \quad \alpha + \beta < 1$$

Equation (5) – Production Function in the Augmented Solow Model

The equation is similar to (1), with the addition of H as human capital, and β as the output elasticity w.r.t. human capital. Notable is the assumption that $\alpha + \beta < 1$, which means that there are decreasing returns to all capital, otherwise there would be no steady state as the model would become an endogenous growth model (contrary to Solow's exogenous growth model, used as the basis of this analysis).

In Mankiw, Romer and Weil (1992), the authors used the share of working age population who are in secondary school, as a proxy for human-capital accumulation. Klenow and Rodríguez-Clare (1997) effectively argued against this variable and also showed an improved measure for human capital. Their main criticism was that the variation of this measure is too high across distant countries and thus it will account for too much of the variation of per capita output, overestimating the explanatory power for human capital. They supplemented this measure with primary school enrollment rates and also accounted for tertiary education. This improved the proxy, which showed much lower explanatory power for human-capital accumulation in the same model.¹¹ However, in the case of the U.S. states, secondary enrollment rates supplemented with primary enrollment rates constitutes no explanatory power for human capital, since there is almost no variation in this measure across U.S. states. All regressions were ran with and without including this measure and its coefficient showed no statistical

¹¹ More accurate and complex measurements for human capital are presented in the growth literature, as reviewed in Kubik (2010). According to Kubik, a Mincerian approach might be the most attractive choice to create a proxy for human capital. However, state level data is not available for such a calculation.

significance, nor did its inclusion increase the explanatory power of any of the models, or change any other coefficients significantly. Thus in my analyses, only tertiary education data was used as a proxy for human-capital.

Controlling for the steady-state is the most debated part in the literature for neoclassical convergence studies, with countless ideas for alternatives for proxies. In order to control for the steady state, one must control for its determinants. These are – as explained earlier – population growth (n), technology growth (g), the depreciation rate (δ), the savings rate (s) and human-capital accumulation in the augmented model. In order for this study to capture convergence, I find controlling for unemployment also crucial, as the Solow model assumes full employment (supply of labor grows at the same rate as population) – controlling for differences in employment should ensure that this assumption holds.

3.1.2. Estimating Convergence with the Dispersion of Variance

σ -convergence is measured by the cross-sectional dispersion of income per capita or GDP per capita. In this thesis, dispersion is measured as the standard deviation of log per capita GDP. If there is a decline in dispersion over time, we can say that states are converging in terms of σ .

The concept of σ -convergence is best understood if introduced with the apparent relationship it has with β -convergence. The relationship is easy to understand at first: if the output of two regions converge to the same steady state, the dispersion of their output should decrease over time as well – since they are “getting closer” to each other in every year. This seems plausible, since countries are assumed to follow a growth path with diminishing returns, thus dispersion of variance should truly decrease through time. However, Quah (1993) argues that such a relationship should be handled with care, since misleading conclusions can be drawn just like in the case of Galton’s Fallacy. As in Galton’s case, taller fathers having closer to average

height sons show regression towards the mean, which may imply that the height of the people is regressing towards the mean; but height ratios within the population are more or less sustained by closer to average height fathers having taller than average sons. A similar analogue applies for the relationship of β and σ : the fact that economies β -converge to a steady state does not necessarily mean that variance in output is also decreasing. Barro et al. (1991)¹² and Sala-i-Martin (1996) takes note of this regression fallacy and goes with separate, non-related interpretations for the two types of convergences, noting that convergence in terms of β is necessary but not sufficient for σ -convergence. They argue that σ -convergence is still of great interest among researchers, since the insight it can give, can be very useful for policy assessment. An event study approach on the time evolution of dispersion of output might also be of great interest, considering the question of how and for what reason did the cross-sectional standard deviation of per capita log GDP across the all states change over time.

In my analysis of σ -convergence, I look at the coefficient of cross-sectional variation of state level log GDP per capita in order to see whether there is σ -convergence. σ -convergence is identified if the dispersion is decreasing over time and divergence in terms of σ is identified if the dispersion increases.

3.2. Description of Data

3.2.1. Data used for Cross-Sectional Estimates

For the neoclassical approach I used four data sets, differing in the period they cover: the main period of 1987-2013, and three sub-period: 1987-1996; 1997-2006; and 2007-2013. Data is collected for all 50 states of the U.S. The District of Columbia is considered and reported

¹² Barro et al. are reflecting to Quah's unpublished paper Quah (1990) in 1991, which was published only later in 1993 (Quah, 1993)

among the states by many databases, however it is not a state, but a federal district for the capital city. Thus from a data point of view D.C. was treated as an outlier and was omitted from the observations. This way all data sets contain 50 observation and various variables explained in details in this chapter.

3.2.1.1. *Dependent Variable*

My variable on the LHS was the average annual growth of per capita GDP across states for the given period. I calculated this variable as the difference of log per capita GDP in the last year of the given period and the log per capita GDP of the base year of the given period, divided by the number of years included in the given period:

$$\text{Average Annual Growth} = \frac{\log(\text{per capita GDP}_{\text{end year}}) - \log(\text{per capita GDP}_{\text{base year}})}{\text{number of years in given period}}$$

Equation (6) – Average Annual Growth of output

Source for per capita real GDP data was the U.S. Bureau of Economic Analysis (BEA) Regional Database. There is a serious problem, however, with the data provided by the BEA for this period. There is discontinuity in the state level per capita GDP time series at 1997, mainly because industry definitions changed from the SIC system to the NAICS system, and 1997 was the year of implementation of the NAICS. As reported by BEA, this discontinuity will persist, as overcoming it is an extremely hard and complex task.

Since the discontinuity is in 1997 (1997 having state level GDP estimates reported under both SIC and NAICS classifications) this problem does not affect any of the sub-period estimates. However, it does affect the estimates for the whole period. Under the NAICS system, all GDP estimates are higher when compared to the SIC system due to the method of estimation reported by BEA. This means that for the convergence estimates for the whole period of 1987-2013, all

convergence estimates should be taken as an upper bound estimate. Since when calculating the average growth rate of GDP per capita, I am subtracting a lower GDP estimate (SIC) from a higher GDP estimate (NAICS). With this in mind, all convergence estimates regarding the whole period should be considered an upper bound estimate with no further notice on the discontinuity.

3.2.1.2. *Independent Variables*

My main RHS variable was the log of base year per capita real GDP level in a given period. Per capita real GDP data was collected from the BEA Regional Database and was also used in construction of the LHS.

I had several control variables in the regression for conditional β -convergence, in order to keep the steady state constant across states. In the following part I will list how each determinant of the steady state was handled in my model.

Employment

I find controlling for employment crucial in order to hold employment constant across the states. To control for employment I used the following variable:

$$\text{Employment} = \frac{\text{number of jobs in all industries in a given state in a given year}}{\text{total population in a given state in a given year}}$$

Equation (7) – Employment

Employment data was collected from the BEA Regional Database, where employment is defined as the number of jobs in all industries in a given state in a given year. State level population data was collected from the BEA Regional Database. The motivation behind this

control is to ensure that state level variation in the employment level is ruled out, thus enabling interpreting population growth as growth of supply of labor.

Population growth

Since employment is controlled for, population growth can be viewed as growth of supply of labor. Population growth in a given period was constructed similarly to the LHS variable. I took logs of base year and end year population data for every period and the difference of these gave the population growth for the given period. Dividing this by the number of years in the given period gives the average annual rate of population growth. The variable was constructed in the following way:

$$\text{Population Growth} = \frac{\log(\text{Population}_{\text{end year}}) - \log(\text{Population}_{\text{base year}})}{\text{number of years in given period}}$$

Equation (8) – Population Growth

Source for population data was BEA Regional Database. Note that control for the size of population is not necessary as the dependent variable is measured in per capita.

Technology growth

Controlling for technology growth can be a real challenge as there can be many measures for this variable and there is no consensus in the literature for a good common choice. Most authors, like Mankiw, Romer and Weil (1992) assume that technology growth is constant across economies. Mankiw stated, “Understanding international experience, the best assumption may be that all countries have access to the same pool of knowledge, but differ by the degree to which they take advantage of this knowledge by investing in physical and human capital.” (Mankiw, 1995, p. 301). While one might find it slightly implausible for countries, it

is much easier to accept this assumption for the U.S., especially if we consider the findings of Little and Triest (1996) about technology diffusion across U.S. states. The authors find that technology diffusion is supported by many aspects across states, especially by geographic proximity and the resulting multi-state establishment firms. The authors state, that “Technology use is remarkably evenly distributed in the United States.” (Little & Triest, 1996, p. 217). Agreeing to the presented arguments I take technology growth rate as being constant across U.S. states.

Depreciation rate

The literature widely agrees that there should be no significant differences in the depreciation rate across countries, and even less across U.S. states. Detailed estimates for state level depreciation rates were calculated in Garofalo and Yamarik (2002), and further updated in Yamarik (2013). The data shows that initial assumption in the literature is true, and there is only marginal variation in the state level depreciation rate with a coefficient of variation of 0.02% (relative to the mean of depreciation rates) for 1987, and even less in later years. In my models the updated depreciation rate data was used from Yamarik (2013).

Savings Rate

State level gross private investment data, as calculated in Garofalo and Yamarik (2002) and updated in Yamarik (2013) were used to calculate the savings rate in the following form:

$$\text{Savings Rate} = \frac{\text{Gross Private Investment for given state in given year}}{\text{state level GDP for given year}}$$

Equation (9) – Savings Rate

Human capital accumulation

As explained earlier, I ended up using only tertiary education rates as a proxy for human capital accumulation: share of population 25 years and over with a bachelor's degree or higher. The data was downloaded from the U.S. Census Bureau's Statistical Abstract for Education.

3.2.2. Data Used for the Dispersion Approach

Under this approach, the cross-sectional dispersion of state level log GDP per capita is studied, thus the only data used is the dispersion of the natural logarithm of the GDP per capita in a given state in a given year. Dispersion is defined as in Barro et al. (1991) and Sala-i-Martin (1996), being the standard deviation of cross-sectional state level log GDP per capita. The scope of data extends to 50 U.S. states (D.C. omitted again) through 27 years from 1987 to 2013, resulting in 1 350 observations. Source of data was the BEA Regional Database. As mentioned earlier, there is a problem, with data discontinuity in the year 1997. In my analysis of σ -convergence this is represented by a sudden jump in the dispersion in 1997. Due to this, pre 1997 values should not be compared to those after 1997, however, the discontinuity does not interfere with the analysis of trends of dispersion, and also poses no threat when studying sub-periods.

4. Empirical Analysis

4.1. Estimating Convergence with Cross-Sectional Data

This chapter presents the implementation of the methodologies and data presented earlier.

4.1.1. Unconditional β -convergence

Unconditional β -convergence is estimated with equation (3) for the period 1987-2013 and its noted sub-periods for the U.S. states. The presented results in Table 1 are mixed for the different periods under this model. For the whole period, the unconditional approximation shows a 1.4% rate of annual convergence, significant at the 1% level, with an adjusted R^2 of

TABLE I
Tests for Unconditional Convergence Across U.S. states

Dependent Variable: log difference GDP per capita for given period				
Period	1987-2013	1987-1996	1997-2006	2007-2013
Observations	50	50	50	50
Constant	0,166***	0,328***	0,122*	0,084
Std. Error	0,029	0,054	0,062	0,064
ln(GDP87)	-0,014***	-0,031***		
Std. Error	0,003	0,005		
ln(GDP97)			-0,010*	
Std. Error			0,006	
ln(GDP07)				-0,008
Std. Error				0,006
Adj. R-squared	0,29	0,58	0,05	-0,01
s.e.e.	0,005	0,006	0,006	0,012

Notes: GDP87, GDP97 and GDP07 are GDP per capita in 1987, 1997 and 2007 respectively. For an easier read, asterisks are included: *, ** and *** shows statistical significance at the 10%, 5% and 1% level respectively. Heteroskedasticity-robust standard errors (variant HC1) used.

Table 1 - Tests for Unconditional Convergence Across U.S. States

Source: Author's own regressions

0.29, which can be considered high given the fact that the steady state is not controlled for. The reason for this might be that in reality, U.S. states are in fact, somewhat similar in their steady states, as stated in Barro et al. (1991). The authors reported their finding of 1.7% rate of unconditional β -convergence for the U.S. states for the period 1880-1988, which is similar in magnitude to my estimates. Looking at the sub-periods is very interesting, as they show information about the dynamics of convergence in the whole period. We can see that in the I. Sub-Period, between 1987 and 1996 there is an estimated rate of convergence of 3.1%, again significant at the 1% level, with an adj. R^2 of 0.58. This higher value for the model's explanatory power may indicate that in this sub-period the states were much more similar in their steady states than through the whole period of 1987-2013. Sub-Period II, between 1997 and 2006 shows that the unconditional model is losing explanatory power compared to the Sub-Period I, with having an estimated annual convergence of 1% (significant on the 10% level) and a very low R^2 of 0.05. Estimate for Sub-Period III is not statistically significantly different from zero, with a negative R^2 , indicating that the model fits the data worse than a horizontal line. This loss of significance in periods II and III can indicate that the states started to diverge in terms of their steady states. In other words, in the last two periods, the states started to behave very differently in terms of their determinants of the steady state.

Concluding the unconditional estimates I found that the estimates for the whole period are in line with previous findings in Barro et al. (1991) and Sala-i-Martin (1996). Furthermore, the 1.4% rate of convergence for the whole period seems to be mainly explained by estimates in the first sub-period and identifiable convergence gradually disappears in the second and third sub-periods. This implies that the states were closer to each other in terms of their steady state levels in the first decade and then gradually grew farther from each other. Conditional estimates are expected to explain this phenomenon better.

4.1.2. Conditional β -convergence

In my tests for conditional β -convergence I use equation (4) with the previously introduced control variables. Table 2 summarizes the findings for conditional estimates.

TABLE II
Tests for Conditional Convergence Across U.S. states

Dependent Variable: log difference GDP per capita for given period				
Period	1987-2013	1987-1996	1997-2006	2007-2013
Observations	50	50	50	50
Constant	0,216***	0,357***	0,191***	0,083
Std. Error	0,042	0,069	0,057	0,093
ln(GDP_base_year)	-0,021***	-0,036***	-0,020***	-0,014
Std. Error	0,005	0,007	0,006	0,010
SAVE_base_year	-0,055**	-0,011	0,052	-0,025
Std. Error	0,026	0,035	0,036	0,026
ln(n+g+ δ)	-0,209***	0,045	-0,071	-0,079
Std. Error	0,077	0,079	0,107	0,424
SCHOOL_base_year	0,030*	-0,015	0,063***	-0,033
Std. Error	0,017	0,031	0,023	0,040
EMP_base_year	0,045**	0,048**	0,027	0,126**
Std. Error	0,022	0,0230	0,023	0,059
Adj. R-squared	0,48	0,58	0,24	0,03
s.e.e.	0,004	0,006	0,006	0,01

Notes. To save space, most variables noted as _base_year, each relevant for the given period. GDP_base_year is GDP per capita in the base year of the given period. SAVE_base_year is the proxy for savings rate in the base year for each period. n is the rate of population growth for each period. g is assumed to be constant across the states. SCHOOL_base_year is the percentage of population (age 25 and above) with at least one Bachelor's- or higher level degree. EMP_base_year is employment rate in the base year for each period in order to control for employment. For an easier read, asterisks are included: *, ** and *** shows statistical significance at the 10%, 5% and 1% level respectively. Heteroskedasticity-robust standard errors (variant HC1) used. Note that all description and any statement related to this table is conditional on the steady state and employment levels.

Table 2 - Tests for Conditional Convergence Across U.S. states

Source: Author's own regressions

For the main period between 1987 and 2013 we can see an estimated 2.1% annual rate of convergence – statistically significant at the 1% level – which is in line with the ubiquitous 2% rate, widely found in the literature (and also in line with the findings of Barro et al. (1991), where the authors identified a 2.2% conditional convergence rate across U.S. states for the period 1880-1988). Adjusted R^2 is also higher (0.48) signaling a stronger explanatory power for this model than the unconditional one. The higher R^2 suggests that in fact the states differed in their steady state during this period. All control variables are statistically significant (though varying in their levels of significance). The coefficients for the proxies also have expected signs except for the Savings Rate – which is surprisingly negative –, signaling the opposite of what the Solow model would predict.

By default, the Solow model assumed that savings in a given economy will be invested in the same economy and contribute to its growth. Contrary to this, the savings rate coefficient suggests that states with higher savings are estimated to have lower growth rates. The reason for this is that the states are open economies with free flow of capital, and savings are most probably invested in the money market. These investments are hard to track, as to which economy's – state, region or even other countries – growth are they financing. The case is, that free flow of capital enables savings to be allocated to economies with high growth rates, since they can pay higher returns. Thus high-growth states within the U.S. are net borrowers of capital with lower savings on their own. On the other hand, states with high savings rate are exhibiting lower growth potential, and are net lenders of capital, since they are investing in economies where they can get higher returns on their investments. This transfer of capital within the country explains the negative sign of the coefficient; and the fact that not all accumulated capital is invested in the U.S. explains the smaller magnitude¹³ of the coefficient.

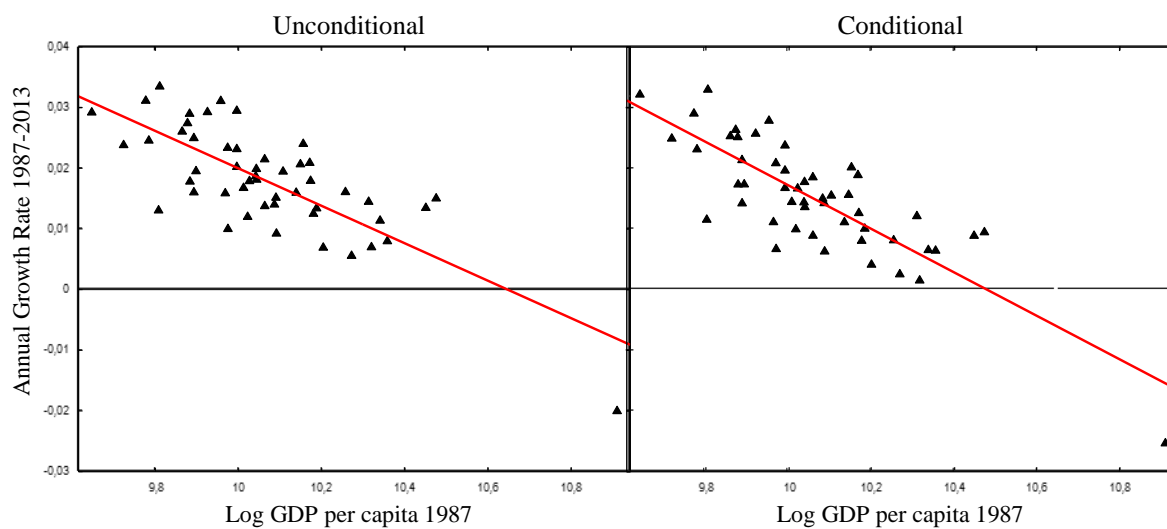
¹³ In Mankiw, Romer and Weil (1992) the coefficient of savings rate for the OECD countries is six times bigger and has a positive sign (0.335, with s.e. 0.175).

Interpreting the results for the sub-periods – as dynamics of convergence – is broadly supporting the findings of the unconditional estimates. In Sub-Period I, the model estimated a strong annual convergence rate of 3.6% – statistically significant at the 1% level – with an R^2 of 0.58. Sub-Period II has an estimated convergence rate of 2% – statistically significant at the 1% level – with an R^2 of 0.24, which shows a significantly better fit than for its unconditional estimates. Sub-Period III remained not statistically significant, with the model failing to prove any explanatory power for the estimation.

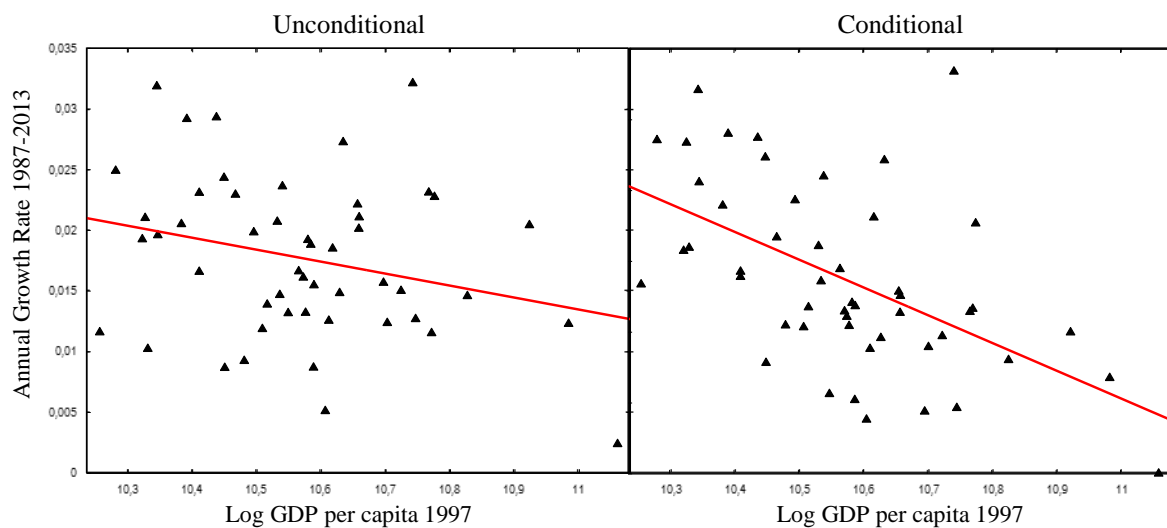
So far, based on the conditional estimates three distinct periods can be identified in terms of conditional convergence behavior between 1987 and 2013.: 1) 1987-1996, the period of strong convergence, poorer states catching up to richer ones; 2) 1997-2006, a period of slow down, states start to differ more in their steady states; 2006-2013, the slowdown of convergence continues until the crisis hits in 2007-2009, completely stopping the catch up process.

In order to further investigate what happens in sub-periods II and III, the following graphs show the differences between unconditional and conditional estimates. Figure 1 compares the cross sectional plots for each sub-period. The graphs show that states tended to cluster less and less in each period in the unconditional plots. Some of this scattering movement is visibly captured by introducing controls, however, it seems that even when controlling for the steady state, the states eventually scatter in the last sub-period. The fact that including the proxies does not rule out all variation might indicate that the states are also different in some other aspects, which determine their steady state. Also, the third sub-period's results indicates that the shock of the 2007-2009 crisis completely distorted any measurable convergence, even with the conditional approach. These results motivate introducing different sub-groupings of the states in order to get more insight on drivers of convergence dynamics.

SUB-PERIOD I.



SUB-PERIOD II.



SUB-PERIOD III.

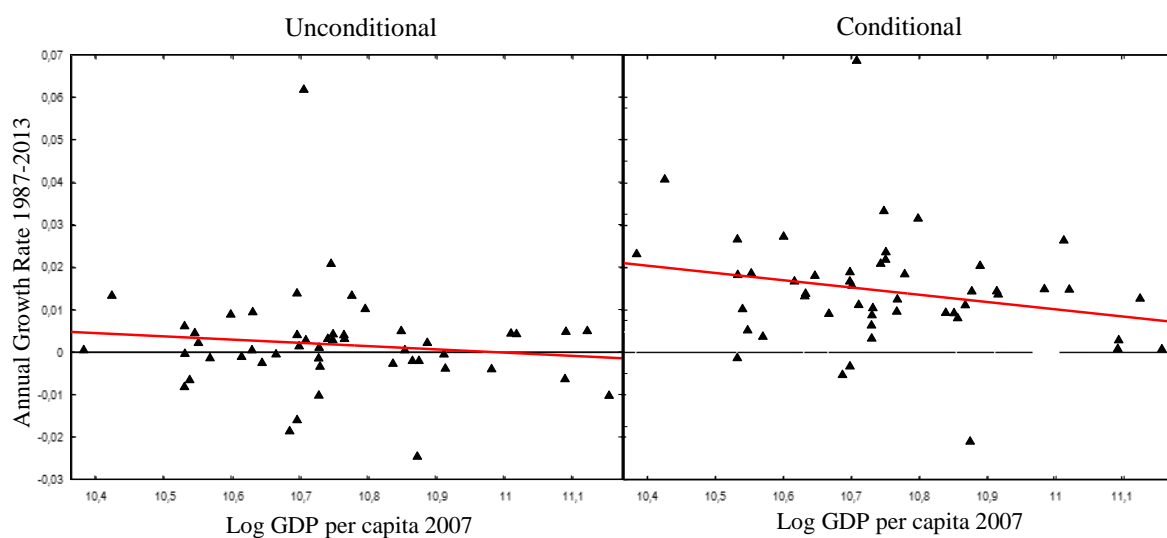


Figure 1 – Unconditional versus Conditional OLS estimates for all sub-periods

Figure 2 shows the same scatter plots as Figure 1, but states are grouped by coastal and non-coastal dummies. The motivation behind the grouping stems from looking at the states ordered descending by their log GDP per capita values. This ranking shows that most states with higher output per capita values are coastal states. In Figure 2 it can be seen that there are clear signs of a tendency for coastal and non-coastal states to cluster to some extent. On average, non-coastal states tend to be the “poorer” economies with lower initial per capita output levels and corresponding higher rates of growth; while coastal states tend to be the “richer” economies with higher levels of initial output per capita and corresponding lower rates of growth. This is easily observable in the first sub-period for both unconditional and conditional scatter plots. In the second sub-period, such a distinction is harder to see on the unconditional plot, however, the conditional plot raises the assumption that a separate fitted line for non-coastal states would be steeper than a separate fitted line for the coastal states. If this is true, it means that these groups of states followed different growth paths corresponding to different steady states, and that separation by coastal and non-coastal groups seem to visibly capture some of these differences. Graphs for the third sub-period show an interesting picture. It seems as if non-coastal states would continue to converge, while coastal states are very much scattered with no obvious signs of convergence or divergence. This might indicate that these groups are reacting differently to an economic shock. This is an interesting implication, which can be checked with conditional regressions, checking for convergence within the groups.

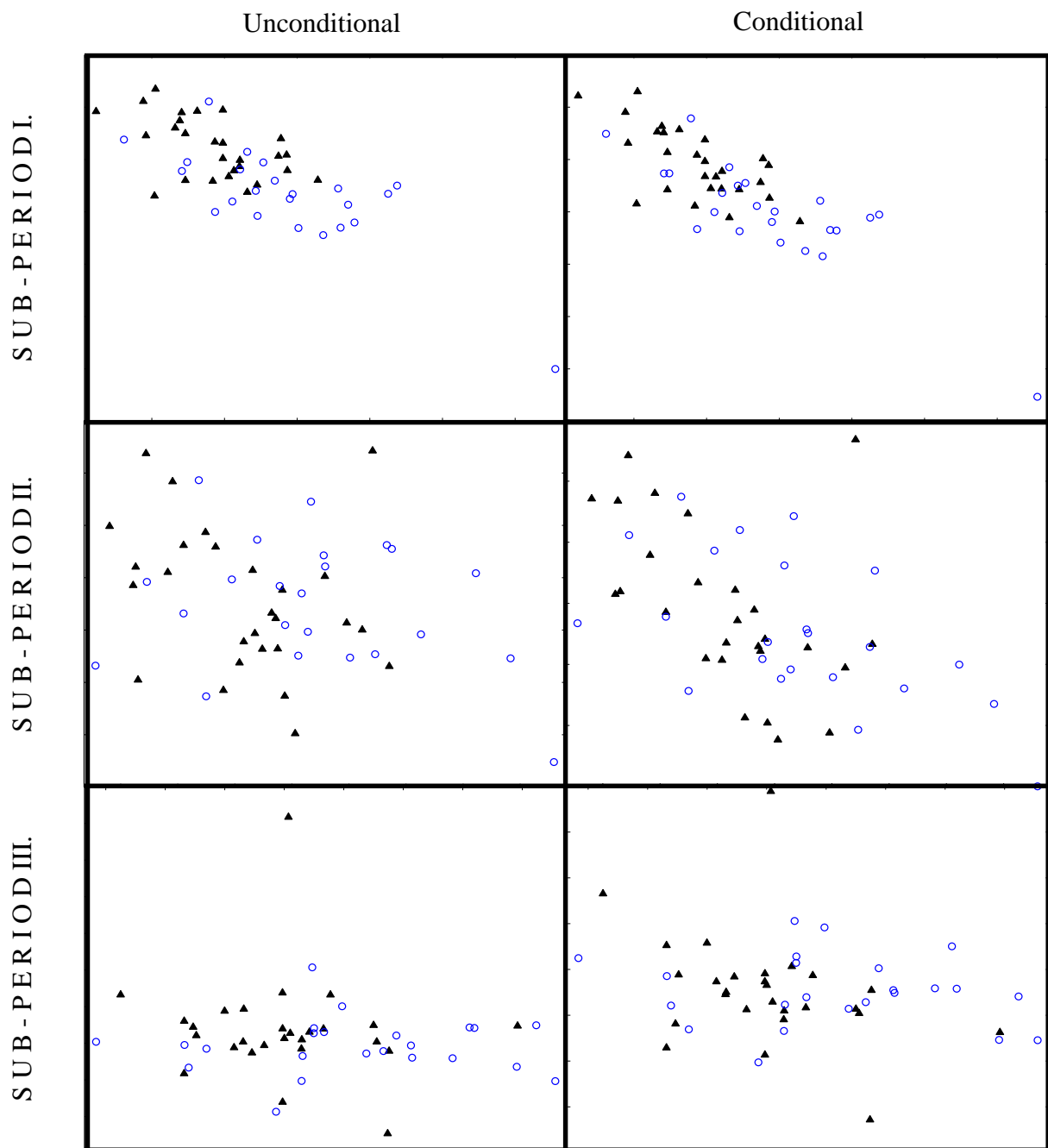


Figure 2 – Partitioning of OLS scatter plots by coastal and non-coastal states

Source: Author's own graph; Notes: black triangles are non-coastal states,; blue circles are coastal states

Figure 2 further motivated that the cross sectional regressions should be ran for coastal and non-coastal states separately. The results for these regressions are summarized in Table 3.

TABLE III
Tests for Conditional Convergence Across Coastal and Non-Coastal States

Dependent Variable: log difference GDP per capita for given period				
Non-Coastal States				
Period	1987-2013	1987-1996	1997-2006	2007-2013
Observations	27	27	27	27
ln(GDP_base_year)	-0,021**	-0,021*	-0,026*	-0,044*
Std. Error	0,009	0,011	0,014	0,022
Adj. R-squared	0,43	0,17	0,27	0,22
s.e.e.	0,004	0,005	0,006	0,01
Coastal States				
Period	1987-2013	1987-1996	1997-2006	2007-2013
Observations	23	23	23	23
ln(GDP_base_year)	-0,019**	-0,031**	-0,019**	-0,002
Std. Error	0,007	0,012	0,007	0,012
Adj. R-squared	0,45	0,58	0,38	-0,21
s.e.e.	0,003	0,006	0,005	0,01

Note: For simplicity, coefficients for control variables and constant are not reported. All regression results are included in the appendix. GDP_base_year is GDP per capita in the base year of the given period. For an easier read, asterisks are included: *, ** and *** shows statistical significance at the 10%, 5% and 1% level respectively. Heteroskedasticity-robust standard errors (variant HC1) used. Note that all description and any statement related to this table is conditional on the steady state and employment levels.

Table 3 - Tests for Conditional Convergence Across Coastal and Non-Coastal States

Results in Table 3 indicate that the first assumptions based on Figure 2 are plausible. While these estimates are not as robust as the ones including all the states – probably due to the small sample size –, they clearly indicate that coastal and non-coastal states behaved very differently in all periods. The only period when coastal states exhibited a stronger – much stronger in fact – conditional convergence than non-coastal ones is the first sub-period. In Sub-Period II, conditional convergence across coastal states slowed down, and in the third sub-period the crisis hit these states much harder, and completely washed away any sign of convergence. The findings for non-coastal states have lower statistical significance (significant at the 10% level in all sub-periods), however, they clearly show that these states followed a different growth

path. Based on Table 3, it seems that coastal and non-coastal states followed opposite trends in growth dynamics as well: Non-coastal states show a trend of increasing convergence through the sub-periods, and a spectacular jump in the third sub-period with an average annual rate of 4.4% conditional convergence. On the other hand, conditional convergence rate for coastal states is gradually decreasing, and completely disappears as the crisis hits in Sub-Period III. In other words, based on the estimates, it seems that coastal states have a more volatile convergence behavior and tend to scatter in terms of convergence, when an economic shock is present. Non-coastal states, on the other hand, have a much more stable convergence behavior, which is strengthened by an economic shock.

Based on the Figure 2 and the results presented in Table 3, I conclude that in fact, coastal and non-coastal states are following a different growth path with diverse growth dynamics. Furthermore, it seems that in times of economic shocks (the crisis in 2007-09), coastal and non-coastal states behave very differently in terms of convergence, implying the emergence of convergence clubs during times of harsh economic climate. With the presented findings in mind, it makes sense to see how the dispersion of per capita output develops for coastal and non-coastal states in the given period.

4.2. Estimating Convergence with the Dispersion of Variance

I conduct simple σ -convergence tests in order to see how does the cross-sectional standard deviation of per capita log GDP across the all states change over time. For this, I analyze the period between 1987 and 2013. For the analysis of σ -convergence, different groupings are used for the U.S. states, motivated by my previous findings. In Figure 3, dispersion of state level log output is shown for all 50 states and also for groups of coastal and non-coastal states. The graph is broken in the year 1997 due to the mentioned data discontinuity, but trends are still observable for the whole period and the sub-periods.

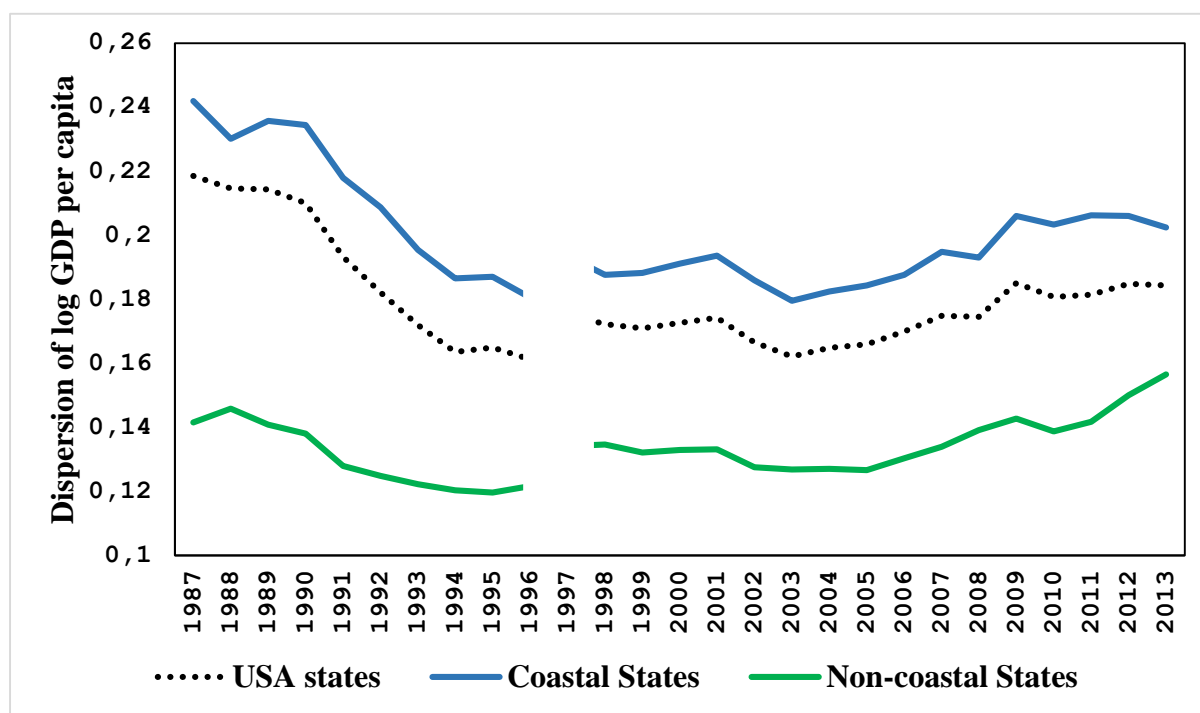


Figure 3 – Dispersion of log per capita GDP for all states, coastal and non-coastal states 1987-2013

Source: Author's own graph, used data is provided by BEA.

The dispersion for all states is different in magnitude from the dispersion figures presented in Barro et al. (1991) for the period 1962-1986. However, the authors' use data that was collected

in 1988, and also exclude Hawaii and Alaska from their analysis. With Hawaii and Alaska omitted, my figures would be much similar to the one the authors presented, differing only by a value of 0.04, which can be accredited to either data quality differences, or it can be the effects of the “Black Monday” in 1987, increasing the level of dispersion significantly for this year.

Figure 3 shows that the trends truly seem to be continuous despite the differences in measurement before and after 1997. The first sub-period shows a similar pattern to what was predicted by the neoclassical model, with a strong decrease in the dispersion between 1987 and 1996, however the rate of convergence was much stronger in terms of σ (0.057 decrease in dispersion – close to a 5.5% decrease in dispersion) than in terms of β (3.6%). The second sub-period shows that dispersion across states decreased by 0.005, while the conditional β estimates were 2% for this period. It is clearly visible that in the last sub-period, especially after the crisis, states experienced divergence in terms of σ , with dispersion increasing by 0.009, while the OLS estimates could not capture any β -convergence in these years. Non-coastal states seem to be much closer to each other than coastal states in their levels of per capita output; this is not true for coastal states, as their dispersion is almost the double of non-coastal dispersion. This motivates further breakdown of coastal states by their location.

In Figure 4, coastal states are categorized as Atlantic coast states; Pacific coast states; and states with coast to the Gulf of Mexico. Upon this further breakdown, we can see that inter-coastal state variation is mainly explained by different bodies of water. States with coast to the Gulf of Mexico show convergence in the first sub-period, but remain relatively flat until the crisis and even in the last years, show only marginal divergence. Convergence for Atlantic coast states is relatively flat in all sub-periods with a notable increase of 0.035 in the dispersion in the last seventeen years, indicating divergence between 1997 and 2013. Pacific coast states show a really vivid picture with continuous high rates of convergence with a 0.157 decrease in

dispersion for the first sub-period and a 0.086 decrease in dispersion for the second sub-period.

While the effects of the crisis are clearly visible in 2009, these states still exhibit convergence

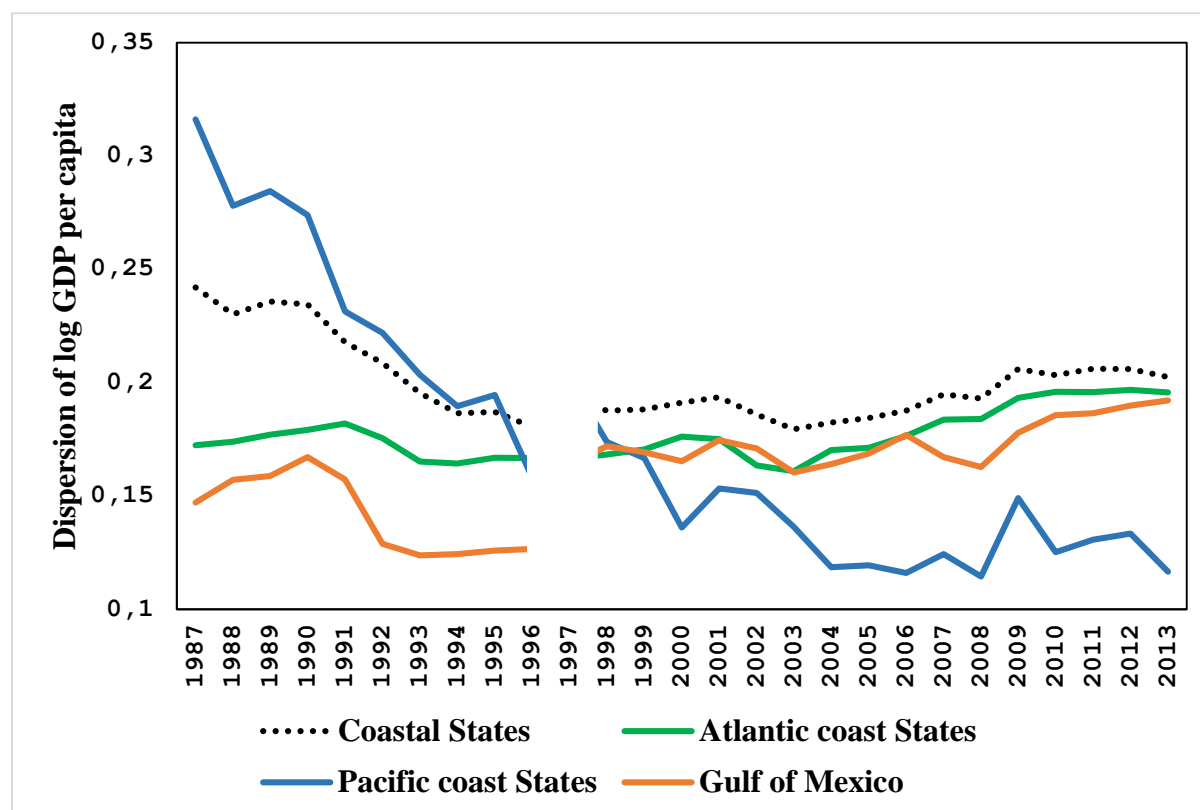


Figure 4 – Dispersion of log per capita GDP for coastal states based on geography 1987-2013

Source: Author's own graph, used data was provided by BEA. Note: Florida is considered as Atlantic coast state

in the last sub period, between 2007 and 2013.

Concluding the analysis for σ -convergence, I showed that while rates of convergence differ from the estimated β -convergence rates, similar trends and dynamics can be identified under both approach, for the first two sub-periods. This similarity is not present in the third sub-period, where non-coastal states showed clear divergence in terms of σ -convergence, while partial non-coastal β -convergence estimates showed a 4.4% rate of conditional convergence. Combining the results, it is visible, that the states experienced three distinct patterns of convergence within the period 1987-2013, which are summarized in Table 4.

TABLE IV
Patterns of convergence under different methods and grouping

All States			
Period	Sub-Period I	Sub-Period II	Sub-Period III
Year	1987-1996	1997-2006	2007-2013
Conditional β	3,6%	2,0%	0,0%
β Trend	Convergence	Convergence	No Convergence
Change in Dispersion	-0,057	-0,005	0,009
σ Trend	Convergence	Convergence	Divergence
Non-Coastal States			
Conditional β	2,1%	2,6%	4,4%
β Trend	Convergence	Convergence	Convergence
Change in Dispersion	-0,020	-0,004	0,023
σ Trend	Convergence	Convergence	Divergence
Coastal States			
Conditional β	3,1%	1,9%	0,0%
β Trend	Convergence	Convergence	No Convergence
Change in Dispersion	-0,061	-0,006	0,008
σ Trend	Convergence	Convergence	Divergence

Note: Statistical significance for β estimates are not presented. Dispersion is calculated as the standard deviation across a given group of states. All state results include 50 states; Non-coastal states include 27 states; Coastal states include 23 states. Only the conditional β estimates are presented, all description and any statement related to these estimates is conditional on the steady state and employment levels.

Table 4 - Summary Table of Findings

Table 4 shows that the conditional β estimates capture real trends – measured as σ -convergence – with relatively high accuracy, and failing to do so only in the third sub-period, in times of an external economic shock (the crisis). While this accuracy is high, it have to be noted that the

variation in the magnitude of change in dispersion is not in line with the variation in magnitude of the β estimates.

The results presented in this chapter shed light on the different behavior of coastal and non-coastal states in terms of convergence dynamics, and specifically to their diverse reaction to the economic shock during the crisis of 2007-09. The showed results identified a polarization across the U.S., identifying threats to the cohesion of the U.S. on the long run. Migration¹⁴ differences between coastal and non-coastal states are also in support of this polarization. Non-coastal states goes through a process of “desertification”, meaning population is slowly deserting these states for the coastal areas. With migration to the coastal states, population growth is much higher in these states, which increase their steady state level of output significantly. This will lead to even higher polarization in terms of convergence on the long run. The assumption that coastal states are much more prone to economic shocks is also a long run threat, especially if paired with the threat of polarization. These combined can lead to the break-up of economic cohesion in the U.S. and eventually making the whole country more vulnerable to external shocks.

These trends clearly support the core-periphery model, proposed in Krugman (1991). New Economic Geography (NEG) and spatial economic theories predict that through self-reinforcing agglomeration, full agglomeration of economic activity can happen across regions within a country. I believe that this research identified growth and convergence trends in support of a slow process of full agglomeration, with coastal states being the core and non-coastal states being the periphery. While this process seems to be slow, it has a visible effect on convergence and growth trends already, and can pose a real threat on the long run. Self-reinforcing agglomeration can be explained by many traits that can pinpoint areas for potential

¹⁴ For detailed state level migration data, visit U.S. Census webpage at: <https://www.census.gov/hhes/migration/data/acs/state-to-state.html>

policy intervention. These areas are often vague, due to their high level of complexity, however, it can still yield important implications for policy planning.

The drivers and process of agglomeration are explained in detail in *How Regions Grow: Trends and Analysis* (2009), a study by OECD. This study identifies four main drivers of agglomeration: infrastructure; human capital; innovation and R&D; and integrated regional policies. While these are important drivers, each has very little effect by itself, and policy interventions focusing on these have effects with considerable lag in time. This is not a problem, since the problem of polarization and potential full agglomeration are long run threats. While each driver can have little effect by itself, together they form synergies, constituting huge effects on the long run.

Infrastructure including institutions as well, is not something that varies much across states, and the U.S. is very advanced in this respect; thus it is not the main concern of policy planning. Developing human capital on the other hand is very important. Especially since well-educated work force will tend to move to areas where they can reap off more benefits from human capital. This is clearly an area for policy targeting and intervention, where non-coastal states should focus on not just investing in human capital, but to keep it from relocating to the coastal areas. Innovation and R&D are probably the most important strategic driver. According to NEG, this driver has the most externalities that induce agglomeration. Such externalities are innovation clustering (R&D tend to cluster within countries, creating high-tech hubs in certain regions), and knowledge spillovers (areas dense in term of R&D activity tend to have interdisciplinary knowledge spillovers, creating more innovation). Finally, integrated regional policies can help a great deal driving growth, if planned strategically, coordinating the previous three drivers into an integrated framework.

These drivers induce agglomeration, which in turn further enhances those, and thus the self-generating agglomeration process can be kick-started. Agglomeration brings further externalities that enhance its own speed, such as amenities; better job opportunities through better matching (job role - employee matching), which leads to higher productivity; higher per capita income; which yields further positive externalities.

The identified threat of polarization is a slow process, and potential remedies to this trend are taking effect slowly as well. With this in mind, policy recommendations in the conclusion formulate a long run strategy, building on synergies between the proposed policies.

5. Conclusion

5.1. Conclusion of analysis

My thesis reached its goal by studying the U.S. states in terms of convergence. I applied the neoclassical growth model based framework estimating β -convergence and conducted analysis in terms of σ -convergence. The two methods combined, showed that convergence across states can be broken down to three phases between 1987 and 2013, in terms of convergence dynamics. These are:

- 1) 1987-1996, a period of strong convergence across all states;
- 2) 1997-2006, a period of slowdown in terms of convergence; and
- 3) 2007-2013, a period of minor divergence, resulting from the economic shock caused by the crisis of 2007-09.

Upon further breakdown, my analysis identified traits of polarization between coastal and non-coastal states. In terms of convergence dynamics, coastal states showed stronger rates in the first period; significantly weaker rates in the second period; and minor divergence in the third period. Non-coastal states on the other hand, showed mediocre rates in the first two periods with a strengthening trend, and a huge jump in convergence rates according to conditional estimates (but minor divergence in reality). This clearly showed the signs of polarization, especially during times of economic shock. The different growth and convergence paths identified in my study can lead to serious differences on the long run, which can eventually lead to the distortion of the national cohesion in the U.S. This is a long run threat which has to be addressed by policy makers in order to slow down – or even stop, if possible – the process of desertification of non-coastal areas. My study predicts that this desertification will

eventually lead to a state of full agglomeration along the coastal areas, with population relocating from the in-land areas, completely deserting them on the long run.

5.2. Policy implications

My results support the core-periphery model proposed in Krugman (1991), which enabled me to identify areas for policy interventions. With no benchmarks for such policies, according to theory, economic environment should be improved in order to motivate companies, population, and economic activity, to relocate to states prone to the dangers of desertification. Policy Makers should recognize the signs of this polarization and create local incentives in non-coastal states for economic activity to relocate to their region. Attracting highly educated work force and high-technology firms can help foster innovation clustering, which leads to knowledge spillovers and other positive externalities, inducing regional agglomeration. This is a long term strategy with no immediate results, which could validate the effectiveness.

Policy Recommendations:

- 1) Relocation of high technology companies should be incentivized at the state level in non-coastal regions with special tax rebates.**

Specialized tax rebates could be introduced in non-coastal states, conditional on the way the rebate is spent. All tax rebates could be spent only on investment in state-of-the-art equipment, or on R&D activities; or on investment in R&D companies that are in the region. This would incentivize companies to relocate to these states, since it makes innovation cheaper in an indirect way, and also channels more money to the state level R&D activities. This policy would contribute to the effects of innovation clustering and possibly to form an R&D hub within the state.

Personal tax incentives should be introduced at the state level, in order to incentivize the labor force and companies to relocate to non-coastal states.

Creating an advantageous tax environment by lowering personal income tax can prove to be a huge driver for relocation for people and companies as well. People will want to work in states where the tax burden on their income is lower; and at the same time, companies will want to relocate as well, since they can offer lower salaries to employees, achieving same wage levels as in other states. Direct cost saving opportunities should be the most effective motivation for both companies and labor force to relocate. While these tax reductions can lead to lower state government income, they could actually reverse the trends of polarization, and bring about a positive change on the long run, with having more people paying the reduced taxes.

2) Higher education should be promoted and state incentives should be introduced in order to de-motivate relocation of highly educated work force.

State level incentives should be introduced in the form of conditional free higher education. Free higher education should be offered to students, conditional on working at least 3 years in their field of study in the given state, after they successfully finished their tertiary education. This policy could result in many fresh, highly educated graduates to stay in their states, contributing to the local technological and innovation environments; this can foster innovation clustering and create positive externalities in the form of knowledge spillovers, which further generates incentives for R&D companies to relocate to these states.

3) Technology adaptation should be incentivized in non-coastal states, creating opportunities for companies to adopt state-of-the-art processes.

Companies adopting or using high-end technologies should be provided with state level loans or other financial incentives in order to upgrade or establish efficient, cutting-edge techniques

and technologies in their production. This can incentivize companies to relocate, since they can improve on their efficiencies with relatively low costs. This further creates jobs for highly educated work force, and enhance R&D activities.

4) Promoting research projects with state level funding can establish new technological hubs in the country.

State level funding for research projects can lead to a sharp increase in R&D activity in non-coastal states, resulting in high R&D activity. This can eventually kick-start innovation clustering.

The presented policy recommendations are planned to have a synergy effect, enhancing each other. These policies can bring about a slow but substantial change on the long run, aimed to create a vivid and active environment for companies and population to relocate to. The composition of these policies should create an active and innovative milieu, kick-starting a self-generating agglomeration process, through positive externalities, such as amenities, better matching, higher productivity, and higher per capita income.

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Appendices

A.1. OLS Regression Results for all states

A.1.1. UNCONDITIONAL LONG PERIOD 1987-2013

Model 1: OLS, using observations 1-50					
Dependent variable: d_GDP					
Heteroskedasticity-robust standard errors, variant HC1					
	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,166033	0,0293382	5,6593	<0,0001	***
GDP87	-0,0139186	0,00289989	-4,7997	<0,0001	***
Mean dependent var	0,025941	S.D. dependent var		0,005561	
Sum squared resid	0,001053	S.E. of regression		0,004683	
R-squared	0,305334	Adjusted R-squared		0,290862	
F(1, 48)	23,03709	P-value(F)		0,000016	
Log-likelihood	198,2619	Akaike criterion		-392,5238	
Schwarz criterion	-388,6997	Hannan-Quinn		-391,0675	

A.1.2. CONDITIONAL LONG PERIOD 1987-2013

Model 2: OLS, using observations 1-50					
Dependent variable: d_GDP					
Heteroskedasticity-robust standard errors, variant HC1					
	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,216279	0,0418127	5,1726	<0,0001	***
GDP87	-0,021445	0,00480587	-4,4623	<0,0001	***
SAVE87	-0,0546633	0,025751	-2,1228	0,0394	**
EMP87	0,0452535	0,022099	2,0478	0,0466	**
ngd	-0,209054	0,0765171	-2,7321	0,0090	***
SCHOOL87	0,0304618	0,0174831	1,7424	0,0884	*
Mean dependent var	0,025941	S.D. dependent var		0,005561	
Sum squared resid	0,000706	S.E. of regression		0,004006	
R-squared	0,533962	Adjusted R-squared		0,481003	
F(5, 44)	7,808191	P-value(F)		0,000025	
Log-likelihood	208,2410	Akaike criterion		-404,4819	
Schwarz criterion	-393,0098	Hannan-Quinn		-400,1133	

A.1.3. UNCONDITIONAL FIRST PERIOD 1987-1996

Model 3: OLS, using observations 1-50
 Dependent variable: d_GDP
 Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,328343	0,0543158	6,0451	<0,0001	***
GDP87	-0,0308382	0,00540904	-5,7012	<0,0001	***
Mean dependent var	0,017953	S.D. dependent var		0,008854	
Sum squared resid	0,001570	S.E. of regression		0,005718	
R-squared	0,591363	Adjusted R-squared		0,582850	
F(1, 48)	32,50392	P-value(F)		7,15e-07	
Log-likelihood	188,2762	Akaike criterion		-372,5524	
Schwarz criterion	-368,7284	Hannan-Quinn		-371,0962	

A.1.4. CONDITIONAL FIRST PERIOD 1987-1996

Model 4: OLS, using observations 1-50
 Dependent variable: d_GDP
 Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,357232	0,0688452	5,1889	<0,0001	***
GDP87	-0,0359894	0,0074895	-4,8053	<0,0001	***
SAVE87	-0,011102	0,0348917	-0,3182	0,7518	
EMP87	0,0483574	0,0230461	2,0983	0,0417	**
ngd	0,0451662	0,0789737	0,5719	0,5703	
SCHOOL87	-0,0148418	0,030616	-0,4848	0,6302	
Mean dependent var	0,017953	S.D. dependent var		0,008854	
Sum squared resid	0,001437	S.E. of regression		0,005715	
R-squared	0,625816	Adjusted R-squared		0,583295	
F(5, 44)	10,04500	P-value(F)		1,84e-06	
Log-likelihood	190,4782	Akaike criterion		-368,9565	
Schwarz criterion	-357,4843	Hannan-Quinn		-364,5878	

A.1.5. UNCONDITIONAL SECOND PERIOD 1997-2006

Model 5: OLS, using observations 1-50
 Dependent variable: d_GDP
 Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,121995	0,0617004	1,9772	0,0538	*
GDP97	-0,00986578	0,00583663	-1,6903	0,0975	*
Mean dependent var	0,017698	S.D. dependent var		0,006549	
Sum squared resid	0,001952	S.E. of regression		0,006377	
R-squared	0,071167	Adjusted R-squared		0,051816	
F(1, 48)	2,857184	P-value(F)		0,097452	
Log-likelihood	182,8281	Akaike criterion		-361,6562	
Schwarz criterion	-357,8321	Hannan-Quinn		-360,2000	

A.1.6. CONDITIONAL SECOND PERIOD 1997-2006

Model 6: OLS, using observations 1-50
 Dependent variable: d_GDP
 Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,191194	0,0570917	3,3489	0,0017	***
GDP97	-0,0196236	0,00558155	-3,5158	0,0010	***
SAVE97	0,0520427	0,035694	1,4580	0,1519	
EMP97	0,027134	0,0230491	1,1772	0,2454	
ngd	-0,0710915	0,107171	-0,6633	0,5106	
SCHOOL97	0,0634442	0,0233514	2,7169	0,0094	***
Mean dependent var	0,017698	S.D. dependent var		0,006549	
Sum squared resid	0,001437	S.E. of regression		0,005715	
R-squared	0,316157	Adjusted R-squared		0,238447	
F(5, 44)	5,154162	P-value(F)		0,000831	
Log-likelihood	190,4831	Akaike criterion		-368,9662	
Schwarz criterion	-357,4941	Hannan-Quinn		-364,5975	

A.1.7. UNCONDITIONAL THIRD PERIOD 2007-2013

Model 7: OLS, using observations 1-50
 Dependent variable: d_GDP
 Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>
const	0,0840169	0,0635011	1,3231	0,1921
GDP07	-0,0076505	0,00586802	-1,3038	0,1985
Mean dependent var	0,001749	S.D. dependent var		0,011783
Sum squared resid	0,006714	S.E. of regression		0,011827
R-squared	0,013149	Adjusted R-squared		-0,007410
F(1, 48)	1,699796	P-value(F)		0,198533
Log-likelihood	151,9425	Akaike criterion		-299,8850
Schwarz criterion	-296,0609	Hannan-Quinn		-298,4288

A.1.8. CONDITIONAL THIRD PERIOD 2007-2013

Model 8: OLS, using observations 1-50
 Dependent variable: d_GDP
 Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>
const	0,0827437	0,09316	0,8882	0,3793
GDP07	-0,0136964	0,00998183	-1,3721	0,1770
SAVE07	-0,0251344	0,0261357	-0,9617	0,3415
EMP07	0,125558	0,0589777	2,1289	0,0389 **
ngd	-0,0788584	0,423748	-0,1861	0,8532
SCHOOL07	-0,0328273	0,0399635	-0,8214	0,4158
Mean dependent var	0,001749	S.D. dependent var		0,011783
Sum squared resid	0,005131	S.E. of regression		0,010799
R-squared	0,245866	Adjusted R-squared		0,160169
F(5, 44)	1,462604	P-value(F)		0,221390
Log-likelihood	158,6662	Akaike criterion		-305,3324
Schwarz criterion	-293,8603	Hannan-Quinn		-300,9638

A.2. OLS Regression Results for all coastal and non-coastal state groups

A.2.1. CONDITIONAL LONG PERIOD 1987-2013 NON-COASTAL STATES

Model 9: OLS, using observations 1-27
Dependent variable: d_GDP
Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,216153	0,0825556	2,6183	0,0161	**
GDP87	-0,021175	0,00946302	-2,2377	0,0362	**
SAVE87	-0,0842045	0,0379192	-2,2206	0,0375	**
EMP87	0,0575996	0,0320877	1,7951	0,0871	*
ngd	-0,206014	0,0947223	-2,1749	0,0412	**
SCHOOL87	-0,0114291	0,0277986	-0,4111	0,6851	
Mean dependent var	0,027886	S.D. dependent var		0,005633	
Sum squared resid	0,000382	S.E. of regression		0,004263	
R-squared	0,537296	Adjusted R-squared		0,427129	
F(5, 21)	10,12873	P-value(F)		0,000048	
Log-likelihood	112,4391	Akaike criterion		-212,8781	
Schwarz criterion	-205,1031	Hannan-Quinn		-210,5662	

A.2.2. CONDITIONAL LONG PERIOD 1987-2013 COASTAL STATES

Model 10: OLS, using observations 1-23
Dependent variable: d_GDP
Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,205425	0,0626501	3,2789	0,0044	***
GDP87	-0,0191148	0,00732526	-2,6094	0,0183	**
SAVE87	-0,0157486	0,0440275	-0,3577	0,7250	
EMP87	-0,0184015	0,0335869	-0,5479	0,5909	
ngd	0,0460647	0,146192	0,3151	0,7565	
SCHOOL87	0,109297	0,0373726	2,9245	0,0095	***
Mean dependent var	0,023657	S.D. dependent var		0,004614	
Sum squared resid	0,000198	S.E. of regression		0,003414	
R-squared	0,577065	Adjusted R-squared		0,452672	
F(5, 17)	3,091595	P-value(F)		0,036441	
Log-likelihood	101,4785	Akaike criterion		-190,9570	
Schwarz criterion	-184,1441	Hannan-Quinn		-189,2436	

A.2.3. CONDITIONAL FIRST PERIOD 1987-1996 NON-COASTAL STATES

Model 11: OLS, using observations 1-27

Dependent variable: d_GDP

Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,232541	0,0948896	2,4506	0,0231	**
GDP87	-0,021379	0,0105723	-2,0222	0,0561	*
SAVE87	-0,0519256	0,0450465	-1,1527	0,2620	
EMP87	0,0201929	0,0325083	0,6212	0,5412	
ngd	0,0637439	0,0863803	0,7379	0,4687	
SCHOOL87	-0,0346731	0,0367065	-0,9446	0,3556	
Mean dependent var	0,022136	S.D. dependent var		0,005809	
Sum squared resid	0,000585	S.E. of regression		0,005280	
R-squared	0,332772	Adjusted R-squared		0,173909	
F(5, 21)	3,537400	P-value(F)		0,017797	
Log-likelihood	106,6653	Akaike criterion		-201,3307	
Schwarz criterion	-193,5557	Hannan-Quinn		-199,0188	

A.2.4. CONDITIONAL FIRST PERIOD 1987-1996 COASTAL STATES

Model 12: OLS, using observations 1-23

Dependent variable: d_GDP

Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,317052	0,101308	3,1296	0,0061	***
GDP87	-0,0309081	0,0118221	-2,6144	0,0181	**
SAVE87	0,0560099	0,0724788	0,7728	0,4503	
EMP87	-0,00116389	0,0578934	-0,0201	0,9842	
ngd	0,157567	0,263175	0,5987	0,5573	
SCHOOL87	0,0273928	0,069791	0,3925	0,6996	
Mean dependent var	0,013043	S.D. dependent var		0,009383	
Sum squared resid	0,000632	S.E. of regression		0,006095	
R-squared	0,673948	Adjusted R-squared		0,578050	
F(5, 17)	7,411326	P-value(F)		0,000748	
Log-likelihood	88,14766	Akaike criterion		-164,2953	
Schwarz criterion	-157,4824	Hannan-Quinn		-162,5819	

A.2.5. CONDITIONAL SECOND PERIOD 1997-2006 NON-COASTAL STATES

Model 13: OLS, using observations 1-27

Dependent variable: d_GDP

Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,243244	0,141983	1,7132	0,1014	
GDP97	-0,0261222	0,0136142	-1,9187	0,0687	*
SAVE97	-0,00606239	0,153455	-0,0395	0,9689	
EMP97	0,0774244	0,0340306	2,2751	0,0335	**
ngd	0,105911	0,130035	0,8145	0,4245	
SCHOOL97	0,0134076	0,029155	0,4599	0,6503	
Mean dependent var	0,017926	S.D. dependent var		0,006927	
Sum squared resid	0,000740	S.E. of regression		0,005936	
R-squared	0,406815	Adjusted R-squared		0,265581	
F(5, 21)	4,453494	P-value(F)		0,006370	
Log-likelihood	103,5022	Akaike criterion		-195,0045	
Schwarz criterion	-187,2295	Hannan-Quinn		-192,6926	

A.2.6. CONDITIONAL SECOND PERIOD 1997-2006 COASTAL STATES

Model 14: OLS, using observations 1-23

Dependent variable: d_GDP

Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,205861	0,0677686	3,0377	0,0074	***
GDP97	-0,0188812	0,00736312	-2,5643	0,0201	**
SAVE97	0,0388398	0,0342608	1,1337	0,2727	
EMP97	-0,0271333	0,0439662	-0,6171	0,5453	
ngd	-0,207236	0,193632	-1,0703	0,2995	
SCHOOL97	0,106128	0,0303333	3,4987	0,0028	***
Mean dependent var	0,017431	S.D. dependent var		0,006219	
Sum squared resid	0,000411	S.E. of regression		0,004916	
R-squared	0,517243	Adjusted R-squared		0,375256	
F(5, 17)	6,318436	P-value(F)		0,001731	
Log-likelihood	93,09368	Akaike criterion		-174,1874	
Schwarz criterion	-167,3744	Hannan-Quinn		-172,4739	

A.2.7. CONDITIONAL THIRD PERIOD 2007-2013 NON-COASTAL STATES

Model 15: OLS, using observations 1-27

Dependent variable: d_GDP

Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,374516	0,210283	1,7810	0,0894	*
GDP07	-0,0442446	0,0217264	-2,0364	0,0545	*
SAVE07	-0,0183704	0,0542043	-0,3389	0,7380	
EMP07	0,204053	0,0866612	2,3546	0,0284	**
ngd	-0,349394	0,527579	-0,6623	0,5150	
SCHOOL07	-0,0845886	0,077392	-1,0930	0,2868	
Mean dependent var	0,003778	S.D. dependent var		0,014190	
Sum squared resid	0,003299	S.E. of regression		0,012533	
R-squared	0,369904	Adjusted R-squared		0,219881	
F(5, 21)	2,635055	P-value(F)		0,053223	
Log-likelihood	83,32483	Akaike criterion		-154,6497	
Schwarz criterion	-146,8746	Hannan-Quinn		-152,3377	

A.2.8. CONDITIONAL THIRD PERIOD 2007-2013 COASTAL STATES

Model 16: OLS, using observations 1-23

Dependent variable: d_GDP

Heteroskedasticity-robust standard errors, variant HC1

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	-0,00300384	0,119289	-0,0252	0,9802	
GDP07	-0,00197815	0,0120776	-0,1638	0,8718	
SAVE07	-0,0220024	0,0301859	-0,7289	0,4760	
EMP07	0,0441474	0,0470951	0,9374	0,3617	
ngd	0,0619757	0,53813	0,1152	0,9097	
SCHOOL07	-0,00618687	0,0407198	-0,1519	0,8810	
Mean dependent var	-0,000633	S.D. dependent var		0,007766	
Sum squared resid	0,001238	S.E. of regression		0,008534	
R-squared	0,066713	Adjusted R-squared		-0,207783	
F(5, 17)	0,198010	P-value(F)		0,958929	
Log-likelihood	80,40444	Akaike criterion		-148,8089	
Schwarz criterion	-141,9959	Hannan-Quinn		-147,0954	