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A Note on the US Regional and Sectoral Convergence

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Contents

Abstract

This study examines labor productivity convergence across the U.S. states for seven major economic sectors from 1987 to 2013. We follow two different approaches; the first one uses cross-section techniques such as beta and sigma convergence analysis and the second adopts panel methods (stochastic convergence) taking advantage of recent developments in panel unit root tests. The results from beta-convergence analysis show evidence of convergence for Mining, Construction, Manufacturing, Transportation and Trade while, according to sigma convergence approach only Construction has a clear trend of convergence. The results from panel methods are contradictory for the Construction sector when our last and more modern unit root test is employed. Finally, Manufacturing seems to exhibit the strongest evidence of convergence in respect to beta and stochastic convergence methods followed by Mining.

1. Introduction

The concept of economic convergence is relatively old in economics. The first article to address convergence was published in 1955 by Simon Kuznets. Since then many economists have worked on this concept using a variety of tools. Most often than not, the target is to check the validity of the neoclassical growth models' prediction of economic convergence among countries (economic unities in general) that is based on the premise that first, countries converge in their balanced growth path, second, capital flows from rich to poor countries due to a higher rate of return in the poor and third, the diffusion of knowledge will shrink productivity differences (Romer, 2012).

In modern research a variety of techniques are used to examine different levels of data at a regional, national and international level. The most common empirical techniques fall into four main categories: sigma convergence, absolute beta convergence, conditional beta convergence, and stochastic convergence. Three of the four techniques concern cross-sectional data while the latter deals with panel data. The bulk of the convergence studies concentrate on income per capita, labor productivity and earnings with varying outputs and conclusions.

In our analysis we investigate labor productivity convergence among the 50 US States and the District of Columbia for seven major economic sectors from 1987 to 2013. The majority of the bibliography for the subject is limited to the twentieth century while there is a general consensus about the validity of convergence hypothesis in the United States, particularly when beta-convergence methods are employed (Rey and Montouri 1999) with the exception of the period of oil shocks, between 1973 and the middle of the eighties, approximately.

Economic convergence refers to the process by which poor countries or regions tend to grow faster than rich ones and eventually reach the same growth rates and level of income, productivity and so on. When growth rates diverge, the study of convergence helps to understand the causes of the produced inequalities among countries or regions and formulate the appropriate policies in order to alleviate those disparities. Productivity convergence in particular is the key driver of economic growth in the long run. A generally accepted fact by many scholars is that if technological convergence, best captured in productivity, does not occur then countries and regions are not catching-up in a sustainable manner (Sondermann, 2013).

In our study, we apply Baumol's (1986) model in order to test for beta convergence while we follow, to a significant degree, the methodological steps of Bernard and Jones (1996) using both cross section and time-series methods. First, we briefly investigate some features of the productivity data such as growth rates and variations across states and sectors and then we proceed to the main analysis which includes beta and sigma convergence methods as well as stochastic convergence techniques

including four unit root tests and a fixed effects model in order to estimate the degree of productivity convergence, if any.

The research starts with the literature review and the rest of our work is organized as follows: Section 3 describes the data and explains the methodology that is used. Section 4 presents the empirical results. Finally, section 5 concludes.

2. Literature Review

The study of economic convergence has attracted the attention of economists since the middle of the twentieth century as already mentioned. However, from the eighties and forward there is a considerable boost in the amount of papers that are involved with the concept. Baumol's (1986) work laid the groundwork for empirical research on beta convergence. By examining productivity convergence hypothesis from 1870 to 1979 among 16 industrialized countries he also introduced the condition under which beta convergence exists. Many other significant works in beta convergence followed such that of Barro and Sala-I-Martin (1991). A more recent technique that is widely applied is that of stochastic convergence. Our study uses, among others, some elements of the paper of Bernard and Jones (1996) on this matter.

So the overall literature is summarized in the following tables:

	Title	Author	Methodology	Data	Theme
1	Productivity and convergence across U.S. States and industries	Bernard and Jones (1996)	Economic growth, labor productivity, convergence, industry composition, panel unit roots	Gross State Data for the 50 US States and the District of Columbia is obtained from the US Department of Commerce, Bureau of Economic Analysis (BEA), covering the period 1963-1989, while state employment data are from The Bureau of Labor Statistics covering the same period	This paper examines the sources of labor productivity growth and convergence across US states and sectors concluding that: first, productivity growth within States can be attributed, mainly, to the manufacturing sector and second, the manufacturing and in a smaller degree the mining sector leads the productivity convergence across US States
2	A Note on the extent of US regional income convergence	Holmes, Otero and Panagiotidis (2013)	Panel data, cross-section dependence, pair-wise approach, income, convergence	Per capita personal income (PCPI) state level data was downloaded from the Federal Reserve Economic Dataset (FRED) for the 48 contiguous States from 1929 to 2009 deflated by CPI. Disaggregated PCPI data for 346 Metropolitan Statistical Areas was also downloaded from Fred over the period 1969-2002	This paper investigates long run income convergence across US States. With the use of PCPI data, pair-wise cointegration approach and bootstrap methodology two main result are drawn: first, income convergence is observed across US States when a weak form of stationarity is used. This is reinforced by bootstrap methodology in MSAs data. Second, the power of convergence is inversely proportional to the distance between the states and the initial income inequality
3	Alternative regional specification and convergence of U.S. regional growth rates	Miller and Genc (2005)		All the income data in this paper are retrieved from BEA. Regional PCPI data in three aggregation degrees (172 BEA economic areas, 48 major economic areas and U.S. Federal Reserve Districts) are used for economic region specifications. For the 48 US States and the District of Columbia the focus is in 1969-1997 and 1929-1997 respectively	In this paper absolute beta convergence techniques are applied for the examination of income convergence across US economic and political region specifications. Strong evidence of convergence is found among the economic regions (all convergence coefficients between -0.30 and -0.36) while convergence in political regions is statistically less important

	Title	Author	Methodology	Data	Theme
4	Convergence and Mobility: Personal Income Trends in U.S. Metropolitan and Nonmetropolitan Regions	Hammond and Thompson (2006)	Income dynamics, convergence, mobility, modality, metropolitan, nonmetropolitan	The data used on PCPI for 722 metropolitan and non metropolitan U.S. Department of Agriculture Economic Research Service (ERS) Commuting Zones are downloaded from BEA's regional Economic Information System (REIS) and extents from 1969 to 1999. Census data of 1980 is used for the investigation of income mobility and educational attainment across the aforementioned regions	This paper analyzes the dynamics of income mobility and modality across 722 ERS regions within the 48 contiguous US States. It is stated that Metropolitan regions show more downward income mobility and a weaker degree of within-group income convergence than non metropolitan regions while education attainment has a positive impact on income growth, mainly for the major metropolitan zones
5	Income convergence in the United States: a tale of migration and urbanization	DiCecio and Gascon (2010)	convergence, migration, urbanization	The data on PCPI for the 50 US States and the District of Columbia are downloaded from www.bea.gov/regional/spi/ while the data on PCPI for the metro and non-metro portions of US States can be found at http://www.bea.gov/regional/reis/ . The period under examination is from 1969 to 2005	This paper investigates US income convergence in three terms. Across states, across metropolitan and non metropolitan regions and over time. It is deduced that States do not show signs of convergence. On the contrary income convergence is apparent when the migration of people in urban areas is introduced which leads to the conclusion that the main cause of convergence is urbanization
6	Investigating Convergence of the U.S. Regions: A Time Series Analysis	Kane (2001)		Three types of data are used: Earnings and population data are from the state personal income series spanning from 1929 to 1998. Per capita employment data are from the Regional Economic Information System (REIS) CD covering the years 1969 to 1998 and earnings-by-industry data are also from the state personal income series from 1958 to 1998. All the above datasets are obtained from BEA, US Department of Commerce	This study examines eight US regions for conditional convergence in terms of per capita earnings. It is concluded these regions exhibit compensating wage differential convergence, albeit in different rates and towards variant steady states. That is, they will never reach the same level of per capita earnings

	Title	Author	Methodology	Data	Theme
7	Regional Convergence: Evidence from a New State-by-State Capital Stock Series	Garofalo and Yamarik (2002)	Convergence, Growth, Regional Capital Stock	The data used in this paper are drawn from 4 sources. Ad hoc state by state capital stock and gross investment time series data are constructed by the Authors. Gross State Product data are obtained from BEA and employment data are reported from Bureau of Labor Statistics. All three datasets cover the period between 1977 and 1996. Finally, human capital data in terms of college educated individuals of 25 years old and above are taken from the 1980 Census	This paper investigates three aspects of regional productivity convergence among US States. With the use of capital stock and investment data from 1977 to 1996 for the 48 States it is showed that there is evidence of constant returns to scale if a two factor model (capital, labor) is used. Furthermore, steady state convergence across the States is found and conditional convergence of about 2% per year among US regions is detected
8	Are U.S. regional incomes converging?: A time series analysis	Carlino and Mills (1993)	Analysis of growth, development and change, economic growth and aggregate productivity, multiple/simultaneous equation models, time series models	In this paper annual income per capita BEA time series data are employed for 8 US regions during the period 1929-1990	This paper examines two conditions of income convergence across 8 US regions between 1929 and 1990: stochastic convergence with the use of time series techniques and β-convergence with the help of cross section techniques. Two results are drawn: first, the impact of stochastic shocks on income is vanishing with time if a convergence break in 1946 is included. Second, evidence of β-convergence are also found. The fulfillment of the two conditions leads to total income convergence across the 8 US regions as the Solow Model predicts
9	Are U.S. regions converging? Using new econometric methods to examine old issues	Tomljanovich and Vogelsang (2002)	Regional per-capita income, time series models, beta convergence, trend function, serial correlation	In this study annual BEA time series data on per capita income from 1929 to 1990 for 8 US regions (the same as of Carlino and Mills (1993)) are used for the examination of β-convergence, utilizing new econometric tests	This article examines income β-convergence among 8 US regions from 1929 to 1990. Two models are estimated, one with known trend break (in 1946) and another with endogenous trend break date. The analysis concludes that the degree of income convergence is higher for the former model and that the bulk of convergence occurred before 1946

	Title	Author	Methodology	Data	Theme
10	Convergence Across States and Regions	Barro and Sala-I-Martin (1991)		The data on PCPI for 47 US States covering the period 1880-1988 are from BEA (1989), Easterlin (1960a, 1960b) and various issues of the Survey of Current Business. The data on population density are from BEA (1990), the data on migration between 1900 and 1987 are from the 1975 Census. The data on the 48 US gross state product between 1963 and 1986 are from Renshaw et al. (1988) Survey of Current Business and the data on employment for 8 non agriculture sectors for the same time period are from Bureau of Labor Statistics	This paper investigates 3 issues: income per capita conditional β-convergence and σ-convergence across 48 US States from 1880 to 1988, the impact of migration on income economic growth and convergence and the gross state product β-convergence as well as σ-convergence among eight sectors of the 48 contiguous US States between 1963 and 1986. Same patterns of β-convergence (approximately 2% per year) and σ-convergence (decline of σ) are found for income and gross state product apart from the period of oil shocks, between 1973 and 1986. It is also noticed that migration explains a small part of income per capita convergence
11	Growth and Convergence across the United States: Evidence from County-Level Data	Higgins, Levy and Young (2006)		The data used are income per capita 3058 county-level observations expressed in 1992 prices and separated into a subset of 867 metropolitan and 2191 nonmetropolitan counties and a subset which contains data for 5 US regions. The main source is BEA-REIS and the period covered is from 1970 to 1990. Apart from income data 41 additional demographic variables are used	This paper investigates economic growth determination and the speed of income convergence in US States. With a sample of 3058 income per capita county-level observations from 1970 to 1990 and 41 demographic variables it is shown that: 1. Whereas OLS methodology yields convergence estimates just above 2%, 3SLS methodology yields 6%-8%. 2. convergence rates vary substantially between regions. 3. the size of public sector and employment in the education industry is negatively correlated with growth while fire sector and entertainment industry are correlated positively. 4. the relationship between educational attainment and growth is non linear

	Title	Author	Methodology	Data	Theme
12	Growth and Convergence in U.S. Cities	Crihfield and Panggabean (1995)		Cross section disaggregated data are used for 282 metropolitan areas spanning from 1960 to 1982 deflated in 1982-1984 us dollars using CPI. However, the bulk of data for the 35 variables employed in the paper refers to the years 1960, 1967, 1972, 1977 and 1982. Sources include Bureau of the Census, State and Metropolitan Area Data Book, County and Data City data book, Statistical Abstract of the United States, Census of Manufactures, Census of Governments and Pacific Northwest Laboratory, State Energy Price System	This paper addresses two main issues. Interregional income convergence among 282 US metropolitan areas and whether endogenous structural determinants, particularly public sector investments, affect the convergence process. With the use of cross section disaggregated data for 282 metropolitan areas it is found that: First, real per capita income converged at the rate of 6% between 1960 and 1977 and diverged between 1977 and 1982. The neoclassical model estimations for public investment coefficients using OLS and 2SLS are statistically insignificant, namely, public investment do not play important role in the growth of metropolitan economies
13	Mobility and Modality Trends in US State Personal Income	Hammond and Thompson (2002)	Income dynamics, Convergence, Mobility, Modality	In this paper are used data on per capita personal income for the 48 contiguous US States and the District of Columbia between from 1929 to 1999. The data are retrieved from the Bureau of Economic Analysis	This paper investigates the modality and mobility trends on per capita personal income for the 48 contiguous US States and the District of Columbia during the period 1929-1999. After disaggregating data into net earnings; dividends, interest, rent; transfer income and dividing the space of income values in five income classes it is concluded that: with the exception of the 1980s, income convergence and mobility is observed around the third income class. The strongest degree of convergence concerns the income distributions of the 1940s and the 1950s

	Title	Author	Methodology	Data	Theme
14	Productivity in the euro area: any evidence of convergence?	Sondermann (2013)	Productivity, Convergence, Panel unit root test, Manufacturing and service sector	In this paper productivity data are used for 10 major sectors as well as aggregated value added and man-hour annual data. The data are transformed in Euros with the help of OECD-Eurostat PPPs. The period under examination is from 1970 to 2007 for 12 Euro Area Countries and the source is EU KLEMS project	This paper studies labor productivity convergence among 12 Euro Area Countries and among the main euro-area sectors and subsectors. The role of R&D, Human Resources and Regulations in the labor productivity growth is also investigated. No evidence of labor productivity convergence among the Countries is observed. Little signs of convergence are found on three sectors (agriculture, transport-communication and Non Market Services) and three low technology sub-industries. Finally regulation burdens affect mainly the services sectors while R&D investments boost the productivity in manufacturing sector.
15	The impact of space and scale on conditional convergence: test results from the United States (1970–2004)	James and Campbell (2014)	Convergence, spatial data analysis, modifiable areal unit problem	In this study personal per capita income data for the years 1970-2004 are recovered from BEA. Additional data are from Minnesota Population Center, US Department of Agriculture and Department of Transportation among others, for the estimation of 13 explanatory variables in 3 levels of aggregation: The 48 contiguous States; BEA economic areas (EA); and BEA counties	This article investigates the impact of spatial aggregation effects on conditional income convergence in the United States from 1970 to 2004 using 3 levels of aggregation, id est States, BEA economic areas and BEA Counties. It is deduced that income convergence is stronger for BEA economic areas and regions than for states. Additionally, the inclusion of spatial effects in the analysis leads to more accurate estimations of the speed of convergence
16	The U.S. Structural Transformation and Regional Convergence: A Reinterpretation.	Caselli and Coleman II (2001)		In this paper labor income panel data are used from Lee et al. (1957) covering the years 1880, 1900, 1920 and 1950 for the 48 continental Sates. Furthermore, new labor income panel data are constructed with the help of the Integrated Public-Use Microdata Series (IPUMS) of the US Census of Population, a project of Minnesota University	This paper presents a joint study on the structural transformation of the US economy (the decline of the agricultural sector and the rise of the non agricultural sectors) and on the income convergence among US regions and sectors. Based on three work assumptions it is concluded that the relative wage rate of agriculture workers has increased and at the same time, their labor supply has fallen leading to income convergence between North and South regions from 1880 to 1980

	Title	Author	Methodology	Data	Theme
17	US Regional Income Convergence: A Spatial Econometric Perspective	Rey and Montouri (1999)	regional income convergence, spatial econometrics, exploratory spatial data analysis	This study uses cross section income data from BEA, US Department of Commerce for the 48 conterminous US States focusing on the period between 1929 and 1994	This study examines regional income convergence across 48 US States, taking into account spatial interactions between the States. With the implementation of a Spatial Error (ML) dependence model it is showed that: the rate of convergence among states is slightly slower than the classical unconditional model predicts. Moreover, strong evidence of spatial autocorrelation is found in per capita income level which suggests that neighboring states have the same pattern of income growth rate and shocks are easily transmitting between states, thus complicating the convergence process
18	How important are human capital, physical capital and total factor productivity for determining state economic growth in the United States, 1840–2000?	Turner, Tamura and Mulholland (2013)	State physical capital, Human capital, Land, Economic growth	In this paper new per worker panel data on human capital, physical capital and land for the 50 US States and the District of Columbia are constructed, covering the period between 1840 and 2000. The main sources are various editions of the Censuses of Agriculture and Manufacturing from the Census Bureau, USDA Farm Balance Sheets from 1960 onwards and the 1940-2000 US Censuses drawn from the Integrated Public Use Microdata Series System	This study applies the methodology of cross country growth accounting id est the investigation of which proportion of output per worker is due to input contributions and which is due to Total Factor Productivity (TFP) among the 50 States and the District of Columbia for the period 1840-2000. The main results are: first, the 70% of the productivity convergence among the States over the 160 years can be attributed to the decline in standard deviation of TFP. Second, the growth in input per worker explains 3/5 to 3/4 of the growth in output per worker and the variation of input growth rates accounts for only 1/4 of the variation of output growth rates across US States
19	Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show	Baumol (1986)		In this paper per capita labor productivity data is used covering the period between 1870 and 1979 among 16 industrialized countries. The primary sources are from Maddison (1982) and Matthews, Feinstein and Odling-Smee (1982) works.	This study examines labor productivity beta-convergence among 16 industrialized countries from 1870 to 1979 finding strong evidence of convergence partly attributed to innovation spillovers and investments while for poorer countries the opposite can be said due to the lack of education and associated skills

3. Data and Methodology

3.1 The Models

In our analysis we use two main models in order to test for beta-convergence as well as stochastic convergence of the labor productivity of seven major US Sectors. Sigma-convergence is presented diagrammatically.

Studies of absolute beta convergence use a cross section of regions to examine the relationship between the growth rate of labor productivity and the initial level of productivity. Convergence appears as a negative beta-coefficient from regressing a measure of the former on the latter. If regions are fairly similar, we assume that they approach the same long run steady state equilibrium level of per capita income (Miller and Genc, 2005). On the other hand, sigma convergence can be defined as the intertemporal decline of cross-sectional variance in productivity levels across time.

The following model was first introduced by Baumol and is broadly applied in research of beta convergence.

$$\ln\left[\left(\frac{Y}{L}\right)_{i,2013}\right]-\ln\left[\left(\frac{Y}{L}\right)_{i,1987}\right]=a+\beta\ln\left[\left(\frac{Y}{L}\right)_{i,1987}\right]+\varepsilon_i \qquad (1)$$

where $\left[\left(\frac{Y}{L}\right)_{i,t}\right]$ is the labor productivity of the state i in year t, α and β are parameters to be estimated and ε_i is a stochastic error term. Y and L are gross state product and state employment respectively.

Stochastic convergence requires that the long run deviations on productivity level differences between two economies, which are caused from a random shock, goes to 0. That is, productivity disparities between economies should follow a stationary process. If this is not the case, relative productivity shocks could lead to permanent deviations in any tendency toward convergence (Carlino and Mills, 1993).

The model implemented here, namely, the following general AR(1) model without state-specific intercepts is a slight variation of that used in the article by Bernard and Jones (1996) which we follow closely in the next paragraph:

$$x_{it}=\rho x_{it-1}+\varepsilon_{it} \qquad (2)$$

where the $\varepsilon_{it} \sim iid(0,\sigma_{\mu}^{2})$ and ρ is the parameter for estimation.

To examine the convergence hypothesis, while taking advantage of the time series aspect of the data, we focus on cross state deviations in labor productivity levels. Letting state 1 denote the benchmark state, our tests will be based on the below equation

$$x_i \equiv D\ln y_{ij}(t) \equiv \ln y_{1j}(t) - \ln y_{ij}(t),\ \text{i=2,.....,N}\text{, for i=state, j=sector}$$

Then state i is converging to state 1 if $D\ln y_{ij}(t)$ is stationary. The relatively short sample (t=27) means that we cannot examine the hypothesis that only a subset of the fifty states are converging. We test the null hypothesis that all fifty states are converging against the alternative that as a whole they are not converging.
The benchmark state is chosen in three different ways: first we pick the most, on average[1], productive state in each sector; second, we use U.S. productivity levels over the period; third, we select the median state in terms of sectoral productivity.

3.2 Data

Our work is concerned with the movements of labor productivity across US states and industries from 1987 to 2013. The industries-sectors analyzed are Mining; Construction; Manufacturing; Transportation and Public Utilities; Trade (Wholesale and Retail); Finance, Insurance, and Real Estate (FIRE) and Services. In order to construct the productivity real values for each sector across the fifty states and the District of Columbia we employ two types of data. We use annual gross state product data of chained 1997 dollars between 1987 and 1997 and chained 2009 dollars between 1997 and 2013 which was retrieved from the US Department of Commerce, Bureau of Economic Analysis (BEA). State employment seasonally adjusted data is from the Bureau of Labor Statistics and represents annual averages for the same time period. All the data is converted in logarithmic form.

The data used here consists of two series. The first one is from 1987 to 1997 and is classified under the Standard Industrial Classification (SIC) system which was developed in the 1930s at a time when manufacturing dominated the U.S. economic scene. The second is between 1997 and 2013 under the North American Industrial Classification System (NAICS) which was introduced in 1997 and is periodically revised to reflect changes in the industrial structure of the U.S. and North American economy. The following table outlines our data:

Source	Type	Classification	Period of Time
U.S. Bureau of Economic Analysis	Annual Gross State Product Data	SIC (1987-1997)	1987-2013
		NAICS (1997-2013)	
U.S. Bureau of Labor Statistics	State Employment Seasonally Adjusted Data	SIC (1987-1997)	1987-2013
		NAICS (1997-2013)	

[1] Bernard and Jones chose the median and most productive state in relevance with the starting year of their sample, namely 1963.

However there are some differences to be taken into account between those series. NAICS codes provide a greater level of detail about a firm's activity than SIC codes. NAICS includes 1,170 industries and SIC includes 1,004 industries. Additionally, the NAICS-based statistics of GDP by state are consistent with U.S. gross domestic product (GDP) while the SIC-based statistics of GDP by state are consistent with U.S. gross domestic income (GDI). As a result there is not exact match between those two classifications. Differences between the two series were also the reason for not being able to adopt a common base year for deflating our data[2]. However, as is shown in the appendix, the transition from SIC to NAICS series in year 1997 is smooth in productivity terms. Besides, according to the 1997 US Economic Census data could be categorized under either NAICS or SIC, therefore certain key data could be published according to the old system as well as the new[3].

Hence, we proceed to the presentation of the parity between the sectors of interest. The chart of the next page shows the NAICS sectors and the SIC divisions from which their primary components were derived[4]. The third column was created for the purpose of our study.

[2] Nevertheless, it should be mentioned that, when examining differentials between pairs of series, the results are not affected by the choice of data in nominal or real terms (Holmes, Mark J., Jesús Otero, and Theodore Panagiotidis, 2013)

[3] Things to Consider When Reviewing Historical Data: http://www.census.gov/econ/census/help/sector/consider_history.html

[4] Details for this table can be found here: http://www.naics.com/history-naics-code/

NAICS Sectors	SIC Divisions	Present Study
Mining	Mining	Mining
Construction	Construction	Construction
Manufacturing	Manufacturing	Manufacturing
Utilities	Transportation, Communications & Public Utilities	Transportation and Public Utilities
Transportation & Warehousing	Transportation, Communications & Public Utilities	
Wholesale Trade	Wholesale Trade	Trade
Retail Trade	Retail Trade	
Accommodation & Food Services	Retail Trade	
Finance & Insurance	Finance, Insurance & Real Estate	Finance, Insurance, and Real Estate
Real Estate & Rental & Leasing	Finance, Insurance & Real Estate	
Information	Services	Services
Professional, Scientific & Technical Services	Services	
Administrative & Support & Waste Management & Remediation Services	Services	
Education Services	Services	
Health Care & Social Assistance	Services	
Arts, Entertainment & Recreation	Services	
Other Services (except Public Administration)	Services	

After finding the equivalent between the two classification systems, the two sets of data were merged using the 1997 data in each data set. Because of missing data early in the sample (mainly employment data), a few states are omitted from our calculations for certain sectors. The following states are omitted from the Mining sector: Delaware, District of Columbia, Florida, Hawaii, Rhode Island and South Carolina. Delaware and Hawaii are also dropped from the Construction sector for the same reason.

3.3 Methodology

The **first step** is to briefly examine the state productivity data that underlies our results by highlighting variations in productivity levels and growth rates across states and sectors.

The **second step** includes the application of absolute beta convergence and sigma convergence techniques to cross sectional productivity data. We run seven regressions for the seven aforementioned sectors of the fifty states based on the model (1) to test for beta convergence. We use the White test (1980) instead of the Breusch-Pagan test to check for heteroskedasticity because the residuals for Manufacturing, Transportation and public utilities and Trade data are not normally distributed. Furthermore, we use robust standard errors for every regression in order to correct the possible bias in standard errors and take reasonably accurate p values in test statistics. Besides, due to the nature of the logarithms (negative values are not permitted) we excluded those States for which data is absent for the year 1987, namely, Alaska from Mining sector; Louisiana, Maryland, Nebraska, South Dakota, Tennessee from Mining and Construction sector; Alabama, District of Columbia, and Oklahoma from Manufacturing sector. Sigma convergence results are depicted diagrammatically.

The **third step** is completed in three stages. We deploy four unit root tests to check for stochastic convergence. We, then, estimate a fixed effects model with instrumental variables. Finally we use those estimations to compute the half life in order to have an approximation of the speed of convergence.

Stage one[5]:

Two generations of panel unit root tests can be distinguished. The first generation builds on the assumption of cross-sectional independence, while the second generation allows (to different extents) dependence to prevail across units in a panel. In the first category are the above three of the four unit root tests that are to be implemented on this stage. These are The Levin-Lin-Chu (2002), Harris-Tzavalis (1999) and Breitung (2000) unit root tests. One reason for choosing those tests is their assumption that all panels share the same autoregressive parameter so that $\rho_i = \rho$ for all i, which is in accordance with our model. Another reason is that they are appropriate for the size of our panel data which consists of 51 panels (N) for a relatively short time period (T) of 27 years. According to Hlouskova and Wagner (2006) the above tests without panel-specific mean terms have a well-defined asymptotic distribution for smaller T than N.
All three tests have as the null hypothesis that all the panels contain a unit root, assume strongly balanced datasets and presuppose that error terms are independently distributed across panels. The Levin-Lin-Chu and Breitung unit root tests were performed with one lag of the dependent variable while for Harris-Tzavalis there is no option for lags.

[5] the analysis of stage one is based on the documentation provided by the statistical software Stata 12 and particularly the panel data reference manual

Stage two:

A growing body of the panel-data literature concludes that panel-data models are likely to exhibit substantial cross-sectional dependence in the errors, which may arise because of the presence of shocks and unobserved components that essentially become part of the error term (De Hoyos, Sarafidis 2006). In the case of a unified economy, such that of US states, with free trade and employment movements that might be especially true. To encounter this possibility we use the Pesaran's CD test (2004). After the detection of cross-sectional dependence we perform the Cross Sectional IPS (CIPS) unit root test introduced by Pesaran (2007) which is a modified version of the t-bar test proposed by Im et al. (2003). On this paper, Pesaran augments the standard DF (or ADF) regressions with the cross-section averages of lagged levels and first-differences of the panel series so that the new panel unit root test be based on the simple averages of the individual cross-sectionally augmented ADF statistics (CADF). The CADF statistics can then be used to develop modified versions of the t-bar test proposed by Im et al. (IPS). New asymptotic results are obtained both for the CADF statistics, and their simple averages, referred to as the cross-sectionally augmented IPS (CIPS) test.
More formally, if our model (2) has cross-sectional dependent errors, it can be written in the following way:

$x_{it} = \phi_i x_{it-1} + u_{it}$, i=1,….,N; t=1,….,T (3)

where the error term u_{it} has the single-factor structure

$u_{it} = \gamma_i f_t + \varepsilon_{it}$ (4)

in which f_t is the unobserved common effect, and ε_{it} is the individual-specific error. Replacing (4) in (3) and taking the first differences we have: $\Delta x_{it} = \beta_i x_{it-1} + \gamma_i f_t + \varepsilon_{it}$, where $\beta_i = -(1-\phi_i)$ and $\Delta x_{it} = x_{it} - x_{it-1}$. The unit root hypothesis , $\varphi_i = 1$ can now be expressed as

H_0: β_i=0 for all i

against the alternatives,
H1 : $\beta_i < 0, i = 1, 2, ...N$, β_i=0, $i = N_1 + 1, N_1 + 2, ...N$

The assumptions to be met are that u_{it}, is serially uncorrelated and ε_{it}, f_t and γ_i are independently distributed for all i.

Next, Pesaran (2007) builds the following CADF regression by further augmenting the standard augmented Dickey–Fuller (ADF) and then he tests the unit root hypothesis

$\Delta x_{it} = b_i x_{it-1} + c_i \overline{x}_{t-1} + d_i \Delta \overline{x}_{t-1} + e_{it}$ (5)

Where $\bar{x}_{t-1}$ and $\Delta\bar{x}_{t-1}$ are regarded sufficient for asymptotically filtering out the effects of the unobserved factor f_t. The hats above x denote averages and the test is based on the t-ratio of the OLS estimate b_i. That t-ratio can be denoted by $t_i(N,T)$. This cross-sectionally augmented Dickey–Fuller statistic is then used for the development of the panel unit root counterpart, namely, the CIPS test:

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T) \qquad (6).$$

Stage three:

The third stage is divided into two parts:
1. First we compute a two stage least square regression of a fixed-effects dynamic model with instrumental variables encountering the problem of cross sectional dependence.
2. Then we use the above estimates to find the half life of the productivity shocks so as to have a notion about the degree of productivity convergence across US states and sectors.

The impact of cross-sectional dependence in estimation depends on a variety of factors, such as the magnitude of the correlations across cross sections and the nature of cross-sectional dependence itself. If we assume that cross-sectional dependence is caused by the presence of common factors, which are unobserved but uncorrelated with the included regressors, the standard fixed-effects and random-effects estimators are consistent, although not efficient, and the estimated standard errors are biased. One may choose to retain the FE/RE estimators and correct the standard errors by following the approach proposed by Driscoll and Kraay (1998) who proposed a nonparametric covariance matrix estimator for coefficients estimated by pooled OLS/WLS and FE regression and produces standard errors that are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. However, if the unobserved components that create interdependencies across cross sections are correlated with the included regressors (which is the case in a first order autoregressive model), these approaches will not work and the FE and RE estimators will be biased and inconsistent (De Hoyos, Sarafidis 2006). One method to encounter this would be to apply an instrumental variables approach using a fixed-effects model. This approach is adopted here.

The idea behind instrumental variables is to find a set of variables, termed instruments, that are both correlated with the explanatory variables in the equation under examination and uncorrelated with the disturbances. These instruments are used to eliminate the correlation between right-hand side variables and the disturbances. The central element of this model is the within transformation of the variables. The within transform of a variable w can be defined as:

$$\tilde{w}_{it} = w_{it} - \bar{w}_{i.} + \bar{w} \qquad (7)$$

where

$$\bar{w}_{i.} = \frac{1}{n}\sum_{t=1}^{T_i} w_{it}$$

and

$$\bar{w} = \frac{1}{N}\sum_{i=1}^{n}\sum_{t=1}^{T_i} w_{it}$$

and n is the number of states while N is the total number of observations. Applying equation 7 in our model (2) the within transformation can then be written:

$$\tilde{x}_{it} = \rho\tilde{x}_{it-1} + \tilde{\varepsilon}_{it}$$

or

$$x_{it} - \bar{x}_{i.} + \bar{x} = \rho(x_{it-1} - \bar{x}_{i.} + \bar{x}) + \varepsilon_{it} - \bar{\varepsilon}_{i.} + \bar{\varepsilon} \qquad (8)$$

A significant problem was the choice of the instrumental variables. On this issue we decided to follow the approach by Anderson and Hsiao (1981) and first differencing equation (2) to obtain

$$x_{it} - x_{it-1} = \rho(x_{it-1} - x_{it-2}) + \varepsilon_{it} - \varepsilon_{it-1} \qquad (9)$$

In this equation the errors ($\varepsilon_{it} - \varepsilon_{it-1}$) are now correlated with the explanatory variable $(x_{it-1} - x_{it-2})$ so we are instrumenting for $(x_{it-1} - x_{it-2})$ with either x_{it-2} or $(x_{it-2} - x_{it-3})$ which are uncorrelated with the disturbance in (3) but correlated with $(x_{it-1} - x_{it-2})$. Arellano (1989) finds that for simple dynamic error components models the estimator that uses differences Δx_{it-2} rather than levels x_{it-2} for instrument has a singularity point and very large variances over a significant range of parameter values. In contrast, the estimator that uses instruments in levels, i.e., x_{it-2}, has no singularities and much smaller variances and is therefore recommended (Baltagi)[6].

This instrument is suggested for a model with similarities in structure with model (8), hence we use it. Nevertheless, someone might wonder why we didn't use this model in the first place and decide to use a fixed-effects approach or could further ask why we choose a fixed-effects model instead of a random-effects model. The answer to the first question is that the null hypothesis of the F-test of the (second stage) regressions that the coefficient on the independent variable is equal to zero could not be rejected for almost all the implemented data for the first-differenced model. Besides, the decision to use a FE model instead of a RE model was taken after the execution of Hausman's specification test (1978) with the null hypothesis that the RE estimator is an efficient and consistent estimator of the true parameters. The null hypothesis was rejected in all cases[7].

After defining our model we use the Two Least Square (2SLS) methodology in order to estimate ρ. As the name suggests, there are two distinct stages in two-stage least

[6] Panel data Methods Notes; prepared for the Handbook of Applied Economic Statistics. 1998. 1st edition. New York: CRC Press

[7] The results of the Hausman test are in the appendix

squares. In the first stage, 2SLS finds the portions of the regressor $(x_{it-1} - \overline{x}_{i.} + \overline{x})$ that can be attributed to the instrument x_{it-2}. This stage involves estimating an OLS regression of the regressor on the instrument. The second stage is a regression of the original equation (8), with all of the variables replaced by the fitted values from the first-stage regression. The coefficient of this regression $\hat{\rho}_{2SLS}$ is the 2SLS estimate.

On the second part we use the method of half life in order to compute the speed of productivity convergence. Half life can be defined as the time that it takes for an economy, starting from an equilibrium point, to transit halfway to a new equilibrium after an initial shock (Mello, 2010). The half-life condition for an autoregressive model of first order is given by $h = \ln(1/2)/\ln(\hat{\rho})$ where $\hat{\rho}$ denotes the estimate of the parameter ρ of the FE model, namely $\hat{\rho}_{2SLS}$.

4. Empirical Results

On this section we present the analysis of the empirical results in accordance to the methodology developed above.

4.1 Summary of the Data

Table 1 summarizes our data by reporting averaged productivity levels, variation as well as growth rates across the fifty states and the District of Columbia.

Table 1

Sector	Average 1987	Coefficient of Variation 1987	Average 2013	Coefficient of Variation 2013	Annual growth rate (percent)
Mining	127372,76	150,3	287064,61	51,4	4,08
Construction	55427,41	19,1	96440,88	16,1	2,60
Manufacturing	55030,15	28,7	152098,47	35,0	4,60
Transportation and public utilities	87191,31	25,7	150685,55	26,8	2,46
Trade	31905,54	11,1	65736,79	13,6	3,41
Finance, insurance, and real estate	175256,55	16,8	374439,13	22,4	3,38
Services	46929,78	12,7	81163,15	20,5	2,99
Total	82730,50	62,3	172518,37	67,1	3,44

As we can see the FIRE and Mining are the most productive sectors as of 2013, at 374.439,13 and 287.064,61 respectively, exceeding by far the aggregate average of the sectors which is at 172.518,37. Additionally, it is apparent that the most dynamic sectors for this time period are Manufacturing, FIRE and Mining. The first had almost tripled between 1987 and 2013 in productivity terms, while the other two were more than doubled. Those results are also confirmed from the annual average growth rates. Besides, variation across States for the Mining sector was very large in 1987 and fell considerably in 2013 showing signs of convergence. US States don't seem to convergence in the other sectors while the same is true for the seven sectors as a total.

4.2 Cross Sectional Convergence Analysis

4.2.1 beta convergence

On this subsection we run seven regressions based on model (1) which, in words, are the regressions of the productivity growth rates on the initial level of the 1987 productivity transformed in natural logarithms. A star, a double star and a triple star denote p-values smaller than 0,05 0,01 and 0,001 significance levels respectively.

Table 2

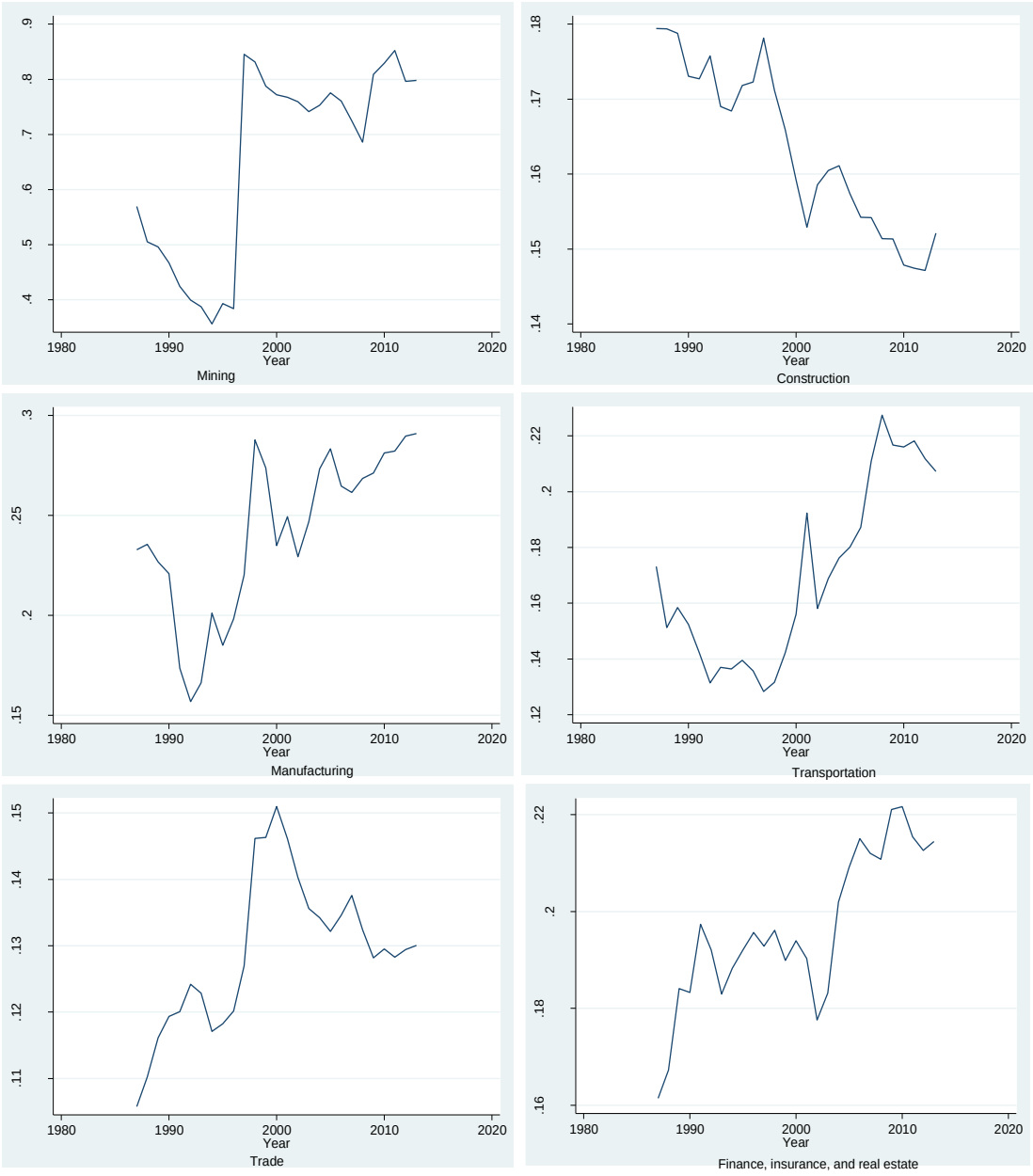
Sector	**b coefficient**	**Robust Std. Err.**	**R^2**	**White Test (Prob > chi2)**
Mining	-0,84539423***	0,11656505	0,6506	0,3821
Construction	-0,49517564***	0,09701101	0,3459	0,8781
Manufacturing	-0,63323541**	0,2337011	0,2194	0,2895
Transportation	-0,28211474**	0,08671627	0,0799	0,6244
Trade	-0,38105327*	0,17939655	0,1140	0,1031
FIRE	-0,08472283	0,09988643	0,0177	0,4382
Services	0,08802695	0,08380272	0,0233	0,6935

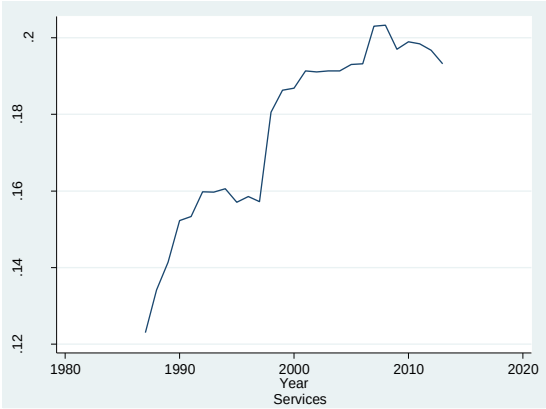
As already mentioned in the methodology section a negative (and significant) coefficient can be taken as evidence in favor of convergence. Hence, the above results indicate beta convergence over the time period 1987–2013 for all the sectors but FIRE and Services. The first four sectors of table 2 have highly significant coefficients (>99,95) while as we can see Mining and Manufacturing show the strongest evidence for convergence. The R^2 can be considered reasonable for a cross section of this nature (Miller and Genc, 2005) with the exception of FIRE and Services which don't fit in the model either way. For those two sectors we limited our data to the more recent classification system i.e. NAICS between 1997 and 2013 in order to gain a better F statistic, to no avail. White test showed no evidence of heteroskedasticity for any sector.

4.2.2 sigma convergence

Figure 1 shows the cross-section standard deviation for the natural logarithm of labor productivity for the seven aggregate sectors across the fifty states.

Figure 1





As we can see from the diagrams of figure 1 the only sector that shows clear reduction in variance of labor productivity over the entire period is Construction. For Mining sector labor productivity dispersion declines until 1994 and then rises dramatically, especially after 1997. This sharp rise is probably due to the transition from SIC to NAICS classification while from then on the trend is not clear. Productivity variance in Manufacturing sector drops until 1993 and then rises steadily. Transportation and public utilities sector exhibits a similar pattern of productivity variance with Manufacturing. Here the standard deviation of productivity drops until 1998 and then rises. Trade sector shows signs of σ-convergence after 2000 while F.I.R.E. as well as Services sectors show no evidence of declining cross-section dispersion.
Comparing those results to our findings in β-convergence analysis we can see obvious contradictions especially for Mining and Manufacturing sector. This can be due to Galton's Fallacy of regression towards the mean, applied in convergence analysis. As shown by Quah (1993) it is possible for a negative cross-sectional relationship between initial income and growth (that is β-convergence) to coexist with a stable cross section variance in income levels. The same can be said for labor productivity. This arises from the presence of shocks to productivity growth rates that can offset the signs of convergence implied by b coefficient.

4.3 Time Series Convergence Analysis

4.3.1 Cross-sectional independence unit root tests

In this subsection we perform three unit root tests to check for stochastic convergence across states in the seven specified sectors when using as benchmark the Median State, the Most Productive State and USA respectively, in line with the methodology. The tests are Levin-Lin-Chu (2002), Harris-Tzavalis (1999) and Breitung (2000) unit root tests. All tests share the same assumptions for the autoregressive parameter, as well as the form of the panels and have similar asymptotics, as explained in the methodology section.

Tables three, four and five present the results for all the tests and benchmarks.

Table 3

Median state as benchmark						
Sector	**Levin-Lin-Chu test**		**Harris-Tzavalis test**		**Breitung test**	
	t^*-Statistic	p-value	z-Statistic	p-value	λ-Statistic	p-value
Mining	-7,43	0,000	-8,88	0,000	-7,06	0,000
Construction	-6,54	0,000	-4,77	0,000	-6,02	0,000
Manufacturing	-5,03	0,000	-6,94	0,000	-4,02	0,000
Transportation	-4,50	0,000	-12,47	0,000	-8,64	0,000
Trade	-3,58	0,000	-2,28	0,011	-2,92	0,002
FIRE	-3,00	0,001	-1,13	0,129	-1,16	0,124
Services	-1,00	0,158	0,04	0,516	-0,27	0,393

Table 4

Most productive state as benchmark						
Sector	**Levin-Lin-Chu test**		**Harris-Tzavalis test**		**Breitung test**	
	t^*-Statistic	p-value	z-Statistic	p-value	λ-Statistic	p-value
Mining	-11,10	0,000	-5,36	0,000	-10.72	0,000
Construction	-6,59	0,000	-2,79	0,003	-9.61	0,000
Manufacturing	-2,81	0,003	-2,14	0,016	-2.16	0,015
Transportation	-5,99	0,000	-5,89	0,000	-8.02	0,000
Trade	-0,13	0,449	0,08	0,530	1.29	0,902
FIRE	-1,13	0,130	-0,67	0,250	-1.06	0,144
Services	4,57	1,000	1,62	0,948	7.29	1,000

Table 5

USA as benchmark						
Sector	**Levin-Lin-Chu test**		**Harris-Tzavalis test**		**Breitung test**	
	t^**-statistic*	*p-value*	*z-statistic*	*p-value*	λ-statistic	*p-value*
Mining	-5,46	0,000	-3,67	0,000	-4,73	0,000
Construction	-3,68	0,000	-1,24	0,107	-2,82	0,002
Manufacturing	-1,14	0,128	-5,63	0,000	-0,58	0,280
Transportation	-2,78	0,003	-3,32	0,001	-2,62	0,004
Trade	-1,79	0,037	-1,09	0,137	-0,71	0,239
FIRE	-0,93	0,177	-0,87	0,191	-0,05	0,481
Services	2,70	0,997	0,72	0,765	4,61	1,000

The Harris-Tzavalis and Breitung tests, when the benchmark state as far as the productivity level is concerned is the Median state, indicate that the hypothesis of no-convergence cannot be rejected for the sectors of Finance, Insurance and Real Estate (FIRE) and Services (Table 3) in any significance level. On the contrary the other five sectors exhibit productivity convergence across the US states. The null hypothesis of no convergence, is also rejected for the FIRE sector according to LLC test.

For the Most productive state as benchmark and the US as benchmark the results are almost unanimous among the three tests. Mining, Construction and Transportation and public utilities sectors show convergence performance among the states at almost all the significance levels while Manufacturing sector seems to diverge according to the two of the three tests for the US benchmark specification (Table 5). It is also worth mentioning that for Services sector the p-value is very high, implying an important degree of productivity divergence among the states.

Considering the above results it may be said that, with respect to the Services and FIRE sectors, problems related to measurement errors might occur. In contrast to manufacturing industries, the value added of (some) services is more prone to measurement errors. This relates in particular to the financial services. That is, the measurement of the output of the banking sector is particularly challenging, for example as banks do not charge explicit fees for many of the services they provide, but rather combine the service payments within the offered interest rates (Sondermann 2013).

4.3.2 Pesaran's (2004) cross sectional dependence test and (2007) unit root test

An assumption of the tests above is that the cross-sectional units have to be independent from each other. This assumption, however, might be very restrictive and consequently, existing correlation could lead to a wrong decision about the rejection or not of the null hypothesis of a unit root. To overcome this possible problem we implement two newer tests which incorporate such issues.
First we check for cross-sectional dependence in the errors using the CD test by Pesaran (2004). The test is appropriate for cases where T is small and N is large so it is suitable for our data. The CD statistic is normally distributed under the null hypothesis of no cross-sectional dependence. Table 6 represents the results of the test for the three benchmark specifications.

Table 6

Cross sectional dependence test by Pesaran (2004)						
Sector	**Median**		**Most**		**US**	
	CD-statistic	*p-value*	*CD-statistic*	*p-value*	*CD-statistic*	*p-value*
Mining	82,28	0,000	74,97	0,000	8,65	0,000
Construction	101,98	0,000	55,34	0,000	22,33	0,000
Manufacturing	47,18	0,000	134,88	0,000	4,99	0,000
Transportation	127,78	0,000	149,38	0,000	2,55	0,0109
Trade	98,33	0,000	101,77	0,000	2,26	0,0239
FIRE	49,18	0,000	132,22	0,000	6,20	0,000
Services	96,98	0,000	109,06	0,000	5,78	0,000

As we can see, the CD test strongly rejects the null hypothesis of no cross-sectional dependence for all benchmark specifications in all significance levels (a= 0,10, a = 0,05, and a= 0,01). The only two exceptions is Transportation and Trade sectors for the US specification which do not reject the null hypothesis for a=0,05. However, the overall performance of those two sectors is in accordance to the assumption of cross-sectional dependence in the error terms across US states. Those results seem reasonable since regions that are geographically close together, or trading partners, may experience common shocks.

The next step after the confirmation of cross section dependence is to implement the cross sectional dependence unit root test also introduced by Pesaran (2007). The test is performed under the null hypothesis of no stationarity. A star, a double star and a triple star denote rejection of the null hypothesis at 0,10 0,05 and 0,01 significance levels respectively

Table 7

Panel Unit Root Test for Cross-Sectional Dependence by Pesaran (2007)			
Sector	**Median**	**Most**	**US**
	CIPS statistic	*CIPS statistic*	*CIPS statistic*
Mining	-1,416	-1,695**	-1,780***
Construction	-0,684	-1,254	-1,139
Manufacturing	-0,937	-1,475*	-1,622**
Transportation	-1,155	-1,635**	-0,862
Trade	-0,378	-1,183	-1,383
FIRE	-0,498	-1,194	-1,445
Services	0,206	-1,409	-1,322

At the 10%, 5% 1% significance levels the critical values of the CIPS statistic for our data are -1,47, -1,57 and -1,74 respectively. According to the CIPS test the null hypothesis of unit root cannot be rejected for all the significance levels and benchmarks for Construction, Trade, Finance, Insurance and Real Estate and Services Sectors. Some evidence of convergence can be found in Mining, Manufacturing and Transportation for the two of the three benchmark specifications. Therefore, the apparent support obtained for the convergence hypothesis for Construction sector using the three cross-sectional independence unit root tests above could be spurious while for the rest sectors the results are similar to a certain degree for all four tests since the productive convergence assumption is verified for at least one benchmark specification in each case. On the other hand, the result for Construction sector is in stark contrast to the previous outcomes in sigma and beta convergence analysis. That might be due to the low power of unit root tests when the speed of income convergence is low (i.e. an autoregressive parameter near unity). Michelacci and Zaffaroni (2000) argue that convergence tests based on the presence of unit roots may perform badly when the true processes exhibit long memory (Durlauf and Aghion, eds. 2006).

4.3.3 The magnitude of labor productivity convergence

On this step we estimate, in line with the methodology section, a fixed effects two stage least squares model using the second lags of labor productive natural logarithms as instrumental variables. The $\hat{\rho}_{2SLS}$ are the coefficients of the second stage regressions.
All the coefficients are statistically significant at 1% level. The results depicted on Table 8 are concerning the Sectors who showed signs of productivity convergence across the US States according to the previous unit root tests.

Table 8

2SLS Regressions with second lags of log productivity as instrumental variables						
Sector	**Median**		**Most**		**US**	
	$\hat{\rho}_{2SLS}$	*Standard Errors*	$\hat{\rho}_{2SLS}$	*Standard Errors*	$\hat{\rho}_{2SLS}$	*Standard Errors*
Mining	0,83995124***	0,02496498	0,86990993***	0,01720728	0,8494027***	0,0196119
Manufacturing	0,81415321***	0,01861979	0,68246222***	0,02286156	0,80062848***	0,01992448
Transportation	0,90131634***	0,03110612	0,78869041***	0,0302609	0,83310786***	0,01815879

The values of the coefficients presented above cannot be interpreted directly so as to have a sense of the magnitude of productivity convergence. Hence, we need to use the half life methodology in order to calculate the degree of convergence. Table 9 below represents the results of these measurement.

Table 9

Half Life				
Sector	**Median**	**Most**	**US**	**Average**
Mining	3,9742072	4,9735889	4,2466559	4,398151
Manufacturing	3,3712285	1,8142929	3,117254	2,767592
Transportation	6,6713567	2,9199724	3,7961497	4,462493

As we can see from table 9 the sector that exhibits the largest degree of productivity convergence across all the US states, on average but also for every individual benchmark, is Manufacturing. That is, after an initial shock in the equilibrium point (steady state) of the Manufacturing sector, the time needed to converge halfway to a new equilibrium is 2.77 years on average. On the other hand, Mining and Transportation sectors need almost 4,5 years to reach this point.
In general, it can be concluded that the manufacturing and industry sector (secondary industry) is moving towards labor productivity convergence while service sector (tertiary industry) is diverging across the US states.

5. Conclusion

The purpose of this study was the investigation of labor productivity convergence of seven major industrial sectors across the US states covering a period of 27 years.

We employed two different methodologies to detect convergence: the first is based on beta and sigma convergence analysis using a model first introduced by Baumol (1986) for the estimation of beta coefficient. Beta convergence appears when the estimation of the beta coefficient has a negative sign while for sigma analysis the same is true when cross-sectional standard deviations in productivity levels across time decline. The second methodology uses unit root tests to determine whether random shocks to labor productivity persist in time, because in such cases the productivity series would contain unit roots. In this framework we used three cross-sectional independence and one cross-sectional dependence unit root test.

Additionally, we estimated a 2SLS fixed-effects model with instrumental variables and used the estimations to compute the half-life for the determination of the speed of convergence.

The results are almost unanimous for the beta-convergence analysis and the cross-sectional independence unit root tests since Mining, Construction, Manufacturing and Transportation are converging in both cases. For the sigma analysis only Construction shows clear reduction in variance of labor productivity over the entire period. When cross-sectional correlation in the errors of panels is taking into account only Mining, Manufacturing and Transportation seem to converge across states. Finally, with the exception of sigma analysis the Manufacturing sector seems to converge in all other cases while it also exhibits the higher speed of convergence according to half-life.

As a concluding remark we can say that capital intensive sectors tend to converge in labor productivity terms while for labor intensive sectors the opposite can be said. The results, especially for manufacturing, are in accord with findings from recent studies such that of Rodrick 2013 who argues that manufacturing industries are converging at quite a fast pace because they can be rapidly integrated into global production networks, facilitating technology transfer and absorption and even when they only produce for the domestic market, they operate under constant threat from foreign suppliers so they must upgrade their operations and remain efficient.

6. Appendix

a) Results of the Hausman specification test for choosing between a Fixed-Effects and a Random-Effects model

Hausman specification test						
Sector	**Median**		**Most**		**US**	
	X^2-statistic	*p-value*	*X^2-statistic*	*p-value*	*X^2-statistic*	*p-value*
Mining	23,16	0,000	23,07	0,000	37,51	0,000
Construction	134,28	0,000	168,77	0,000	72,17	0,000
Manufacturing	63,32	0,000	59,06	0,000	71,80	0,000
Transportation	10,21	0,001	26,46	0,000	84,06	0,000
Trade	80,38	0,000	111,57	0,000	80,09	0,000
FIRE	119,33	0,000	183,18	0,000	124,79	0,000
Services	131,16	0,000	161,90	0,000	144,39	0,000

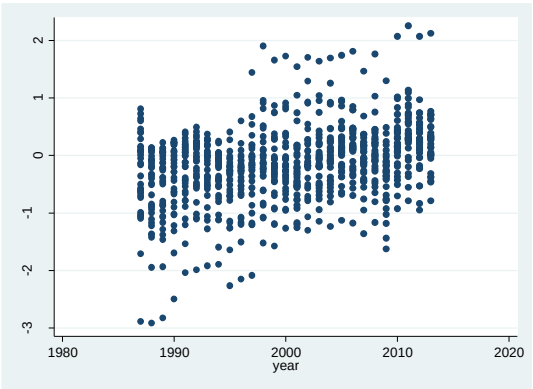
2SLS estimator with IV ρ_{FE} = consistent under Ho and Ha

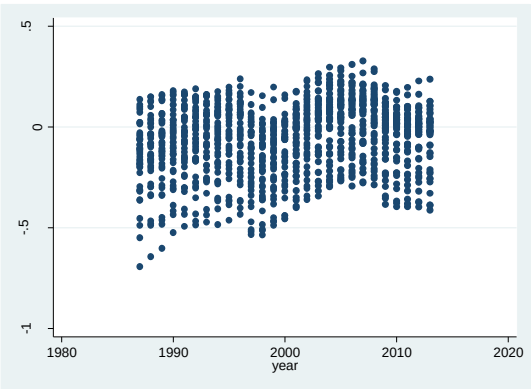
2SLS estimator with IV ρ_{RE} = inconsistent under Ha, efficient under Ho

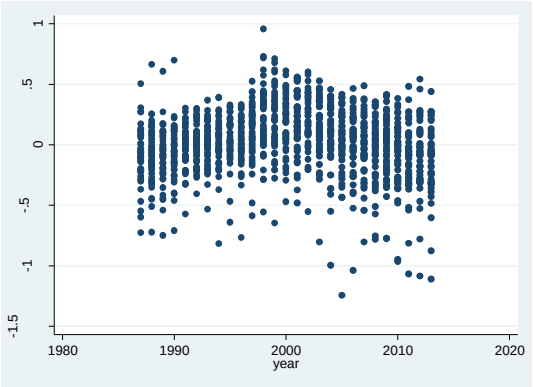
Ho: difference in coefficients not systematic

b) Below we present 21 graphs that show the smoothness in the transition from SIC to NAICS series, in productivity terms, for the seven sectors and the three benchmark specifications. The reference year for the transition is 1997.

i) Median State as Benchmark



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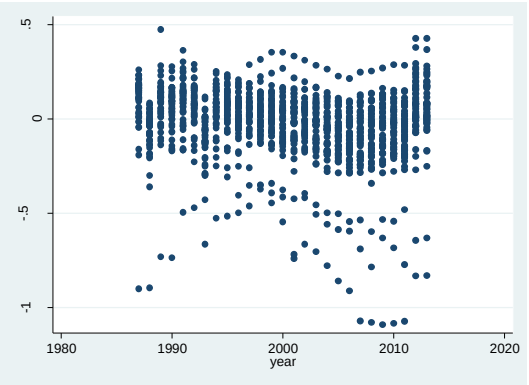
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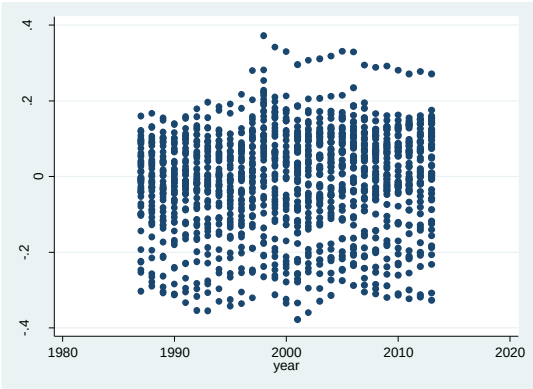
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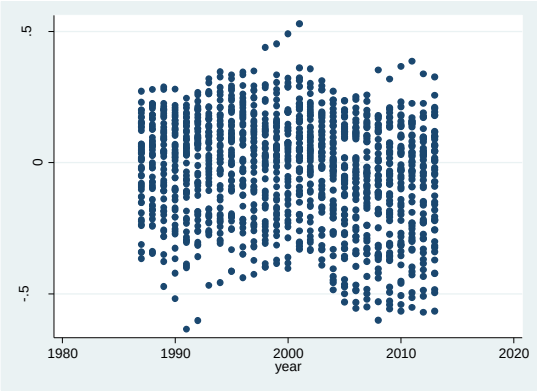
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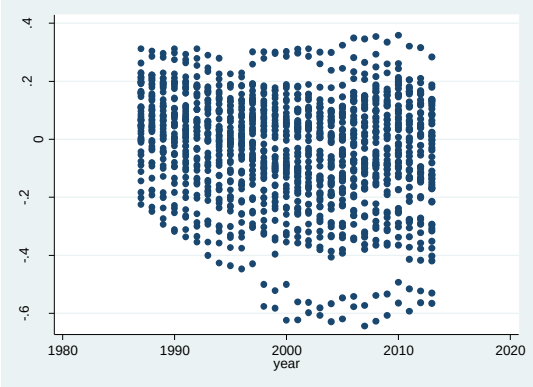
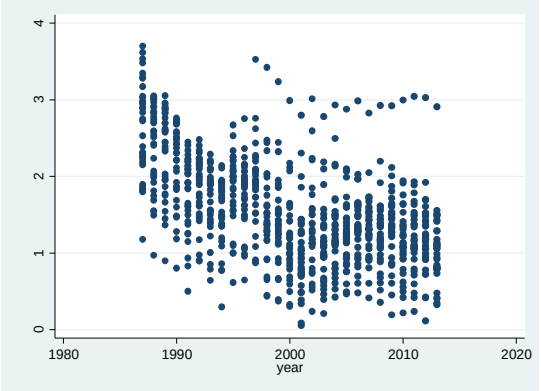
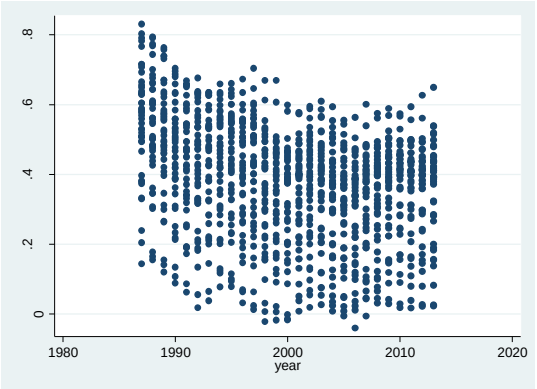
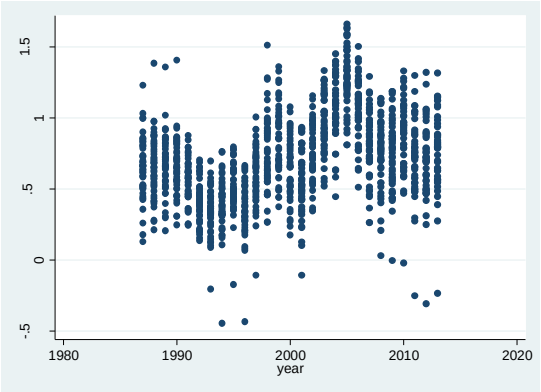
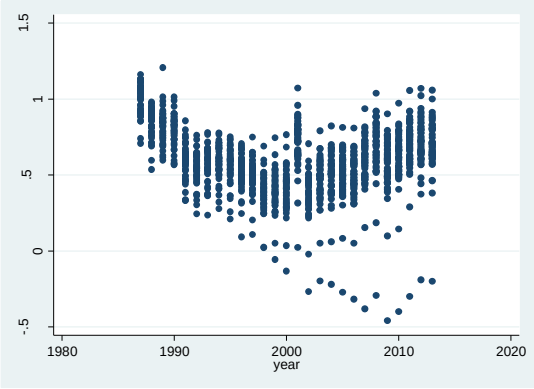

.4
.2
0
-.2
-.4
-.6
1980
1990
2000
2010
2020
year

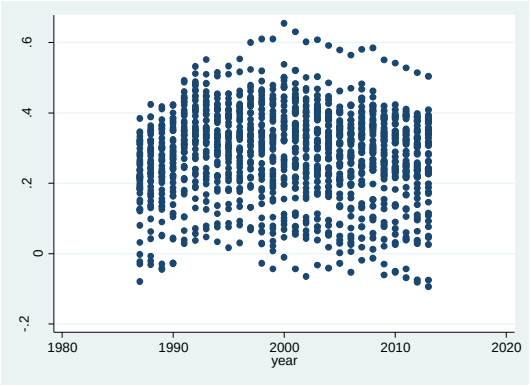
ii) Most Productive State as Benchmark

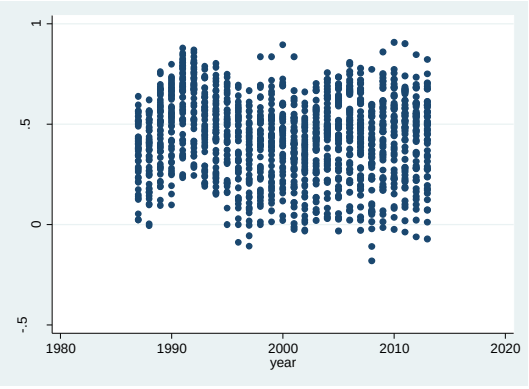


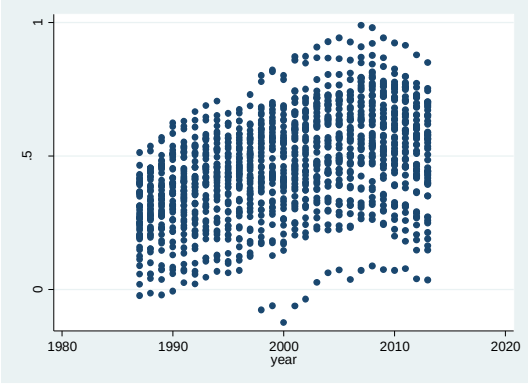




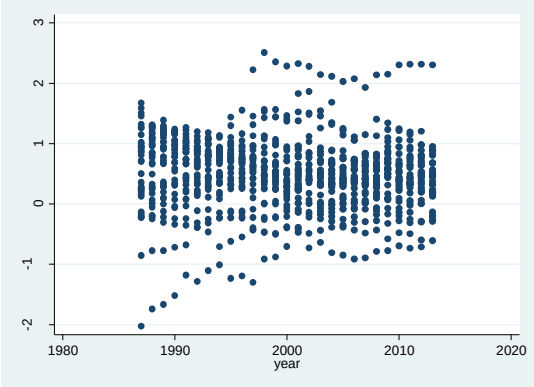


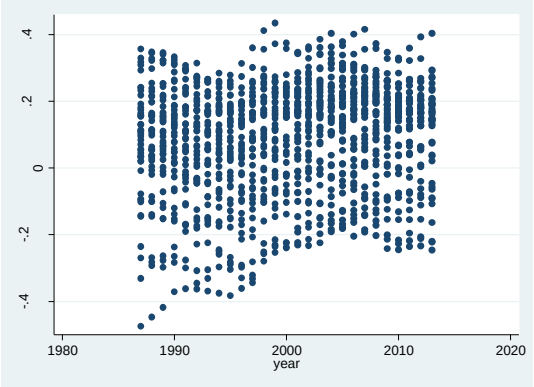


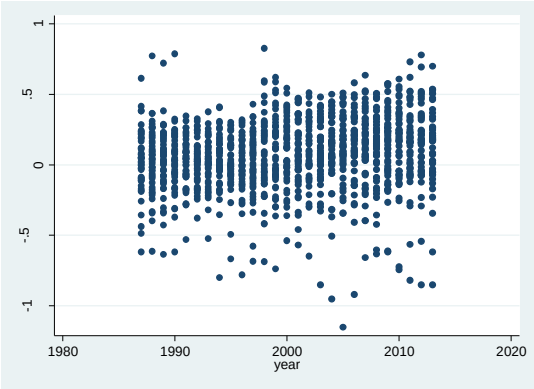


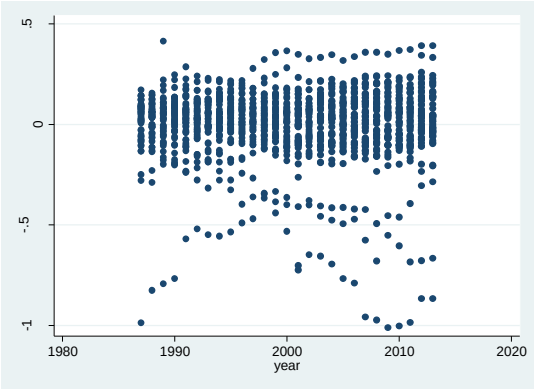


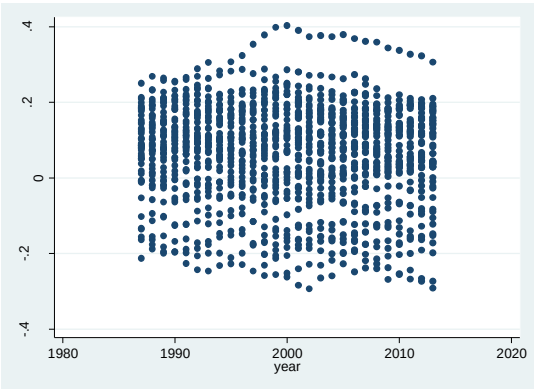
iii) USA as Benchmark

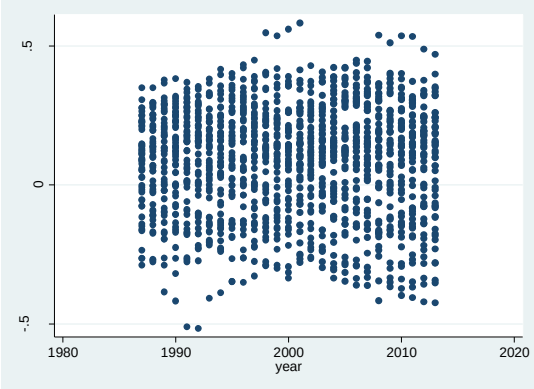












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