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Cover Page Footnote
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AN ANALYSIS OF POVERTY CONVERGENCE: EVIDENCE FROM PENNSYLVANIA COUNTIES

ABSTRACT

This paper extends applications of unconditional and conditional β-convergence and σ-convergence analysis to poverty rates in a panel data sample of Pennsylvania counties during the period 1990-2019. Spatial structural breaks between rural and urban counties in Pennsylvania plus the possibility that Philadelphia County is an outlier are acknowledged to avoid spurious inferences. The findings support the existence of unconditional β-convergence in the pooled, urban, and rural samples with non-metropolitan areas exhibiting the greatest convergence. However, the largest conditional β-convergence is observed for urban counties, and this outcome is robust to the exclusion of Philadelphia County. Graphical evidence evinces a greater degree of σ-divergence in rural areas relative to the pooled and urban samples with metropolitan areas exhibiting neither convergence nor divergence in the absence of Philadelphia County. Statistical evidence based on ADF and DF-GLS tests reveals the presence of σ-divergence in the pooled and rural samples but weaker findings for the urban counties. Panel data tests for unit roots indicate σ-convergence for the full and rural samples but mixed results for the urban sample depending upon the test employed and whether Philadelphia County is included or not. The findings indicate that further investigation of tailored policy responses to poverty in different geographic areas within the same state is warranted.

Keywords: Convergence Analysis, Poverty, Pennsylvania, Rural, Urban, Unit Root, Stationarity

JEL Codes: C23, I32, O18

1. INTRODUCTION

Convergence generally denotes that two data series are moving toward one another. Within the field of economics, convergence is a mainstay of the economic growth literature and refers to the process whereby countries with low levels of income per capita tend to grow more rapidly than those nations with high levels of income per capita and "catch up" with their wealthier counterparts (Ram, 2018; Thompson & Yerger, 2021). Due to the abundance of studies showing evidence of income convergence across different nations and regions, it is commonly considered a given (Barro, 1996; Barro & Sala-i-Martin, 1992; Dobson & Ramlogan, 2002; Mankiw, Romer, & Weil, 1992; Sala-i-Martin, 1996). Ravallion (2012) explains that these enhanced rates of income growth among cross-sectional units starting out with higher poverty rates should experience greater rates of poverty reduction than those that are initially richer. In other words, disparities in poverty measures will be transitory rather than permanent, but their convergence tends to be slower than income convergence (Asadullah & Savoia, 2018; Crespo Cuaresma, Klasen, & Wacker, 2017; Ouyang, Shimeles, & Thorbecke, 2019).

Nationwide, poverty impacted 37.9 million people in 2021, according to the U.S. Census (2023), and rural locations endure more poverty than urban areas (Fisher, 2007; Datt, Ravallion, & Murgai, 2020). Consistent with that observation, the poverty rate in non-metropolitan areas in 2021 was 15.4%, while it was 12.3% in metropolitan areas amounting to a 25% rural-urban divide (Rural Health Information Hub, n.d.).

In the commonwealth of Pennsylvania, among the 33 counties in 2021 with poverty rates exceeding the Pennsylvania average of 12%, 28 are rural counties (Center for Rural Pennsylvania, n.d.; U.S. Census, 2022a). Duren and Stelle (2023) report that, according to Small Area Income and Poverty Estimates (SAIPE) data published by the U.S. Census (2022a), four

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out of the five highest-poverty-rate counties in Pennsylvania are rural (i.e., Forest, Columbia, Potter, and Fayette). They note for context that while Forest County ranks second with a 19.6% poverty rate behind first-ranked Philadelphia County with 22.3%, the inhabitants of Forest County amount to less than 1% of Philadelphia County's populace, which is the largest in the state (Duren & Stelle, 2023).

Despite poverty reduction's importance as a social concern and policy target, relatively little attention in the literature has been paid to poverty convergence (Ouyang, Shimeles, & Thorbecke, 2018). Conventional wisdom suggests that enhancing regional economic growth improves economic well-being and combats poverty (Aiyemo, 2020; Sissoko, Sloboda, and da Silva, 2022). Nevertheless, Latzko (2002) ascertains that unfavorable wage structure (i.e., lower wages for the same job) in poor (typically, rural) counties is responsible for the absence of income convergence in Pennsylvania during 1969-1999, because it enlarges the disparity between the richest and poorest counties. Aiyemo (2020) emphasizes that such rising income inequality can offset the poverty-reducing impact of income growth and favors a two-pronged approach wherein promoting economic growth is complemented by direct intervention to address income inequality. Jenkins and Jozefowicz (2006) correlate educational attainment with favorable changes in income inequality across Pennsylvania counties during the 1990s, and Aiyemo (2020) and Latzko (2002) assert that education and training will better prepare poor individuals to avail themselves of the opportunities spawned by greater economic activity. Within the Pennsylvania State System of Higher Education (PASSHE), nine of the 14 universities are in rural counties. Meanwhile, seven of the 24 Penn State campuses are situated in rural counties. The access to higher education among higher-poverty rural Pennsylvania counties afforded by these institutions may mitigate the tradeoff between income growth and rising income inequality in favor of poverty reduction in those locales.

Sissoko et al. (2022) identify other potentially effective policy avenues including adequately supporting transportation infrastructure spanning urban and rural regions of Pennsylvania to expand much-needed access to health care, education and training, and employment for rural residents (Young, 2018). Parent Pathways is a partnership of non-profit organizations and institutions of higher learning targeting needs in rural Pennsylvania counties by offering services such as job training, access to housing, food, pre-school programs, and higher education (Moran, 2023). While private efforts may ameliorate challenges faced by people living in poverty in rural areas, government resources could offer more long-term assistance to the needy (Creamer, 2022). Sissoko et al. (2022) also assert that rural counties should promote their unique amenities of natural beauty and opportunities for outdoor recreation to residents of the increasingly urbanized counties to stimulate tourism and possibly facilitate job creation as small, local businesses develop in response.

As might be anticipated, the majority of the existing poverty convergence studies focus on countries as the unit of observation (Asadullah & Savoia, 2018; Crespo Cuaresma et al., 2017, 2022; Ouyang et al., 2018, 2019; Ravallion, 2012; Thorbecke & Ouyang, 2018). However, Ram (2018) encourages the use of subnational units in convergence analyses, and Drennan, Lobo, and Strumsky (2004) and Higgins, Levy, and Young (2006) emphasize that counties are an appropriate unit of observation for convergence analysis but note that relatively few such studies have been conducted. Heavily disaggregated data (i.e., counties) offer advantages for convergence studies including a) greater homogeneity than states or countries, b) more time-invariant structural factors, c) consistent borders, and d) diminished risk of aggregation bias

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(Drennan et al., 2004; Gayán-Navarro, Sanso-Navarro, & Sanz-Gracia, 2020; Higgins et al., 2006; Levernier, Partridge, & Rickman, 2000; Young, Higgins, & Levy, 2008). Thus, in accordance with Higgins et al. (2006), Latzko (2002, 2019), Sissoko et al. (2022), and Young et al. (2008), this study utilizes a county-level sample for Pennsylvania to provide a more accurate view of poverty rate behavior across rural and urban settings.

While the convergence behavior of income among Pennsylvania counties has been investigated (Latzko, 2002, 2019; Sissoko et al., 2022), this is the first study to the authors' knowledge that extends the applications of convergence analysis utilized by Asadullah and Savoia (2018), Crespo Cuaresma et al. (2017), and Drennan et al. (2004) to poverty rates in Pennsylvania. It contributes to the ongoing debate regarding whether or not poverty convergence is observed in different samples (Crespo Cuaresma et al., 2017; Ouyang et al., 2018, 2019; Ravallion, 2012), and as opposed to other analyses of poverty that have singularly focused on β-convergence (Asadullah & Savoia, 2018; Crespo Cuaresma et al., 2017; Ouyang et al., 2018, 2019; Ravallion, 2012; Thorbecke & Ouyang, 2018), it provides a comprehensive investigation of convergence behavior that differentiates between rural and urban counties. Pennsylvania represents an interesting case study because the approximately 3.4 million people (i.e., 26% of state residents) living among its 48 rural counties ranks third in the nation among states with the largest rural populations (Center for Rural Pennsylvania, n.d.; U.S. Census, 2022b). Meanwhile, for context, Census data report a rural population in the Northeast region of 16% and a corresponding value of 20% for the entire country (U.S. Census, 2022b).

1.3 Outline of Paper

The rest of this paper is organized as follows: The second section offers a review of relevant literature on poverty and convergence. The sample and variables are discussed in the third section. The methods employed in this study are described in the fourth section. In the fifth section, the results are examined. The final section discusses conclusions, policy implications, and extensions of the research.

2. LITERATURE REVIEW

Crespo Cuaresma et al. (2022) emphasize the conflicting evidence in the empirical literature on poverty convergence, and they argue that evidence of poverty convergence depends on the sample under consideration. Ravallion (2012) asserts that proportionate poverty rate convergence is not observed when analyzing a cross-country sample of 90 less developed nations 1977-2007 in support of the claim. However, Crespo Cuaresma et al. (2017) uncover support for poverty unconditional and conditional β-convergence using the Ravallion (2012) sample of nations by focusing on absolute rather than proportionate poverty convergence. Ouyang et al. (2019) study the sample of less developed nations analyzed by Ravallion (2012) over the extended time frame of 1980-2014. Their results reveal strong poverty convergence only in Sub-Saharan Africa. Thorbecke and Ouyang (2018) investigate samples of 94 developing countries during 1982-2007 and 102 developing nations across 1986-2012 with a particular focus on Sub-Saharan Africa. While a lack of unconditional and conditional β-convergence in poverty is observed among less developed countries similar to Ravallion (2012), Thorbecke and Ouyang (2018) identify strong unconditional and conditional poverty convergence in Sub-Saharan Africa and conclude that variations in the structure of growth explain the different outcomes.

Asadullah and Savoia (2018) conduct tests of β-convergence using poverty measures from a sample of 89 developing countries over the period 1990-2013. They detect both unconditional and conditional β-convergence of poverty. Rahman, Hayati Hakim, and Syafii (2022) analyze poverty in the North Sumatra Province of Indonesia during 2011-2021 with tests of β-convergence and σ-convergence. They find support for both unconditional and conditional β-convergence and σ-convergence in their study. Ouyang et al. (2018) employ dynamic panel data methods to

https://collected.jcu.edu/jep/vol28/iss1/3
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investigate poverty convergence using cross-country and within-country samples of less developed countries. They discover poverty convergence across 90 nations during the 1977-2014 period as well as across regions within Rwanda and Ethiopia from 1995-2010 and 2000-2010.

Adding to previous literature, López-Calva, Ortiz-Juarez, and Rodríguez-Castelán (2021) use disaggregated data for roughly 2,400 municipalities in Mexico over 1992-2014 to test unconditional and conditional β-convergence and σ-convergence. Differentiating between urban and rural locales, evidence of poverty convergence at the municipality level is found with varying speeds of convergence as a function of the geographic area considered. Specifically, rates of convergence in rural municipalities generally exceed those of urban ones.

3. DATA

The poverty rate (POVERTY) collected from the U.S. Census Bureau measures the percent of the population below the federal poverty line for the 67 counties in Pennsylvania, and it is observed over the 1990–2019-time frame. By analyzing a sample that ends in 2019, this study offers a more recent assessment of convergence behavior in Pennsylvania than Latzko (2019) and Sissoko et al. (2022) and avoids exogenous shocks that may have been introduced by the COVID-19 pandemic.

The control variables span economic and demographic determinants, and they reflect regressors prevalent in the existing literature (Benfica & Henderson, 2021; Clain, 2008; Gayán-Navarro et al., 2020; Levernier et al., 2000; Sissoko et al., 2022). UNEMP is the county-level unemployment rate. MANU and CONST are the shares of the workforce employed in the manufacturing and construction sectors, respectively. NONWHITE is the percent of the population that is not Caucasian, and YOUNG is the percent of the population between 18 and

24 years old. HSDROP is the high school dropout rate, while BACH is the percentage of the population with a college degree.

Table 1. Descriptive statistics for the pooled, urban, and rural samples

	1990	2000	2010	2019
Pooled				
Mean	13.33	9.77	13.67	12.36
Standard Deviation	4.41	2.65	3.71	3.17
Median	13.05	9.70	13.60	12.30
Maximum	30.69	18.50	26.40	24.30
Minimum	5.30	4.40	5.80	5.90
Observations	67	67	67	67
Pooled (No Philadelphia)				
Mean	13.07	9.64	13.47	12.18
Standard Deviation	3.88	2.43	3.38	2.83
Median	13.03	9.70	13.60	12.30
Maximum	26.00	15.10	20.70	18.20
Minimum	5.30	4.40	5.80	5.90
Observations	66	66	66	66
Urban				
Mean	12.07	8.04	12.03	11.22
Standard Deviation	5.47	3.17	4.78	4.31
Median	11.40	8.00	11.00	10.80
Maximum	30.69	18.50	26.40	24.30
Minimum	5.30	4.40	5.80	5.90
Observations	19	19	19	19
Urban (No Philadelphia)				
Mean	10.99	7.46	11.23	10.51
Standard Deviation	3.19	1.96	3.38	3.01
Median	10.98	7.80	10.80	10.60
Maximum	15.62	11.10	17.20	16.00
Minimum	5.30	4.40	5.80	5.90
Observations	18	18	18	18
Rural				
Mean	13.83	10.46	14.31	12.81
Standard Deviation	3.86	2.07	3.01	2.51
Median	13.78	10.80	14.20	12.80
Maximum	26.00	15.10	20.70	18.20
Minimum	7.23	6.20	9.00	7.80
Observations	48	48	48	48

In 1990, the county with the largest poverty rate (30.69) was 579% greater than the county with the smallest rate of poverty (5.3). That disparity had fallen to 412% in 2019 for the

https://collected.jcu.edu/jep/vol28/iss1/3
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pooled sample. In the absence of Philadelphia County, the initial difference in the pooled sample was 491% declining to 308% over the period. Considering the urban counties minus Philadelphia, the maximum poverty rate in 1990 was 295% larger than the minimum, and that difference fell slightly to 271% by the end of the study time frame. Rural areas possessed a maximum poverty rate of 26% in 1990, which was 360% higher than the minimum of 7.23% in that same year. By 2019, rural counties had witnessed a decline in that gap to 233%. It is apparent from these statistics that the ranges of poverty-rate values across the samples of Pennsylvania counties have decreased over the 30-year period under consideration.

4. METHODS

4.1 Convergence Measures

Two different types of convergence are considered in the analysis. The presence of unconditional β-convergence suggests that counties with high initial levels of poverty tend to experience larger reductions in poverty, while those regions with initially less poverty witness smaller such declines going forward (i.e., a catch-up effect) (Asadullah & Savoia, 2018; Bernard & Durlauf, 1996; Ram, 2018). On the other hand, σ-convergence indicates a narrowing of the county-level (i.e., cross-sectional) distribution of poverty rates across time observations, which is a more stringent form of convergence (Asadullah & Savoia, 2018; Bernard & Durlauf, 1996; Ram, 2018; Young et al., 2008). It is important to note that while β-convergence is a necessary condition for σ-convergence, it is not a sufficient condition (Higgins et al., 2006; Latzko, 2019; Sala-i-Martin, 1996). In contrast, σ-convergence is both a necessary and a sufficient condition for β-convergence (Young et al., 2008). Ram (2018) notes that while β-convergence has garnered more attention in the empirical literature (Asadullah & Savoia, 2018; Crespo Cuaresma et al., 2017; Thorbecke & Ouyang, 2018), σ-convergence is a more basic concept, and Young et al. (2008) aver that it is of greater interest.

4.2 Beta Convergence

To assess the existence of unconditional β-convergence in poverty rates in Pennsylvania counties, a simple OLS regression model is estimated (Asadullah & Savoia, 2018)

$$\Delta Poverty_{iT} = \alpha + \beta\ Poverty_{i0} + \varepsilon_{\mathrm{i}} \qquad (1)$$

where the dependent variable represents the absolute change in the poverty rate in county *i* across the entire study period (i.e., from 1990 to 2019). The key independent variable is the county-level poverty rate in 1990, which marks the beginning of the period (i.e., the initial level of poverty in county *i*). Given this specification, β-convergence is indicated by a negative and statistically significant coefficient on the initial level of poverty, and the magnitude of the coefficient conveys the speed of convergence (Asadullah & Savoia, 2018). Conditional β-convergence analysis acknowledges the "heterogeneity of places" by also incorporating control variables representing varying initial conditions in equation (1) (Drennan et al., 2004 p. 584; Higgins et al., 2006; Ram, 2018; Rey & Montouri, 1999; Sissoko et al., 2022; Young et al., 2008). Due to heteroskedasticity concerns, the regression results are based on White heteroskedasticity-corrected standard errors (Asadullah & Savoia, 2018; Crespo Cuaresma et al., 2022; Higgins et al., 2006; Ravallion, 2012).

Crespo Cuaresma et al. (2017) and Asadullah and Savoia (2018) enumerate the advantages of a linear specification as opposed to a log-linear functional form, including a) an insensitivity to low poverty incidence, b) greater appeal to policymakers who are concerned about percentage-point fluctuations rather than percentage changes in poverty measures, and c)

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no requirement that a high-initial-poverty locale should experience a higher proportionate rate of poverty decline (e.g., a geographic unit should have a higher likelihood of decreasing poverty from 60% to 30% than from 10% to 5% (Crespo Cuaresma et al., 2017, p. 5)).

4.3 Sigma Convergence

Identifying σ-convergence involves calculating a measure of dispersion, such as the coefficient of variation (i.e., the ratio of the standard deviation to the mean), for each year for all the counties in the sample (Boyle & McCarthy, 1999; Drennan et al., 2004; Ram, 2018; Sissoko et al., 2022; Thompson & Yerger, 2021). In other words, the level of variation is computed across the counties for 1990, 1991, and so on, resulting in a total of 30 values. It is possible to identify σ-convergence either via visual inspection of a plotted measure of dispersion or more formally by testing for the presence of a unit root in the underlying time series (Bernard & Durlauf, 1996; Drennan et al., 2004; Young et al., 2008). If a data series is determined to be non-stationary (i.e., has a unit root) then it is highly unlikely that σ-convergence exists, because any shocks will persist indefinitely into the future (Drennan et al., 2004; Rey & Montouri, 1999).

4.4 Structural Breaks

Albeit in the context of income convergence, Drennan et al. (2004) warns that equivalently treating urban and rural areas may risk a sample selection bias toward convergence, but López-Calva et al. (2021) and Higgins et al. (2006) separate metropolitan and non-metropolitan areas in their convergence analyses. Bernard (2019), Datt et al. (2020), and Levernier (2003), among others, highlight differences in poverty rates across urban and nonurban areas, and in the case of Pennsylvania, 48 of its 67 counties are classified as rural by the Center for Rural Pennsylvania (n.d.). To test for a structural break, a Chow (1960) test is performed with the null hypothesis that the coefficients in the urban and rural β-convergence regressions are equal. Using the urban subsamples with and without Philadelphia County, the Chow (1960) test statistics are 3.68 (p-value = 0.05) and 2.55 (p-value = 0.10), respectively, which confirm a structural break between rural and urban Pennsylvania counties, with and without Philadelphia County. Consequently, rural and urban Pennsylvania counties are analyzed separately.

5. Results

Unconditional β-Convergence Findings

Table 2 presents the results of estimating equation (1) in order to detect the existence of unconditional β-convergence in the poverty rate during the period of study. For the pooled Pennsylvania sample, statistically significant at the 1% level negative coefficients of -0.53 and -0.59 (with and without Philadelphia County, respectively) are obtained indicating β-convergence across the 1990–2019-time frame consistent with Asadullah and Savoia (2018) and Crespo Cuaresma et al. (2017). Analysis of the pooled sample indicates that when the 1990 poverty rate increases by one point, the average change in the poverty rate over 20 years is a decrease of slightly more than 0.5 point. These findings offer strong evidence of β-convergence occurring for the entire sample period and demonstrate that the speed of convergence is slightly enhanced in the absence of Philadelphia County. In contrast, Latzko (2019) finds no evidence of unconditional β-convergence of per capita personal income among Pennsylvania counties between 1969 and 2017.

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

Table 2. Unconditional beta convergence results: Pooled, Urban, and Rural samples

	Pooled 1990-2019	**Pooled (No Philadelphia) 1990-2019**	**Urban 1990-2019**	**Urban (No Philadelphia) 1990-2019**	**Rural 1990-2019**
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	6.04***	6.86***	3.48***	4.83**	8.38***
	(5.73)	(6.70)	(4.33)	(2.19)	(6.60)
$Poverty_{i0}$	-0.53***	-0.59***	-0.36***	-0.48**	-0.68***
	(-6.86)	(-8.27)	(-4.89)	(-2.11)	(-8.41)
$\overline{R}^2$	0.48	0.48	0.34	0.23	0.58

Notes: A one-tailed t-test was used for the $Poverty_{i0}$ covariate. t-statistics in parentheses are based on White heteroskedasticity-consistent standard errors. ***, **, * denote coefficient significant at 1%, 5%, and 10% levels, respectively. *Source: authors' calculations.*

In the case of the urban Pennsylvania counties in Table 2, negative coefficient estimates, which are significant at the 1% level with a one-tailed test, suggest that a one-point increase in the initial poverty rate will lead to average poverty-rate reductions of 0.36 point and 0.48 point (with and without Philadelphia County, respectively) across the ensuing 20 years. These findings support the existence of unconditional β-convergence, and similar to the pooled sample, it is apparent that slightly faster convergence occurs when Philadelphia County is not influencing the results.

The rural subsample (i.e., 48 counties) in Pennsylvania experiences the most rapid unconditional poverty-rate β-convergence as observed in Table 2. The -0.68 coefficient, which is significant at the 1% level, indicates that the rural counties experience an average decrease in the poverty rate of 0.68 point over two decades when the 1990 poverty rate rises by one point. Thus, rural convergence during 1990-2019 exceeds that of the full 67-county sample (i.e., -0.68 vs. -0.53). However, the difference is marginally less in the absence of Philadelphia County (-0.68 vs. -0.59). The poverty rate in rural Pennsylvania counties also converges nearly twice as quickly as it does in the urban sample (-0.68 vs. -0.36). Although the gap is not quite as wide when Philadelphia County is omitted from the urban subsample (-0.68 vs. -0.48). These findings echo

López-Calva et al. (2021), who found a greater degree of convergence among rural municipalities than urban ones in Mexico. Goodness-of-fit measures notably suggest that initial poverty accounts for a significant portion of the variation in the dependent variable, especially among the pooled (48%) and rural (58%) samples (Asadullah & Savoia, 2018).

Conditional β-Convergence Findings

The results of estimating equation (1) with the addition of control variables to investigate the possibility of conditional β-convergence in Pennsylvania appear in Table 3. For the pooled 1990-2019 sample, the statistically significant coefficients for the initial level of poverty are -0.72 and -0.73 (including and excluding Philadelphia County, respectively). These values translate into an almost 0.75-point average decline in the poverty rate during 1990-2019 in response to a one-point increase in its starting value *ceteris paribus*. This finding is consistent with the unconditional β-convergence results. Latzko (2002) similarly identified β-convergence during 1969-1999 conditioned on demographic and economic factors for per capita income in Pennsylvania counties.

In the urban sample in Table 3, conditional β-convergence occurs across the 1990-2019 period at a 1% significance level. Based on coefficients of -1.08 and -0.94, with and without Philadelphia County, respectively, there is very strong conditional β-convergence apparent. Specifically, holding all else equal, when the 1990 poverty rate increases by one point, the average change in the poverty rate over 20 years is a decrease of approximately one point. These results evince greater degrees of β-convergence than the unconditional outcomes for metropolitan areas.

https://collected.jcu.edu/jep/vol28/iss1/3
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Table 3. Conditional beta convergence results: Pooled, Urban, and Rural samples

	Pooled 1990-2019	**Pooled (No Philadelphia) 1990-1999**	**Urban 1990-2019**	**Urban (No Philadelphia) 1990-2019**	**Rural 1990-2019**
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	3.59	6.80	-10.33*	7.40	5.80
	(0.97)	(1.54)	(-1.94)	(0.60)	(1.09)
$Poverty_{i0}$	-0.72***	-0.73***	-1.08***	-0.94***	-0.69***
	(-9.84)	(-9.32)	(-9.13)	(-2.39)	(-8.09)
UNEMP	0.49**	0.54**	2.09***	1.26*	0.54**
	(2.06)	(2.41)	(5.52)	(1.78)	(2.17)
MANU	0.03	-0.01	-0.002	0.04	0.02
	(0.55)	(-0.17)	(-0.02)	(0.21)	(0.47)
NONWHT	0.19***	0.02	0.23***	0.02	-0.10
	(3.26)	(0.34)	(3.14)	(0.10)	(-0.35)
YOUNG	0.39***	0.34***	0.51	0.31	0.28***
	(3.39)	(2.98)	(1.13)	(0.48)	(2.88)
HSDROP	-0.07	-0.20	0.36	-0.26	-0.25
	(-0.40)	(-1.05)	(1.24)	(-0.43)	(-1.06)
BACH	-0.16*	-0.13	-0.02	-0.21	-0.02
	(-1.83)	(-1.39)	(-0.16)	(-0.81)	(-0.13)
$\bar{R}^2$	0.64	0.61	0.73	0.27	0.66

Notes: A one-tailed t-test was used for the $POVERTY_{i0}$ covariate. t-statistics in parentheses are based on White heteroskedasticity-consistent standard errors. ***, **, * denote coefficient significant at 1%, 5%, and 10% levels, respectively. *Source: authors' calculations.*

Conditional β-convergence takes place during 1990-2019 in rural counties based on a coefficient of -0.69 in Table 3, which is statistically significant at the 1% level. Thus, both the conditional and unconditional β-convergence findings imply that a one-point uptick in the 1990 poverty rate in rural Pennsylvania leads to a roughly 0.69-point decrease, on average, in the poverty rate over the next 20 years holding all else constant.

It is notable that the speeds of conditional β-convergence generally exceed those of unconditional β-convergence in absolute value to varying degrees for the 1990-2019 period across the pooled, urban, and rural samples in Pennsylvania (Higgins et al., 2006; Thompson & Yerger, 2021).[1] In particular, the 67-county sample's conditional β-convergence coefficient is

[1] Potential multicollinearity in the results warrants caution in the interpretation of the coefficients.

-0.72 as opposed to -0.53 for the unconditional model, which is an increase in the speed of convergence of about one third. Urban areas have an especially stark disparity with a conditional estimate of -1.08 versus -0.36 for the unconditional analysis, which is a 200% difference. Meanwhile, the coefficients of -0.69 and -0.68 in the presence and absence of control variables, respectively, for the rural counties are comparable. In accordance with Asadullah and Savoia (2018), the adjusted R^2 values are larger for the conditional regression than for the unconditional regression. The differences between the conditional and unconditional β-convergence coefficients suggest that the latter may suffer from omitted variable bias (Mankiw et al., 1992). These conditional β-convergence findings contrast with Higgins et al. (2006) where similar results were obtained for metropolitan and non-metropolitan counties using income.

Latzko (2002, 2019) and Sissoko et al. (2022) utilize a log-linear functional form in their analyses of income convergence in Pennsylvania counties. In order to compare these rates of income convergence with the rates of poverty convergence in this study, equivalent regressions are estimated.[2] Latzko (2019) obtains a 1.2% rate of unconditional income convergence only during 2004-2017, whereas the speed of unconditional poverty convergence across 1990-2019 in this analysis is 1.5% (the corresponding speeds for the urban and rural subsamples are 1.2% and 2%, respectively). Latzko (2002) estimates a speed of conditional income convergence in the range of 1-2% from 1969-1999, while Sissoko et al. (2022) find conditional income convergence with speeds between 1% and 4%, depending upon the method used and the time period chosen within 1980-2018. In contrast, the rate of conditional poverty convergence is 2.3% throughout 1990-2019 (with corresponding convergence rates of 3.63% and 2.1% for the urban and rural subsamples, respectively). It is important to note that differences in the time periods analyzed

[2] These results are available from the authors upon request.

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

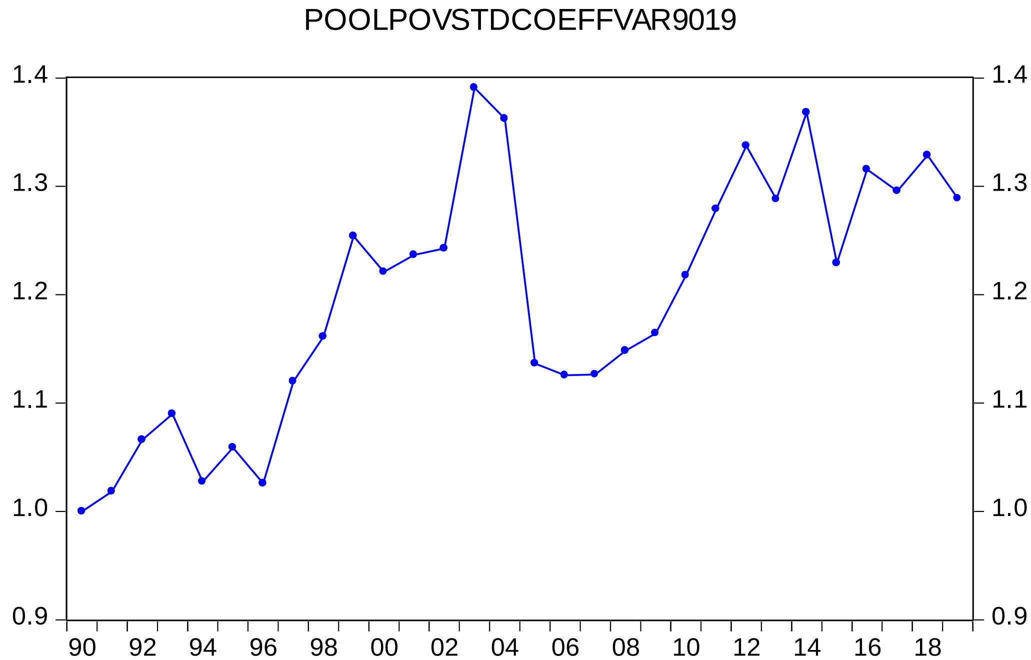
and/or variation in the selection of control variables among these studies may explain the generally higher rates of poverty convergence relative to income convergence. In particular, Aiyemo (2020) mentions that the relationship between income and poverty may evolve over time.

Visual Inspection σ-Convergence Findings

Coefficient of Variation

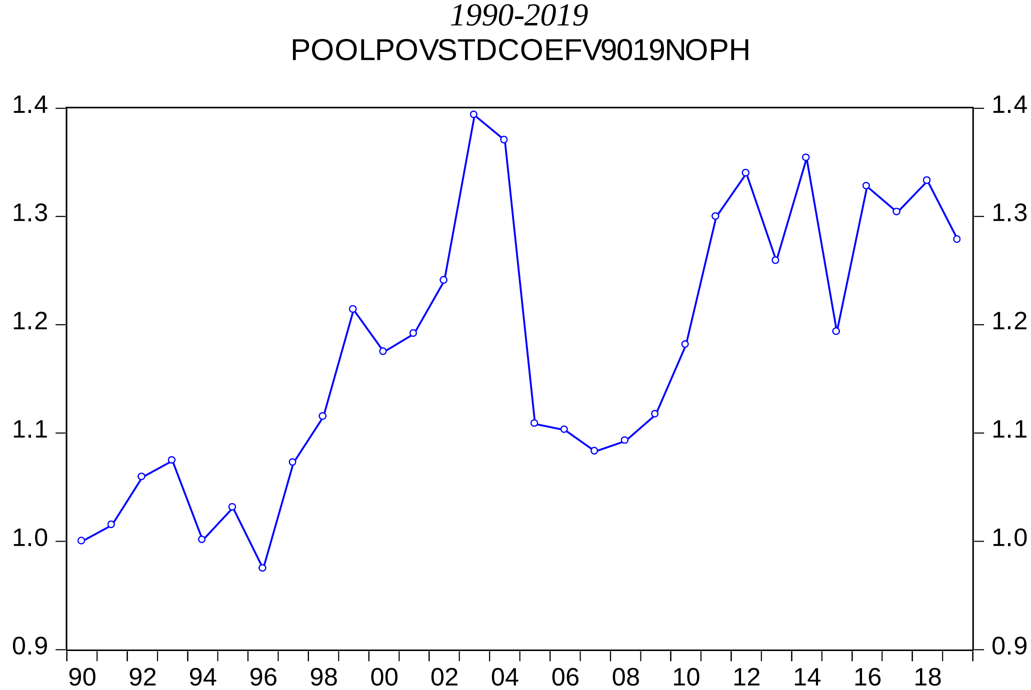
Figure 1 presents the plot of the standardized (i.e., adjusted so that the initial value is equal to 1 to facilitate interpretation) coefficients of variation for the pooled sample of the 67 Pennsylvania counties across 1990-2019 (Cook & Winfield, 2013). When the standardized final value in the time frame under consideration is greater than unity, σ-divergence is apparent and vice-versa (Cook & Winfield, 2013). Strong divergence through the 1990s peaks in 2003 followed by convergence until the vicinity of the Great Recession when divergence returns. Despite the vagaries of the coefficients of variation observed, it is apparent that σ-divergence exists based on the ending value of 1.29. This same pattern holds true when Philadelphia County is omitted from the sample based on a comparable final value of 1.28. Latzko (2019) and Sissoko et al. (2022) observed σ-divergence in per capita personal income among Pennsylvania counties. In Table 4, a regression of the pooled coefficient of variation for 1990-2019 on a constant and time trend confirms the existence of a positive trend (i.e., divergence) both with and without Philadelphia, which is significant at the 5% and 1% levels, respectively, with a one-tailed t-test.

Figure 1. Standardized Coefficient of Variation: Pooled Sample, 1990-2019



Source: authors' calculations.

Figure 2. Standardized Coefficient of Variation: Pooled Sample without Philadelphia, 1990-2019



Source: authors' calculations.

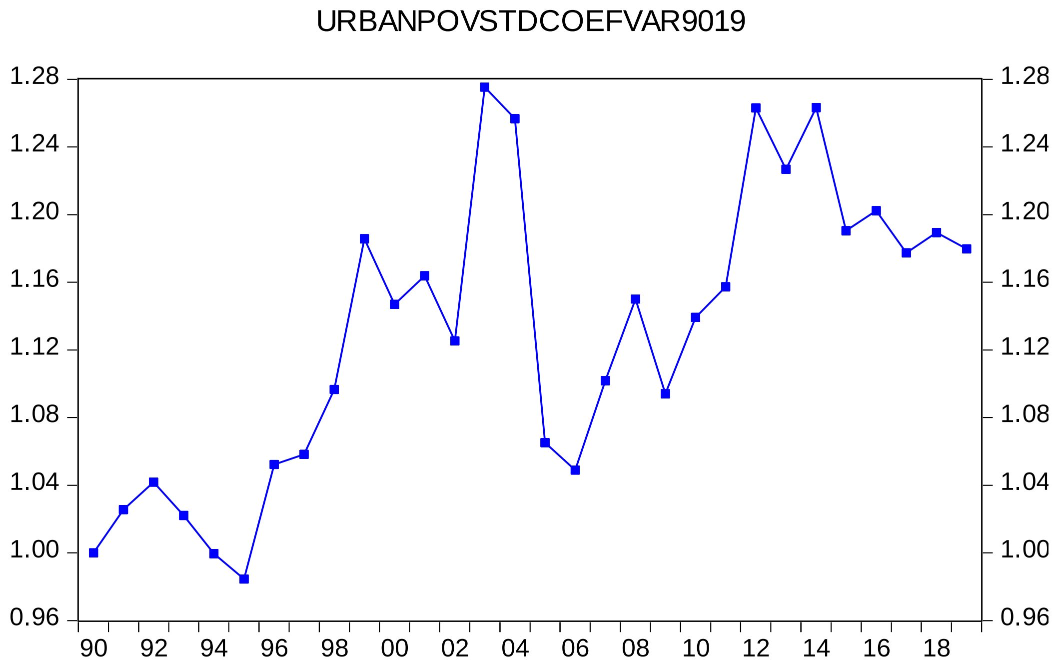
https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

Table 4. Trend analysis with coefficient of variation

	Pooled 1990-2019	Pooled (No Philadelphia)	Urban 1990-2019	Urban (No Philadelphia)	Rural 1990-2019
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	3.2708***	3.5062***	2.2999***	3.5424***	4.2303***
	(17.10)	(15.55)	(23.54)	(19.24)	(12.24)
TREND	0.0253**	0.0322***	0.0136***	0.0034	0.0348**
	(2.42)	(2.59)	(2.51)	(0.34)	(1.85)
$\bar{R}^2$	0.64	0.60	0.56	0.21	0.57

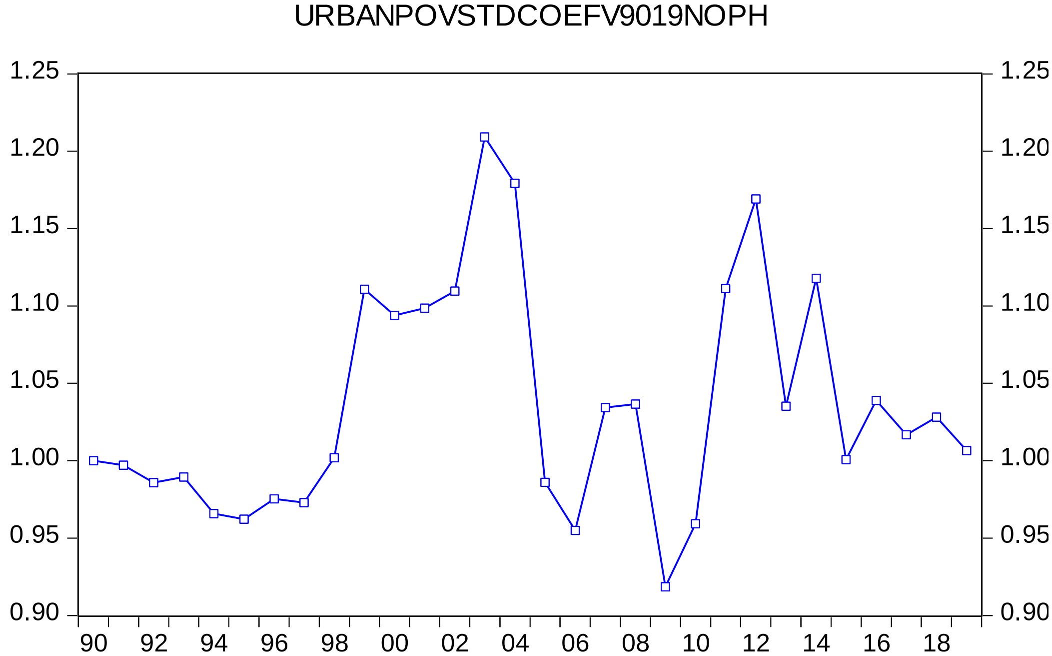
Source: authors' calculations.

Figure 3. Standardized Coefficient of Variation: Urban Sample, 1990-2019



Source: authors' calculations.

Figure 4. Standardized Coefficient of Variation: Urban Sample without Philadelphia, 1990-2019



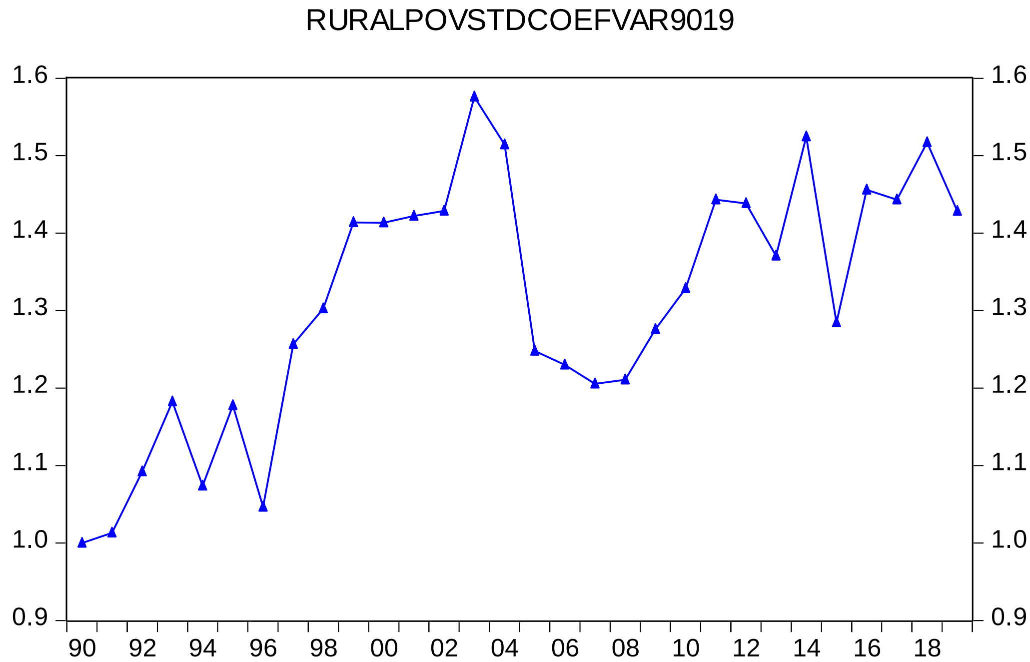
Source: authors' calculations.

Turning attention to Figure 3, which displays the graph of the coefficients of variation for the urban sample of 19 counties from 1990 to 2019, σ-divergence exists, but to a lesser degree than that of the pooled sample, with an ending value of 1.18. However, when Philadelphia County is omitted from the sample in Figure 4, the concluding value of 1.006 casts doubt on the divergence conclusion. Much like the pooled sample of 67 counties, variation between convergence and divergence early in the 1990s reaches an apex in 2003 followed by a brief stint of convergence leading to divergence coupled with some volatility in the latter portion of the period. In the absence of Philadelphia, the urban Pennsylvania counties' pattern is less volatile. The results of a regression in Table 4 support the existence of a statistically significant positive trend across 1990-2019 in urban areas only when Philadelphia County is included in the sample. Otherwise, there is no evidence of a trend when Philadelphia County is excluded. However,

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

Drennan et al. (2004) argues that such a preliminary finding should be formally confirmed via unit-root testing.

Figure 5. Standardized Coefficient of Variation: Rural Sample, 1990-2019



Source: authors' calculations.

Examining the standardized coefficients of variation in Figure 5, the greatest degree of σ-divergence across 1990-2019 among the three samples is observed for the rural sample of 48 counties. The ending value for the coefficient of variation is 1.43 in contrast to final values of 1.29 and 1.18 for the pooled and urban samples, respectively. While there is movement between convergence and divergence across the period similar to the pooled graph, the values overall tend to be more pronounced and there is less convergence when it occurs. A positive time trend significant at the 5% level is apparent from regression results in Table 4 for the rural sample during the 1990-2019 period, which is consistent with the visual examination.

Statistical Analysis σ-Convergence Findings

In order to formally test for unconditional σ-convergence in Pennsylvania, Augmented Dickey-Fuller (ADF) and Dickey-Fuller GLS (DF-GLS) tests for the presence of a unit root are conducted in accordance with Drennan et al. (2004). They explain that if a series follows a random walk with drift (i.e., has a unit root) then the impact of local and transitory shocks, such as public policy action, will persist into the future and become permanent casting doubt on the possibility of σ-convergence (Drennan et al., 2004). Critical values and one-sided *p*-values for the ADF tests are provided by MacKinnon (1996). Drennan et al. (2004) assert that the unit-root testing equations should be specified with a constant and a time trend consistent with the plotted measure of dispersion, and that same approach is adopted herein.

Augmented Dickey-Fuller Unit-Root Testing

Considering the pooled sample in Table 5, ADF tests of the coefficient of variation based on the t-statistic and the z-statistic do not reject the presence of a unit root. When considering the pooled sample minus Philadelphia County, the t-statistic and z-statistic still fail to reject the presence of a unit root (Drennan et al., 2004). ADF t-tests when testing the coefficient of variation for the urban sample of 19 Pennsylvania counties do not reject non-stationarity based on the MacKinnon (1996) finite sample *p*-values. Alternatively, when considering the ADF z-tests, comparison to the Dickey-Fuller critical values indicates that the null hypothesis of non-stationarity is rejected. This same pattern of outcomes is observed when Philadelphia County is omitted from the urban sample. Drennan et al. (2004) recommends cautious interpretation of such a finding since it may be an aberration if, for instance, the underlying data-generating process has not remained stable throughout the time frame under investigation. Both the ADF t-

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

test and z-test fail to reject the unit root in the coefficient of variation for the rural sample of 48 counties.

Table 5. Unit-root test results for coefficient of variation of Poverty

	Augmented Dickey-Fuller Unit Root Test		**Dickey-Fuller GLS Unit Root Test**
Sample	**t-stat (*k*)**	**z-stat (*k*)**	**t-stat (*k*)**
Pooled	-2.484 (1) (0.3330)	-15.068 (1) (0.1132)	-2.528 (1)
Pooled (No Philadelphia)	-2.607 (1) (0.2802)	-17.117 (1) (0.0645)	-2.711 (1)
Urban	-2.882 (1) (0.1827)	-21.678 (1) (0.0156)	-3.006 (1)
Urban (No Philadelphia)	-2.974 (1) (0.1565)	-22.806 (1) (0.0106)	-3.111 (1)
Rural	-2.174 (1) (0.4850)	-10.097 (1) (0.3598)	-2.065 (1)
Critical Values	**t-stat**	**z-stat**	**t-stat**
1%	-4.324	-22.970	-3.77
5%	-3.581	-17.995	-3.19
10%	-3.225	-15.534	-2.89

Notes: MacKinnon approximate (finite sample) one-sided *p*-values for ADF in parentheses below test statistics. *k* denotes the degrees of augmentation in the underlying test equations. The DF-GLS test is sensitive to the selection of lag length. The outcomes shown are robust with up to 5 lags.

Dickey-Fuller Generalized Least Squares Unit-Root Testing

Due to concerns about the low power of the ADF test and the corresponding weakness associated with its rejection of a random walk, DF-GLS tests are performed (with 1-5 lags) on the pooled, urban, and rural samples (Drennan et al., 2004). According to Drennan et al. (2004), the null hypothesis of the DF-GLS test is consistent with the series following a random walk, potentially with an accompanying drift, which suggests the existence of divergence.

In Table 5, based on the appropriate critical values and the *p*-values, the unit root is not rejected for the pooled (with and without Philadelphia) and rural Pennsylvania samples when analyzing the coefficient of variation with the DF-GLS test. In contrast, the urban samples achieve rejection with significance at the 10% level. These urban outcomes cast doubt on the possibility of a random walk in the coefficient of variation series. Rather, the test results support the conclusion that the series are stationary around a linear trend (Drennan et al., 2004). Drennan et al. (2004) notes that the power of unit-root tests hinges on the duration of the sample rather than the size in terms of the number of time periods included. In the current case, the 30-year time span under consideration, which is considered to be relatively long, offers a level of confidence, assuming that the data generating process has been constant across the sample period (Drennan et al., 2004; López-Calva et al., 2021).

Panel Data Unit-Root Testing

Finally, Drennan et al. (2004) recommend panel data unit-root tests of the underlying natural logarithm of the series to further investigate the existence of unconditional σ-convergence. There are two broad types of panel data unit-root tests, which differ depending upon whether the null hypothesis assumes a common unit-root process or an individual unit-root process. Based on *p*-values equal to zero, the results in Table 6 for the Levin, Lin, and Chu test reject the null of a common unit root in the panel-data pooled, urban, and rural samples. However, Breitung tests reject a common unit root solely in the pooled and rural cases. Similarly, the Im, Pesaran, and Shin (IPS) test, the ADF test, and the Phillips and Perron test all reject the null of an individual unit root for the natural logarithm of the poverty rate at the 1% level in the 67-county pooled and 48-county rural Pennsylvania panels for the 1990-2019 span. While the IPS test rejects non-stationarity for the urban samples with and without Philadelphia

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

County at roughly the 1% level, the ADF and Phillips and Perron tests do not. The ADF and Phillips and Perron tests reject the null at approximately the 10% level in the presence of Philadelphia County. However, in the absence of Philadelphia County, the ADF test does not reject while the Phillips and Perron test rejects at the 10% level. Thus, there are uniform findings of stationarity indicative of σ-convergence for the pooled and rural samples, but a degree of inconsistency across the unit-root results when considering the urban subsamples.

Table 6. Panel unit-root test results for Ln(Poverty)

	Tests for Common Unit Root Process		**Tests for Individual Unit Root Process**		
Sample	**Levin, Lin & Chu t-stat**	**Breitung t-stat**	**Im, Pesaran & Shin W-stat**	**ADF Fisher Chi-square**	**Phillips-Perron Fisher Chi-square**
Pooled	-6.5248 (0.00)	-3.8745 (0.00)	-4.6286 (0.00)	194.877 (0.00)	442.684 (0.00)
Pooled (No Philadelphia)	-6.699 (0.00)	-3.6783 (0.00)	-4.8374 (0.00)	198.117 (0.00)	441.001 (0.00)
Urban	-3.6067 (0.00)	-1.0450 (0.1469)	-2.5454 (0.01)	52.0462 (0.064)	49.4038 (0.102)
Urban (No Philadelphia)	-3.3314 (0.00)	-0.39954 (0.3463)	-1.9362 (0.026)	45.5774 (0.1316)	47.7213 (0.0915)
Rural	-5.5059 (0.00)	-4.3524 (0.00)	-3.8663 (0.00)	142.830 (0.00)	393.280 (0.00)

Notes: Parentheses contain *p*-values. The *p*-values for Fisher tests are calculated using an asymptotic Chi-square distribution, but the other tests assume asymptotic normality.

6. CONCLUSION

Evidence of β-convergence among Pennsylvania counties of different types obtained herein strengthens the response to Ravallion (2012) advanced by Asadullah and Savoia (2018) and Crespo Cuaresma et al. (2017) that absolute poverty convergence exists. However, acknowledging that β-convergence is a necessary, but not sufficient condition for σ-convergence, testing for σ-convergence via both visual and statistical methods is conducted. Despite findings of unconditional and conditional β-convergence for the pooled and rural samples, σ-divergence is observed suggesting that their poverty rates follow a random walk with drift (Drennan et al., 2004; Young et al., 2008). Thompson and Yerger (2021) explain that a finding of β-convergence coupled with σ-divergence is consistent with low-poverty-rate counties in 1990 experiencing faster poverty reductions (i.e., β-convergence), which persist after these counties have eclipsed other counties yielding greater dispersion (i.e., σ-divergence). Urban samples offer weaker evidence of rising poverty dispersion, which is sensitive to the inclusion of Philadelphia County. However, this result may reflect changes in the underlying data generating process across the sample period, a lack of power in the unit-root testing, or an insufficient time span of data.

In an effort to further evaluate the robustness of the foregoing findings, panel unit-root tests are directly applied to the underlying natural logarithm of the poverty rate series. The convincing rejection of unit roots in favor of stationarity across the pooled and rural samples implies that any poverty shocks will be transitory and dissipate over time. In other words, as explained by Drennan et al. (2004), the poverty rate in the pooled and rural samples does not follow a random walk over time. Less clear-cut evidence of stationarity characterizes the urban samples. As noted by Bernard and Durlauf (1996), this type of time-series analysis represents a stricter notion of convergence than a cross-sectional test can assess and adds support for the existence of poverty convergence among most Pennsylvania counties.

Heretofore, the application of unit-root testing to assess the presence or absence of σ-convergence of poverty rates has not been widespread. Yet, allowing conclusions regarding poverty convergence to rest solely on β-convergence outcomes risks an incomplete

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

understanding of poverty rate behavior, which might be afforded by a more comprehensive statistical examination. Furthermore, Friedman (1992) and Quah (1993) assert that σ-convergence is the only valid test of convergence due to the vulnerability of β-convergence to Galton's fallacy of regression to the mean (Drennan et al., 2004).

6.1 Policy Implications

The variation in σ-convergence outcomes across counties has potential policy ramifications as emphasized by Levernier et al. (2000), who argue that remedies must be tailored to different locales. Otherwise, policy measures that might reduce poverty in metropolitan counties may hold limited applicability in non-metropolitan counties and vice-versa due to variation in the influence of growth policies on poverty rates across geographic areas (Aiyemo, 2020; Gayán-Navarro et al., 2020; Levernier et al., 2000). In the context of this study, σ-divergence suggests that local and temporary public policy actions will become permanent rather transitory (Drennan et al., 2004). Thus, focusing specifically on the panel unit root tests, policymakers may anticipate that rural counties will see the impact of poverty-fighting efforts dissipate over time whereas urban counties may not.

Pennsylvania has existing policies and programs to help those in poverty, such as the Supplemental Nutrition Assistance Program (SNAP), Children's Health Insurance Program (CHIP), Low Income Home Energy Assistance Program (LIHEAP), and Medicaid, but the analysis shows that these blanket programs may not be as effective as targeted remedies (Alcantara, Brewer, & Jozefowicz, 2023). In rural Pennsylvania counties, Pennsylvania CareerLink and PAsmart address economic (i.e., place-based) needs by providing employment training programs and apprenticeships in trade jobs (Levernier et al., 2000). Meanwhile, Pennsylvania's Department of Community and Economic Development (DCED) offers the Rural

Jobs and Investment Tax Credit Program to aid small businesses in rural counties establish jobs and generate growth. Similarly, the Pennsylvania Rural Health Model (PARHM) endeavors to financially stabilize rural hospitals and facilitate healthcare access to vulnerable populations (Wagner, 2022).

Since the 1980s, Pennsylvania has experienced a decline in both steel and coal production employment (United States Bureau of Labor Statistics, n.d. -b). All told, from 1990 to 2023, Pennsylvania has lost 31,400 jobs in coal mining and steel production (United States Bureau of Labor Statistics, n.d. -a), and 49 of the approximately 80 coal towns in Pennsylvania are found in rural counties. As an example of recent focused policy action in response to these sectoral shifts, Pennsylvania's Department of Community and Economic Development (DCED) (2023) has published coal-fired power plant redevelopment playbooks to combat the loss of employment and revitalize former coal towns. In addition, the Appalachian Regional Commission has invested in these areas, awarding $17.3 million to grow economies in Pennsylvania coal towns (Appalachian Regional Commission, n.d.).

Alternatively, urban Pennsylvania counties require a person-based approach rather than job creation, and initiatives such as the Pennsylvania Minority Business Development Authority and the Pennsylvania State Small Business Credit Initiative: Diverse Leaders Venture Program are working to deliver that assistance (Levernier et al., 2000). Jones and Kodras (1990) support action to address the gender wage gap, improve welfare assistance, increase the federal minimum wage, and provide supplementary income for women and children in order to lower poverty rates among mothers while Madgavkar, White, Krishnan, Mahajan, and Azcue (2021) favor subsidies to childcare, which would afford mothers time to enroll in higher education or training programs that could raise their wages and reduce poverty.

https://collected.jcu.edu/jep/vol28/iss1/3
DOI: 10.59604/1046-2309.1059

6.2 Extensions of Research

Several aspects make Pennsylvania counties a unique sample that perhaps is not representative of other states. Those characteristics specifically include several pockets of highly dense population concentration, strong rural county representation, and Philadelphia's status as the poorest big city in the U.S. (Saffron, 2020). Therefore, like poverty rates in general, perhaps poverty-rate convergence behavior also varies across states and nations. In future contributions, given the dearth of subnational studies of poverty convergence and the sensitivity of the results to sample selection (Crespo Cuaresma et al., 2022; Higgins et al., 2006; Ram, 2018), it would be worthwhile to analyze poverty convergence for counties in different states and/or to expand the sample to encompass all the counties across the nation. Additionally, the time dimension of the sample could be expanded to include observations prior to 1990 and/or after 2019 (Drennan et al., 2004). The omission of the COVID-19 pandemic from the period of study is a limitation, which merits attention in future analyses (Thompson & Yerger, 2021).

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