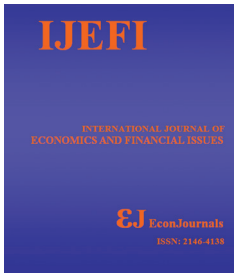

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Rural-Urban Differences in Poverty: An Analysis of Pennsylvania Counties

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ABSTRACT

This study examines the determinants of poverty in rural and urban Pennsylvania counties. Economic and demographic characteristics are evaluated in their relation to the poverty rate using panel data from 2000 to 2019 for the 67 Pennsylvania counties. A two-way fixed effects model is estimated to account for unobserved county-specific and time-specific heterogeneity. The results indicate that there are rural-urban differences in the impacts of explanatory variables. In rural Pennsylvania counties, economic factors have significant effects on the poverty rate. The percentage of employment in manufacturing and construction are negatively related to the poverty rate, while the percentage of renters and employment in agriculture are positively related. In contrast, only the percentage of female-headed households has a positive, statistically significant impact in urban counties. Oaxaca (1973) decomposition indicates that structural characteristics in rural counties help mitigate their poverty rates. The results suggest that different policies must be implemented in urban and rural counties to alleviate poverty.

Keywords: Poverty, Demographics, Pennsylvania, Oaxaca Decomposition
JEL Classifications: I32, J10, C33

1. INTRODUCTION

1.1. Background

Poverty is a persistent issue in the U.S. that affected 37.9 million people in 2021, according to the U.S. Census (2023), and it is distributed across geographic areas. Fisher (2007), Kharas et al. (2020), and Mba et al. (2018) specifically observe that rural locales are more susceptible to poverty than urban regions. Consistent with that observation, the poverty rate in non-metropolitan areas nationwide in 2021 was 15.4%, while it was 12.3% in metropolitan areas (Rural Health Information Hub, n.d.). Thus, rural settings experienced 25% more poverty than urban ones. While Cebula and Davis (2022) and Gayán-Navarro et al. (2020) argue that policymakers must comprehend the predictors of poverty, Levernier et al. (2000) and Kneebone and Reeves (2016) emphasize the importance of developing effective remedies across different geographies in a regionally disparate environment. Yet, Levernier et al. (2000) also note that the existing empirical literature primarily has focused on explaining poverty in metropolitan areas, which potentially limits its applicability to other regions. Poverty is not a one-size-fits-all problem, so there is not a one-size-fits-all solution to its persistence. While one set of policy measures might reduce poverty in metropolitan counties, those identical responses might be inappropriate in non-metropolitan counties (Gayán-Navarro et al., 2020; Levernier et al., 2000; Murphy and Allard, 2015).

The commonwealth of Pennsylvania is no exception to this observed rural-urban divide in poverty rates. In fact, among the 33 counties in 2021 with poverty rates higher than the Pennsylvania average of 12%, 28 are rural counties (Center for Rural Pennsylvania, n.d.; U.S. Census, 2022a). Furthermore, Duren and Stelle (2023) report that, according to Small Area Income and Poverty Estimates (SAIPE) data published by the

U.S. Census (2022a), four 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 <1% of Philadelphia County's populace, which is the largest in the state (Duren and Stelle, 2023).

Among the most significant barriers to escaping poverty in rural counties is a lack of accessibility to a wide variety of needed services. Young (2018) finds that people living in poverty in rural Pennsylvania struggle to access healthy food and federal assistance. To help ameliorate these rural poverty problems, entities such as Parent Pathways, a partnership of non-profit organizations and institutions of higher learning, is addressing needs in rural Pennsylvania counties by offering services such as job training, access to housing, food, pre-school programs, and higher education (Moran, 2023). These private efforts may help people living in poverty in rural areas, but government resources could provide more long-term aid to those in need (Creamer, 2022). Keith (2022) reports that while 4% of Pennsylvanians lack access to the internet at broadband speeds, 13% of Pennsylvanians in rural counties lack access. Mamula (2023) discusses that even as the federal government unleashes billions of grant dollars to assist rural broadband expansion, an undercount in many Pennsylvania counties where broadband access is lacking will mean those areas may miss out on hundreds of millions of dollars partly because county governments lacked expertise and resources to mount a challenge to Federal Communications Commission maps.

People who live in poverty in urban Pennsylvania counties tell a different story even though they have greater access to opportunities. Since the 1990s, Philadelphia has shifted from being a manufacturing city to one focused on education, medicine, and services, and today it is the poorest big city in the U.S. (Saffron, 2020). Disenfranchised manufacturing workers now face skills mismatching to qualify for higher paying educational and medical work, and they find themselves relegated to the low-wage service sector (Saffron, 2020). Howell et al. (2019) state that, in Pittsburgh, Pennsylvania's second largest city, childhood poverty is greater than in most other U.S. cities, and that black women in 85% of U.S. cities have lower poverty rates than black women in Pittsburgh.

1.2. Rural versus Urban Differences

Results from the Oaxaca (1973) decomposition technique can offer policymakers insight into the degree to which differences in the characteristics between rural and urban counties account for the rural-urban divide in poverty rates (Djal-Gadom and Mboutchouang Kountchou, 2016). This approach divides the rural-urban poverty gap into the component explained by the variation in the features between rural and urban counties and the portion left unexplained. To the degree that the poverty rate difference is not elucidated by differences in a county's features, then a universal policy is not necessarily the optimal approach to reducing poverty rates in Pennsylvania (Gayán-Navarro et al., 2020).

County-level data is appropriately disaggregated for this investigation because it displays greater homogeneity and exhibits less variation in structural factors over time than state-level data, which mitigates aggregation bias (Gayán-Navarro et al., 2020; Levernier et al., 2000). Counties also have time-invariant boundaries, unlike metropolitan statistical areas (MSAs), and counties offer larger sample sizes, which reduce omitted variable bias as they enable the incorporation of more control variables, yielding more precise estimated coefficients (Andresen, 2013; Phillips and Land, 2012). In addition, Brown and Kandel (2006) argue that "counties actually present fewer problems than most other geographies" as a unit of observation (p. 14), and Wells and Weisheit (2012) emphasize that numerous social services, community organizations, and political institutions are integral to counties. Arguably, if the underlying causes of rural-urban differences in poverty rates can be distinguished, the best chances of appropriate policy development and implementation are at the state and local levels. Thus, focusing on the rural-urban divide within a single state is an appropriate approach to the analysis.

This study extends the literature on poverty by leveraging the advantages of county-level data while applying the Oaxaca decomposition in a novel way to yield insight specifically into the causes of rural and urban poverty and potential remedies in Pennsylvania 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 reports a rural population in the Northeast region of 16% and a corresponding value for the country as a whole of 20% (U.S. Census, 2022b).

1.3. Outline of Paper

The rest of this paper is organized as follows: The second section will offer a literature review that explores various factors that can affect poverty rates, and how they differ in urban and nonurban areas. The data and variables included in this study will be discussed in the third section. The methods employed in this study will be described in the fourth section. In the fifth section, the results will be examined. The final section will discuss conclusions, policy implications, and extensions of the research.

2. LITERATURE REVIEW

Differential studies of poverty across metropolitan and non-metropolitan areas span different geographic levels. Investigating changes in poverty in rural and urban Nigeria, Olowa and Olowa (2019) reveal that economic growth and redistribution have a stronger effect on rural areas than urban areas and recommend growth-based policies to increase employment and create opportunities for those in poverty. Benfica and Henderson (2021) analyze the rural-urban decomposition of poverty in 70 low-and middle-income countries and show that agricultural growth contributes relatively little to rural and urban poverty reduction, while non-agricultural growth makes substantial improvements in both rural and urban areas. Bernard (2019) examines rural-urban poverty disparities in European countries and demonstrates that household-level variables, such as educational attainment, foreign country of origin, and employment in agriculture, have greater

effects on poorer European countries than wealthy nations, and that the rural manifestation of poverty is greater in less economically developed countries.

Using more disaggregated data, Levernier et al. (2000) investigate the economic and demographic determinants of poverty in metropolitan and non-metropolitan U.S. counties and identify poverty-reduction roles for education and labor force participation in non-metropolitan counties and a commensurate role of relieving hardships for female household heads in metropolitan counties. Levernier (2003) studies a cross section of southern U.S. counties and attributes to population characteristics the major difference in poverty rates between metropolitan and non-metropolitan locales. Fisher (2007) collects individual-level data on income, demographics, education, employment, and household structure to determine that a concentration of less educated individuals coupled with diminished economic opportunities is responsible for non-metropolitan poverty persistence. Utilizing census-tract data, Gayán-Navarro et al. (2020) observe that poverty is explained by labor market features and the vulnerability of female household heads, and they emphasize tailoring policies to specific geographic areas.

3. DATA

This study utilizes balanced panel data from the U.S. Census Bureau for the 67 Pennsylvania counties during the period 2000 to 2019 (Benfica and Henderson, 2021; Bernard, 2019; Cebula and Davis, 2022; Clain, 2008; Fisher, 2007). The data sample ends in 2019 to avoid any irregularities in 2020 and thereafter due to the COVID-19 pandemic (Cebula and Davis, 2022).

The dependent variable is the poverty rate (POVERTY), which is the percentage of the population below the federal poverty level. The independent variables have been divided into demographics (DEMO) and economic factors (ECON) (Biewen and Jenkins, 2005; Clain, 2008; Levernier et al., 2000). A complete list of definitions and sources for these variables can be found in Table 1.

Table 1: Definitions of variables

Variable	Definition
Dependent variable	
POV	Percentage of population below the federal poverty level. Source: U.S. Census Bureau
Independent variables	
ECON	
UNEMP	County unemployment rate. Source: U.S. Census Bureau
RENT	Percentage of renter-occupied housing units. Source: U.S. Census Bureau
MANU	Percentage of employed population 16 years and older in manufacturing. Source: U.S. Census Bureau
AGRI	Percentage of employed population 16 years and older in agriculture, forestry, fishing and hunting, and mining. Source: U.S. Census Bureau
CONST	Percentage of employed population 16 years and older in construction. Source: U.S. Census Bureau
DEMO	
NONWHT	Percentage of nonwhite population. Source: U.S. Census Bureau
YOUNG	Percentage of population 18–24 years. Source: U.S. Census Bureau
HSDROP	Percentage of population that dropped out of high school. Source: U.S. Census Bureau
BACH	Percentage of population that received a bachelor's degree. Source: U.S. Census Bureau
FEMHEAD	Percentage of female-headed households. Source: U.S. Census Bureau

3.1. Economic Variables

The unemployment rate (UNEMP) is expected to have a positive relationship with the poverty rate (Clain, 2008; Fowler and Kleit, 2014; Gentilcore, 2017; Wahyuningsih et al., 2020), and the results of Gayán-Navarro et al. (2020) suggest that there is a direct, positive association between poverty and renter-occupied housing units (RENT), stating that "owners are less poor than renters" (p. 991).

The percentages of the employed population 16 years and older in manufacturing (MANU); in agriculture, forestry, fishing, and mining (AGRI); and in construction (CONST) represent the labor market opportunities within a county. Deaton et al. (2014) and Benfica and Henderson (2021) make the case that a greater share of employment in non-agricultural sectors, including manufacturing, reduces poverty. Conversely, Levernier et al. (2000) and Nasrun and Fariastuti (2020) conclude that higher shares of the workforce in agriculture result in higher rates of poverty. Levernier et al. (2000) report a positive correlation between employment in construction and poverty rates. However, Adegboyo (2020) finds that construction is inversely related to the poverty rate. Therefore, the expected sign for CONST is ambiguous.

3.2. Demographic Variables

According to Levernier et al. (2000), nonwhite residents may encounter racial prejudice against them in the labor market, so the percentage of the nonwhite population (NONWHT) is expected to have a positive relationship with the poverty rate (Duren and Stelle, 2023). Similarly, Duren and Stelle (2023), Wallace and Moonansingh (2021), Clain (2008), and Shaukat et al. (2020) found the poverty rate to be an increasing function of the percentage of young people (YOUNG), perhaps because they have less work experience and therefore earn less.

Higher educational attainment will lead to lower rates of poverty (Clain, 2008; Gayán-Navarro et al., 2020; Levernier et al., 2000; Liu et al., 2021; Wallace and Moonansingh, 2021). Therefore, the percentage of population that dropped out of high school (HSDROP) is expected to be positively related, and BACH is expected to be negatively correlated with the poverty rate.

Studies by Clain (2008), Duren and Stelle (2023), Fisher (2007), Gayán-Navarro et al. (2020), Levernier et al. (2000), Shaukat et al. (2020) have found that the percentage of female-headed households (FEMHEAD) is positively related to the poverty rate, possibly due to having one income supporting a larger household. Mba et al. (2018) note an increased vulnerability to poverty among

female-headed households, surmising that constraints faced by females may prevent them from allocating more time to working outside the home.

3.3. Descriptive Statistics

Tables 2 and 3 detail a complete summary of descriptive statistics for the dependent and independent variables. The mean poverty rate for the 67 Pennsylvania counties for the years 2000-2019 is 12.24, with a standard deviation of 3.47. The maximum poverty rate of 27.90 is in Philadelphia County, which has the highest poverty rates overall. Meanwhile, neighboring Bucks County's poverty rate of 4.20 in 2009 is the lowest poverty rate. The percentage of nonwhite people has a wide disparity between the maximum and minimum values, with the highest reading of 58.6% in Philadelphia County in 2010 and the lowest measurement of 1% in Elk County in 2001. Philadelphia County also has the highest percentage of female-headed households of 20.6% in 2010. Using boxplots, data from Philadelphia County exhibits outliers in the poverty rate, the unemployment rate, the percentage of renters, the percentage of nonwhite people, the high school dropout rate, and the percentage of female-headed households.

The mean poverty rates in rural and urban counties are 12.81% and 10.81%, respectively, which represents an 18.5% difference. Urban counties have higher means for the percentage of renters (29.11%) and percentage of female-headed households (8.80%) compared to rural counties with 24.26% and 7.04%, respectively. There is a wide disparity between the means of urban and rural counties in the percentage of people with a bachelor's degree, with 22.24% and 13.83%, respectively, and percentage of nonwhite people, with 14.18% and 4.74%, respectively. Rural counties have higher mean shares of employment in manufacturing, agriculture, and construction (17.50%, 3.29%, and 7.13%, respectively) relative to those in urban counties (13.67%, 0.95%, and 5.68%, respectively).

Table 2: Descriptive statistics for pooled sample

Variable	Minimum	Maximum	Mean	SD
Dependent variable				
POV	4.20	27.90	12.24	3.47
Independent variables				
UNEMP	2.80	17.30	6.29	1.76
RENT	14.20	46.95	25.64	4.91
MANU	6.33	43.98	16.41	6.31
AGRI	0.10	9.50	2.63	1.86
CONST	1.70	12.28	6.72	1.72
NONWHT	1.00	58.60	7.42	8.21
YOUNG	6.37	34.17	12.71	3.65
HSDROP	4.13	40.84	11.24	3.94
BACH	5.11	43.26	16.21	6.29
FEMHEAD	3.10	20.60	7.54	2.24

SD: Standard deviation

Table 3: Descriptive statistics for subsamples

Variable	Rural		Urban		Urban without Philadelphia	
	Mean	SD	Mean	SD	Mean	SD
Dependent variable						
POV	12.81	2.88	10.81	4.32	10.07	3.02
Independent variables						
UNEMP	6.56	1.75	5.60	1.60	5.50	1.51
RENT	24.26	4.01	29.11	5.24	28.28	3.96
MANU	17.50	6.64	13.67	4.30	14.01	4.15
AGRI	3.30	1.74	0.95	0.77	0.99	0.77
CONST	7.13	1.78	5.68	0.97	5.78	0.89
NONWHT	4.74	3.96	14.18	11.60	11.90	6.52
YOUNG	13.31	3.93	11.21	2.22	11.10	2.18
HSDROP	11.88	4.06	9.62	3.06	9.16	2.36
BACH	13.83	4.26	22.24	6.58	22.54	6.62
FEMHEAD	7.04	1.57	8.80	3.06	8.30	2.19

SD: Standard deviation

4. MODEL

Consistent with Benfica and Henderson (2021), Cebula and Davis (2022), and Clain (2008), the empirical model estimated for county i at year t is as follows:

$$POVERTY_{it} = \beta_0 + \beta_1 ECON_{it} + \beta_2 DEMO_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where $i = 1\ldots N$ and $t = 1\ldots T$ represent the county and time dimensions of the panel data set, respectively, β_0 is the constant, $ECON_{it}$ is the set of economic regressors, $DEMO_{it}$ is the set of demographic covariates, α_i is a county-specific effect, λ_t represents a time-specific effect, and ε_{it} is the error term.

The equation is estimated with a two-way fixed effects model to control for unobserved county-specific and year-specific heterogeneity in accordance with the results of Hausman (1978) specification tests (Blake, 2021; Cebula and Davis, 2022; Cebula and Duquette, 2022; Cebula and Alexander, 2020). The test statistics are 268.42 (P = 0) and 216.74 (P = 0) with individual-specific effects and year-specific effects, respectively. Comparable values of 275.19 (P = 0) and 228.25 (P = 0) are obtained in the absence of Philadelphia County. Breusch and Pagan (1979) tests reveal heteroskedasticity, and all models are adjusted with Driscoll and Kraay (1998) standard errors.

4.1. Chow Test

Bernard (2019), Levernier (2003), and Olowa and Olowa (2019), among others, highlight differences in poverty rates across urban and nonurban areas. To test for a structural break, a Chow (1960) test is performed with the null hypothesis that the coefficients in the urban and rural regressions are equal. Using the urban subsamples with and without Philadelphia County, the Chow (1960) test statistics are 9.1258 (P = 0.01) and 10.1232 (P = 0.01), respectively, which confirm a structural break between rural and urban Pennsylvania counties, with and without Philadelphia County, and support separate regression analyses in an effort to avoid potential misspecification (Levernier et al., 2000).

4.2. Oaxaca Decomposition

The Oaxaca (1973) decomposition technique ascertains the extent to which the rural-urban difference in average poverty rates (i.e., the left-hand-side of equation [2]) can be understood based on the differences in the average characteristics of rural and urban counties in the sample (i.e., the first term on the right-hand-side of equation [2]):

$$POVERTY_{Rural} - POVERTY_{Urban} = \Sigma\beta_{Rural}(X_{Rural} - X_{Urban}) + \Sigma X_{Urban}(\beta_{Rural} - \beta_{Urban}) \quad (2)$$

The unexplained portion of the average poverty rate difference between urban and rural counties is determined by the differences in the estimated regression coefficients (i.e., the second term on the right-hand-side of equation [2]), and it conveys the residual disadvantage of rural counties relative to urban ones (Fisher, 2007). Thus, even if rural and urban counties had identical sample characteristics, on average, rural areas would retain a higher poverty rate.

5. RESULTS

5.1. Pooled Sample

Model 1 in Table 4 includes all 67 Pennsylvania counties; MANU, CONST, and FEMHEAD are significant at the 1% level, RENT is significant at the 5% level, and AGRI and NONWHT are statistically significant at the 10% level. UNEMP, HSDROP, and BACH are not statistically significant. The overall fit of the model is 0.9127 based on the adjusted R^2. This is similar to the R^2 value of 0.893 obtained by Levernier et al. (2000). Wald (1939) tests indicate joint significance within both variable groups.

In the economic grouping, MANU and CONST are found to be negatively correlated to the poverty rate, which is consistent with Adegboyo (2020), Benfica and Henderson (2021), and Deaton et al. (2014). These inverse relationships between the poverty rate and employment in manufacturing and construction may be because jobs in these fields often do not require high levels of education, and therefore may provide an attainable pathway for those at higher risk of poverty. Ewing and Levernier (2000) suggest that jobs in manufacturing and construction may be union jobs, which often pay higher wages. RENT and AGRI are found to be positively related to the poverty rate, which aligns with the results of Cebula and Davis (2022) and Gayán-Navarro et al. (2020). The positive association between the poverty rate and the percentage of renters could stem from higher housing costs (Tunstall et al., 2013). A positive correlation of employment in agriculture, forestry, fishing, and mining with the poverty rate could be because these industries offer significant seasonal work; there is little to no income in the off-season, and lower skilled jobs with lower wages are prevalent (Gayán-Navarro et al., 2020). Nasrun and Fariastuti (2020) suggest that larger cohorts of workers in agriculture cause a declining marginal product of labor, which depresses wages.

In the demographic grouping, NONWHT and FEMHEAD are positively related to the poverty rate, which is consistent with Levernier et al. (2000). YOUNG is negatively associated with the poverty rate, which is unexpected. This could reflect higher welfare participation rates, individuals living with parents or with roommates rather than on their own, or a decreased risk of poverty among younger age groups because of their opportunity to devote more time to working across multiple jobs since they have fewer household and caregiver responsibilities (Mba et al., 2018).

Model 2 in Table 4 excludes Philadelphia County and experiences a small decline in the adjusted R^2 to 0.8947. Otherwise, the results mirror those of Model 1 and exhibit robustness to the omission of Philadelphia County. Wald (1939) tests continue to demonstrate joint significance among both the economic and demographic variable groups.

5.2. Rural versus Urban Subsamples

A comparison of the rural and urban regressions in Models 3 and 4, respectively, reveals different effects of specific regressors on the dependent variable. Wald (1939) tests for the rural model reveal joint significance only in the economic variable grouping while the same tests for the urban model show joint significance only in the demographic grouping. The overall fit of the rural regression is 0.8506 while the adjusted R^2 for the urban regression is 0.9789, which mirrors Cebula and Davis (2022).

In the rural model, CONST is statistically significant at the 1% level, RENT, MANU, AGRI, and YOUNG are significant at the 5% level, HSDROP is significant at the 10% level, and UNEMP, NONWHT, BACH, and FEMHEAD lack significance at conventional levels. The negative coefficient on HSDROP is unexpected, although it only achieves significance at the 10% level. It is conceivable that people who did not finish high school are able to work in manufacturing and construction where the

Table 4: Fixed effects regression estimates

Variable	Pooled model 1	Pooled without Philadelphia model 2	Rural model 3	Urban model 4	Urban without Philadelphia model 5
Constant	10.7608*** (5.5217)	12.1189*** (5.7655)	15.0342*** (6.1371)	2.6062 (1.0109)	2.9783 (0.9840)
UNEMP	−0.0769 (−1.0947)	−0.0836 (−1.1794)	−0.0948 (−1.2867)	0.1026 (0.8648)	0.1353 (1.0627)
RENT	0.1409** (2.2348)	0.1157* (1.8145)	0.1409** (2.0011)	0.0971 (1.1530)	0.0488 (0.5231)
MANU	−0.0774*** (−2.5620)	−0.0901*** (−2.8924)	−0.0838** (−2.2686)	−0.0510 (−1.1064)	−0.0540 (−1.1245)
AGRI	0.1726* (1.8404)	0.1716* (1.8352)	0.2014** (2.1524)	−0.1841 (−0.5556)	−0.1669 (−0.5055)
CONST	−0.2611*** (−4.3331)	−0.2634*** (−4.3517)	−0.3441*** (−4.9092)	−0.1927 (−1.2377)	−0.1908 (−1.2201)
NONWHT	0.0820* (1.9408)	0.0809* (1.8847)	0.0827 (1.1865)	0.0040 (0.1344)	0.0023 (0.0726)
YOUNG	−0.0554* (−1.8864)	−0.0603** (−2.0451)	−0.0740** (−2.5325)	−0.0484 (−0.5691)	−0.0137 (−0.1436)
HSDROP	−0.0379 (−1.6018)	−0.0343 (−1.4217)	−0.0413* (−1.6665)	0.0538 (0.9993)	0.0908 (1.4437)
BACH	−0.0077 (−0.5059)	−0.0096 (−0.6280)	−0.0191 (−0.7209)	0.0071 (0.5902)	0.0053 (0.4354)
FEMHEAD	0.2085*** (3.6029)	0.1507** (2.4411)	−0.0591 (−0.7881)	0.7480*** (9.6454)	0.7438*** (8.9480)
R^2	0.9127	0.8946	0.8506	0.9789	0.9575
Counties (n)	67	66	48	19	18
Periods	2000–2019	2000–2019	2000–2019	2000–2019	2000–2019

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. t-statistics are based on Driscoll and Kraay (1998) SE. SE: Standard error

work is frequently specialized and potentially dangerous leading to higher wages (Reyes et al., 2014). Alternatively, this outcome may evince that individuals have left school to secure employment to help keep their family unit afloat financially and lift them out of poverty. The signs on the statistically significant coefficients in the rural model match the findings in the pooled models. In fact, the insignificance of NONWHT and the significance of HSDROP are the only departures from the pooled regressions in Models 1 and 2. However, it is important to note that NONWHT was statistically different from zero in the pooled models at only the 10% level.

In contrast to the rural case, the urban subsamples in Models 4 and 5 (with and without Philadelphia County, respectively) have FEMHEAD as the sole significant covariate, and it carries its anticipated positive sign. This outcome could reflect inadequate access to childcare, which limits the ability of mothers to leave the home and go to work and constrains their ability to gain the skills and education required to get higher paying jobs (McLaughlin and Sacks, 1988). Buvinic and Gupta (1997) suggest that this positive influence is because women carry a higher dependency burden and have lower average earnings than men. In addition, women in urban areas may experience more interruptions in their employment due to family commitments than rural women (Sittig and Jozefowicz, 2016). Various studies (Buvinic and Gupta, 1997; Fisher, 2007; Gayán-Navarro et al., 2020; Levernier et al., 2000) identify a positive and significant relation between female-headed households and the poverty rate, and Levernier et al. (2000) underscore that the robustness of this correlation across subsamples allays concerns over the potential simultaneity between poverty and female-headship.

5.3. Oaxaca Decomposition

The total difference in the average poverty rates between rural and urban counties is 2.0034. The Oaxaca (1973) decomposition reveals that the explained variation is −1.51, while the unexplained variation is 3.52. This result may imply that the structural differences between rural and urban counties are mitigating poverty rates in rural counties (Biewen and Jenkins, 2005; Jann, 2008). In other words, if characteristics in rural and urban counties were the same, then poverty rates in rural counties would be roughly 75% higher than they are. However, Ewing and Levernier (2000) caution that decomposition results can be vulnerable to omitted variable bias leading to the unexplained portion of the variation being overstated. Among potentially relevant variables absent from the model are per pupil education expenditures, public transportation services, and extended family ties that can mitigate some childcare issues.

6. CONCLUSION

This study analyzes a 20-year panel of Pennsylvania counties to ascertain the extent to which specific factors account for poverty. The results suggest diverging impacts of the explanatory variables on poverty rates when examining rural and urban counties separately. Both economic factors and demographic characteristics influence the poverty rate within Pennsylvania counties. However, economic variables play a more significant role in rural areas while demographic determinants have more influence on the poverty rates in urban locales. Oaxaca decomposition reveals an amelioration of poverty rates due to specific structural factors in rural counties.

A comparison of the characteristics of rural and urban Pennsylvania counties provides context for the Oaxaca decomposition findings. The higher mean percentage of employment in manufacturing and construction in rural counties than in urban counties may alleviate the poverty rate (Adegboyo, 2020; Benfica and Henderson, 2021; Deaton et al., 2014). Rural counties in this study also have a lower mean percentage of female-headed households than urban counties and a significantly lower percentage of nonwhite people, both of which may abate poverty (Gayán-Navarro et al., 2020; Levernier et al., 2000; Makhalima, 2022). Williams and Baker (2021) suggest that black mothers are at higher risk of poverty than other marginalized groups while Levernier et al. (2000) cite racial discrimination in earnings as a cause of poverty. Thus, the confluence of these determinants may account for rural poverty rates being lower than they would be if rural and urban counties shared identical characteristics.

6.1. Policy Implications

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 these programs typically utilize a one-size-fits-all approach. Oaxaca decomposition analysis shows that different policy measures must be taken in urban and rural Pennsylvania counties to alleviate poverty in accordance with Cebula and Davis (2022).

In rural Pennsylvania counties, economic (i.e., place-based) needs must be addressed (Levernier et al., 2000). Employment in manufacturing and construction are shown to be inversely correlated with the poverty rate, so training people in these fields could ameliorate poverty. Pennsylvania CareerLink and PAsmart address this issue by offering employment training programs and apprenticeships in trade jobs. Pennsylvania's Department of Community and Economic Development (DCED) offers the Rural Jobs and Investment Tax Credit Program to help small businesses in rural areas create jobs and stimulate growth. Supplementary income could be offered to people working in agricultural jobs to keep them afloat in the off-season. Agricultural policies (e.g., Next Generation Farmer Loan Program, Beginning Farmer Tax Credit Program, and Pennsylvania Dairy Investment Program) indirectly address poverty in rural areas. Increased funding toward public housing agencies could reduce the financial burden among renters and lift them out of poverty (Lum and Zhou, 2019). Meanwhile, the Pennsylvania Rural Health Model (PARHM) seeks to financially stabilize rural hospitals and ensure healthcare access to vulnerable populations (Wagner, 2022).

In urban Pennsylvania counties, because the share of female-headed households is the only significant regressor, an approach that supports mothers (i.e., person-based) must be utilized rather than job creation measures, such as the Pennsylvania Minority Business Development Authority and the Pennsylvania State

Small Business Credit Initiative: Diverse Leaders Venture Program (Levernier et al., 2000). Jones and Kodras (1990) suggest that policies should be implemented to close the gender wage gap, increase welfare assistance, raise the federal minimum wage, and provide supplementary income for women and children in order to lower poverty rates among mothers. The government could subsidize childcare, which would provide time for mothers to pursue higher education or training programs that could increase their wages and reduce poverty (Jones and Kodras, 1990; Madgavkar et al., 2021). While this study does not include the pandemic period, the childcare responsibilities faced by women anecdotally emerged as a significant obstacle during the crisis, because women took on more of the childcare burden when schools were closed, and then upon their return to the labor force, they received compensation offers 7%< a currently employed candidate (Brower, 2021). Furthermore, women before the crisis were more strongly represented in sectors negatively affected by the pandemic, such as service and retail jobs (Madgavkar et al., 2021).

6.2. Limitations of the Study

One limitation of this study is that the data sample ends in 2019, before the Coronavirus outbreak; future research could extend the timeframe to include the pandemic period (Martin, 2021). Doing so might allow for a deeper understanding of policy effectiveness due to the extraordinary measures deployed by lawmakers and government agencies in response to the crisis. Additionally, a longer time dimension would reinforce robustness of the claims made here (Cebula and Davis, 2022).

6.3. Extensions of Research

Further research should include variables that were omitted from this study, such as welfare participation rates and Social Security income, the distribution of wealth, the presence of healthcare facilities, higher education institutions, and correctional institutions, employment growth, broadband coverage, political party affiliation distribution, and public transportation infrastructure. Another line of inquiry highlighted by Hennen (2023) would be to replicate the existing study for the child poverty rate and the elderly poverty rate for additional public policy insights. To generalize these findings for the U.S. and to increase the sample size, other states and all their counties could be incorporated into the data set for Oaxaca decomposition. Doing so would facilitate an evaluation of the robustness of the mitigating impact of structural features on poverty rates revealed by this analysis.

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