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RESEARCH ARTICLE

Did Health Care Reform Help Kentucky Address Disparities in Coverage and Access to Care among the Poor?

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Objective. To evaluate the impact of Kentucky's full rollout of the Affordable Care Act on disparities in access to care due to poverty.

Data Source. Restricted version of the Behavioral Risk Factor Surveillance System (BRFSS) for Kentucky and years 2011–2015.

Study Design. We use a difference-in-differences framework to compare trends before and after implementation of the Affordable Care Act (ACA) in health insurance coverage, several access measures, and health care utilization for residents in higher versus lower poverty ZIP codes.

Principal Findings. Much of the reduction in Kentucky's uninsured rate appears driven by large uptakes in coverage from areas with higher concentrations of poverty. Residents in high-poverty communities experienced larger reductions, 8 percentage points (pp) in uninsured status and 7.5 pp in reporting unmet needs due to costs, than residents of lower poverty areas. These effects helped remove pre-ACA disparities in uninsured rates across these areas.

Conclusion. Because we observe positive effects on coverage and reductions in financial barriers to care among those from poorer communities, our findings suggest that expanding Medicaid helps address the health care needs of the impoverished.

Key Words. Health reform, Medicaid expansion, disparities, access to care

Expanding Medicaid eligibility to a larger share of the low-income population can address disparities in health care utilization and outcomes by closing gaps in health insurance coverage and diminishing some of the financial barriers for seeking health services. Regarding the Medicaid expansions stimulated by the Affordable Care Act (ACA), the largest gains in coverage and subsequently access to care should be concentrated among those made newly eligible for public health insurance coverage (Courtemanche, Marton, and Yelowitz 2016; Frean, Gruber, and Sommers 2016). In particular, groups appearing to be "primed" for benefiting from the coverage expansions are predominantly low- and near-low-income; therefore, we anticipate observing larger effects for areas with high concentrations of poor and near-poor individuals. Building on the several reports already highlighting Kentucky's early-stage experiences under the ACA's coverage expansions (Sommers et al. 2015b; State Health Access Data Assistance Center 2015, 2016; Avery, Finegold, and Whitman 2016; Benitez, Creel, and Jennings 2016a, b; Sommers, Blendon, and Orav 2016), this study presents a within-state analysis to determine whether there was geographic variation in the impact of the ACA within Kentucky. Our study compares trends in coverage and other health care access indicators utilizing ZIP code-level variation in pre-2014 poverty rates to make inferences about the ACA's effects on health disparities in Kentucky.

Prior to expanding Medicaid, Kentucky was among the states with the highest overall uninsured rate (Witters 2014). In 2013, Kentucky tied for tenth-highest uninsured rate with Arizona at just over 20 percent. Of the ten states with the highest uninsured rates, it was one of just four (AR, AZ, CA, and KY) to expand Medicaid. Similarly, Kentucky was one of a handful of states to implement a state-based health exchange—*kynect.* In that same vein, Kentucky was also among the arguably unhealthiest states in the United States, ranking 45th in overall health status according to the 2013 edition of *America's Health Rankings* (United Health Foundation 2016). Some of the major implications of Kentucky's overall poorer health status include a high frequency of preventable hospitalizations as well as a lack of regular access to a primary health care provider (Schoen et al. 2013). Even though state-level participation in the ACA faced many political hurdles, the effects were generally positive changes that may signal a pathway forward for improving access to care while also improving the financial well-being of low-income individuals who, prior to the ACA, would have been at risk for falling into a coverage gap (Antonisse et al. 2016; Gourevitch and Sommers 2016; Simon, Soni, and Cawley 2016).

By expanding Medicaid eligibility, Kentucky's low-income populations will likely experience short-term improvements in coverage, potentially decreased reliability on emergency departments as source of care (Wherry

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et al. 2015), reductions in medical debt and other financial barriers associated with medical care (Boudreaux, Golberstein, and McAlpine 2016), and ultimately improved health outcomes in the long run (Kaestner, Joyce, and Racine 2001). Early evaluations of the ACA provisions find substantial uptakes in insurance participation and possible improved access to care among the low-income population (Sommers, Baicker, and Epstein 2012; Sabik, Tarazi, and Bradley 2015; Sommers et al. 2015a; Benitez, Creel, and Jennings 2016a; Sommers, Blendon, and Orav 2016). Coinciding with the timing of Kentucky's Medicaid expansion, the uninsured rate among households with annual incomes below $25,000 dropped from 35 percent in 2013 to almost 10 percent by the end of 2014 (Benitez, Creel, and Jennings 2016a); similarly, the same households also saw a 50 percent reduction in the fraction of people foregoing needed medical care due to cost constraints.

Little is known, however, about the impact of the ACA on disparities, although evidence on linking pre-ACA Medicaid expansions to reductions in preventable deaths exists (Sommers, Baicker, and Epstein 2012), and other work suggests such expansions are making screening and follow-up procedures for cancer more affordable (Choi et al. 2015). Medicaid and CHIP have already been shown to have an effect on alleviating the burden of high medical expenses (Gross and Notowidigdo 2011; Sommers and Oellerich 2013; Wherry, Kenney, and Sommers 2016), which may increase the share of the low-income population with chronic conditions who then have the ability to afford adequate chronic disease management (Garfield and Damico 2012).

Using Kentucky as a case example to study the effects of the ACA across geographic areas holds lessons for policy makers weighing the costs and benefits of ACA participation. If impacts vary significantly across geographic areas of one state, for example, this could add to the growing literature on sources of upward income mobility related to location (Chetty et al. 2016). We focus on the timing of the rollout of the health insurance exchange as well as the expansion's effects on disparities in the first two full years of health care reform under the ACA. Our study draws similar parallels to other recent work highlighting the impact of the ACA on health disparities (Chen et al. 2016) using regional variation in concentrated poverty to investigate whether Kentucky's full participation in the ACA may have facilitated closing gaps in coverage, access, and health care utilization between high- and low-income communities. Concentrated poverty is commonly accepted as a key social determinant of health correlated with adverse outcomes (Auchincloss and Hadden 2002; Schulz et al. 2002; Bower et al. 2014; Gaskin et al. 2014); our analysis may provide a way to determine whether the ACA's rollout can help overcome the adverse health implications of income inequality.

Methodology

Data

Our study outcomes include trends in insurance coverage, financial barriers to seeking/utilizing health care, primary care utilization, and self-reported health status. We obtained a special version of the Behavioral Risk Factor Surveillance System (KY-BRFSS) from Kentucky's Department for Public Health with county and ZIP code identifiers for sample observations (Kentucky Cabinet for Health and Family Services 2016).[1] We use 2011–2015 waves of the data so we are able to observe pre-implementation (2011–2013) trends of the outcomes and 2 years of postimplementation data (2014–2015).

Poverty rates from the ZIP code level were obtained from the American Community Survey 5-year estimates for 2009–2013 (U.S. Census Bureau 2016). Because geographic poverty rates tend to be fairly static over short intervals of time, we expect our approach to inform what we know about the reform's effects on disparities at the community level. While the data are based on microdata, our key point of variation is at the ZIP code of the resident's home address—which we then use to define our treatment groups.

Empirical Approach

To identify the impacts by geographic area, we utilized the area variation in poverty levels and completed a difference-in-differences-styled regression approach. Specifically, we exploit ZIP code–level variation in the fraction living below the poverty line to identify treatment and control groups. This approach draws some inspiration from others utilizing geographic variation in treatment group "intensity" to examine the effects of other reforms. In particular, Courtemanche et al.'s approach to capture the effects of the both the Medicaid and non-Medicaid (e.g., the state-based and federally facilitated exchanges) components of the ACA's coverage expansions by allowing for more "intense" uptake of the new benefit in areas with a previously higher uninsured rate (Courtemanche et al. 2016). In their approach, the authors use geographic variation in uninsured rates at the Public Use Microdata Area level to capture treatment intensity of the policy changes. In contrast, our geographic variation comes from the ZIP code level, representing a much smaller geographic area so we can make inferences about group-level trend changes within a single state.[2] While this approach does not exploit variation in pre-expansion coverage rates for identification, comparing the trends along poverty lines may be a better indicator of the ACA's role in minimizing low income as a barrier to quality health care.

We address the possible endogeneity of reported income using the prerollout poverty status of the respondent's community to characterize our treatment and control groups. When state-level policy decisions alter the eligibility restrictions for publicly sponsored programs such as Medicaid or income-based tax incentives, they alter the incentives for wage earning activity and could potentially distort the labor market (Yelowitz 1995; Garthwaite, Gross, and Notowidigdo 2014). If some in our sample are incentivized to "reduce" their actual income by altering their participation in the labor market by working fewer hours or exiting the labor market altogether, this would lead to concerns with endogeneity.[3] While a recent study finds this phenomenon not to be true (Kaestner et al. 2015), an analysis of Massachusetts' 2006 health care reform suggests its plausibility (Shi 2016) and yet another suggests this potential problem may be overstated (Hinde 2016).

One limitation with our data source is that the BRFSS does not collect information on Medicaid status; therefore, we can only observe whether the respondent had any insurance coverage at the time of the survey. Because of this limitation, we cannot infer whether reductions in uninsured rate were driven by the expanded Medicaid eligibility or whether it was from uptakes in private health insurance coverage. Also, because the BRFSS uses categorical groupings rather than including a continuous measure of income, we cannot precisely determine the residents' eligibility for Medicaid—either traditional or expanded Medicaid under the ACA or eligibility status for tax incentives to purchase coverage through the state health insurance exchange.

Our approach provides a first-year monitoring of the ACA's implications for changes in disparities in coverage and access across geographic areas differing in poverty level. The difference-in-differences model used to assess these trends allows for both a changing trend in outcomes for the high-poverty communities, as well as a separate trend for the low-poverty areas. Allowing these trends to be independent of one another means that reduction in disparities can be driven by the groups experiencing trend changes converging on one another as the policy is implemented and time elapses. A desirable outcome is for the trend lines of the two groups to collapse on one another but to then trend in the same direction. The primary regression model specification is detailed in the equation below:

$$Y_{izt} = \alpha + \beta HighPov_z + \rho(\textbf{\textit{High Poverty}} \times \textbf{\textit{Year 2014}}_{\textbf{\textit{zt}}}) + \tau(\textbf{\textit{High Poverty}} \times \textbf{\textit{Year 2015}}_{\textbf{\textit{zt}}}) + \Gamma X_i + \theta_z + \lambda_{zt} + \varepsilon_{izt}. \quad (1)$$

The above equation extends the traditional difference-in-differences approach by allowing for two postpolicy indicators that allow us to better assess changes in the trends throughout the postimplementation period. Y_{hzt} represents the outcome of interest while subscript i indexes the individual/household, z indexes the ZIP code where the observation resides, and t references time. High Poverty_z indicates the observation was sampled from a ZIP code whose 2013 poverty rate was above the median poverty level (i.e., 20 percent), and observations from ZIP codes whose 2013 poverty rates were below this 20 percent rate are classified as "low poverty" observations and act as our reference group.

The interaction terms High Poverty $\times$ Year 2014_{zt} and High Poverty $\times$ Year 2015_{zt} are the variables of interest; thus, ρ and τ are the policy parameters reflecting the percentage point (pp) change in the outcome for adults in higher poverty areas from 2013 to 2014 and 2013 to 2015. On October 1, 2013, the rollout of the nongroup insurance marketplace (i.e., exchanges) began, and while this period is the open enrollment period for the plans purchased in the exchanges, coverage benefits were not effective until January 1, 2014, as were new Medicaid enrollments under expansion. Hence, we should not observe any meaningful changes in 2013 and earlier work from Kentucky finds the largest uptakes in coverage occurred toward the tail end of the year, with the most substantial reductions on financial obstacles to medical care occurring in the fourth quarter (Benitez, Creel, and Jennings 2016a).

Controls in the model include individual-/household-level controls for age, marital status, parental status, and household size. ZIP code-level fixed effects (θ_z) to account for time-invariant differences in access to or the propensity to take up insurance coverage that are correlated with one's area of residence. Additionally, Kentucky has five Medicaid Managed Care Organizations (MCOs) operating in eight regions in Kentucky (Palmer et al. 2012; Kentucky Department for Medicaid Services 2016), and part of the patterns in coverage may be partly responsive to administrative differences between the dominant MCOs in a given region. Unique time-invariant geographic factors that could influence uptake and other access measures should be picked up in the ZIP code fixed effects in θ_z. Because unobservable time-varying factors attributable to where one lives could also influence coverage trends (e.g., some communities may have become target areas for enrollment assistance programs not available to other communities), we allow each ZIP code to have its own linear time trend, λ_{zt}. We expect this term to soak up variation across time that could also be correlated with changes at the neighborhood (i.e., ZIP code) as well as subtler local changes common across all residents within a ZIP code that could also explain disparities.

Because we are more concerned with the ACA's impact across poverty lines, we consider the following regression specification to better assess the impacts of the ACA by group-level poverty:

$$Y_{izt} = \alpha + \sum_{j=1}^{3} \beta_j \text{PovQuartile}_z^j + \sum_{k=1}^{3} \rho_k \left(Y2014_t \times \text{PovQuartile}_z^k \right) + \sum_{k=1}^{3} \tau_k \left(Y2015_t \times \text{PovQuartile}_z^k \right) + \Gamma X_i + \theta_z + \lambda_{zt} + \varepsilon_{izt}. \qquad (2)$$

To summarize the ACA's effects, we focus on the changes at the end of 2014 and 2015—the first full implementation year and the second year. Observations residing in the second, third, and fourth (i.e., highest) quartiles of 2013 (i.e., pre-implementation) ZIP code-level poverty are allowed to trend independently from one another against ZIP codes with the lowest concentrations of poverty (i.e., first quartile) as coverage uptake and access effects are unlikely to be the same across groups based on their income—or in this case poverty—at the community level. The basic structure of equation (2) is similar to equation (1); however, having six difference-in-differences estimators to consider offers a more finely differentiated approach than simply cutting the data at the median poverty rate.

All regressions use standard errors clustered at the ZIP code level because observations sampled from the same community are likely to be correlated with one another. To account for the BRFSS's complex sampling design, we incorporate the recommended survey weights. We exclude observations from the sample with missing ZIP code identifiers. A large share of observations with missing geographic identifiers may lead to having a study sample not reflective of the state's population; however, only 19 (i.e., 2.5 percent) of Kentucky's 769 total U.S. Postal Service ZIP codes, as of 2014, were not present in the sample.[4] All 120 Kentucky counties were represented in the sample and 44 percent dwelled in rural counties (Economic Research Service 2013).

Our empirical strategy assumes the disparate "gaps" between our poverty-based groups would have remained had it not been for Kentucky's full participation in the ACA; therefore, our results would be biased if there was any evidence of pre-implementation changes in coverage. We test for parallel trends between quantile group outlined in equations (1) and (2), and do not find evidence to suggest the parallel trends assumption was violated.[5]

RESULTS

Table 1 shows the sociodemographic characteristics of the residents in higher versus lower level poverty areas. Per expectation, we see significantly higher levels of uninsured (24 vs. 19 percent) and unmet need (25 vs. 21 percent) among residents in the higher versus lower poverty areas prior to the ACA. Those in the poorer areas also report less access to care and poorer health. There are also systematic differences in family structure across these areas with residents in the higher poverty areas being less likely to be married and more likely to be childless adults. The larger share of childless adults in the higher poverty suggests their residents would be more susceptible to the rollout of the Medicaid expansion due to the lack of Medicaid coverage of this categorical eligibility group prior to the ACA. Classification of the areas by higher versus lower level poverty is consistent with a significantly higher percentage (39 vs. 24 percent) of observations with household income below $25,000.[6]

Graphical Analysis

Figure 1 presents the pre-ACA gaps coverage rates for residents in the higher versus lower poverty areas. In the post-ACA period, we see reduced uninsured in both areas due to the coverage mandate which applies to all residents, the availability of coverage options on the state's nongroup marketplace, and the Medicaid expansion. What is noteworthy from this visual inspection of the data is that in spite of a large reduction in the low-poverty areas, the mean uninsured rate among the high-poverty communities converged on the mean for the low-poverty areas, thus eliminating the pre-implementation gap in coverage rates between the two groups. Similarly, the ACA's effect on financial barriers in seeking health care led to the rate for the high-poverty communities approaching the rate for the low-poverty communities—also indicating that prereform disparities could be diminishing in response to the coverage expansions.

Table 1: Summary Table of Sample Characteristics by ZIP Code–Level Pre-Expansion Poverty Rate (Pooled for 2011–2013)

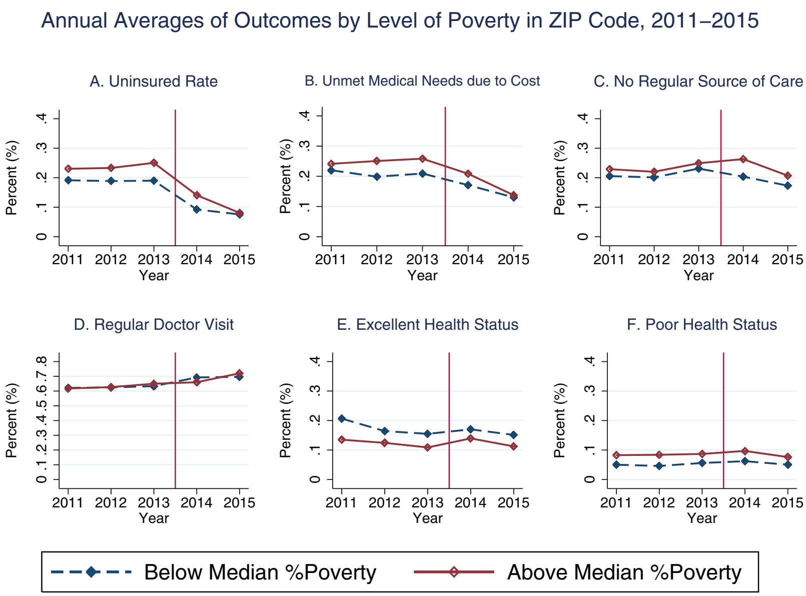
Percent of Residential ZIP Code in Poverty	*Below Median Poverty Rate (Less Impoverished) 0–20.2% in Poverty*	*Above Median Poverty Rate (More Impoverished) 20.2–100% in Poverty*
Outcomes		
%Uninsured	18.7	24.0
%Unmet medical need due to cost	20.6	25.3
%Do not have a regular source of health care	21.3	22.9
%Dr. visit within the past year	63.2	62.3
%Self-reported excellent health status	17.4	12.4
%Self-reported poor health status	4.9	8.5
Demographics		
Age (mean)	41.8	41.4
%Male	50.2	49.0
%Female	49.8	51.0
%Married	56.4	51.7
%Parents	45.4	42.8
%Childless adults	54.6	57.2
%White, Non-Hispanic	88.5	86.9
%Black, Non-Hispanic	7.2	8.5
%Other, Non-Hispanic	1.7	1.8
%Total Nonwhite/Non-Hispanic	8.9	10.2
%Hispanic (any race)	2.5	2.9
%Has one or more adverse Health conditions	59.7	63.3
%Annual household income <\$25,000	24.3	38.5
%Annual household income <\$15,000	11.9	20.2
%Less than high school completion	11.6	16.9
%High school diploma/equivalent	31.5	35.1
%Some college/technical school	32.4	30.9
%BA/BS or higher	24.4	17.0
%Unemployed	7.5	9.0
Observations	8,067	8,659
Fraction of sample	48.2%	51.8%

Note. ZIP code–level poverty rates were obtained using the 5-year sample file for 2011–2013 American Community Survey. The median poverty rate at the ZIP code level for 2013 was 20.2% while the mean was 23% (interquartile range: 13–30%).
Source: Author's own analysis of 2011–2013 Kentucky Behavioral Risk Factor Surveillance System data.

Regression Analysis

The results of our econometric analyses are shown in Tables 2 and 3. In both tables, the percentage point changes from the baseline period (2011–2013) to 2014 and 2015 for each of the dependent variables are shown for the higher

Figure 1: Unadjusted Trends in Insurance Coverage, Access, and Self-Reported Health Indicators by ZIP Code–Level Pre-Expansion Poverty Groupings, 2011–2015



Note. All graphics represent trends among nonelderly Kentucky adults aged 18–64. The poverty rates for the ZIP code level were obtained from the U.S. Census Bureau's American Community Survey via the *American Fact Finder*. ZIP code–level poverty rates were obtained using the 5-year sample file for 2009–2013 American Community Survey. The median poverty rate at the ZIP code level for 2013 was 20.2% while the mean was 23% (interquartile range: 13–30%). The fraction of people reporting difficulty getting prescription medicine due to cost, currently having medical bills, and frequency of doctor visits are only available beginning with the 2013 wave of the BRFSS; therefore, a longer time series plot is presently unavailable. [Color figure can be viewed at wileyonlinelibrary.com]
Source: Author's own analysis of data from the Kentucky Behavioral Risk Factor Surveillance System for 2011–2015.

and lower poverty areas. There are consistent, significant drops in uninsured in both areas in each postimplementation year, and while the decline in higher poverty areas is greater, the difference is not statistically significant until 2015. The only other statistically significant ($p < .10$) result is a 7.5 percentage point difference in the level of unmet need due to costs for residents of higher versus lower poverty areas in 2015.

Based on the results in Table 2, there are reductions in the fraction without a regular source of care in both groups, but there are no major differences between the trends for either group. The lack of significance could indicate

Table 2: Effects of Full ACA Implementation in Kentucky on Coverage, Access, and Health Status by Postimplementation Quarter and Residential ZIP Code's 2013 Level of Poverty

	Baseline Mean (2011–2013)	*2014–2013 Change*		*2015–2013 Change*	
		Coeff.	*(SE)*	*Coeff.*	*(SE)*
A. Uninsured (n = 26,118)					
Low poverty	18.7	−10.2***	(1.9)	−11.3***	(2.6)
High poverty [treatment group]	24.0	−14.6***	(2.0)	−19.8***	(3.1)
Difference-in-differences		−4.5	(2.7)	−8.4**	(4.0)
B. Unmet medical need due to cost (n = 26,086)					
Low poverty	20.6	−3.0	(1.9)	−5.4**	(2.7)
High poverty [treatment group]	25.3	−7.1***	(2.0)	−12.8***	(3.0)
Difference-in-differences		−4.1	(2.8)	−7.5*	(4.0)
C. No regular source of care (n = 26,080)					
Low poverty	21.3	−2.3	(2.2)	−6.0*	(3.4)
High poverty [treatment group]	22.9	−1.2	(2.4)	−7.1**	(3.2)
Difference-in-differences		1.0	(3.3)	−1.1	(4.6)
D. Dr. visitation within past year (n = 25,699)					
Low poverty	63.2	6.0**	(2.5)	5.4	(3.3)
High poverty [treatment group]	62.3	−0.4	(2.5)	3.5	(3.4)
Difference-in-differences		−6.4*	(3.5)	−1.9	(4.8)
E. Reporting excellent health (n = 26,118)					
Low poverty	17.4	4.0**	(1.7)	5.4**	(2.4)
High poverty [treatment group]	12.4	5.1**	(2.1)	2.7	(2.8)
Difference-in-differences		1.1	(2.7)	−2.7	(3.7)
F. Reporting poor health (n = 26,118)					
Low poverty	4.9	0.5	(1.3)	−0.1	(1.7)
High poverty [treatment group]	8.5	−0.2	(1.7)	−2.0	(2.1)
Difference-in-differences		−0.7	(2.2)	−1.9	(2.7)

Note. *p < .10, **p < .05, ***p < .01. All regressions represent linear probability models for ease of interpretation, and the coefficients are scaled by 100 for presentation. Robust standard errors in parentheses are clustered at the ZIP code level. All regression models include controls for gender, marital status, parental status, age (and age squared to control for nonlinearities in the relationship between age and the dependent variable), racial/ethnic group, and level of educational attainment (i.e., BA/BS+ [reference group], less than high school completion, high school diploma or its equivalent, or some college/technical school training). Additional controls included present employment status and income. Time-invariant differences in levels of the outcome are adjusted for using ZIP code fixed effects.
Because of unobservable yet potentially influential time-varying factors that could be correlated with the outcomes and where people live, we allow each ZIP code to have its own linear time trend.
Source: Author's own analysis of 2011–2015 Kentucky Behavioral Risk Factor Surveillance System data.

that it took a while for the provider system to "catch up" with the increase in insured demand in high-poverty areas as some were "crowded out" of provider system at first. We would need a lot more information to substantiate this

Table 3: Difference-in-Differences Effects of Full ACA Implementation in Kentucky on Coverage, Access, and Health Status by Quartile of ZIP Code-Level Poverty

	(1) Uninsured	(2) Unmet Medical Need Due to Cost	(3) No Regular Source of Care	(4) Dr. Visit in the Past Year	(5) Reporting Excellent Health	(6) Reporting Poor Health
Pre-implementation Mean of outcome ZIP codes in 1st quartile of poverty	15.8	18.3	19.1	64.8	18.8	4.2
Year effects						
Year 2014	−5.5**	−0.4	0.4	2.2	5.2**	−0.0
	(2.5)	(2.9)	(3.4)	(3.7)	(2.5)	(2.2)
Year 2015	−4.2	−5.5	−4.8	4.3	6.6*	−1.0
	(3.5)	(3.9)	(5.6)	(5.3)	(3.9)	(2.8)
Difference-in-differences estimators						
Year 2014 × 2nd quartile of poverty	−8.9**	−4.8	−5.1	7.3	−2.4	1.0
	(3.7)	(3.7)	(4.5)	(5.0)	(3.3)	(2.7)
Year 2015 × 2nd quartile of poverty	−13.6***	0.1	−2.4	2.1	−2.4	1.8
	(4.9)	(5.3)	(6.8)	(6.7)	(5.0)	(3.4)
Year 2014 × 3rd quartile of poverty	−7.9**	−5.3	2.1	−3.3	−0.8	0.0
	(3.4)	(3.7)	(4.5)	(4.9)	(3.7)	(2.9)
Year 2015 × 3rd quartile of poverty	−14.5***	−6.4	2.8	−6.2	−5.7	−1.4
	(5.1)	(5.4)	(6.6)	(6.9)	(5.3)	(3.5)
Year 2014 × 4th quartile of poverty	−12.1***	−10.1**	−10.6**	−1.0	1.5	−0.7
	(4.1)	(4.6)	(5.1)	(5.3)	(3.9)	(4.1)
Year 2015 × 4th quartile of poverty	−18.0***	−9.5	−14.5*	12.1*	0.2	−0.0
	(6.8)	(6.7)	(7.9)	(7.2)	(5.6)	(5.8)
Observations	26,118	26,086	26,080	25,699	26,118	26,118

Note. $*p < .10$, $**p < .05$, $***p < .01$. All regressions represent linear probability models for ease of interpretation, and the coefficients are scaled by 100 for presentation. Robust standard errors in parentheses are clustered at the ZIP code level. All regression models include controls for gender, marital status, parental status, age (and age squared to control for nonlinearities in the relationship between age and the dependent variable), racial/ethnic group, and educational attainment (i.e., BA/BS+ [reference group], less than high school completion, high school diploma or its equivalent, or some college/technical school training). Additional controls included present employment status and income. Time-invariant differences in levels of the outcome are adjusted for using ZIP code fixed effects. Because of unobservable yet potentially influential time-varying factors that could be correlated with the outcomes and where people live, we allow each ZIP code to have its own linear time trend.
Source: Author's own analysis of 2011–2015 Kentucky Behavioral Risk Factor Surveillance System data.

assertion; however, this pattern is consistent with more recent findings by Sommers et al., who show that effects of the recent expansions become easier to identify the longer the expansion is in place (Sommers et al. 2016).

In Table 3, we present an additional analysis using the difference-in-differences approach to test for more subtle differences within the second, third, and fourth quartiles of poverty compared to the lowest quartile. Beyond those from the first quartile of poverty, the relatively poorer communities saw increased uptake in coverage between the first and second years after implementation. Focusing on the second year of implementation, the difference in the effect of the ACA increases from the second quartile of poverty (−13.6 pp; $p < .01$) to the third (−14.5 pp; $p < .01$) to the fourth quartile (−18 pp; $p < .01$). The major reductions in unmet medical needs due to costs were concentrated in the poorest (i.e., fourth quartile) areas of the state as the decline is −10.6 pp ($p < .05$) through 2014 and −9.5 pp (nonsignificant) through 2015. In addition to the effect on financial barriers to seeking care, residents of the poorest communities also saw meaningful increases in having a regular source of care (e.g., a primary care provider) in the first (10.6 pp [$p < .05$]) and second (14.5 pp [$p < .10$]) year of implementation, and by the second year, there was a 12 pp increase ($p < .10$) increase in the fraction who had a regular (e.g., scheduled) doctor visit in the past year.[7]

Discussion

Our study is the first, to our knowledge, to use substate variation in poverty levels to evaluate the heterogeneity in the ACA impacts. Ours are consistent with other findings suggesting large gains in coverage among the poor—poor children in particular (Courtemanche, Marton, and Yelowitz 2016). Our results show that full ACA implementation in Kentucky produced the largest benefits for Kentuckians living in areas with high concentrations of poverty. Residents in higher poverty communities experienced the largest reductions in uninsured status and in reporting unmet needs due to costs when compared to those in lower poverty areas. These effects have helped reduce the pre-ACA disparities in uninsured rates between low-income parts of Kentucky. The substate results have particular importance for continued state legislative debates around the ACA, especially with the uncertainty caused by the recent election. While full ACA implementation has reduced Kentucky's uninsured rate and lowered unmet need due to costs, the future of the ACA is in the hands of a new administration. Previous work has shown that state policy makers favor their own state data over national data (Blewett and Davern 2006) and that politics are "local," and our work represents an effort to move the area of analysis toward lawmakers' own geographic constituencies.

Increasing access to coverage options was realized among people in the state's poorest areas as evidenced by our findings. Aggregated data can muddle the existence of heterogeneity in the impact of a new policy, and we show pre-implementation concentrations in neighborhood poverty was a larger indicator of where some of the larger effects of the ACA were felt in Kentucky.[8] Kentucky's coverage expansion generated net increases in coverage enrollment and motivated subsequent improvements in access to care. We did not observe detectable improvements in health comparable to studies investigating other expansions in public health coverage (Finkelstein et al. 2012) despite having 2 years of postimplementation data. The Oregon Health Insurance Experiment (OHIE) provides a recent example of a state-based expansion in Medicaid eligibility followed by meaningful improvements in both self-reported and clinical health outcomes (Baicker and Finkelstein 2011; Finkelstein et al. 2012; Baicker et al. 2013), although the OHIE was a randomized trial while our work was based on an observational study. Within Kentucky, it may also be too early to identify meaningful improvements in health status; however, given the promising results for coverage, access, and utilization among some of the economically vulnerable population, meaningful long-term effects in health and longevity may be on the horizon (Busch and Duchovny 2005; Sommers, Baicker, and Epstein 2012; Sommers unpublished data). Pre-ACA Medicaid expansions for adults have been shown to produce reductions in mortality (Sommers, Baicker, and Epstein 2012), and a recent review concluded that expansions of public insurance for children reduced out-of-pocket expenses, increased short- and long-run financial stability and family material well-being, decreased mortality due to chronic conditions, and led to better education attainment and less reliance on government support later in life (Wherry, Kenney, and Sommers 2016).

Our study is not without limitations; for one, analysis of a single state limits the generalizability of the findings—particularly to other states and even states with nominally similar expansions under the ACA. However, all state Medicaid programs are independent of one another and had differing structures regarding eligibility and benefits prior to the ACA. Our analysis of Kentucky provides an example of one state's experience under a traditional Medicaid expansion. We cannot generalize to other expansion states (e.g., Arkansas, Indiana, and Michigan) using a waiver from the Centers for Medicare and Medicaid Services (CMS) to implement alternative strategies to expand Medicaid eligibility, although our results suggest people benefitting most from the expansions were among those in most need.

Conclusions

The results presented in this study help shed more light on the implications of expanding Medicaid on disparities in access to care and health insurance coverage. When Kentucky expanded Medicaid in 2014, not only did uptakes in insurance coverage occur, but the uptakes were generally larger in areas with higher concentrations of poverty; hence, areas most likely benefiting are poorer on average and signaling some of the realized value from expanding Medicaid eligibility. Our results suggest expanding access to Medicaid coverage has the potential to address existing disparities in access to care along the income gap. As the effects of Kentucky's expansion continue to unfold, those concerned with the role of Medicaid as a tool to improve social welfare may be able to use this iteration of Kentucky's ACA involvement as a case study. While disparities are likely to persist in several dimensions for vulnerable populations such as the poor, this work offers an assessment of policy levers as a partial solution. Future work in this area should investigate the impact of the recent Medicaid expansions and related ACA provisions in the context of reducing disparities in health. Additional work can also help to assess the longevity of these first-year effects determining whether they translate into long-term health gains.

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Notes

1. This special version of the BRFSS contains county and ZIP code–level identifiers for more than 95 percent of the survey's respondents, which allow us to more precisely compare the differential effects of health care reform on residents in some of Kentucky's arguably poorest communities against those from communities with lower

levels of concentrated poverty. County-level identifiers (i.e., State-County FIPS codes) are not commonly available for the public use version of the 50-state BRFSS, and it does contain ZIP code identifiers. Residential ZIP codes were available for almost 98 percent of the initial sample of nonelderly adults aged 18–64. Because this represents such a small fraction (around 2.4 percent) of the sample, we do not expect the findings to be meaningfully influenced by excluding these observations.

2. PUMAs are statistical geographic areas for the purposes of analyzing census data such as the ACS and the Current Population Survey (CPS).
3. In nonexpansion states, it is plausible for the opposite to occur because the income-based tax credits for purchasing coverage in the exchanges have a minimum income threshold at 100 percent FPL, most frequently, and people below the income floor would be incentivized to increase their labor market participation by working more hours so they would have earned enough income to qualify for the tax breaks.
4. Another plausible reason certain ZIP codes may have not been present in the KY-BRFSS is some of them may have belonged to institutions or businesses that have a single ZIP code for themselves; therefore, some of the omitted ZIP codes could plausibly be nonresidential ZIP codes.
5. Table S1 in Appendix SA2 provides the regression results testing for parallel trends between the strata based on ZIP code–level poverty for each approach: (1) cutting the data at the median percent poverty (20.5 percent); and (2) dividing the data based on the quartiles for ZIP code–level poverty. Regressions focused on the joint significance of the interaction between the group indicator and the linear year trend, and the *p*-value from each regression was >.10 for each of the outcomes.
6. To conserve space, we provide summary characteristics of the sample by quartile of poverty at the ZIP code level as a supplement in the Appendix SA2 (see Table S2). Unsurprisingly, people in the highest quartile of poverty had a larger share of people with incomes below $25,000 and $15,000 per year in addition to being uninsured. Comparatively, people in the more impoverished areas were more likely to have at least one chronic illness and report being in poor health. Furthermore, as we think about this group also having the largest share to have faced a financial barrier to seeking needed health care, there are likely to be people with difficulty managing their chronic illness because they lack the financial means to follow the recommended treatments, and to some extent will be assisted largely due to the Commonwealth's coverage expansions.
7. Table S3 in Appendix SA2 provides a similar analysis using a flexible difference-in-differences approach whereby we interact the postimplementation variables with the 2013 poverty rates. The results highlight a similar pattern to the main results presented in the text, which we use as an additional robustness check on the specification of our model.
8. In addition to our regression tables presented in the main text of the manuscript, we also include Table S2 in Appendix SA2, which includes an analysis of a flexible difference-in-differences approach where we interact the year 2014 and 2015 variables with the 2013 poverty rate for the ZIP code. This approach is to support our underlying hypothesis that it was poorer communities, on average, who experienced a larger impact from the ACA rollout, and inspection of the interaction terms in this approach

should produce coefficients whose signs match their counterparts from the regressions separating the sample into two (see Table 2) and four (see Table 3) groups. Because the Table S2 in Appendix SA2 corresponds logically to the previous tables in terms of direction of the relationship as well as statistical significance, we believe this can provide a type of robustness check to guide our earlier assumptions.

References

Antonisse, L., R. Garfield, R. Rudowitz, and S. Artiga. 2016. "The Effects of Medicaid Expansion under the ACA: Findings from a Literature Review" [accessed on July 14, 2016]. Available at http://kff.org/medicaid/issue-brief/the-effects-of-medicaid-expansion-under-the-aca-findings-from-a-literature-review/

Auchincloss, A. H., and W. Hadden. 2002. "The Health Effects of Rural-Urban Residence and Concentrated Poverty." *Journal of Rural Health* 18 (2): 319–36.

Avery, K., K. Finegold, and A. Whitman. 2016. "Affordable Care Act Has Led to Historic, Widespread Increase in Health Insurance Coverage" [accessed on October 3, 2016]. Available at https://aspe.hhs.gov/pdf-report/affordable-care-act-has-led-historic-widespread-increase-health-insurance-coverage

Baicker, K., and A. Finkelstein. 2011. "The Effects of Medicaid Coverage—Learning from the Oregon Experiment." *New England Journal of Medicine* 365 (8): 683–5.

Baicker, K., S. L. Taubman, H. L. Allen, M. Bernstein, J. H. Gruber, J. P. Newhouse, E. C. Schneider, B. J. Wright, A. M. Zaslavsky, and A. N. Finkelstein. 2013. "The Oregon Experiment—Effects of Medicaid on Clinical Outcomes." *New England Journal of Medicine* 368 (18): 1713–22.

Benitez, J. A., L. Creel, and J. A. Jennings. 2016a. "Kentucky's Medicaid Expansion Showing Early Promise on Coverage and Access to Care." *Health Affairs* 35 (3): 528–34.

———. 2016b. "Who and Where Are Kentucky's Remaining Uninsured?" *Medical Care* 55 (3): 215–9.

Blewett, L. A., and M. Davern. 2006. "Meeting the Need for State-Level Estimates of Health Insurance Coverage: Use of State and Federal Survey Data." *Health Services Research* 41 (3): 946–75.

Boudreaux, M. H., E. Golberstein, and D. D. McAlpine. 2016. "The Long-Term Impacts of Medicaid Exposure in Early Childhood: Evidence from the Program's Origin." *Journal of Health Economics* 45: 161–75.

Bower, K. M., R. J. Thorpe Jr, C. Rohde, and D. J. Gaskin. 2014. "The Intersection of Neighborhood Racial Segregation, Poverty, and Urbanicity and Its Impact on Food Store Availability in the United States." *Preventive Medicine* 58: 33–9.

Busch, S. H., and N. Duchovny. 2005. "Family Coverage Expansions: Impact on Insurance Coverage and Health Care Utilization of Parents." *Journal of Health Economics* 24 (5): 876–90.

Chen, J., A. Vargas-Bustamante, K. Mortensen, and A. N. Ortega. 2016. "Racial and Ethnic Disparities in Health Care Access and Utilization under the Affordable Care Act." *Medical Care* 54 (2): 140–6.

Chetty, R., M. Stepner, S. Abraham, S. Lin, B. Scuderi, N. Turner, A. Bergeron, and D. Cutler. 2016. "The Association between Income and Life Expectancy in the United States, 2001–2014." *Journal of the American Medical Association* 315 (16): 1750–66.

Choi, S. K., S. A. Adams, J. M. Eberth, H. M. Brandt, D. B. Friedman, R. D. Tucker-Seeley, M. P. Yip, and J. R. Hébert. 2015. "Medicaid Coverage Expansion and Implications for Cancer Disparities." *American Journal of Public Health* 105 (S5): S706–12.

Courtemanche, C., J. Marton, and A. Yelowitz. 2016. "Who Gained Insurance Coverage in 2014, the First Year of Full ACA Implementation?" *Health Economics* 25 (6): 778–84.

Courtemanche, C., J. Marton, B. Ukert, A. Yelowitz, and D. Zapata. 2016. "Early Impacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States." *Journal of Policy Analysis and Management* 36 (1): 178–210.

Economic Research Service. 2013. "Rural/Urban Continuum Codes 2013" [accessed on March 12, 2013]. Available at www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, and K. Baicker, and The Oregon Health Study Group. 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year." *Quarterly Journal of Economics* 127 (3): 1057–106.

Frean, M., J. Gruber, and B. D. Sommers. 2016. *Premium Subsidies, the Mandate, and Medicaid Expansion: Coverage Effects of the Affordable Care Act.* National Bureau of Economic Research Working Paper Series w22213.

Garfield, R. L., and A. Damico. 2012. "Medicaid Expansion under Health Reform may Increase Service Use and Improve Access for Low-Income Adults with Diabetes." *Health Affairs* 31 (1): 159–67.

Garthwaite, C., T. Gross, and M. J. Notowidigdo. 2014. "Public Health Insurance, Labor Supply, and Employment Lock." *Quarterly Journal of Economics* 129 (2): 653–96.

Gaskin, D. J., R. J. Thorpe Jr, E. E. McGinty, K. Bower, C. Rohde, J. H. Young, T. A. LaVeist, and L. Dubay. 2014. "Disparities in Diabetes: The Nexus of Race, Poverty, and Place." *American Journal of Public Health* 104 (11): 2147–55.

Gourevitch, R., and B. D. Sommers. 2016. "Medicaid Expansion in Kentucky: Early Successes, Future Uncertainty" [accessed on February 6, 2016]. Available at http://www.commonwealthfund.org/publications/blog/2016/jul/medicaid-expansion-in-kentucky

Gross, T., and M. J. Notowidigdo. 2011. "Health Insurance and the Consumer Bankruptcy Decision: Evidence from Expansions of Medicaid." *Journal of Public Economics* 95 (7–8): 767–78.

Hinde, J. M. 2016. "Do Premium Tax Credits Increase Private Health Insurance Coverage? Evidence from the 2006 Massachusetts Health Care Reform." *Economics Letters* 143: 121–4.

Kaestner, R., T. Joyce, and A. Racine. 2001. "Medicaid Eligibility and the Incidence of Ambulatory Care Sensitive Hospitalizations for Children." *Social Science & Medicine* 52 (2): 305–13.

Kaestner, R., B. Garrett, A. Gangopadhyaya, and C. Fleming. 2015. *Effects of ACA Medicaid Expansions on Health Insurance Coverage and Labor Supply.* National Bureau of Economic Research NBER Working Paper No. 21836.

Kentucky Cabinet for Health and Family Services. 2016. *Kentucky Behavioral Risk Factor Surveillance System.* Frankfort, KY: Kentucky Department for Public Health.

Kentucky Department for Medicaid Services. 2016. "Kentucky Medicaid Managed Care Organization Option Information" [accessed on June 20, 2016]. Available at http://chfs.ky.gov/dms/mcolinks.htm

Palmer, A., E. Howell, J. F. Costich, and G. M. Kenney. 2012. "Evaluation of Statewide Risk-Based Managed Care in Kentucky: A First Year Implementation Report" [accessed on March 24, 2012]. Available at http://www.urban.org/research/publication/evaluation-statewide-risk-based-managed-care-kentucky-first-year-implementation

Proctor, B. D., J. L. Semega, and M. A. Kollar. 2016. "Income and Poverty in the United States: 2015" [accessed on October 25, 2016]. Available at http://www.census.gov/library/publications/2016/demo/p60-256.html

Sabik, L. M., W. W. Tarazi, and C. J. Bradley. 2015. "State Medicaid Expansion Decisions and Disparities in Women's Cancer Screening." *American Journal of Preventive Medicine* 48 (1): 98–103.

Schoen, C., D. Radley, P. Riley, J. Lippa, J. Berenson, C. Dermody, and A. Shih. 2013. "Health Care in the Two Americas: Findings from the Scorecard on State Health System Performance for Low-Income Populations, 2013" [accessed on July 14, 2013]. Available at http://www.commonwealthfund.org/publications/fund-reports/2013/sep/low-income-scorecard

Schulz, A. J., D. R. Williams, B. A. Israel, and L. B. Lempert. 2002. "Racial and Spatial Relations as Fundamental Determinants of Health in Detroit." *Milbank Quarterly* 80 (4): 677–707.

Shi, J. 2016. "Income Responses to Health Insurance Subsidies: Evidence from Massachusetts." *American Journal of Health Economics* 2 (1): 96–124.

Simon, K., A. Soni, and J. Cawley. 2016. *The Impact of Health Insurance on Preventive Care and Health Behaviors: Evidence From the 2014 ACA Medicaid Expansions.* National Bureau of Economic Research Working Paper Series No. 22265.

Sommers, B. D., and D. Oellerich. 2013. "The Poverty-Reducing Effect of Medicaid." *Journal of Health Economics* 32 (5): 816–32.

Sommers, B. D., K. Baicker, and A. M. Epstein. 2012. "Mortality and Access to Care Among Adults after State Medicaid Expansions." *New England Journal of Medicine* 367 (11): 1025–34.

Sommers, B. D., R. J. Blendon, and E. J. Orav. 2016. "Both the 'Private Option' and Traditional Medicaid Expansions Improved Access to Care for Low-Income Adults." *Health Affairs* 35 (1): 96–105.

Sommers, B. D., K.-P. Chua, G. M. Kenney, S. K. Long, and S. McMorrow. 2015a. "California's Early Coverage Expansion under the Affordable Care Act: A County-Level Analysis." *Health Services Research* 51 (3): 825–45.

Sommers, B. D., B. Maylone, K. H. Nguyen, R. J. Blendon, and A. M. Epstein. 2015b. "The Impact of State Policies on ACA Applications and Enrollment among

Low-Income Adults in Arkansas, Kentucky, and Texas." *Health Affairs (Millwood)* 34 (6): 1010–8.

Sommers, B. D., R. J. Blendon, E. Orav, and A. M. Epstein. 2016. "Changes in Utilization and Health among low-Income Adults after Medicaid Expansion or Expanded Private Insurance." *Journal of the American Medical Association Internal Medicine* 176 (10): 1501–9.

State Health Access Data Assistance Center. 2015. *Study of the Impact of the ACA Implementation in Kentucky.* Louisville, KY: Foundation for a Healthy Kentucky.

State Health Access Data Assistance Center. 2016. "Study of the Impact of the ACA Implementation in Kentucky" [accessed on March 30, 2016]. Available at http://www.healthy-ky.org/sites/default/files/REVISED%20FINAL%20FULL%20Annual%20Report%203.21.pdf

United Health Foundation. 2016. "America's Health Rankings: 2015 Annual Report" [accessed on May 10, 2016]. Available at http://www.americashealthrankings.org/

U.S. Census Bureau. 2016. "American Fact Finder: American Community Survey Data" [accessed on November 9, 2016]. Available at https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

Wherry, L. R., G. M. Kenney, and B. D. Sommers. 2016. "The Role of Public Health Insurance in Reducing Child Poverty." *Academic Pediatrics* 16 (3): S98–104.

Wherry, L. R., S. Miller, R. Kaestner, and B. D. Meyer. 2015. *Childhood Medicaid Coverage and Later Life Health Care Utilization.* National Bureau of Economic Research Working Paper Series No. 20929.

Witters, D. 2014. "Highest Uninsured States Less Likely to Embrace Health Law" [accessed on May 10, 2014]. Available at http://www.gallup.com/poll/167321/highest-uninsured-states-less-likely-embrace-health-law.aspx

Yelowitz, A. S. 1995. "The Medicaid Notch, Labor Supply, and Welfare Participation: Evidence from Eligibility Expansions." *Quarterly Journal of Economics* 110 (4): 909–39.

SUPPORTING INFORMATION

Additional supporting information may be found online in the supporting information tab for this article:

Appendix SA1: Author Matrix.

Appendix SA2: Supplementary Appendices.

Table S1. Test for Parallel Trends Assumption across Poverty Strata.

Table S2. Summary Characteristics of Kentucky by Quartile of Poverty at the ZIP Code Level, 2011–2013.

Table S3. Flexible Difference-in-Differences Approach of the Effect of State Based ACA-Related Health Reforms in Kentucky.