The Value of Health Insurance during a Crisis: Effects of Medicaid Implementation on Pandemic Influenza Mortality *

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Abstract

This paper studies how better access to public health insurance affects infant mortality during pandemics. Our analysis combines cross-state variation in mandated eligibility for Medicaid with two influenza pandemics – the 1957-58 "Asian Flu" Pandemic and the 1968-69 "Hong Kong Flu" Pandemic – that arrived shortly before and after the program's introduction. Exploiting heterogeneity in the underlying severity of these two shocks across counties, we find no relationship between Medicaid eligibility and pandemic infant mortality during the 1957-58 outbreak. In contrast during the 1968-1969 pandemic, which occurred after Medicaid implementation, we find that better access to insurance in high-eligibility states substantially reduced infant mortality. The reductions in pandemic infant mortality are too large to be attributable solely to new Medicaid recipients, suggesting that the expansion in health insurance coverage mitigated disease transmission among the broader population.

JEL Codes: I13, I18, N32, N52

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1 Introduction

Does improved access to public health insurance save lives during a pandemic? On the one hand, the health benefits from extending medical services to uninsured populations may be especially large during a health crisis. On the other hand, the high case volume caused by an infectious disease outbreak may overwhelm medical resources, lowering the quality of care that patients receive.

This paper studies how better access to public health insurance affects infant mortality during a pandemic. Our analysis combines the expansion in public insurance following the introduction of Medicaid in 1965 with two influenza pandemics – the 1957-58 "Asian Flu" Pandemic and the 1968-69 "Hong Kong Flu" Pandemic – that arrived shortly before and after the program's introduction. Each outbreak was responsible for more than 100,000 deaths in the United States, although pandemic severity varied widely across localities (Glezen, 1996; Simonsen et al., 1997).

Our empirical strategy builds on Goodman-Bacon (2018) by combining *cross-state* variation in Medicaid eligibility with *cross-county* differences in the underlying size of the health shock to estimate the impact of Medicaid on pandemic-related infant mortality. Following Goodman-Bacon (2018), we use cross-state differences in the share of women receiving benefits under the Aid to Families with Dependent Children (AFDC) program in 1965 as a plausibly exogenous source of variation in Medicaid eligibility. Variation in AFDC rates across states stemmed from long-standing institutional differences in welfare programs, and we confirm that outcomes in high- and low-AFDC states trended similarly prior to 1965.

We link this cross-state variation in Medicaid eligibility with cross-county variation in pandemic severity. We focus on two predictors of pandemic severity: urbanization – measured by the county urban population share, and local air pollution – measured by total capacity of coal-fired power plants, which were the leading source of air pollution by mid-century. Both factors have been linked to pandemic severity (Clay, Lewis and Severnini, 2018, 2019; Aiello et al., 2010; Goscé, Barton and Johansson, 2014), and we document a strong empirical relationship between each county-level measure and excess infant mortality during both pandemics.

Our analysis is based on an annual county-level dataset on infant mortality from 1950 to 1976.[1] We adopt a triple-difference estimation strategy that compares the deviation from trend in infant mortality during the 1968-69 Pandemic (first difference) across counties that were more or less exposed to the shock (second difference) across states with higher or lower AFDC-based Medicaid eligibility (third difference). We also exploit the preceding 1957-58 Pandemic to estimate a series of "placebo" regressions, and evaluate the validity of our triple-difference research design.

We find that expansions in healthcare access from Medicaid substantially mitigated the severity of the 1968-69 pandemic. The point estimates for infant mortality are large, negative, and statistically significant. The effects are stable across various specifications and unaffected by controls for county-level trends. In contrast, we find no relationship between future Medicaid expansions and infant mortality during the 1957-58 influenza pandemic, supporting our identifying assumption that the 1968-69 outbreak would have been similarly severe across states absent the expansion in health insurance under Medicaid.

The effects are quantitatively meaningful. Our estimates imply that the introduction of Medicaid averted more than 2,500 infant deaths during the 1968-69 pandemic, nationwide. These effects represent mortality reductions over and above the health benefits of public insurance in non-pandemic years. Comparing the size of the mortality effects to the expansion in coverage under Medicaid, we find that the health

[1] Infant health was acutely sensitive to pandemic influenza, which affected mortality through both post-birth infection and prenatal exposure (see Section 2.1).

improvements were too large to have accrued solely to newly insured households. Instead, the results are consistent with a local health externality, in which improved healthcare access among a subset of households reduced disease transmission to the broader population.

Why did expansions in insurance eligibility mitigate pandemic-related infant mortality? The results appear to have been driven by improved access to physician services and hospital care, consistent with experimental evidence on the effects of Medicaid expansions in the 2000s (Finkelstein et al., 2012; Baicker et al., 2013; Taubman et al., 2014; Finkelstein et al., 2016; Baicker et al., 2017). Comparing the effects by age of death within the first year, we find that health benefits from Medicaid were concentrated during the first hours after birth. These patterns could reflect impacts on newborn health through improved maternal health, better access to acute care during and immediately after delivery, or both (Currie and Schwandt, 2013; Schwandt, 2018; Almond et al., 2010). We also estimate differential effects for non-white infant mortality, consistent with patterns in categorical eligibility for Medicaid by race (Goodman-Bacon, 2018).

This paper contributes to the literature on pandemics. The risk of global pandemics represents a substantial cost to societies due to both the economic disruption and the loss of life (Fan, Jamison, and Summers, 2016). Scholars have focused on the 1918 Spanish Flu Pandemic, and a large medical literature has sought to understand the characteristics of the H1N1 strain responsible for the pandemic (see Taubenberger and Morens, 2006). Economists have also explored the long-run health and economic effects of in utero exposure (Almond, 2006; Beach et al., 2017). Much less is known about what can be done to mitigate the threat posed by pandemics. Our results suggest that improved access to medical care, through expansions in public insurance, may play an important role in reducing mortality during an outbreak.

This paper also contributes to the literature on the impact of public insurance on health. Despite extensive research, evidence on the health benefits of public health insurance has been mixed. Evidence from the Oregon Health Insurance Experiment shows increased health care utilization, and improved self-reported health, but no effects on clinical measures or one-year mortality (Baicker et al., 2013; Finkelstein et al., 2012). In contrast, Currie and Gruber (1996) find that expansions in Medicaid eligibility during the 1980s led to improved health outcomes. Goodman-Bacon (2018) finds that Medicaid introduction led to more rapid reductions in infant and child mortality in high Medicaid eligibility states. Mortality for nonwhite children on Medicaid fell by 20 percent, with most of the effect coming from declines in infant mortality. Our results show that the health benefits of public insurance may be especially large during health crises – effects that may not be fully captured in the immediate aftermath of eligibility expansions.

2 Background

2.1 The Influenza Pandemics of 1957-58 and 1968-69

In February 1957, a new influenza A (H2N2) virus emerged in East Asia, triggering the "Asian Flu Pandemic." The virus reached U.S. coastal cities in the summer of 1957 and there was an upsurge in cases in October and November. An estimated 25 percent of the U.S. population was infected during this two month period (Henderson et al., 2009). By March, 69,800 pandemic-related deaths had occurred in the U.S., and by its end the pandemic is estimated to have killed 116,000 Americans (CDC and Diseases, 2018).

A second influenza pandemic hit the U.S. roughly a decade later. The "Hong Kong Influenza Pandemic" of 1968-69 was a global outbreak that originated in China in July

1968. The pandemic was caused by the influenza A (H3N2) virus. It arrived in the United States in September 1968. Although the virus was highly contagious, the case-fatality rates were significantly lower than the Asian Flu, and overall U.S. mortality rates were estimated to be 100,000 (CDC and Diseases, 2018).

During both outbreaks, the spread of the disease was largely unaffected by vaccines and non-pharmaceutical health measures. Effective vaccine were unavailable (Saunders-Hastings and Krewski, 2016). Similarly, preventative public health measures such as quarantines and closures were not widely implemented, and had minimal influence on disease transmission (Henderson et al., 2009).

Infants were acutely sensitive to pandemic influenza through both in utero exposure and post-birth infection. Figure 1 documents a sharp increase in the infant mortality rate during during both pandemic periods.

2.2 Air Pollution and Urban Density

Two factors have been shown to be important determinants of severity during the 1918-1919 pandemic: air pollution and urban density (Clay, Lewis and Severnini, 2018, 2019).

An emerging body of evidence suggests that air pollution may exacerbate pandemic mortality. In randomized control trials, mice exposed to higher levels of particulate matter (PM) experienced increased mortality when infected with a common strain of the influenza virus (Hahon et al., 1985; Harrod et al., 2003; Lee et al., 2014). Microbiology studies of respiratory cells also identify a link between pollution exposure and respiratory infection (Jakab, 1993; Jaspers et al., 2005). Ciencewicki and Jaspers (2007) review a number of epidemiological studies showing associations between exposure to air pollutants and increased risk for respiratory virus infections. Recent historical studies find links between pollution, infectious disease, and mortality (Hanlon, 2018; Clay, Lewis and Severnini, 2018, 2019).[2]

Urban areas often have greater influenza mortality because of the combination of higher transmission and lower socioeconomic characteristics (Aiello et al., 2010; Goscé, Barton and Johansson, 2014; Hadler et al., 2016; Dalziel et al., 2018). Dalziel et al. (2018, p.76) find that "larger cities, with higher base transmission potentials, have more diffuse influenza epidemics." This occurs because of higher transmission and thus greater spread outside of peak season. During the 1918-1919 pandemic, higher transmission worked to the advantage of larger cities, since they experienced greater spread during the milder spring wave. This conferred partial immunity during fall wave and led to lower influenza mortality in urban areas (Clay, Lewis and Severnini, 2018, 2019).

Table 1 shows significant heterogeneity in pandemic infant mortality according to underlying air pollution and urban density during the 1957-68 and 1968-69 Pandemics. Column 1 provides evidence that infant mortality exceeded its trend during both pandemics.[3] Columns 2 and 3 indicate that during the 1957-58 Pandemic, excess infant mortality was significantly more elevated in counties with higher levels of coal capacity and urban population. Notably, these relationships are positive but less pronounced during the 1968-69 Pandemic. In Section 5, we assess the role of Medicaid in mitigating coal- and urban-based pandemic mortality.

2.3 Medicaid

The Social Security Amendments of 1965 established the Medicaid program, with the goal of improving medical access for the poor and reducing inequalities in health

[2]Air pollution also appears to contribute to mortality during the ongoing COVID-19 pandemic Wu et al. (2020).

[3]Excess infant mortality is calculated as the deviation from a linear county mortality trend. Counties are weighted by total population.

outcomes. Since the 1950s, the federal government had provided matching grants to states to provide medical care to the poor. Nevertheless, these payments were limited and states varied widely in their funding for low-income individuals. The introduction of Medicaid program increased access to medical services among the nation's poor, especially for children and pregnant women (Goodman-Bacon, 2018).

Under Medicaid, the federal government expanded payments to states for the costs of providing health services to eligible individuals. The program eliminated caps on federal financing and increased the federal reimbursement rate. While there was considerable latitude in how states set up their medical assistance programs, states were required to extend coverage by 1970 or else lose federal reimbursements for existing medical programs. Twenty-six states adopted Medicaid in 1966, 11 in 1967, and the rest between 1968 and 1970, except Alaska (1972) and Arizona (1982). In the five years after Medicaid implementation, the share of children with public insurance increased by 10 percentage points, and the share of adults increased by 2 percent.

The Medicaid program mandated coverage for recipients of federally funded welfare programs, which led to a close link between welfare program participation and Medicaid eligibility. As a result of underlying state-specific demographics and welfare program funding, there were significant cross-state differences in the size of the population eligible for Medicaid beginning in 1965. Given the low employment rates among the eligible population, Medicaid coverage represented new access to insurance as there was little scope for crowd-out of existing private insurance.

3 Data

To study the effects of Medicaid eligibility on pandemic mortality, we combine annual county-level health outcomes, state-level information on insurance eligibility, and baseline county-level characteristics that influenced pandemic severity.

Our main health outcome is the infant mortality rate, measured as the number of infant deaths per 1,000 live births. We obtain annual county-level infant mortality from 1950 to 1976 from the *Vital Statistics* (Bailey et al., 2018).

To measure eligibility for coverage under the Medicaid program, we use state-level information on the share of women receiving benefits under AFDC at the year of Medicaid implementation (Goodman-Bacon, 2018). Given the close link between welfare participation and Medicaid enrollment, this variable captures cross-state differences in the size of the population eligible for the program. Indeed, Goodman-Bacon (2018) demonstrates a strong empirical relationship between state-level AFDC rates and the expansion in public health insurance under Medicaid. We focus on female AFDC participation, given its importance for both prenatal and postnatal healthcare access. We construct an indicator above- versus below-median state Medicaid eligibility based on this variable. Appendix Figure A.1 displays states with above- and below-median AFDC-based eligibility. Eight states that implemented Medicaid after 1969 are not included in our sample.

Data for coal fired power generation and percent urban are from Clay, Lewis and Severnini (2016) and Haines and ICPSR (2010), respectively. Because direct measures of air pollution are limited through the 1960s, total capacity of coal-fired power plants within the county boundaries is used as a proxy for air pollution (Clay, Lewis and Severnini, 2016).[4] Coal-fired electricity generation was the leading source of air pollution by mid-century (Figure A.2). The dispersion of power plant emissions was localized, with more than 90 percent of particulate matter falling within a 30-mile radius of the plant (Levy et al., 2002). Both county-level predictors are measured in 1965. Appendix Figure A.3 shows the distribution of coal capacity and percent urban across counties.

[4]Data for a sample of 85 counties with air quality monitoring show a strong relationship between local coal-fired capacity and TSP concentrations (Appendix Table A.1).

Summary statistics are in Appendix Table A.2.

4 Empirical Strategy

To examine the role of Medicaid in offsetting the impacts of health shocks, we estimate the following triple difference regression:

$$
\begin{aligned}
IMR_{ct} = {} & \beta_1(Pand68_t \times Mod_c) + \beta_2(Pand68_t \times HighAFDC_s) \\
& + \beta_3(Pand68_t \times Mod_c \times HighAFDC_s) \\
& + \sum_{t \in \{Pand57, Post65\}} I_t\Big(\gamma_1^t Mod_c + \gamma_2^t HighAFDC_s + \gamma_3^t Mod_c \times HighAFDC_s\Big) \\
& + \eta_c + \eta_c \times t + \lambda_{rt} + \psi X_{ct} + \epsilon_{ct} \qquad (1)
\end{aligned}
$$

where IMR_{ct} denotes infant mortality rate per 1,000 live births in county c in year t. The variable $Pand68_t$ is a dummy for the 1968-69 Pandemic. The term Mod_c denotes county-level modifiers (coal capacity, percent urban) that may have contributed to the underlying severity of the pandemic, while $HighAFDC_s$ is an indicator for states that had above-median AFDC-based Medicaid eligibility. ϵ_{ct} represents an error term. Robust standard errors are clustered at the county-level to adjust for heteroskedasticity and within-county serial correlation.[5] All regressions are weighted by the number of live births.

The regression includes county fixed effects, η_c, county-specific linear time trends, $\eta_c \times t$, region-by-year fixed effects, λ_{rt}, and annual climatic variables, X_{ct}, that may have influenced disease spread (precipitation, average temperature, days above 29 degrees Celsius, and days below 10 degrees Celsius).[6]

[5] Standard errors that are clustered at state-level are similar in magnitude (available upon request).

[6] Information on annual county climatic conditions are from the National Oceanic and Atmospheric

The regression specification also allows for separate triple interaction effects between the variables Mod_c and $HighAFDC_s$ and indicators for the 1957-58 Asian Flu pandemic, I_{Pand57}, and the post-1965 Medicaid period, I_{Post65}. The coefficient on the first triple interaction, γ_3^{Pand57}, provides a placebo test for the research design, since Medicaid eligibility should not affect pandemic mortality *prior* to its implementation in 1965. The coefficient γ_3^{Post65} captures the post-1965 triple difference interaction, allowing Medicaid to mitigate the direct mortality effects of coal capacity and percent urban in non-pandemic years.

The β_1 coefficients identify the relationship between county-level modifiers and pandemic infant mortality in low-AFDC eligibility states. These coefficients capture the extent to which the change in mortality during the 1968-69 Pandemic was systematically related to baseline coal capacity and percent urban. The estimates provide a measure of underlying heterogeneity in severity of the health shocks according to these two county-level predictors. Meanwhile, the estimates of β_2 capture the extent to which underlying pandemic severity differed across high- and low-AFDC states.

The main coefficients of interest are represented by β_3. These coefficients capture the differential in the pandemic-modifier gradient in high AFDC-based eligibility states relative to low eligibility states during the 1968-69 Pandemic. The estimates capture the extent to which the relative expansion in AFDC-based public insurance under Medicaid mitigated infant mortality in counties that were exposed to particularly severe health shocks.

Our identification assumption is that heterogeneity in pandemic severity would have been similar across high- and low-AFDC states absent the implementation of Medicaid. This assumption is supported by four pieces of evidence.

First, AFDC-based Medicaid eligibility was based on long-standing institutional

Administration (NOAA).

and demographic differences across states. Factors that influenced state-level eligibility, including long-run institutional barriers, family structure, and household incomes, had differed across states since the 1930s (Alston and Ferrie, 1985; Moehling, 2007). Moreover, AFDC rates were stable across states in the decades prior to Medicaid, suggesting no anticipatory changes in welfare generosity (Goodman-Bacon, 2018).

Second, we find little evidence that state AFDC eligibility are correlated with levels or trends in state socioeconomic conditions. Appendix Table A.3 presents results from balancing tests for differences in levels and trends in pre-1965 characteristics across states with different rates of AFDC eligibility. We find no evidence of differential trends according to state AFDC eligibility. The estimated coefficients are all small and (with the exception of annual precipitation) statistically insignificant. The overall patterns are consistent with the results of Goodman-Bacon (2018), who finds that welfare-based eligibility is uncorrelated with either the levels or trends across a range of state characteristics.

Third, estimates of "placebo" triple interaction effects based on the 1957-58 Asian Flu pandemic are statistically insignificant and small in magnitude (reported below in section 5). These insignificant estimates show that there were no unobservable differences across high- and low-AFDC states that impacted heterogeneity in pandemic-related infant mortality prior to 1965.

Fourth, triple interaction effects based on an "event-study" version of equation (1) are significant for the 1968-69 years, but insignificant in non-pandemic years both before and after 1965, as well as during the 1957-58 pandemic (reported below in section 5). These results are obtained from a flexible specification in which we interact the term $\left(\gamma_1^t Mod_c + \gamma_2^t HighAFDC_s + \gamma_3^t Mod_c \times HighAFDC_s\right)$ with a full series of year dummy variables. Each coefficient, γ_3^t, captures the triple interaction effect in year t relative to 1965 (the last year prior to Medicaid implementation). These findings further suggest that the role of Medicaid in offsetting excess coal or urban based mortality arose solely during the 1968-69 Pandemic and not in other years.

5 Results

5.1 Coal Capacity, Percent Urban, and the Impact of Medicaid on Pandemic Mortality

The first set of results investigate the effects of coal capacity and urbanization and the extent to which greater access to public insurance offsets excess infant mortality. Table 2 reports the estimates of β_1 and β_3 from different versions of equation (1). Columns 1-3 report the results for coal capacity, columns 4-6 report the results for percent urban. In columns 1 and 4, we report estimates from models that include county fixed effects, region-by-year fixed, and annual climatic variables. In columns 2 and 5, we also control for county-specific linear time trends. In columns 3 and 6, we report the 1968 and 1969 triple interaction terms based on a generalized version of equation (1) that includes the full vector of triple interaction terms by year.

We find substantial heterogeneity in excess pandemic mortality across counties with different levels of coal capacity and percent urban. In columns 2 (the main specification), the estimate on the coal-pandemic interactions term, β_1, is positive and statistically significant, consistent with previous research suggesting that poor air quality exacerbates influenza severity (Clay, Lewis and Severnini, 2018; Hanlon, 2018). In column 5, coefficient estimate for β_1 is positive and significant, consistent with previous research on heightened transmission in densely populated areas (Clay, Lewis and Severnini, 2019; Aiello et al., 2010; Goscé, Barton and Johansson, 2014).

The triple interaction estimates suggest that better access to public health insurance under Medicaid significantly reduced excess pandemic mortality in higher coal capacity and more urban areas. For coal capacity, the coefficients on the 1968-69 pandemic triple interaction term, β_3, are negative and statistically significant, and similar in magnitude to the main coal-pandemic interaction effects. The positive coal capacity-pandemic mortality gradient in low-AFDC states was largely offset in high-AFDC states during the 1968-69 pandemic, suggesting that better access to healthcare substantially mitigated the impact of the severe health shock. Multiplying the estimate in column 2 by average exposure to coal, we calculate that better access to Medicaid in high-AFDC states led to a 0.3 per 1,000 live births = (0.054×5.8) relative reduction in pandemic-related infant mortality. For percent urban, the estimates on the 1968-69 triple interaction term are also negative, statistically significant, and large in magnitude, implying that better access to healthcare largely offset the differential impact of the shock in urban areas.

The broad patterns in Table 2 are robust to a range of alternative specifications. Appendix Table A.4 reports the results for the "placebo" triple interactions based on the 1957-58 Pandemic. These estimates identify average differences in the pandemic mortality gradient in high-AFDC states relative to low-AFDC states prior to the enactment of Medicaid. Across the various specifications the point estimates are small and statistically insignificant, supporting our identifying assumption that absent Medicaid implementation, heterogeneity in pandemic severity would have been similar across high- and low-AFDC states.

Appendix Table A.5 reports the full vector of year-by-year triple interaction terms from 1970 to 1975, based on the "event-study" version of equation (1).[7] Prior to 1965, all but one of the estimates are statistically insignificant, including the triple interaction effects from the 1957-58 pandemic. In the post-1965 period, the triple interactions

[7]The triple-interaction term for 1976 is excluded, since it is collinear with the linear county trend.

are significant during the pandemic, but generally insignificant in other years. Appendix Table A.4 also reports the triple-difference estimates on γ_3^{Post65}, which capture the average differences in coal and urban based mortality across high- and low-AFDC states across all post-1965 non-pandemic years. In columns 2 and 5 (the main specification), these estimates are small and statistically insignificant, suggesting that Medicaid had little impact on the direct mortality effects of coal capacity and urbanization in non-pandemic years. Together, these findings suggest that the effects of Medicaid implementation in averting coal- and urban-related mortality were concentrated during the 1968-69 pandemic period and not in other years, either before or after 1965.

Appendix Table A.6 reports the results from several additional robustness tests. Column 2 reports estimates for a restricted sample of states that had implemented Medicaid by 1967, prior to the onset of the pandemic. This restriction addresses concerns regarding endogeneity in state decisions to implement Medicaid, which may have been influenced by the pandemic itself. The results from these regressions are similar to the baseline findings in sign, significance, and magnitude. In columns 3 and 4, we report estimates from regressions for sub-samples with positive coal capacity and with non-zero urban population. Despite the decreases in sample size, the findings are similar to the baseline results. Column 5 reports results from an unbalanced sample that includes an additional 109 counties with incomplete data. The estimates are similar in terms of sign, significance, and size. In columns 6 and 7, we assess the extent to which state-level AFDC rates provide a good proxy for county-level eligibility. Using information on 1976 county-level AFDC rates, we re-estimate the baseline models, excluding observations in which there are discrepancies between county and state AFDC rates. The main results are unaffected by these sample restrictions. Finally, in column 8, we estimate horserace regressions that include triple interactions based on both coal capacity and percent urban. Interestingly, the estimates for coal capacity are largely unchanged, whereas both the β_1 and β_3 estimates for percent urban are smaller in magnitude and not statistically significant. Together, these findings suggest that the urban pandemic mortality penalty may be largely attributable to worse air quality in large cities.

Lastly, we assess whether the observed link between AFDC recipiency and excess mortality during the 1968-69 pandemic might reflect the impact of other social policies that were adopted in the 1960s under the War on Poverty. We focus on two major policies – Head Start and the Food Stamps program – both of which have been linked to relative improvements in infant health (Ludwig and Miller, 2007; Almond, Hoynes and Schanzenbach, 2011). In Appendix Table A.7, the inclusion of interactions based on per capita spending on Head Start or the Food Stamps program has little impact on the main AFDC interaction effects for both coal capacity and percent urban. Moreover, the point estimates for these other programs are all statistically insignificant. Together, these results suggest that relative decreases in excess pandemic mortality in high-AFDC states cannot be attributed to contemporaneous adoption of War on Poverty programs.

5.2 Pandemic Infant Mortality by Age and Race

Table 3 reports estimates for infant mortality by age at death (first day, days 2-27, post-neonatal, and first year) and by race.[8] Panel A reports the effects by coal capacity and Panel B reports the effects by percent urban.

The results in columns 1 to 4 of Table 3 show that nearly all of the impact of Medicaid on coal- and urban-related pandemic mortality occurred during the first day of life. In both Panels A and B, the point estimates for first day mortality are negative and statistically significant, and similar in magnitude to the total effects on one year

[8]County-level infant mortality data by age of death and race are available beginning in 1960 and in 1962, respectively.

mortality reported in column 4. The expansion in Medicaid may have reduced day one mortality through a number of channels. Greater access to healthcare services may have improved in utero health by mitigating the severity of influenza and secondary pneumonia infection among pregnant mothers.[9] Better access to acute care, such as early heartbeat detection and oxygenated respirators, may have increased survival conditional on health at birth.[10] Finally, better access to public insurance may have decreased local transmission of the virus, thereby reducing the likelihood of maternal infection even among non-Medicaid recipients.

The estimates in column 5 of Table 3 reveal systematically larger impacts of Medicaid eligibility on non-white infant mortality. In both the coal capacity and percent urban models, we estimate significantly larger reductions in non-white pandemic infant mortality in high-AFDC states. For coal, the estimates are significant for both groups, but twice as large for non-whites, which is roughly proportional to the racial infant mortality gap. For urban, the effects are concentrated entirely among non-white infants, and the estimates for white infant mortality is not statistically significant. These patterns are consistent with previous research showing disproportionate direct impacts of Medicaid on non-white infant and child mortality (Goodman-Bacon, 2018).

6 Medicaid during the 1968-69 Pandemic

In this section, we explore the quantitative implications of the findings to evaluate how the expansion in health insurance under Medicaid mitigated the infant mortality burden during the 1968-69 pandemic. We focus on excess pandemic mortality associ-

[9]We find no significant impact of Medicaid implementation on maternal mortality (results available upon request), consistent with the fact that excess mortality during the 1968-69 Pandemic was largely limited to infants and the elderly.

[10]Because county-level measures of health at birth, such as birthweight or Apgar scores, are not available prior to the 1968 pandemic, we are unable to evaluate the relative importance of these two channels.

ated with coal capacity, since the results in column 8 of Appendix Table A.6 suggest that the urban pandemic mortality penalty was largely attributable to pollution in large cities. We quantify the effects of Medicaid access in two ways: 1) the *relative* decrease in pandemic infant deaths in high-AFDC versus low-AFDC states due to differential expansion in Medicaid access, and 2) the *absolute* decrease in pandemic infant deaths due to the expansion of Medicaid access in both high- and low-AFDC states after 1965.

The estimates in Table 4, Panel A imply that the differential expansion in healthcare services under Medicaid led to large relative decreases in the pandemic infant mortality rate across high- versus low-AFDC states. These estimates capture the average difference in coal-related infant mortality across high- and low-AFDC states during the 1968-69 Pandemic.[11] The preferred point estimates imply that better access to health insurance in high-AFDC states offset excess pandemic infant mortality rate by 0.36 ($= 0.054 \times 6.67$) to 0.33 ($= 0.054 \times 6.09$) per 1,000 live births.[12]

We find that improved access to healthcare under Medicaid averted a substantial number of infant deaths that would have otherwise occurred during the 1968-69 pandemic. In Panel B, we combine the relative decreases in excess infant mortality with the size of the exposed population to calculate the number of pandemic infant deaths averted due to Medicaid. The estimates in column 1 imply that the relative expansion of public insurance in high-AFDC states averted 809 infant deaths that would have occurred if access were the same as in low-AFDC states.[13]

In column 2 of Panel B, we combine the relative estimates for mortality with infor-

[11] We obtain these estimates by multiplying the triple interaction coefficient reported in column 2 of Table 2 by county-level means for coal capacity.

[12] The county-level means for coal capacity are weighted by total live births to capture average infant exposure. The estimates in column 1 capture average exposure in high-AFDC states. The estimates in column 2 capture average exposure across both high- and low-AFDC states.

[13] This estimate is obtained by multiplying the implied infant mortality reductions by the number of exposed infants in high-AFDC states: $\beta_3/1,000 \times \text{Number of live births} = 0.000364 \times 2,222,527 = 809$.

mation on AFDC rates in *both* high- and low-AFDC states to calculate the absolute decrease in pandemic infant mortality.[14] Nationwide, we calculate that 2,527 pandemic infant deaths were averted as a result of Medicaid implementation. This figure is similar Goodman-Bacon's (2018) estimates of the average number of annual child deaths from all causes that were averted as a result of Medicaid over the period 1966 to 1979. Notably, our estimates reflect lives saved over and above the health benefits from public insurance in non-pandemic years.

To conclude the analysis, we explore whether the effects on pandemic infant mortality can be attributed solely to new insurance coverage among the Medicaid eligible population. We estimate the average treatment effect on the treated (ATET), dividing the triple-difference estimates by the cross-state difference in insurance access implied by a first-stage regression of overall children's insurance rates on the fraction of women age 15-44 on AFDC reported in Goodman-Bacon (2018). The resulting estimates capture the pandemic mortality per program beneficiary.

We find that the effects on pandemic infant mortality are too large to be attributed solely to newly insured households. In Panel C of Table 4, the ATETs for the effect of coal-related pandemic mortality range from 5.8 to 6.3. Given that these effects are driven entirely by reductions in neonatal mortality (with a mean of 13.8 per 1,000 live births), the results imply implausibly large improvements in health among the newly insured population, suggesting that the health benefits from Medicaid implementation extended beyond newly insured households.[15] The significant impacts of Medicaid access on white infant mortality reported in column 5 of Table 3 also highlights the role of local spillovers during the pandemic, given that the direct health effects of

[14]Specifically, we divide the relative estimates by the difference in AFDC rates across high- and low-AFDC states to calculate the change in pandemic mortality per percentage point change in AFDC eligibility. We then apply these estimates (weighted by the number of exposed infants) to calculate the total number of deaths averted separately in high- and low-AFDC states.

[15]Notably, more than one third of neonatal deaths in 1968-69 were from causes entirely unrelated to the pandemic such as congenital anomalies, maternal conditions, and injuries at birth.

Medicaid were concentrated almost entirely among non-white populations (Goodman-Bacon, 2018).

Our pandemic ATET estimates are substantially larger than the average effects of Medicaid of infant health across all years – both pandemic and non-pandemic (Goodman-Bacon, 2018). In normal times, Medicaid's effects should be concentrated among recipient households whose access to medical services was directly affected by the program. During the pandemic, however, expansions in public insurance may influence local disease transmission and generate health externalities to non-recipient households. Better access to doctors may increase the likelihood that parents isolated sick children at home. Access to better healthcare may decrease viral load and shorten the period of contagion. The shift from home-based to hospital care for those with acute illnesses may further reduce transmission through an isolation effect. Understanding the role of the health system in influencing disease transmission may be a fruitful area of future research.

7 Conclusion

This paper provides new evidence on the role of public health insurance in mitigating pandemic severity. Our research strategy leverages cross-state variation in Medicaid implementation with two influenza pandemics that arrived shortly before and after the program's passage. Prior to Medicaid implementation, we find no relationship between excess mortality during the 1957-58 "Asian Flu Pandemic." After Medicaid implementation, we find that better access to healthcare significantly reduced infant mortality during the 1968-69 "Hong Kong Flu Pandemic." The effects on mortality were sizeable and too large to be solely attributable to newly insured households. Instead, our findings suggest that better access to healthcare services for a subset of the population reduced local transmission more broadly.

Our findings provide new insights into the health benefits of public insurance. Whereas previous research on the health impacts of Medicaid have been mixed, our results show that the potential for public healthcare to save lives may be particularly large during health crises. Because these episodes arrive infrequently, however, the benefits may not be captured by policy evaluations focused on the immediate aftermath of implementation.

Pandemics pose a continued threat to population health. Despite modern testing capabilities and contact tracing, governments have struggled to contain the spread of the coronavirus disease 2019 (COVID-19). By demonstrating the value of improved healthcare access in reducing pandemic severity, this study's findings may have relevance for the mitigation of current and future outbreaks. Understanding how best to integrate the public and medical response to limit the spread and lethality of infectious disease outbreaks is a critical area for future research.

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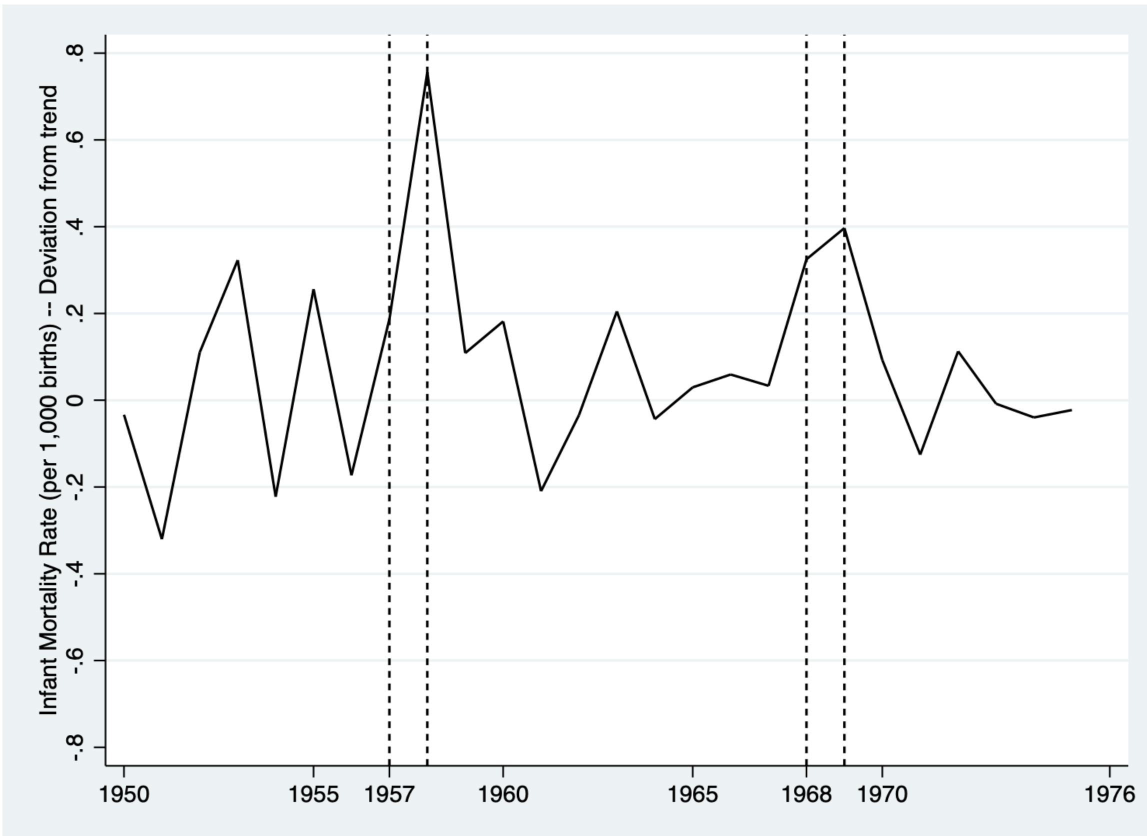
Figures and Tables

Figure 1: Infant Mortality Rate and Influenza Pandemics



Notes: This figure displays deviations from trend in the infant mortality rate for the period 1950 to 1976. Deviations are constructed relative to a linear trends over each five-year interval during the sample period. The vertical short-dashed lines highlight the flu pandemics of 1957-58 and 1968-69.

Table 1: Heterogeneity in Pandemic Infant Mortality across Counties

Excess Infant Mortality Rate (per 1,000 live births)	All Counties (1)	Difference Above vs. Below Median: Coal (2)	Difference Above vs. Below Median: Percent Urban (3)
1957-58 Pandemic	0.449	0.578***	1.142***
		(0.004)	(0.004)
1968-69 Pandemic	0.298	0.006	0.158***
		(0.004)	(0.004)
Counties	2,361		

Notes: Column (1) reports the deviation from trend in the infant mortality rate during the 1957-58 and 1968-69 Pandemics (shown in Figure 1). Columns (2) and (3) report the difference in excess pandemic mortality across with above and below median levels of coal capacity and percent urban. Counties are weighted by total population. Standard errors from two-sample tests are reported in parenthesis. *** denotes statistical significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 2: Medicaid and Pandemic Infant Mortality

	Dependent Variable: Infant Mortality Rate					
	Coal	Coal	Coal	Urban	Urban	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
P 1968-69 x Mod	0.039***	0.068***		0.005	0.012***	
	(0.013)	(0.015)		(0.004)	(0.005)	
P 1968-69 x AFDC x Mod	-0.056***	-0.054***		-0.021***	-0.015**	
	(0.017)	(0.019)		(0.006)	(0.007)	
P 1968 x AFDC x Mod			-0.053**			-0.018**
			(0.024)			(0.010)
P 1969 x AFDC x Mod			-0.052*			-0.020**
			(0.027)			(0.010)
Dep Var: Mean (S.D.)			22.3 [8.2]			
Coal Capacity: Mean (S.D.)			5.8 [9.3]			
Percent Urban: Mean (S.D.)			70.2 [28.5]			
County-Year	63,747	63,747	63,747	63,747	63,747	63,747
Counties	2,361	2,361	2,361	2,361	2,361	2,361
Adj. R-Squared	0.541	0.593	0.594	0.543	0.592	0.593
Region x Year, County FE	Y	Y	Y	Y	Y	Y
Annual Climate Vars	Y	Y	Y	Y	Y	Y
County Time Trends		Y	Y		Y	Y
"Event Study" Controls			Y			Y

Notes: This table reports the main coefficients of interest estimated of equation (1) for coal capacity and percent urban. Climate variable controls include temperature and precipitation variables (five bins each). Columns (3) and (6) include the full set of year-by-year triple interaction terms, $\gamma_1^t Mod_c \times Year_t + \gamma_2^t HighAFDC_s \times Year_t + \gamma_3^t Mod_c \times HighAFDC_s \times Year_t$, based on the "event-study" version of equation (1), with estimates reported relative to the 1965 reference year. Standard errors clustered at the county level are reported in parentheses. *** denotes statistical significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 3: Pandemic Mortality by Age and Race

	Dependent Variable: Infant Mortality Rate				
	By Age				By Race
	Day 1	Day 2-27	Day 28+	Year 1	
	(1)	(2)	(3)	(4)	(5)
Panel A: Effects by Coal Capacity					
P 1968-69 x AFDC x Coal	-0.041***	-0.015**	0.005	-0.049***	
	(0.011)	(0.009)	(0.006)	(0.014)	
x White					-0.052***
					(0.016)
x Non-white					-0.108***
					(0.039)
Panel B: Effects by Percent Urban					
P 1968-69 x AFDC x Pct Urban	-0.011**	0.001	0.001	-0.010	
	(0.005)	(0.004)	(0.003)	(0.006)	
x White					-0.002
					(0.008)
x Non-white					-0.066***
					(0.020)
Dep Var: Mean	7.9	5.9	4.1	19.2	16.5 (White) 29.5 (Non-white)
Coal Capacity: Mean (S.D.)			6.0 (9.5)		
Percent Urban: Mean (S.D.)			71.3 (27.6)		
Observations	34,615	34,615	34,615	34,615	43,626
Counties	2,308	2,308	2,308	2,308	2,308
Region x Year, County FE	Y	Y	Y	Y	Y
Annual Climate Vars	Y	Y	Y	Y	Y
County Time Trends	Y	Y	Y	Y	Y

Notes: This table reports regressions on infant mortality by age of death and by race. County-level data on infant mortality by race and by age are available beginning in year 1962, but 1,776 counties do not have data on IMR by-race until 1968. Panel A reports the triple interaction estimates of β_3 for coal capacity, Panel B reports the estimates for percent urban, and Panel C reports the estimates from models that include both coal capacity and percent urban. All regressions report the full controls described in Table 2. Standard errors clustered at the county level are reported in parentheses. *** denotes statistical significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

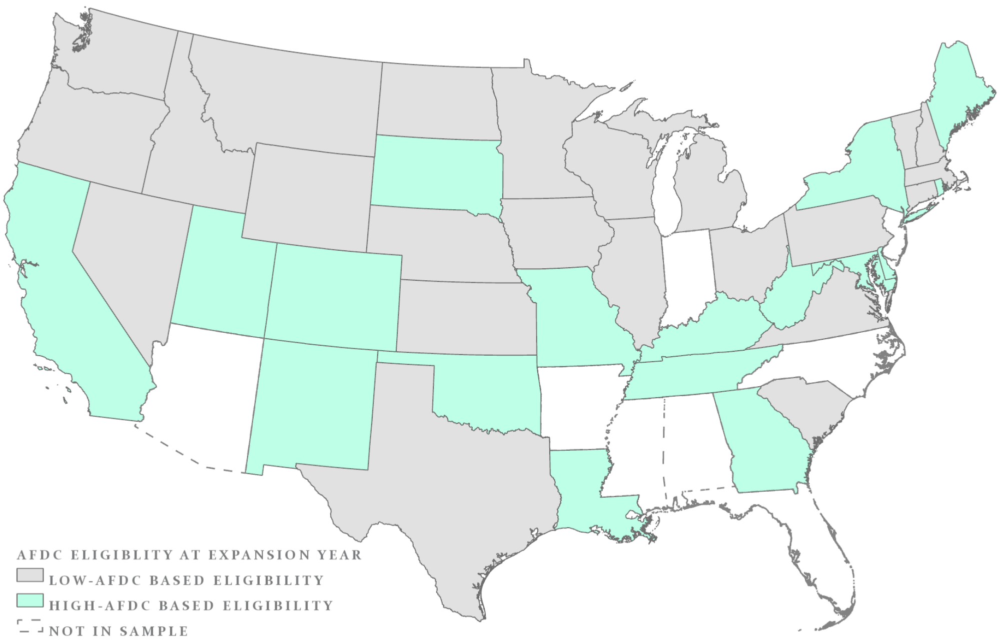
Table 4: Infant Death Averted and Average Treatment Effects on the Treated (ATETs)

	Relative	Absolute
	(1)	(2)
	A. 1968-69 Pandemic Infant Mortality	
Δ IMR	-0.362	-0.329
	[-0.608, -0.116]	[-0.552, -0.105]
	B. 1968-69 Pandemic Infant Deaths	
Δ Infant Deaths	-809	-2527
	[-1359, -259]	[-4246, -809]
	C. Avg. Treatment Effect on the Treated	
Δ IMR per Newly Insured Household	-6.34	-5.78
	[-7.10, -4.59]	[-6.47, -4.17]

Notes: Panel A reports the implied differentials in pandemic infant mortality between high- and low-AFDC states associated with coal capacity. These estimates are derived by multiplying the triple interaction coefficient estimates for coal capacity (Table 2, col. 2) by the average infant exposure to coal in high-AFDC states (column 1) or in all states (column 2). Panel B reports the implied decrease in pandemic infant deaths due to the expansion in Medicaid. Column 1 reports the relative effects for high- vs low-AFDC states, by multiplying the estimates in Panel A by the number of exposed infants in high-AFDC states. Column 2 reports the absolute impact of Medicaid implementation on pandemic infant mortality, by adjusting for the total expansion in AFDC-based eligibility across all states, nationwide. Panel C reports the average treatment effect on the treated (ATET) among newly insured households. These effects were obtained by dividing the reduced form estimates in Panel A by the first-stage relationship between state-level AFDC eligibility and public insurance recipiency: coefficient (s.e.) = 3.83 (0.94) (Goodman-Bacon, 2018). We derive confidence intervals for Panel C based on bootstrap draws from normal distributions with means and standard deviations equal to the coefficient estimates and standard errors from the reduced-form and first-stage regressions. The 95% confidence intervals are reported in square brackets.

A Appendix

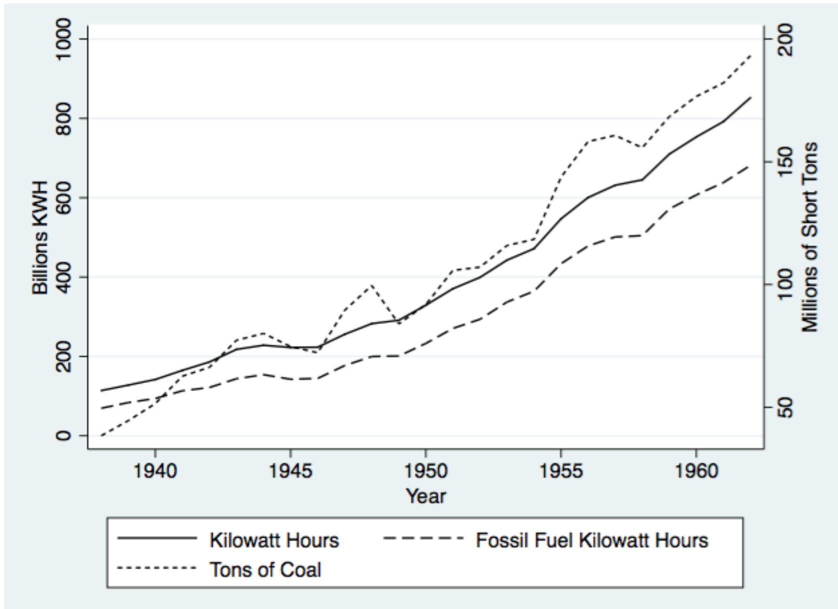
Figure A.1: Exposure to Medicaid Across U.S. States



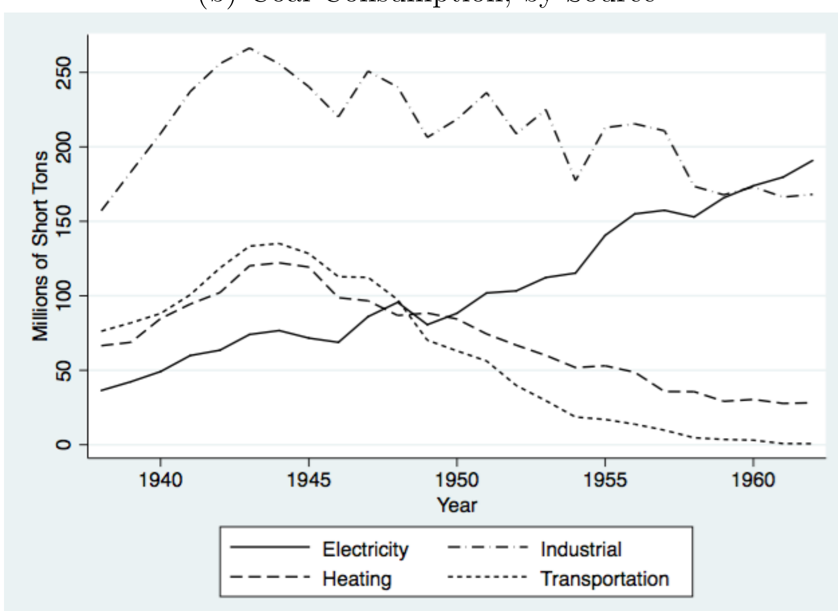
Notes: This map presents high-AFDC (green) and low-AFDC (grey) states by date of Medicaid implementation. *Data Sources*: Goodman-Bacon (2018) and ACIR (1968). States that implemented Medicaid after 1969 are not included in this sample (AL, AR, AZ, FL, IN, MS, NC, NJ). Massachusetts is included in some robustness checks but is not included in our main specification, because county-level infant mortality data is not available for the 1957-58 pandemic years or for 1953, 1954, 1956. Data in those years are only available at state-level. This is the explanation given in the introduction of Volume I of the Vital Statistics of the United States: "Errors in the transcription of birth and death certificates in the Massachusetts State office made it undesirable to tabulate data by place of residence for the individual urban places and counties in that State." (U.S. Department of Health, Education, and Welfare, 1955 [1956], page XIII).

Figure A.2: Trends in U.S. Electricity Generation and Coal Consumption

(a) Trends in Electricity Generation



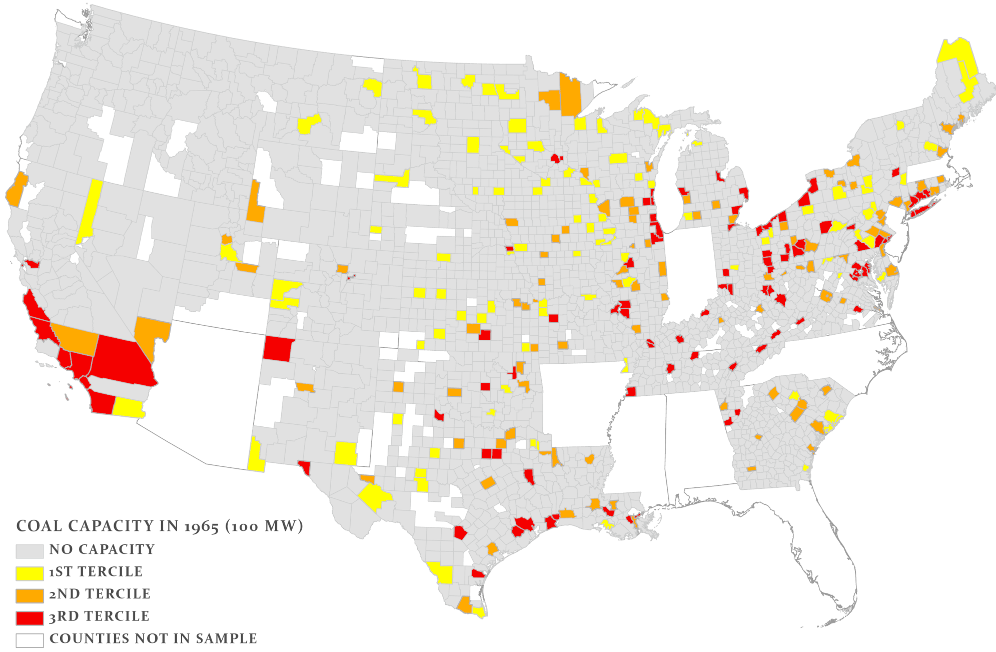
(b) Coal Consumption, by Source



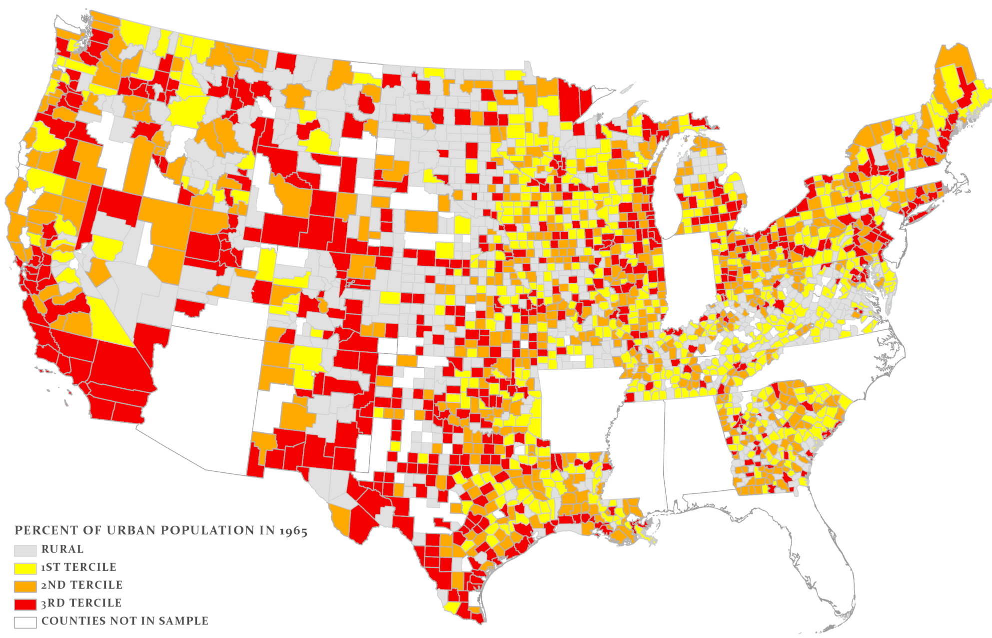
Notes: (a) Data from Gartner (2006), *Historical Statistics of the United States*, Table Db218-227. Electric utilities-power generation and fossil fuel consumption by energy source: 1920-2000. (b) Data from United States Bureau of Mines, *Minerals Yearbook* (various years).

Figure A.3: Variation in Coal-fired Electricity Generating Capacity and Percent Urban

(a) Coal Capacity



(b) Percent Urban



Notes: This map presents the sample counties identified by tercile of coal capacity (panel a) and tercile of percent urban (panel b) in 1965.

Table A.1: Total Suspended Particulates (TSP) Concentration and Coal Capacity

	Dependent variable: Total Suspended Particulates	
	(1)	(2)
Coal capacity ($\leq$ 30 miles)	2.3245**	
	(1.0228)	
Coal capacity ($\leq$ 50 miles)		2.2378***
		(0.6451)
Observations	433	433
Counties	85	85
R-squared	0.723	0.753
Mean dep var in 1957	141	
Mean dep var in 1962	100	
State-by-Year FE	Y	Y
Geographic Controls	Y	Y

Notes: This table reports the relationship between coal-fired electricity generating capacity and total suspended particulates (TSP), a measure of particulate matter collected by the EPA for the period 1957-1962. Coal capacity measures total coal-fired generating capacity within x miles of the county centroid. Geographic controls include percent urban, percent employed in manufacturing, percent non-white, and climatic controls.

Table A.2: Summary Statistics

	1950	1960	1970	All Years (1950-1976)
	(1)	(2)	(3)	(4)
Infant Mortality Rate(per 1,000 births)				
All	29.02	25.15	19.44	23.16
	(9.84)	(6.75)	(5.33)	(7.73)
Non-white			28.35	28.76
			(35.67)	(27.59)
White			17.77	17.79
			(4.66)	(5.53)
Day 1			8.71	8.21
			(3.16)	(3.75)
Day 2-27			6.04	6.03
			(2.48)	(2.87)
Post-neonatal			4.07	4.40
			(1.96)	(2.50)
Maternal Mortality(per 100,000 adult women)				1.40
				(3.68)
AFDC rate for Adult women (year of Medicaid)				
All				2.07
				(0.77)
High AFDC states				2.82
				(0.51)
Low AFDC states				1.52
				(0.34)
Non-white				10.24
				(3.63)
White				1.27
				(0.71)
Coal Capacity(100 MW)	1.66	4.51	7.73	5.30
	(3.18)	(7.85)	(12.32)	(9.67)
Pct Urban Population	61.75	69.67	73.34	70.07
	(30.33)	(28.38)	(27.56)	(28.09)
Counties	2,361	2,361	2,361	2,361

Notes: This table presents summary statistics for variables included in the analysis. All variables are weighted by live births. AFDC rates are for women aged 18 to 44, evaluated at the year of Medicaid implementation.

Table A.3: Pre-trend Analysis

	(1)	(2)	(3)	(4)
	Obs	Mean	Pre-Med	AFDC
A. IMR, Coal, Climate Var (1950-1965)		at 1965	AFDC	x (Yr - 1965)
IMR (per 1,000 births)	546	24.3	0.047	-0.037
			(0.851)	(0.056)
Coal Capacity (100 MW)	546	1.0	0.388	0.030
			(0.258)	(0.018)
Annual Average Temperature (F)	546	11.7	0.338	-0.008
			(1.277)	(0.022)
Annual Precipitation (mm)	546	850.4	-31.02	-5.26***
			(65.01)	(1.52)
Annual Absolute Humidity (g/kg)	546	6.0	-0.208	-0.001
			(0.379)	(0.005)
Per capita Hospital Beds	532	3.1	0.111	0.001
			(0.217)	(0.006)
		Mean	Pre-Med	AFDC
B. Census Demographics (1950, 1960)		at 1960	AFDC	x (Yr - 1960)
Pct Urban Pop	78	68.7	2.212	0.117
			(3.675)	(0.231)
Pct White	78	91.3	0.577	0.024
			(1.181)	(0.076)
Pct 25yrs+ w/ High School	78	56.7	2.755	0.179
			(2.414)	(0.147)
Median Housing Income	76	37000	1838.4	143.4
			(1484.1)	(89.5)
Pct Manufacturing Employment	78	21.7	-1.301	-0.072
			(1.912)	(0.143)

Notes: The table presents results from balancing tests for correlation between baseline AFDC rates and trends and levels in pre-1965 state outcomes. The model is: $y_{st} = \alpha + \beta_0 AFDC^*_s + \beta_1 AFDC^*_s \times (Year - Year_{pre}) + \mu_{st}$. Year 1965 is the latest pre-Medicaid year ($Year_{pre}$) except in panel B (1960) and panel C (1950). β_0 is the relationship between pre-Medicaid AFDC level and levels of each characteristics. β_1 is the relationship between pre-Medicaid AFDC and linear trends of each variable. Virginia counties are not included in the test for per capita hospital beds and median household income because of missing data.

Table A.4: Placebo Estimates from the 1957-58 Pandemics

	Dependent Variable: Infant Mortality Rate					
	Coal	Coal	Coal	Urban	Urban	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
P 1957-58 x Mod	0.052**	0.054**		0.016***	0.016***	
	(0.021)	(0.022)		(0.004)	(0.005)	
P 1957-58 x AFDC x Mod	-0.002	-0.008		-0.004	-0.005	
	(0.024)	(0.025)		(0.007)	(0.007)	
P 1968-69 x Mod	0.039***	0.068***		0.005	0.012***	
	(0.013)	(0.015)		(0.004)	(0.005)	
P 1968-69 x AFDC x Mod	-0.056***	-0.054***		-0.021***	-0.015**	
	(0.017)	(0.019)		(0.006)	(0.007)	
Post 1965 x AFDC x Mod	-0.023	-0.014		0.025***	-0.000	
	(0.029)	(0.022)		(0.008)	(0.009)	
P 57 x Mod			0.029			0.008
			(0.052)			(0.018)
P 58 x Mod			0.061			-0.011
			(0.068)			(0.019)
P 68 x Mod			-0.053**			-0.018**
			(0.024)			(0.010)
P 69 x Mod			-0.052*			-0.020**
			(0.027)			(0.010)
$\beta_3 = \gamma_3^{Pand57}$	0.029	0.065		0.076	0.281	
County-Year	63,747	63,747	63,747	63,747	63,747	63,747
Counties	2,361	2,361	2,361	2,361	2,361	2,361
Adj. R-Squared	0.541	0.593	0.595	0.543	0.592	0.594
Region x Year, County FE	Y	Y	Y	Y	Y	Y
Annual Climate Vars	Y	Y	Y	Y	Y	Y
County Time Trends		Y	Y		Y	Y
"Event Study" Controls			Y			Y

Notes: This table reports the main coefficients of interest estimated of equation (1). Columns (3) and (6) include the full of year-by-year triple interaction terms, $\gamma_1^t Mod_c \times Year_t + \gamma_2^t HighAFDC_s \times Year_t + \gamma_3^t Mod_c \times HighAFDC_s \times Year_t$, based on the "event-study" version of equation (1), with estimates reported relative to the 1965 reference year. P-values for tests of the equality of γ_3^{Pand57}, the coefficient of P 1957-58 x AFDC x Modifier, and β_3, the coefficient of P 1968-69 x AFDC x Modifier are reported in columns 1, 2, 4, and 5. Column 3 and 6 reports the triple interaction coefficients for each of the four pandemic years. Standard errors clustered at the county level are reported in parentheses. *** denotes statistical significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.5: Medicaid and Infant Mortality in Pandemic and Non-Pandemic Years

	Coal (1)	Urban (2)
1950 x AFDC x Mod	0.097	0.013
	(0.084)	(0.030)
1951 x AFDC x Mod	0.099	0.029
	(0.081)	(0.028)
1952 x AFDC x Mod	0.059	-0.006
	(0.089)	(0.028)
1953 x AFDC x Mod	0.062	0.004
	(0.062)	(0.024)
1954 x AFDC x Mod	0.013	0.003
	(0.056)	(0.022)
1955 x AFDC x Mod	0.023	-0.000
	(0.059)	(0.022)
1956 x AFDC x Mod	0.073	0.009
	(0.056)	(0.020)
1957 x AFDC x Mod	0.029	0.008
	(0.052)	(0.018)
1958 x AFDC x Mod	0.061	-0.011
	(0.068)	(0.019)
1959 x AFDC x Mod	0.057	0.001
	(0.054)	(0.017)
1960 x AFDC x Mod	0.033	-0.006
	(0.049)	(0.015)
1961 x AFDC x Mod	0.040	0.013
	(0.045)	(0.014)
1962 x AFDC x Mod	0.043	-0.001
	(0.040)	(0.013)
1963 x AFDC x Mod	0.082**	-0.005
	(0.042)	(0.014)
1964 x AFDC x Mod	0.012	-0.006
	(0.029)	(0.011)
1965 x AFDC x Mod	–	–
1966 x AFDC x Mod	-0.033*	-0.012
	(0.020)	(0.010)
1967 x AFDC x Mod	0.004	-0.008
	(0.025)	(0.010)
1968 x AFDC x Mod	-0.053**	-0.018**
	(0.024)	(0.009)
1969 x AFDC x Mod	-0.052*	-0.020**
	(0.027)	(0.010)
1970 x AFDC x Mod	0.020	-0.003
	(0.022)	(0.009)
1971 x AFDC x Mod	0.030	-0.016*

	(0.022)	(0.009)
1972 x AFDC x Mod	-0.020	-0.006
	(0.029)	(0.012)
1973 x AFDC x Mod	-0.029	-0.003
	(0.023)	(0.009)
1974 x AFDC x Mod	-0.020	-0.004
	(0.030)	(0.009)
1975 x AFDC x Mod	-0.023	-0.005
	(0.021)	(0.009)
County-Year	63,747	63,747
Counties	2,361	2,361
P-Values for Tests of Joint Significance of Estimates		
Pre-1957	0.206	0.243
Pand 57 = 0 & Pand 58 = 0	0.624	0.304
Year 1959-65	0.139	0.549
Year 1966-67	0.213	0.463
Pand 68 = 0 & Pand 69 = 0	0.025	0.051
Post 1969	0.069	0.734
Adj.R-Squared	0.594	0.593
Region x Year, County FE	Y	Y
Annual Climate Vars	Y	Y
County Time Trends	Y	Y

Notes: This table reports the triple interaction coefficient estimates for the full of year-by-year triple interaction terms, $\gamma_1^t Mod_c \times Year_t + \gamma_2^t HighAFDC_s \times Year_t + \gamma_3^t Mod_c \times HighAFDC_s \times Year_t$, based on the "event-study" version of equation (1). All the effect are relative to year 1965. Coefficient of year 1976 is omitted because of the inclusion of both county fixed effect and county-specific linear trends. At the end of the table, we report the p-values from tests for the joint significance of the triple difference coefficients. *** denotes statistical significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.6: Robustness Exercises

	Dependent Variable: Infant Mortality Rate							
	Base	Med Impl. 1966-67	Coal Cap. > 0	Urban Pop > 0	Unbalanced Sample	Restriction on AFDC Status		Horserace
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
P 1968-69 x Coal	0.068***	0.069***	0.078***	0.068***	0.051***	0.075***	0.066***	0.044***
	(0.015)	(0.015)	(0.018)	(0.015)	(0.014)	(0.016)	(0.016)	(0.014)
P 1968-69 x AFDC x Coal	-0.054***	-0.056***	-0.076***	-0.050***	-0.044***	-0.062***	-0.052***	-0.033***
	(0.019)	(0.019)	(0.022)	(0.019)	(0.016)	(0.020)	(0.019)	(0.017)
P 1968-69 x Pct Urban	0.012***	0.011**	0.017**	0.013**	0.012***	0.015***	0.015***	0.004
	(0.005)	(0.005)	(0.008)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)
P 1968-69 x AFDC x Pct Urban	-0.015**	-0.014*	-0.017	-0.008	-0.014**	-0.019***	-0.019**	-0.009
	(0.007)	(0.007)	(0.012)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
County-Year	63,747	56,511	15,120	41,742	64,033	54,999	54,864	63,747
Counties	2,361	2,093	560	1,546	2,374	2,037	2,032	2,361
Region x Year, County FE	Y	Y	Y	Y	Y	Y	Y	Y
Annual Climate Variables	Y	Y	Y	Y	Y	Y	Y	Y
County-specific Linear Trends	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the coefficients of several robustness exercises. Column 1 reports the baseline estimates from column 2 and column 4 in Table 2. Column 2 reports results for the subsample of 34 states that implemented Medicaid by 1967. Columns 3 and 4 shows results for counties with positive coal capacity in any year during the sampling period and positive urban population. Column 5 includes an additional 13 counties in Massachusetts which has missing information on infant mortality in the 1957-58 pandemic years and various non-pandemic years. Column 6 and 7 present the coefficient estimates from equation (1) on the sample excluding counties with $HighAFDC$ status evaluated using the county-level AFDC rate in 1976 being different to their state-level $HighAFDC_s$ value in 1976. Column 6 reports estimates from the sample excluding the counties with different $HighAFDC$ status to their state-level value. Column 7 reports estimates from the sample excluding all counties in the states that have a large number of counties (> 30%) having different $HighAFDC$ status to their state-level value. The states include PA, OH, WA, WI, MD, VT, OR. Column 8 reports estimation from a horse race regression that includes both coal and percent of urban population as the modifier.

Table A.7: Effects of AFDC and Other War on Poverty Programs

	Dependent Variable: Infant Mortality Rate		
	Baseline (1)	Head Start (2)	Food Stamps (3)
Panel A: Effects by Coal Capacity			
AFDC	-0.054***	-0.046**	-0.064***
	(0.019)	(0.019)	(0.020)
Head Start		0.043	
		(0.034)	
Food Stamps			-0.026
			(0.026)
Panel B: Effects by Percent Urban			
AFDC	-0.015**	-0.014**	-0.017**
	(0.007)	(0.007)	(0.007)
Head Start		-0.009	
		(0.008)	
Food Stamps			-0.008
			(0.007)
County-Year	63,747	63,747	63,747
Counties	2,361	2,361	2,361
All controls	Y	Y	Y

Notes: This table reports the effects of the AFDC, Head Start, and Food Stamps programs on pandemic-related infant mortality. The table reports the triple interaction coefficient estimates (β_3) based on equation (1). Head Start and Food Stamps are indicators for states with above median level in per capita program funding or case number in the first year of Medicaid. All regressions include the full set of controls reported in Table 2, column 2. Standard errors clustered at the county level are reported in parentheses. *** denotes statistical significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.