Health Insurance and Fertility:

Evidence from the Advent of Blue Cross

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Abstract

After decades of decline, U.S. fertility began to rise in the mid-1930s, well before the postwar Baby Boom. At the same time, employer-sponsored health insurance was expanding nationwide for the first time. Did the emergence of employer-sponsored hospital insurance contribute to this reversal? I construct a new dataset documenting the staggered geographic rollout of Blue Cross hospital plans and their enrollment and link it to county-level data on hospital births and vital statistics. Using both stacked difference-in-differences and instrumental variables designs, I find that Blue Cross entry increased insurance enrollment and hospital childbirth. Hospital births increased by an average of 0.37 per 100 women aged 15–44 following Blue Cross introduction, with little evidence of a corresponding decline in non-hospital births. The estimated effect on total fertility is also positive, although imprecisely estimated. Instrumental-variables estimates yield a similar pattern: greater Blue Cross enrollment significantly increased hospital childbirth, while the estimated effects on total fertility remained positive but imprecise. The effects are larger in areas with higher baseline medical costs, suggesting that the financial cost of childbirth played an important role. Meanwhile, infant and maternal mortality show little change. Blue Cross contributed meaningfully to the mid-1930s fertility decline reversal in the United States, highlighting how health-care policy can shape demographic outcomes beyond its direct effects on medical care.

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1 Introduction

The reversal of the long-run decline in U.S. fertility in the mid-1930s coincided with the emergence of employer-sponsored hospital insurance. U.S. fertility rates had declined for much of the nineteenth and early twentieth centuries, but this trend came to an end well before the postwar Baby Boom [Bailey and Hershbein, 2018]. During the Great Depression, Baylor University Hospital pioneered a prepaid hospital plan for groups of employees, an arrangement that became an early model for Blue Cross hospital plans. These plans became one of the earliest widespread forms of employer-sponsored prepaid hospital coverage in the United States (Figure 1). The coincidence of these developments raises a natural question: did the expansion of Blue Cross hospital plans contribute to the reversal of the long-run decline in U.S. fertility?

The expansion of Blue Cross was particularly relevant for childbirth, as hospital deliveries were becoming increasingly common but remained financially burdensome for many families. The share of births occurring in hospitals rose from less than five percent in 1900 to roughly 50 percent by 1939 [Leavitt, 1986; Wertz and Wertz, 1979]. This transition had begun well before the emergence of Blue Cross. However, hospital delivery represented a substantial medical expense for many families [U.S. Children's Bureau, 1941; U.S. Bureau of Labor Statistics, 1930]. Hospital insurance changed not only how households financed medical care, but potentially the economic cost of childbirth and having a child.

Health insurance can affect fertility through the financial cost of childbirth, maternal health, and infant survival, with potentially offsetting effects that make its overall impact on fertility theoretically ambiguous. Insurance could increase fertility by reducing the financial burden of childbirth. Greater access to medical care could also improve maternal health, potentially encouraging childbearing by reducing its health risks or discouraging it by increasing women's opportunity costs. Improvements in infant survival could further encourage fertility by increasing the likelihood that a birth results in a surviving child. Despite the central role that employer-sponsored health insurance eventually came to play in the U.S. healthcare system, relatively little is known about how its initial large-scale expansion affected childbearing. Studying the emergence of Blue Cross provides an opportunity to examine the

broader consequences of health insurance while also evaluating an important institutional change that occurred alongside the reversal of the long-run decline in U.S. fertility.

To study the effects of Blue Cross on hospital childbirth and fertility, I construct a new dataset linking the geographic expansion of Blue Cross hospital plans to county-level birth outcomes. I digitize historical records on each plan's first year of enrollment, geographic coverage, and subsequent plan-level enrollment. I link these data to county-level measures of hospital births from the American Medical Association's *Hospital Service in the United States* and to birth registration records, which allow me to quantify hospital, non-hospital, and total births at the county-year level. These data allow me to examine the impact of Blue Cross on hospital delivery and total fertility.

My empirical strategy exploits variation in the timing and geographic rollout of Blue Cross plans using both stacked difference-in-differences and instrumental variables approaches. I first estimate the reduced-form effects of Blue Cross entry using a weighted stacked difference-in-differences approach [Wing et al., 2024]. I then use Blue Cross entry as an instrument for insurance enrollment to estimate the effects of coverage on hospital childbirth and fertility.

I first document the effect of Blue Cross entry on insurance enrollment. Enrollment increased steadily in the years following a plan's introduction. Within two years of a plan's introduction, approximately 2% of individuals living in areas served by Blue Cross were enrolled. Coverage continued to expand, reaching approximately 8% of the population after five years and 19% after ten years.

I find that the introduction of Blue Cross substantially increased the use of hospitals for childbirth. The hospital birth rate increased by 0.37 births per 100 women aged 15–44, relative to a pre-treatment mean of 0.91. However, I do not find evidence of an impact on the non-hospital birth rate, suggesting that the increase in hospital births was not driven solely by a shift in the location of deliveries that would otherwise have occurred outside hospitals. The estimated effect on the total birth rate is also positive, at approximately 0.31 births per 100 women, although the estimate is not statistically distinguishable from zero. Instrumental variables estimates, which use the introduction of Blue Cross plans as an instrument for insurance enrollment, yield qualitatively similar results: greater Blue Cross enrollment significantly increases hospital births, while the estimated effects on

total fertility are positive but is imprecisely estimated.

The evidence points to the financial cost of childbirth as an important mechanism linking Blue Cross to fertility, with little evidence of improvements in maternal or infant mortality. To investigate the financial channel, I compare counties with high and low baseline medical costs. The effects on hospital births are significantly larger in counties with high baseline medical costs, and the estimated fertility response is also larger in these areas, although the difference in total fertility is imprecisely estimated. In contrast, I find little evidence that Blue Cross improved maternal or infant mortality. These results suggest that reducing the financial burden of hospital childbirth may have contributed to the fertility response to Blue Cross.

A back-of-the-envelope calculation suggests that the expansion of Blue Cross could account for roughly 13 percent of the observed increase in the U.S. birth rate over this period. Although this estimate is imprecise, it suggests that the emergence of employer-sponsored hospital insurance may have contributed meaningfully to the rise in fertility that began in the mid-1930s.

By focusing on the turning point when fertility began to rise after decades of decline, I first contribute to the literature on the reversal of U.S. fertility in the mid-1930s and the origins of the subsequent Baby Boom, a period of elevated fertility in the United States from 1946 to the mid-1960s. A wide range of explanations has been proposed for this rise in fertility, including the relative income hypothesis, which argues that individuals who grew up during the Great Depression had relatively low material aspirations and were therefore more inclined to have children as their incomes rose during the prosperous postwar period [Easterlin, 1966; Hill, 2015], improvements in maternal health [Albanesi and Olivetti, 2014], the diffusion of household technologies [Greenwood et al., 2005; Bailey and Collins, 2011; Lewis, 2018], the economic disruption of the Great Depression [Bellou et al., 2025], the effects of World War II [Doepke et al., 2015; Brodeur and Kattan, 2022], the expansion of modern U.S. mortgage markets [Dettling and Kearney, 2025], and the expansion of labor unions following the 1935 National Labor Relations Act, which improved male workers' earnings and job security while reducing women's labor market opportunities [Downes, 2024]. While much of this literature focuses on the Baby Boom more broadly, this paper focuses on the earlier turning point

when fertility began to rise in the mid-1930s. I identify the role of a major institutional development occurring during this period—the emergence of employer-sponsored hospital insurance—and show that the expansion of Blue Cross substantially increased hospital childbirth and also contributed to the rise in fertility.

Second, I contribute to the literature on the effects of health insurance on fertility by providing new historical evidence from the first nationwide employer-sponsored health insurance system. Existing evidence is mixed, with most studies focusing on modern policy changes and relatively limited evidence from historical settings. Several papers exploit quasi-experimental variation from Medicaid eligibility expansions for pregnant women and children and document mixed effects on fertility outcomes [DeLeire et al., 2011; Zavodny and Bitler, 2010]. Using experimental evidence, Leibowitz [1990] studies a setting in which medical costs were directly reduced and finds a positive effect on fertility. Historical evidence is more limited. Troland and Figinski [2019] examine an expansion of health insurance coverage for unionized workers in the mining industry and find negative effects on fertility. A related literature studies insurance mandates for assisted reproductive technologies. These studies find that reducing the financial burden associated with infertility treatments increases fertility, particularly among women of advanced maternal age [Bitler and Schmidt, 2012; Schmidt, 2007]. My paper contributes to this literature by providing new historical evidence on the relationship between health insurance and fertility, during the early expansion of employer-sponsored hospital insurance in the United States. By studying Blue Cross hospital plans, I examine a broad form of insurance that covered hospital childbirth and therefore directly altered the financial cost of delivery.

The remainder of the paper is organized as follows. I begin in Section 2 with the historical background on the development and expansion of Blue Cross hospital plans and the broader transition toward hospital childbirth. Section 3 then develops the conceptual framework, highlighting the channels through which hospital insurance may affect fertility. The data sources and construction of the main variables are described in Section 4, followed by the empirical strategy in Section 5. Section 6 presents the main empirical results and examines the mechanisms through which Blue Cross may have affected hospital childbirth and fertility. Section 7 discusses hospital capacity and the absence

of detectable mortality improvements despite greater hospital use. Section 8 concludes.

2 Historical Background

2.1 Childbirth Practices

Childbirth practices in the United States underwent a profound transformation over the nineteenth and early twentieth centuries. While childbirth was historically a female-centered event attended by women in the community and often a midwife, the presence of male physicians at home births began increasing in the late eighteenth century. [Leavitt, 1986].[1]

Despite the growing medicalization of childbirth, hospitals initially played only a limited role. Before the turn of the twentieth century, hospitals primarily served as charitable institutions for poor or unmarried women who lacked the resources to have a physician or midwife attend a home birth. This pattern changed rapidly in the early twentieth century as hospital delivery became increasingly common, rising from less than five percent of births in 1900 to roughly 50 percent (and nearly 75 percent in urban areas) by 1939 [Leavitt, 1986; Wertz and Wertz, 1979].

From the perspective of healthcare providers, hospitals offered important advantages. Physicians could care for patients in a controlled hospital environment, eliminating the need to travel to patients' homes, transport medical equipment, and remain there through lengthy labors. Concentrating childbirth within hospitals made the provision of obstetric care more efficient. In addition, maternity hospitals became important training grounds for medical students and young physicians, providing a steady flow of patients for clinical observation and instruction [Leavitt, 1986; Wertz and Wertz, 1979].

Hospital delivery also became increasingly attractive from the perspective of expectant mothers. Prenatal and postnatal care eventually came to be viewed as increasingly important for managing

[1]The decline in midwife-attended births continued into the twentieth century. Table 1 shows that the share of births attended by midwives in New Jersey declined from over 40 percent in 1919 to 20 percent in 1926. In New York, the share declined from 16 percent in 1916 to 8 percent in 1924. In Michigan, the share declined from 6.9 percent in 1921 to 4.4 percent in 1924 [U.S. Department of Labor, Children's Bureau, 1926]. In Richmond, Virginia, the share declined from 41 percent in 1907 to 18 percent in 1922 [Medical Society of Virginia, 1923].

pregnancy-related risks. Hospitals adopted practices such as routine urine testing to detect conditions like eclampsia at earlier stages. Influential figures such as John Whitridge Williams—often regarded as the founder of academic obstetrics—promoted hospital delivery as a safer and more modern form of childbirth, reinforcing public confidence in institutional care. The introduction of innovations such as Twilight Sleep, which promised to alleviate the pain of childbirth, as well as access to emergency interventions such as C-sections, further increased the appeal of hospital delivery [Wertz and Wertz, 1979].

Despite their growing popularity, hospitals did not yet have a clear safety advantage. Medical practice was still evolving, and physicians were sometimes criticized for excessive or unnecessary intervention [Leavitt, 1986]. Children's Bureau reports likewise reflected uncertainty about the safety of hospital delivery: 57 percent of maternal deaths were classified as hospital cases [U.S. Children's Bureau, 1934].[2] The Bureau also noted that "In normal cases delivery can be safely carried out in the home" [U.S. Children's Bureau, 1938].

At the same time, hospital childbirth was expensive. In the early twentieth century, postpartum hospital stays often lasted up to two weeks, allowing charges to accumulate over an extended period [Temkin, 1999]. In six New York counties in 1935–36, estimates suggest that hospital costs associated with delivery ranged from approximately $40 to $59, with the estimated total cost of a hospital delivery ranging from approximately $65–$70. In Berkeley, California, total obstetric care in 1928 was estimated at approximately $200–$215, including an average physician fee of approximately $92 [U.S. Children's Bureau, 1941; U.S. Bureau of Labor Statistics, 1930].[3] These expenses were substantial relative to median household income of about $83–$104 per month in the mid-1930s [National Resources Committee, 1938]. A hospital delivery could absorb a meaningful share of a household's monthly resources, even though childbirth itself was generally anticipated in advance.[4]

[2] Although these figures do not provide a direct comparison of mortality risk between hospital and non-hospital births, they illustrate that a substantial share of maternal deaths continued to occur in hospitals during this period.

[3] Figure A1 provides examples of hospital receipts issued following childbirth in the late 1920s and 1930s, highlighting the financial burden associated with hospital delivery.

[4] Contemporary accounts suggest that these costs were salient for fertility decisions. In a 1923 letter published in *Ladies' Home Journal*, one reader wrote: "The reason for the decrease in American babies is the high cost of obstetrics... Our first baby cost: for layette – with strictest economy – $25; ten days in a maternity hospital, $35; dressings and laundry at the hospital, $5; doctor's charge, $25; anesthetic, $5; total, $95. My mother had seven babies and I doubt if they all cost her $100 put together" [Wertz and Wertz, 1979].

By the time Blue Cross hospital plans emerged, the transition toward hospital-based childbirth was already well underway. Hospital delivery had become increasingly desirable to both patients and providers even though its health advantages were not yet firmly established. At the same time, the substantial cost of institutional childbirth made hospital delivery a significant financial burden for households. This combination of growing appeal and high cost created a setting in which health insurance could play an important role in shaping childbirth decisions.

2.2 Early Health Insurance Initiatives

Despite the growing importance and cost of hospital care, health insurance remained extremely limited in the United States. Prior to the emergence of Blue Cross, efforts to provide health insurance were fragmented and highly localized, often limited to particular cities, employers, or industries, and failed to achieve broad coverage, leaving most households exposed to substantial medical cost risks. One barrier to expansion was the reluctance of private insurance companies to offer health insurance, which they viewed as particularly risky due to adverse selection [Morrisey, 2013]. A second barrier to the expansion came from organized medicine. The American Medical Association (AMA) actively opposed alternative insurance models, including cooperatives and prepaid group practice arrangements, which it viewed as threats to physician autonomy and the prevailing fee-for-service model, and leveraged its influence over physician licensing and lobbying efforts to restrict their development [Starr, 2017].

In parallel with these private initiatives, repeated efforts were made to establish publicly organized health insurance. In 1912, Teddy Roosevelt endorsed social insurance against sickness as part of the Progressive Party platform. In 1915, the American Association for Labor Legislation developed and promoted a model bill for compulsory health insurance. Although the proposal initially received support from the AMA, political support subsequently weakened amid opposition from organized labor and other groups, the AMA's eventual reversal of its position, and growing anti-German and anti-socialist sentiment tied to World War I [Institute of Medicine, 1993]. Efforts to establish compulsory health insurance continued at the state level, including several proposals during the 1930s, but these initiatives also failed to pass state legislatures [Reed, 1939]. Thus, by the beginning

of the 1930s, neither private insurance markets nor compulsory public insurance had produced a system capable of providing health coverage on a broad scale.

2.3 Blue Cross Hospital Plans

Against this backdrop, a new model of hospital insurance emerged that would ultimately achieve broader coverage. The origins of this model can be traced to a 1929 initiative at Baylor University Hospital in Dallas, Texas, which was experiencing financial difficulties as declining patient incomes reduced demand for hospital care. Dr. Justin Ford Kimball developed an experimental hospital plan that allowed schoolteachers to make small monthly payments in exchange for hospital services when needed, attracting more than 1,500 enrollees. Its early success drew interest from other employee groups and hospitals in Dallas and quickly gained attention nationwide, contributing to the emergence of the Blue Cross Plan Movement in 1932. In 1934, the American Hospital Association endorsed the development of group hospitalization plans but favored community-wide plans over single-hospital plans, allowing patients to choose among participating hospitals rather than limiting them to a single institution [Cunningham III and Cunningham Jr., 1997]. The subsequent expansion of Blue Cross was rapid. Figure 1 shows that Blue Cross enrollment increased from fewer than one million enrollees in 1935 to more than 24 million by 1946 [Reed, 1947].

Blue Cross was able to achieve this scale in part because its institutional structure addressed several of the barriers that had limited earlier insurance arrangements. First, enrollment was organized primarily through employment groups rather than through the individual market, which facilitated risk pooling and reduced concerns about adverse selection. Second, participation by employers and employees remained voluntary, avoiding many of the political objections directed toward compulsory insurance. Finally, Blue Cross restricted coverage primarily to hospital services rather than physician fees, reducing direct conflict with organized medicine. Monthly premiums typically ranged from \$0.60 to \$3.60, depending on the plan and type of contract [Reed, 1947]. These institutional features allowed Blue Cross to become the first viable system of large-scale prepaid hospital insurance in the United States.

While the core benefits offered across Blue Cross plans were broadly similar—typically including

hospital room and board, nursing services, and use of the operating room—coverage of additional services varied across plans, in part because of disagreements over whether particular services constituted hospital expenses or physician services. For example, some plans covered anesthesia and X-rays, while others did not [Reed, 1947]. This distinction between hospital and physician services was institutionally important because Blue Cross initially insured hospital expenses rather than the full cost of medical care. Resistance from organized medicine delayed the development of Blue Shield plans, which provided coverage for physician services and emerged later than Blue Cross plans (Figure 2).

One particularly important application of this hospital coverage—and the one most relevant to this study—was maternity care. Some early plans were hesitant to provide maternity benefits because the need for maternity care could often be anticipated, raising concerns that households might enroll when they expected to use maternity services. However, the experience of plans that successfully offered maternity coverage contributed to its broader adoption, and maternity benefits eventually became standard across Blue Cross plans [Cunningham III and Cunningham Jr., 1997]. Maternity coverage was generally available through couple and family plans [Reed, 1947]. Depending on the plan, maternity benefits covered hospital stays of approximately 10 to 30 days at full benefits, reflecting the substantially longer postpartum hospital stays common during this period [Temkin, 1999]. To limit adverse selection, plans commonly imposed waiting periods of approximately 9 to 12 months before maternity benefits became available although these waiting periods could sometimes be waived for employer groups with sufficiently high participation [Reed, 1947].

Maternity hospitalization became one of the most important uses of hospital insurance. Table 2 shows that maternity accounted for the largest share of cases covered by the New York plan during the 1940s. A similar pattern appears in the New Jersey plan: as shown in Table 3, maternity accounted for the largest share of cases, total days of hospital care, and total hospital expenses in 1943 [Reed, 1947]. The prominence of maternity care in Blue Cross utilization highlights the importance of childbirth-related hospital expenses to the early development of hospital insurance and raises the question of whether insurance coverage for these expenses affected households' fertility decisions.

3 Conceptual Framework

The historical evidence above shows that maternity care was an important component of early Blue Cross coverage and that hospital childbirth represented a substantial expense for households during this period [United States Department of Labor, Children's Bureau, 1938; U.S. Children's Bureau, 1941; U.S. Bureau of Labor Statistics, 1930]. The expansion of Blue Cross therefore changed the costs and conditions associated with childbearing. Whether these changes affected fertility depends on how insurance altered households' incentives to attempt conception and, through this behavioral response, the probability of a realized live birth.

I use a simple conceptual framework, building on the household fertility and labor supply model of Eckstein et al. [2019], to illustrate three channels through which health insurance may affect fertility: the financial cost of childbirth, maternal health, and infant survival. I simplify their dynamic framework and incorporate health insurance into household decisions by allowing coverage to affect out-of-pocket childbirth expenses, maternal health, and infant survival. I also distinguish between the decision to attempt conception and the probabilistic realization of a live birth, whereas Eckstein et al. [2019] assume that pregnancy leads deterministically to the arrival of a child. In making this decision, households take into account the financial and time costs of childbearing, the health cost to the mother, and the expected benefit of an additional surviving child. Insurance can affect the incentive to attempt conception by changing the costs and benefits associated with a realized birth. I describe the intuition behind each channel here and present the formal framework in Appendix B.

First, insurance can affect fertility by reducing the financial burden of childbirth. As noted above, hospital delivery represented a substantial household expense during this period.[5] Blue Cross reduced the amount that insured households paid out of pocket for covered hospital care at the time of delivery. More generally, existing work has emphasized that insurance coverage for pregnancy can affect fertility by reducing the financial cost of having a child [Leibowitz, 1990]. A lower out-of-pocket expense increases the resources available to the household in the event of a live birth and

[5] Contemporary accounts characterized maternity hospitalization as a relatively large and unpredictable expense for the family budget [United States Department of Labor, Children's Bureau, 1938].

therefore raises the value of the live-birth state relative to the no-live-birth state. This increases the incentive to attempt conception when the financial benefit of coverage is sufficiently large relative to the insurance premium.

The financial channel also generates a useful prediction for heterogeneity. For a given coverage rate, insurance produces a larger dollar reduction in out-of-pocket childbirth expenses where baseline childbirth costs are higher. The model therefore predicts a larger effect of insurance on the incentive to attempt conception in higher-cost markets. If differences across markets in the share of households near the conception-attempt threshold do not offset this larger incentive effect, realized births should also respond more strongly in higher-cost markets.

Second, insurance may affect fertility through maternal health. Improved access to hospital care can improve women's health, with potentially opposing effects on the conception decision. Better maternal health can reduce the health cost associated with pregnancy and childbirth, increasing the value of a live birth and therefore the incentive to attempt conception [Jayachandran and Lleras-Muney, 2009; Albanesi and Olivetti, 2014]. At the same time, better health can increase women's ability to engage in market work [Albanesi and Olivetti, 2016; Stephens and Toohey, 2022; Gilleskie et al., 2017], thereby raising the opportunity cost of childbearing. The net effect of the maternal-health channel on conception attempts and realized fertility is therefore theoretically ambiguous. To assess whether maternal health could have been an operative channel, I examine whether Blue Cross entry affected maternal health.

Finally, insurance may affect fertility through infant survival. If access to insured hospital care increases the probability that a live-born infant survives, it raises the expected value of a live birth [Becker and Barro, 1988; Cigno, 1998; Guinnane, 2011]. Within the framework developed here, in which households value an additional surviving child, improved infant survival raises the value of the live-birth state relative to the no-live-birth state and increases the incentive to attempt conception. I consider whether improvements in infant survival provide an alternative explanation for the fertility response to Blue Cross by examining whether infant survival improved following Blue Cross entry.

These channels provide guidance for the empirical analysis. In particular, heterogeneity in the effects

of Blue Cross by baseline medical costs is consistent with the financial channel if fertility responds more strongly in higher-cost areas, while effects on maternal and infant mortality provide evidence on whether improvements in maternal health or infant survival may account for the observed fertility response. Evaluating these channels requires data that jointly capture the expansion of Blue Cross, fertility outcomes, health outcomes, and local medical conditions.

4 Data

This paper combines several newly digitized and existing historical data sources to construct a county-level panel spanning 1927 to 1947. The data link the rollout of Blue Cross hospital plans to measures of fertility, mortality, hospital use and supply, and local medical costs.

4.1 Data Sources and Variable Construction

I compile data on Blue Cross hospital plans from Louis S. Reed's *Blue Cross and Medical Service Plans*, a 1947 report published by the U.S. Public Health Service. As voluntary health insurance expanded during this period, the U.S. Public Health Service undertook a comprehensive survey of Blue Cross and Blue Shield programs. I use the report to identify the first year of Blue Cross enrollment in each county and to construct annual measures of plan enrollment.[6] Because the report records plan activity through 1947, I observe first-year enrollments through that year. To construct annual enrollment shares, I interpolate county-level population using the 1920, 1930, 1940, and 1950 Censuses and aggregate these estimates to the plan service-area level. I also collect monthly group subscription rates and Blue Shield enrollment from the report.[7]

[6] Information on the geographic areas served and the timing of first enrollment comes from Table 3, Appendix B, and the "Note on Recent Changes" on p. 31. Annual plan-level enrollment comes from Appendix C and is directly observed for 1935–1946. Because the analysis sample spans 1927–1947, I impute enrollment for years not covered by these annual enrollment data. Eight of the 85 plans in the sample began enrollment before 1935—one in 1932, four in 1933, and three in 1934. For these plans, I assume enrollment is zero immediately prior to the first enrollment year and linearly interpolate between zero and the observed 1935 enrollment level. Appendix Figure A2 supports this interpolation approach: using only observed enrollment data, it plots average enrollment shares by years since first enrollment and shows approximately linear growth during the early years following enrollment. I impute 1947 enrollment using each plan's enrollment growth rate over 1944–1946. These imputed values are used when enrollment shares enter the regression analysis, either as an explanatory variable or as an outcome.

[7] Group subscription rates come from Appendix D, Table 2, which reports monthly rates as of December 1, 1946. Blue Shield enrollment comes from Appendix I, which reports enrollment in each medical service plan as of January 1 for 1940–1947.

I use vital statistics data from multiple sources to measure fertility and mortality outcomes. County-level data on births, infant deaths, and total deaths from 1927 to 1947 come from the ICPSR dataset *U.S. County-Level Natality and Mortality Data, 1915–2007* [Bailey et al., 2018]. I define the birth rate as the number of births per 100 women aged 15 to 44, with annual counts of women in this age group linearly interpolated between the 1920, 1930, 1940, and 1950 Censuses.[8] The infant mortality rate is defined as the number of infant deaths per 100 births.[9] I define the total mortality rate as total deaths relative to the county population, with annual population counts likewise interpolated between decennial Censuses. For maternal mortality, I use city-level data from 1929 to 1940 compiled by Thomasson and Treber [2008]. These data are drawn from U.S. vital statistics for cities with populations exceeding 10,000, and maternal mortality is defined as deaths related to childbirth and its complications per 100,000 live births.

All hospital-related data are drawn from the American Medical Association's annual *Hospital Service in the United States* reports, using the 1927–1942 data digitized by Thomasson and Treber [2008] and newly digitized reports for 1943–1947. The reports provide measures of hospital use, supply and capacity, including hospital counts, bed capacity, bassinet availability, hospital births, average census, and admissions.[10] I aggregate the hospital-level measures to the county level.

To capture cross-sectional variation in medical care costs prior to widespread insurance coverage, I digitize data from *Intercity Differences in Costs of Living in March 1935*, a 1937 Works Progress Administration research monograph comparing living costs across 59 U.S. cities [Stecker, 1937].[11]

[8] Whenever available, I use births by county of residence rather than county of occurrence. Residence-based births more closely capture fertility among county residents, whereas occurrence-based births assign births to the county in which the delivery takes place. This distinction is particularly relevant in this setting because women may travel to neighboring counties to give birth in hospitals, so changes in hospital access may affect the geographic distribution of births by occurrence. Because county-level births by residence are unavailable before 1937, I use births by occurrence from 1927–1936 and births by residence from 1937 onward. Following Holt et al. [2026] and Downes [2024], I assess the comparability of the two measures during years in which both are available by calculating the cross-county correlation between births by residence and births by occurrence for each year. Appendix Figure A3 reports these correlations, which exceed 0.99 in every overlapping year.

[9] As with birth counts, infant deaths by county of residence are preferred because they more closely capture mortality among county residents. However, county-level infant deaths by residence are available only beginning in 1942. I use infant deaths by occurrence from 1927–1941 and infant deaths by residence from 1942 onward. To maintain a consistent geographic basis for the infant mortality rate, I use births by occurrence as the denominator from 1927–1941 and births by residence from 1942 onward.

[10] Hospital counts and bed capacity are observed in all years. Average census, average number of patients occupying hospital beds on a given day, is available in all years except 1928, and bassinet availability is reported beginning in 1928. Hospital birth counts are available in 1929, 1931, and annually from 1933 onward, while admissions are observed beginning in 1931.

[11] Minimum medical service costs are drawn from Appendix Table 14 of the report.

The report constructs a measure of minimum medical service costs based on the expected minimum medical care required over a lifetime, prorated to an annual amount for a four-person family. The measure reflects the cost of a standardized bundle of medical services, including physicians', hospital, nursing, and dental services, rather than the realized medical expenditures of a particular family in a given year. Because cost data are available for only 59 cities, I assign each county the medical cost measure of the geographically nearest city to proxy for local medical costs. I use this measure to capture baseline differences in the cost of medical care faced by households prior to the expansion of hospital insurance. Figure 3 illustrates the geographic distribution of medical costs, with crosses indicating the 59 cities for which cost data are directly observed. I classify counties with minimum medical service costs above the sample mean as "High Baseline Medical Cost Areas" and those below the mean as "Low Baseline Medical Cost Areas."

Finally, I construct additional county-level control variables from a range of historical sources to account for demographic and economic conditions. Appendix C provides detailed definitions, sources, and construction procedures for these variables. Table A1 reports descriptive statistics for the variables used in the analysis.

4.2 Blue Cross Roll-out and Treatment Variation

The county-level Blue Cross data capture variation in both the timing and geographic reach of plan entry. Blue Cross coverage expanded gradually across the country during the 1930s and 1940s.[12] Plans began enrollment at different points in time and differed in their geographic scope. Some plans served entire states, while others covered only particular cities or groups of counties. Figure 4 maps the first year of Blue Cross enrollment for each county. There is no obvious geographic gradient in the timing of entry, as earlier- and later-adopting areas appear across different regions of the country.

By 1947, 31 states and the District of Columbia were each covered by a Blue Cross plan spanning the entire jurisdiction. In another 15 states, coverage was provided through local plans: seven were

[12]When a county was served by more than one Blue Cross plan, I assign the first enrollment year of the earliest plan.

fully covered by networks of local plans, while eight contained counties that remained outside the service area of any Blue Cross plan. Two states had no Blue Cross plan. Across these jurisdictions, 85 Blue Cross plans were in operation by 1947.

By the end of the sample period, Blue Cross had reached most U.S. counties. To examine whether earlier- and later-adopting counties differed systematically, I estimate a cross-sectional regression of the first year of Blue Cross enrollment on baseline county demographic and economic characteristics. Table 4 shows that earlier enrollment was more common in larger counties, indicating that the timing of Blue Cross entry was correlated with some baseline county characteristics. These differences in levels motivate an empirical design that compares changes in outcomes over time rather than levels across counties. In the next section, I describe the stacked difference-in-differences design used to exploit the staggered timing of Blue Cross entry.

5 Empirical Strategy

5.1 The Effect of Blue Cross Hospital Plans

This section describes the empirical strategy used to estimate the effects of Blue Cross hospital plans on insurance enrollment, fertility, hospital use, and mortality. Identification exploits variation in the timing and geographic spread of Blue Cross plans across counties.

An important feature of this setting is that the expansion of Blue Cross was not primarily motivated by fertility or maternity-specific objectives. Blue Cross plans were broad hospital insurance programs intended to finance hospital care across a range of medical conditions, with maternity care representing only one component of covered hospital services. The timing of Blue Cross entry is therefore less likely to have been driven by county-specific changes in fertility or fertility intentions. This institutional feature supports the use of variation in Blue Cross introduction to identify its effects on fertility, subject to the identifying assumptions discussed below.

To exploit this variation, I account for the staggered timing of Blue Cross introduction across counties. In settings with staggered treatment adoption, conventional two-way fixed-effects difference-in-

differences estimators may combine comparisons between newly treated counties and counties that were treated earlier. As shown by Goodman-Bacon [2021] and de Chaisemartin and D'Haultfœuille [2020], such comparisons can complicate the interpretation of the estimated treatment effect when treatment effects vary across cohorts or over time since treatment. This concern is particularly relevant in my setting because relatively few counties remain untreated by the end of the sample period.

To address this issue, I employ a stacked difference-in-differences approach [Cengiz et al., 2019; Deshpande and Li, 2019; Butters et al., 2022; Wing et al., 2024]. The stacked approach organizes the staggered rollout into a series of cohort-specific sub-experiments. For each treatment cohort, counties receiving Blue Cross in a given year are compared with counties that remain untreated throughout the corresponding event window, thereby excluding comparisons between newly treated and previously treated counties. The resulting sub-experiments are then stacked, with corrective weights applied to account for differences in the implicit weighting of treated and control trends across cohorts [Wing et al., 2024]. I restrict the analysis to a common event window and maintain a consistent composition of treatment cohorts across event time. Under the identifying assumptions, this weighted stacked estimator identifies a trimmed aggregate average treatment effect (ATT) on the treated and facilitates the interpretation of dynamic treatment effects [Wing et al., 2024].

For each first-enrollment year, I construct a sub-experiment containing counties first exposed to Blue Cross in that year and control counties that remain untreated through the end of the sub-experiment's post-treatment window. I retain five pre-treatment years and ten post-treatment event years, from $e = -5$ through $e = 9$, and normalize the year immediately preceding treatment, $e = -1$, to zero. Given the 1927–1947 sample period, a balanced event window is available for treatment cohorts from 1932 through 1938.[13]

I estimate the following weighted event-study specification:

$$\text{Outcome}_{ise} = \beta_0 + \sum_{k \neq -1} \delta_k \left[\text{Treated}_{is} \times \mathbf{1}(e = k)\right] + \beta_1 \text{Treated}_{is} + \lambda_e + X'_{ise}\Gamma + \varepsilon_{ise}$$

[13]This restriction also helps isolate the effects of Blue Cross, as Blue Shield began expanding substantially around 1940.

where i indexes counties, s indexes stacked sub-experiments, and e denotes event time relative to the first enrollment year. Treated_{is} equals one for counties belonging to the treatment cohort in sub-experiment s, and λ_e denotes event-time fixed effects. The vector X_{ise} contains county-level demographic and economic controls, including log population, the shares of the population that are Black, urban, and foreign-born, and retail sales per capita. The parameter of interest is δ_k, the population-weighted trimmed aggregate ATT at event time k, defined as

$$\delta_k = \sum_{s \in \Omega} \frac{Pop_s^D}{Pop_\Omega^D} ATT(s, s+k)$$

where Ω denotes the set of treatment cohorts included in the trimmed sample, Pop_s^D is the total population of treated counties in cohort s, and $Pop_\Omega^D = \sum_{s \in \Omega} Pop_s^D$ is the total population across all treated cohorts in the trimmed sample. Each cohort-specific ATT is weighted by its share of the total treated population, assigning greater weight to cohorts representing larger populations. These weights are non-negative, sum to one, and remain constant across event time, ensuring that changes in δ_k reflect treatment-effect dynamics rather than changes in cohort composition. To summarize the overall treatment effect over the post-treatment period, I also calculate the average of δ_k across the ten post-treatment event years ($k = 0, \ldots, 9$). While the event-time estimates characterize the dynamic effects of Blue Cross introduction, the average post-treatment ATT provides a summary of its effects over the first decade following introduction. Standard errors are clustered by Blue Cross plan for counties served by a plan and by state for counties without a Blue Cross plan.

The coefficients δ_k trace the evolution of the effect of Blue Cross relative to the year immediately preceding treatment. Identification requires that, absent Blue Cross introduction, treated and control counties would have followed parallel trends in the outcomes. Estimates for $k < 0$ provide evidence on the plausibility of this assumption by showing whether treated and control counties exhibited differential trends prior to Blue Cross entry, while estimates for $k \geq 0$ capture the dynamic effects following introduction. I also report the average of the post-treatment event-study coefficients as a summary measure of the treatment effect.

5.2 The Effect of Enrollment

The event-study specification above estimates the reduced-form effect of the introduction of Blue Cross hospital plans on fertility. While these estimates capture the overall effect of Blue Cross introduction, they do not directly quantify how changes in health insurance coverage affect fertility. To examine this relationship, I employ an instrumental-variables approach that uses the introduction of Blue Cross as an instrument for the county-level enrollment share. This approach allows me to estimate the effect of an increase in Blue Cross coverage on fertility, using variation in enrollment induced by the introduction of Blue Cross hospital plans.[14]

$$\text{Outcome}_{ise} = \gamma_0 + \theta \text{Enrollment}_{ise} + \gamma_1 \text{Treated}_{is} + \mu_e + X'_{ise}\Theta + \nu_{ise}$$

I consider three IV specifications for the county-level enrollment share to examine the sensitivity of the estimates to alternative assumptions about how enrollment responds to Blue Cross introduction.[15] The baseline Binary IV specification uses an indicator that equals one for treated counties beginning in the year Blue Cross becomes available, capturing the change in enrollment associated with plan availability. The Event-Time IV specification allows the effect of Blue Cross introduction on enrollment to vary flexibly with the number of years since entry by using separate post-treatment event-time indicators as instruments. Finally, the Linear Trend IV specification uses a single instrument that increases linearly with the number of years since Blue Cross entry, capturing a gradual

[14] The weighted stacked difference-in-differences estimator developed by Wing et al. [2024] is not extended to instrumental-variables estimation. I assess the finite-sample performance of the IV estimator using a Monte Carlo simulation that preserves the stacked sample structure, corrective weights, fixed effects, and plan-level clustering used in the empirical analysis. In each replication, I simulate county-year enrollment and outcome errors with separate plan-level components and correlated county-year components, with the latter generating endogeneity between enrollment and the outcome. The first-stage parameters are calibrated to match the empirical strength of the relationship between Blue Cross availability and enrollment: the simulated median first-stage F-statistic is 62.2, compared with 61.6 in the data using a binary instrument. Across 10,000 replications under a true treatment effect of zero, the mean IV estimate is -0.008, the Monte Carlo standard deviation of the estimates is 0.136, and the mean cluster-robust standard error reported by the estimator is 0.132. Thus, the reported standard errors closely approximate the actual sampling variation of the IV estimator across repeated samples. In addition, nominal 95 percent confidence intervals contain the true treatment effect in 95.1 percent of the simulated samples. In other words, if the sampling process were repeated many times under the simulated data-generating process, confidence intervals constructed using the estimated cluster-robust standard errors would include the true parameter approximately 95 percent of the time. Overall, the close correspondence between the simulated sampling variation and reported standard errors suggests that the weighted stacked IV estimator performs well for inference in this empirical setting.

[15] As noted in Section 4, enrollment data are available at the Blue Cross plan level rather than the county level. I construct county-level enrollment shares by assigning each county the enrollment share of the Blue Cross plan serving that county.

increase in enrollment following plan introduction. Together, these specifications assess whether the estimated effect of insurance coverage on fertility is sensitive to how the relationship between plan introduction and enrollment growth is modeled. Across all specifications, I retain the same stacked sample, corrective weights, controls, fixed effects, and standard error clustering as in the reduced-form analysis. The IV interpretation additionally requires that, conditional on the stacked design and included controls, the introduction of Blue Cross affects the outcomes through its effect on insurance enrollment.

The coefficient θ captures the effect of Blue Cross enrollment induced by the introduction of a Blue Cross plan. Because enrollment is measured as a share ranging from zero to one, θ represents the effect on the outcome of a one-unit, or 100-percentage-point, increase in enrollment.

6 Empirical Results

This section presents the main empirical results. I begin by investigating the effect of Blue Cross introduction on insurance enrollment, which establishes the first-stage relationship underlying the instrumental-variables analysis. I then examine effects on hospital childbirth and fertility by Blue Cross entry and enrollment, followed by evidence on potential mechanisms.

6.1 The Effect of Blue Cross Hospital Plans on Enrollment Shares

I first estimate the first-stage effect of Blue Cross hospital plans on enrollment shares. Because enrollment is observed at the plan level, I conduct this analysis at the plan level. Table 5 reports the average pre- and post-treatment estimates for enrollment and fertility outcomes, while Figure 5 plots the dynamic event-study estimates for enrollment share and corresponding 95 percent confidence intervals. The estimates show a gradual and sustained increase in enrollment following the introduction of Blue Cross. This pattern is consistent with the way Blue Cross coverage expanded: the introduction of a plan made coverage available, but enrollment did not occur immediately, as employers first had to offer the plan and households then had to enroll. Enrollment therefore accumulated over time rather than increasing discretely upon plan entry. By nine years after Blue Cross

introduction, the enrollment share had increased by approximately 19 percentage points.[16]

6.2 The Effect of Blue Cross Hospital Plans on Fertility

I turn to the main outcome of interest: fertility. I begin with hospital births, the form of care most directly affected by hospital insurance. I then consider non-hospital births to assess whether increases in hospital births primarily reflect a shift in the location of delivery or an increase in births overall. Finally, I examine the total birth rate. Table 5 summarizes the average pre- and post-treatment estimates for the three fertility outcomes, while Figures 6–8 present the corresponding dynamic event-study estimates.

Figure 6 presents event-study estimates for hospital births per 100 women aged 15–44. The estimated effects generally increase with years since Blue Cross introduction, broadly tracking the expansion of Blue Cross enrollment documented above and suggesting a gradual response to the expansion of hospital insurance. To summarize the effects over the post-treatment period, I report the average treatment effect across the ten post-treatment event years. Blue Cross increases the hospital birth rate by an average of 0.37 births per 100 women, an estimate statistically significant at the 1 percent level. Relative to the pre-treatment mean of 0.91 hospital births per 100 women, this represents an increase of approximately 41 percent.[17] The pre-treatment coefficients provide little evidence of differential trends prior to Blue Cross entry.

I next examine the effect of Blue Cross introduction on non-hospital births. Figure 7 presents event-study estimates for non-hospital births per 100 women aged 15–44. In contrast to the increase in hospital births, I find no statistically significant effect on non-hospital birth rates following Blue Cross introduction.

Finally, Figure 8 presents the effect of Blue Cross hospital plans on the total birth rate, measured as births per 100 women aged 15–44 regardless of delivery location. Averaging across the ten post-

[16] The average effect across the ten post-treatment event years is approximately 8.8 percentage points, which summarizes the enrollment response over the post-treatment period and provides a useful benchmark for the subsequent IV analysis. The county-level specification produces very similar dynamics: the estimated effect rises to roughly 17 percentage points by event year 9, and the average post-entry effect is 7.5 percentage points. Appendix Figure A4 and Appendix Table A2 report the corresponding county-level estimates.

[17] By event year 9, the estimated effect reaches approximately 0.85 hospital births per 100 women.

treatment event years, Blue Cross increases the birth rate by approximately 0.31 births per 100 women. The estimate is similar in magnitude to the increase in hospital birth rate, although it is estimated imprecisely. As with hospital birth rate, the estimated effect grows gradually over the post-treatment period, consistent with the gradual expansion of Blue Cross enrollment. I also examine heterogeneity by hospital availability. Appendix Figure A8 and Appendix Table A3 show that the post-treatment point estimate is larger in counties with a hospital than in counties without one. However, neither subgroup estimate is statistically significant, and I cannot reject equality of the two post-treatment effects.

The reduced-form estimates suggest that the introduction of Blue Cross increased hospital birth rates without a statistically significant decline in non-hospital birth rates, while the estimated effect on the total birth rate was similar in magnitude to the effect on the hospital birth rate.[18] This pattern is consistent with Blue Cross entry affecting not only the location of delivery but also fertility, although the total birth rate estimate is imprecisely estimated.

6.3 The Effect of Enrollment on Fertility

The reduced-form estimates above capture the effect of the introduction of Blue Cross hospital plans. I use the introduction of Blue Cross as an instrument for Blue Cross enrollment share to estimate the effect of insurance enrollment on fertility. Table 6 reports estimates from OLS and the three IV specifications described in Section 5.2: the Binary IV, Event-Time IV, and Linear Trend IV specifications.

The OLS estimates are somewhat smaller than the corresponding IV estimates, particularly for the total birth rate. One possible explanation is measurement error in the county-level enrollment share, which may attenuate the OLS estimates toward zero. Another possibility is that enrollment growth was correlated with changes in local employment conditions that independently affected fertility. For example, expanding wage employment may have facilitated Blue Cross enrollment through employer groups while also influencing fertility decisions. As household resources increase, parents may choose

[18] Corresponding estimates using birth counts rather than rates per 100 women aged 15–44 are reported in Appendix Figures A5–A7 and Appendix Table A4.

to invest more in child quality rather than have additional children, consistent with the quantity–quality tradeoff [Becker and Lewis, 1973; Becker and Tomes, 1976; Galor and Weil, 2000]. Such a mechanism could contribute to downward bias in the OLS estimates.[19]

The IV estimates are broadly consistent across the three specifications. The similarity of the estimates suggests that the results are not particularly sensitive to whether the first-stage relationship is modeled as a discrete shift, allowed to vary flexibly with event time, or approximated by a linear trend. For hospital births, an increase in enrollment from 0 to 100 percent is associated with an increase of approximately 4.8 hospital births per 100 women aged 15–44 across all three specifications. To put this magnitude into perspective, a 10-percentage-point increase in enrollment implies approximately 0.48 additional hospital births per 100 women, equivalent to about 53 percent of the pre-treatment mean of 0.91. The estimates are statistically significant at the 1 percent level. The corresponding estimates for the total birth rate are also positive, although imprecisely estimated. The Event-Time and Linear Trend IV specifications imply an increase of approximately 2.5–2.6 births per 100 women as enrollment increases from 0 to 100 percent, while the Binary IV estimate is 3.6. None of the total birth rate IV estimates is statistically significant. The first-stage F-statistics indicate strong relationships between Blue Cross introduction and enrollment in the Binary and Linear Trend IV specifications, while the more flexible Event-Time IV specification yields a lower F-statistic.

To gauge the economic magnitude of the fertility response, I use the Event-Time IV estimate of 2.53 births per 100 women. Blue Cross enrollment increased from less than 1 percent in the mid-1930s to approximately 20 percent by the end of the sample period. Applying the IV estimate to an approximately 20-percentage-point increase in enrollment implies an increase in the birth rate of about 0.5 births per 100 women. Over the same period, the U.S. birth rate rose by 3.75 births per 100 women. The point estimate corresponds to roughly 13 percent of the observed increase in the birth rate over this period. The upper bound of the 95 percent confidence interval corresponds to an increase of approximately 1.5 births per 100 women, or about 41 percent of the overall increase in the birth rate. Because the confidence interval includes zero, the data are also consistent with no effect

[19] Although retail sales per capita is included as a proxy for local economic conditions, it may not fully capture changes in employment and household earnings.

of Blue Cross enrollment on fertility. I interpret the 13 percent figure as an illustrative calculation based on the point estimate rather than as a precise estimate of Blue Cross's contribution to the reversal of fertility.

6.4 Mechanisms

Having established that Blue Cross enrollment increased hospital births and may also have increased fertility, I next investigate the mechanisms through which these effects may have operated. The conceptual framework in Section 3 provides three empirical predictions that help distinguish among potential mechanisms. First, if Blue Cross affects childbirth and fertility through the financial cost of hospital delivery, its effects should be larger where the underlying cost of medical care is higher, since insurance provides greater financial protection in these areas. Second, if maternal health is an important channel, Blue Cross introduction should be accompanied by improvements in maternal health outcomes. Third, if the fertility response operates through improved infant survival, Blue Cross should reduce infant mortality if increased access to hospital delivery and medical care improved infant survival. The following subsections examine these predictions in turn.

6.4.1 Financial Channel

I examine the financial channel by testing whether the effects of Blue Cross are larger in areas with higher baseline medical costs.[20][21] Because Blue Cross reduced the out-of-pocket cost of hospital

[20] One potential concern is that Blue Cross premiums may have reflected local medical costs, which could attenuate or remove heterogeneity in the effects of coverage by baseline medical costs. To examine this possibility, Appendix Figure A9 plots 1935 city-level medical costs against the corresponding monthly Blue Cross premiums reported in Reed [1947] for two-person and family plans, separately for semiprivate rooms and wards. I focus on two-person and family plans because these plan types typically included maternity benefits. The figure shows little correlation between Blue Cross premiums and baseline medical costs.

[21] To assess the extent of cross-subsidization in maternity coverage, I conduct a back-of-the-envelope calculation using Blue Cross premiums and maternity benefits reported in Reed [1947]. I restrict the analysis to fewer than 20 plans for which premium and maternity benefit information are available and maternity coverage was included in two-person but not one-person contracts. Assuming that Blue Cross enrollees faced the same birth rate as the population in the areas served by each plan, I calculate expected maternity benefits by multiplying the local birth rate by the maternity benefit. I approximate the additional annual premium associated with maternity coverage as the difference between the two-person premium and twice the one-person premium. The implied dollar subsidy is the difference between expected maternity benefits and this additional premium, and the implied subsidization rate is the dollar subsidy divided by expected maternity benefits. The implied subsidization rate ranges from 12% to 180% across plans. A rate below 100% indicates that the inferred additional premium covers only part of expected maternity benefits, while a rate of 100% indicates that two-person contracts included maternity benefits without an additional premium beyond the cost of two one-person contracts. Rates exceeding 100% arise when two-person contracts cost less than two one-person contracts combined. These estimates are consistent with cross-subsidization of maternity benefits, although differences in contract premiums may also reflect other pricing considerations.

care, the financial benefit of coverage should be greater in areas where hospital and medical services were more expensive. To examine this prediction, I divide counties into high- and low- baseline medical cost areas based on 1935 medical costs and estimate the effect of Blue Cross separately for the two groups.

I first focus on the hospital birth rate, the outcome most directly affected by hospital insurance. Figure 9 presents the event-study estimates, and Table 7 reports the corresponding average pre- and post-treatment effects and IV estimates. In counties with high baseline medical costs, Blue Cross increases hospital births by 0.51 births per 100 women aged 15–44, compared with 0.16 births per 100 women in counties with low baseline medical costs. The difference in the average post-treatment effects is 0.35 births per 100 women and is statistically significant at the 10 percent level. The dynamic estimates also show a substantially larger increase in hospital births in high-cost counties following Blue Cross entry.

The IV estimates exhibit a similar pattern. Under the Binary IV specification, a 10-percentage-point increase in Blue Cross enrollment is estimated to increase hospital births by 0.57 births per 100 women in high-cost counties, compared with 0.21 births per 100 women in low-cost counties. Although the difference between the Binary IV estimates is not statistically significant ($p = 0.234$), the larger point estimate in high-cost counties is consistent with the financial benefit of hospital insurance being greater where medical care was more expensive.[22]

I next look at whether the same pattern is present for the total birth rate. Figure 10 shows that the estimated effect is also larger in high-cost counties. The average post-treatment estimate is 0.55 births per 100 women in high-cost counties, compared with -0.06 births per 100 women in low-cost counties (Table 7). The difference of 0.61 births per 100 women is economically sizable, although it is not statistically significant. The IV estimates exhibit a similar pattern. Under the Binary IV specification, a 10-percentage-point increase in Blue Cross enrollment is estimated to increase the total birth rate by 0.60 births per 100 women in high-cost counties, compared with a decrease of 0.31 births per 100 women in low-cost counties. Although the difference between the IV estimates is

[22]The Event-Time and Linear Trend IV specifications yield similar results, with larger estimated effects in high-cost counties. The differences between high- and low-cost counties are not statistically significant under any of the three specifications.

not statistically significant ($p = 0.127$), the larger point estimate in high-cost counties is consistent with a stronger fertility response where medical care was more expensive.[23]

The findings are consistent with the prediction that Blue Cross had larger effects in areas where medical care was more costly. Both the reduced-form and IV estimates generally indicate stronger responses in high-cost counties, although the differences are not consistently statistically significant. This pattern provides suggestive evidence of a financial channel through which hospital insurance reduced the financial burden of childbirth.

6.4.2 Maternal Health Channel

I next turn to the health-related mechanisms, beginning with maternal health. If Blue Cross affected fertility by improving maternal health, its introduction should be associated with better maternal health outcomes. Because broader measures of maternal health are unavailable for this period, I use maternal mortality as a proxy. This is a particularly severe measure of maternal health and may fail to capture improvements that do not translate into changes in mortality.

The evidence does not indicate a decline in maternal mortality following Blue Cross entry. Table 8 shows an average post-treatment estimate of 38, relative to a pre-treatment mean of 813; the estimate is not statistically significant. The event-study estimates in Figure 11 likewise fluctuate around zero rather than exhibiting a sustained decline.[24]

These results should be interpreted with the limitation that maternal mortality captures only the most severe maternal health outcomes. Thus, the absence of a mortality decline does not rule out improvements in other dimensions of maternal health. Nevertheless, within the outcome available in the historical data, I find little evidence from maternal mortality in support of the maternal health channel.[25]

[23] The Event-Time and Linear Trend IV specifications yield similar patterns, with larger estimated effects in high-cost counties. The differences between high- and low-cost counties are statistically significant at the 10 percent level under both specifications. Corresponding estimates for hospital birth counts, non-hospital birth rates and counts, and total birth counts are reported in Appendix Figures A10–A13 and Appendix Table A5.

[24] The event-study window is shorter than for the other outcomes because the maternal mortality data span only 1928–1940 [Thomasson and Treber, 2008].

[25] The main specification uses a balanced panel of 262 cities. Estimates using an unbalanced panel of more than 800 cities are qualitatively similar. Thomasson and Treber [2008] also reports maternal mortality rates separately by race. Race-specific estimates yield a similar conclusion and are reported in Appendix Table A6 and Appendix Figure

6.4.3 Infant Survival Channel

The final mechanism I consider is infant survival. For improved infant survival to explain the fertility response, Blue Cross should have reduced infant mortality following its introduction.

Table 8 reports the average pre- and post-treatment estimates. The results provide little evidence that Blue Cross reduced infant mortality. The average post-treatment effect is 0.044 infant deaths per 100 births and is not statistically significant, relative to a pre-treatment mean of 5.845. Figure 12 presents the corresponding event-study estimates. The coefficients similarly show no systematic decline in infant mortality following the introduction of Blue Cross.[26]

These results provide little evidence that the expansion of Blue Cross improved infant survival over this period, suggesting that improvements in infant survival are less likely to account for the estimated fertility response to Blue Cross.

7 Discussion

The main results show that Blue Cross substantially increased hospital childbirth but had little detectable effect on maternal or infant mortality. To better understand these findings, this section examines two additional aspects of the expansion of hospital insurance. First, I investigate whether Blue Cross introduction was accompanied by an expansion in hospital capacity, which could have helped accommodate the increased demand for hospital delivery. Second, I examine potential explanations for why the increase in hospital childbirth did not translate into detectable improvements in maternal or infant mortality.

7.1 Hospital Capacity

The substantial increase in hospital childbirth following Blue Cross entry occurred largely without a detectable expansion in measured hospital capacity. This suggests that existing hospital infrastructure may have accommodated the increased demand for hospital delivery. To provide context

A14.

[26] Results using the number of infant deaths rather than the infant mortality rate are reported in Appendix Table A6 and Appendix Figure A15.

for this finding, I first assess whether existing maternity capacity was sufficient to accommodate observed hospital births and then examine whether Blue Cross induced changes in hospital capacity.

By a simple measure of maternity capacity, existing capacity appears to have been sufficient in most counties and years. In 97 percent of county-year observations in the sample, the number of bassinets was at least as large as the number required to accommodate observed hospital births.[27] This suggests that existing maternity capacity was generally sufficient to accommodate the observed level of hospital childbirth.

I next examine whether Blue Cross induced an expansion in hospital capacity. Appendix Table A7 reports the average pre- and post-treatment estimates, and Appendix Figure A16 presents the corresponding event-study coefficients. I first examine bassinet capacity, which is most directly relevant for hospital childbirth. I find little evidence that Blue Cross increased bassinet capacity relative to the population of women of childbearing age. The average post-treatment effect on bassinets per 100 women aged 15–44 is 0.001 and is not statistically significant, relative to a pre-treatment mean of 0.097.[28]

I also consider hospital beds as a broader measure of capacity. Although the post-treatment estimates for hospital beds are positive, the event-study estimates raise concerns about the identifying pre-trends. In particular, the average pre-treatment estimate for beds per capita is negative and statistically significant. I therefore interpret the post-treatment increases in bed capacity with caution rather than as evidence of a causal supply response to Blue Cross.

Finally, I assess whether Blue Cross was associated with changes in the number of general hospitals. On the extensive margin, the probability that a county had a general hospital is essentially unchanged following Blue Cross entry, with an average post-treatment estimate of -0.008. On the intensive

[27] Assuming a 10-day hospital stay for each birth, I calculate the number of bassinets required to accommodate observed hospital births as the annual number of hospital births multiplied by 10 and divided by 365. I then compare this implied number of required bassinets with the observed number of bassinets in each county and year. I classify a county-year as having sufficient capacity when the observed number of bassinets is at least as large as the implied number required.

[28] When I instead use the number of bassinets as the outcome, the average post-treatment estimate is positive and statistically significant: Blue Cross entry is associated with an increase of 6.85 bassinets, relative to a pre-treatment mean of 9.98. However, this increase in the absolute number of bassinets does not translate into an increase in bassinets per 100 women aged 15–44. I interpret the results as providing little evidence that Blue Cross increased bassinet capacity relative to the population potentially requiring maternity care.

margin, the estimates for both general hospitals per capita and the total number of general hospitals are small and statistically insignificant.

Overall, the results suggest that the substantial increase in hospital childbirth following Blue Cross entry was accommodated largely within existing hospital infrastructure, rather than through a detectable contemporaneous expansion in measured hospital capacity.

7.2 Other Health Outcomes

I consider why the substantial increase in hospital childbirth did not translate into detectable improvements in maternal or infant mortality. Contemporary accounts show that greater use of hospital childbirth did not necessarily translate into mortality improvements during this period. Hospital delivery provided access to medical intervention for complicated births, but these interventions could also introduce additional risks. Polak [1929], for example, attributed persistently high maternal mortality in part to unnecessary intervention in uncomplicated deliveries, avoidable cesarean sections, and exposure to cross-infection in hospitals. As documented by Thomasson and Treber [2008], medical intervention had little effect on maternal mortality before the widespread introduction of sulfa drugs in the late 1930s but became mortality-reducing after these drugs lowered the risk of infection. This finding suggests that the health benefits of hospital delivery changed over the period studied. Although sulfa drugs improved the safety of obstetric interventions, their introduction did not necessarily eliminate other risks associated with hospital childbirth. Contemporary accounts also document risks for newborns, including outbreaks of highly fatal diarrhea in hospital nurseries that raised concerns about cross-infection associated with congregate newborn care [Spivek, 1938; Abramson and Frant, 1938; Oppenheimer and United States Children's Bureau, 1936]. While advances in medical technology increased the potential benefits of hospital childbirth, the net effects on maternal and infant mortality may have depended on the quality of care and the risks associated with hospital delivery.

I also investigate whether the effects of Blue Cross extended beyond childbirth to broader hospital utilization and population mortality. Appendix Table A8 reports the average pre- and post-treatment estimates, and Appendix Figure A17 presents the corresponding event-study coefficients. Average

daily census, defined as the average number of inpatients present in a hospital each day, provides a measure of overall hospital utilization. The average post-treatment estimate for average daily census per capita is 0.068, relative to a pre-treatment mean of 0.354, while the level of average daily census increases by approximately 121 patients, relative to a pre-treatment mean of 169. However, both measures exhibit differential pre-treatment dynamics, making it difficult to attribute these increases to Blue Cross introduction.

I then turn to mortality outcomes for the broader population. The average post-treatment effect on the mortality rate is 0.003 and is not statistically significant, relative to a pre-treatment mean of 1.009. The number of deaths also shows no statistically significant change. The corresponding event-study estimates show no systematic decline in either measure following Blue Cross entry. These findings extend the earlier results for maternal and infant mortality, suggesting that Blue Cross did not produce detectable improvements in population-wide mortality.

8 Conclusion

This paper examines whether the emergence of employer-sponsored hospital insurance affected childbirth and fertility during the period in which the long-run decline in U.S. fertility began to reverse. I construct a new dataset tracing the geographic expansion and enrollment of Blue Cross hospital plans and link these data to county-level measures of hospital childbirth, fertility, and mortality. Exploiting variation in the timing and geographic rollout of Blue Cross, I estimate weighted stacked difference-in-differences models and use Blue Cross introduction as an instrument for insurance enrollment. Together, these approaches provide evidence on how the early expansion of hospital insurance affected both the use of hospital care and childbearing behavior.

The results show that Blue Cross substantially increased insurance enrollment and hospital childbirth. Following Blue Cross introduction, hospital births increased by an average of 0.37 births per 100 women aged 15–44 over the first ten post-treatment years, relative to a pre-treatment mean of 0.91. The effect grows over time, reaching approximately 0.85 births per 100 women by the ninth year after introduction. I find little evidence of a corresponding decline in non-hospital births, suggesting

that the increase in hospital childbirth was not driven solely by a shift in the location of deliveries that would otherwise have occurred outside hospitals. The estimated effect on the total birth rate is also positive and similar in magnitude, although it is estimated imprecisely. Instrumental-variables estimates yield the same qualitative pattern: greater Blue Cross enrollment significantly increases hospital childbirth, while the estimated effects on total fertility are positive but imprecise.

The mechanism evidence points most strongly toward the financial cost of childbirth. The effects of Blue Cross on hospital births are significantly larger in areas with higher baseline medical costs, where insurance provided greater financial protection, and the estimated fertility response is also larger in these areas, although the difference is less precisely estimated. In contrast, I find little evidence that Blue Cross reduced maternal or infant mortality.

The results highlight the demographic consequences of changes in the financing of medical care. Blue Cross emerged not as a fertility policy but as a broad system for financing hospital services, yet maternity care quickly became one of its most important uses. Its expansion altered the economic environment surrounding childbirth at the same time that U.S. fertility was beginning to rise after decades of decline. Although the fertility estimates are imprecise and do not imply that Blue Cross alone explains the reversal, the evidence suggests that the emergence of employer-sponsored hospital insurance may have been one institutional development that contributed to this turning point. More generally, the results show that the consequences of health insurance can extend beyond health-care utilization itself, influencing household decisions about childbearing and family formation.

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Tables and Figures

Table 1: Midwife-Attended Births in New Jersey, 1919–1926

Year	Total Births	Midwife-Attended Births	Percent Midwife-Attended
1919	70,935	30,000	42.2
1920	76,431	21,571	28
1921	78,172	21,106	27
1922	74,479	19,205	26
1923	74,611	18,365	24.5
1924	76,530	17,645	23
1925	74,193	16,077	21.6
1926	72,386	14,739	20.3

Notes: The table reports total births, births attended by midwives, and the share of births attended by midwives in New Jersey from 1919 to 1926. Percent midwife-attended is calculated as midwife-attended births divided by total births multiplied by 100.

Source: 50th Annual Report of the Department of Health of the State of New Jersey (1927).

Table 2: Hospital Cases for Selected Diagnoses, Associated Hospital Service of New York, 1943

Disease Classification	Percent of Total Cases
Maternity	
Delivery	20.89
Others	2.87
Respiratory System	
Tonsillectomy	11.75
Influenza, Bronchitis, and Pneumonia	5.72
Others	4.92

Notes: The table reports the most common diagnostic categories among hospital cases under the Associated Hospital Service of New York in 1943, selected based on their share of total cases. Percent of total cases is calculated relative to all hospital cases reported by the plan.

Source: Reed [1947].

Table 3: Hospital Utilization and Expenses for Selected Diagnoses, New Jersey Blue Cross Plan, 1943

Diagnosis	Percent of Total Cases	Percent of Total Days' Care	Percent of Total Expenses
Maternity	22.97	25.29	28.19
Tonsils & Adenoids	16.69	2.73	4.48
Appendicitis	9.97	11.95	12.03
Female Diseases	9.74	10.62	10.84

Notes: The table reports selected diagnoses from among the most common hospital cases under the New Jersey Blue Cross plan in 1943, based on their share of total cases. Percent of total cases is the share of all hospital cases accounted for by each diagnosis; percent of total days' care is the share of all inpatient days attributable to each diagnosis; and percent of total expenses is the share of total hospital expenses attributable to each diagnosis.

Source: Reed [1947].

Table 4: Baseline County Characteristics and Timing of Blue Cross Entry

	First Blue Cross Enrollment Year
Log total population	-1.178^{***}
	(0.326)
Retail sales per capita	0.001
	(0.001)
Share of Black population	0.011
	(0.042)
Share of foreign-born population	-0.136
	(0.084)
Share of urban population	0.031^{**}
	(0.014)
Log medical costs	2.944
	(4.11)
Has a hospital	-0.406
	(0.428)

Notes: The table reports coefficients from a cross-sectional regression of the first year of Blue Cross enrollment in a county on baseline county characteristics. Explanatory variables are measured in the earliest year in which they are available. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table 5: The Effect of Blue Cross Hospital Plans

	Average Pre	Average Post
Enrollment Share	0.045	8.8***
	(0.355)	(0.849)
Hospital Birth Rate	0.010	0.370***
	(0.057)	(0.129)
Pre-treatment Outcome Mean	0.91	
Non-Hospital Birth Rate	0.159	0.131
	(0.172)	(0.248)
Pre-treatment Outcome Mean	7.96	
Birth Rate	0.046	0.306
	(0.152)	(0.298)
Pre-treatment Outcome Mean	8.94	

Notes: The table summarizes event-study estimates of the effect of Blue Cross plan entry on insurance enrollment and birth outcomes. The Average Pre column reports the average of the event-study coefficients for event years -5 through -2, with event year -1 omitted as the reference period. The Average Post column reports the average of the event-study coefficients for event years 0 through 9. Enrollment share is measured on a 0–100 percentage scale. Hospital, non-hospital, and total birth rates are measured as births per 100 women aged 15–44. The enrollment-share analysis is conducted at the Blue Cross plan level, while the birth-outcome analyses are conducted at the county level. Pre-treatment outcome means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table 6: The Effect of Enrollment on Fertility

	OLS	IV		
		Binary	Event-Time	Linear Trend
		Hospital Birth Rate		
Enrollment Share	4.384***	4.774***	4.798***	4.809***
	(1.502)	(1.577)	(1.540)	(1.545)
First-stage F-statistic		61.482	12.886	56.899
		Birth Rate		
Enrollment Share	1.747	3.577	2.529	2.637
	(1.523)	(3.751)	(2.600)	(2.676)
First-stage F-statistic		61.277	12.761	56.998

Notes: The table reports estimates of the effect of Blue Cross enrollment on hospital birth rates and total birth rates. The OLS specification directly relates Blue Cross enrollment share to each outcome. In the IV specifications, Blue Cross enrollment share is treated as endogenous. The Binary IV specification uses an indicator for the introduction of Blue Cross as the instrument. The Event-Time IV specification allows the first-stage effect of Blue Cross introduction on enrollment to vary by years since entry, while the Linear Trend IV specification assumes that this effect changes linearly with years since entry. Enrollment share ranges from 0 to 1, and birth rates are measured as births per 100 women aged 15–44. First-stage F-statistics are reported. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table 7: The Effect of Blue Cross Hospital Plans by Baseline Medical Costs

	High Baseline Medical Costs	Low Baseline Medical Costs	Difference
Panel A. Hospital Birth Rate			
Average Pre (Reduced Form)	-0.018	0.048	–
	(0.067)	(0.094)	
Average Post (Reduced Form)	0.512***	0.160	0.352*
	(0.162)	(0.147)	(0.179)
Binary IV	5.717***	2.101	3.616
	(1.945)	(2.677)	(3.014)
F-stat	64.171	34.979	–
Event-Time IV	5.408***	3.158	2.251
	(1.852)	(2.299)	(2.482)
F-stat	14.649	25.781	–
Linear Trend IV	5.457***	3.092	2.365
	(1.874)	(2.292)	(2.503)
F-stat	50.874	37.323	–
Pre-treatment Outcome Mean	0.821	1.049	–
Panel B. Birth Rate			
Average Pre (Reduced Form)	0.010	0.146	–
	(0.224)	(0.155)	
Average Post (Reduced Form)	0.553	-0.058	0.611
	(0.374)	(0.324)	(0.369)
Binary IV	5.978	-3.114	9.092
	(4.388)	(5.635)	(5.896)
F-stat	64.259	34.439	–
Event-Time IV	4.973	-3.680	8.653*
	(2.990)	(4.327)	(4.458)
F-stat	15.125	25.392	–
Linear Trend IV	5.050	-3.537	8.588*
	(3.093)	(4.356)	(4.486)
F-stat	51.600	36.829	–
Pre-treatment Outcome Mean	9.016	8.830	–

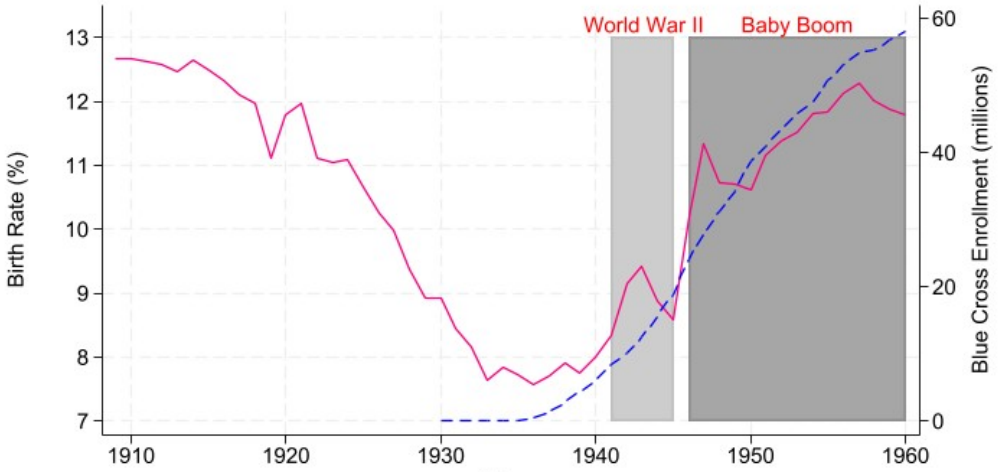
Notes: The table reports reduced-form event-study estimates and instrumental-variables (IV) estimates separately for counties with high and low baseline medical costs, defined relative to the sample mean of baseline medical costs. The Average Pre row averages event-study coefficients for event years -5 through -2 (event year -1 is the omitted reference period), while Average Post averages coefficients for event years 0 through 9. These reduced-form estimates measure the effect of Blue Cross introduction. The IV specifications instead instrument the county-level Blue Cross enrollment share: Binary IV uses an indicator for plan availability after introduction; Event-Time IV uses separate indicators for post-treatment event years 0 through 9; and Linear Trend IV uses years since introduction (zero before entry). IV coefficients represent the effect of an increase in the enrollment share from 0 to 1. The Difference column reports high-cost minus low-cost effects. All specifications use population-based corrective weights, the stated controls and fixed effects, and standard errors clustered at the Blue Cross plan level. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table 8: The Effect of Blue Cross Hospital Plans on Maternal and Infant Mortality Rates

	Average Pre	Average Post
Maternal Mortality Rate	-33.583	37.971
	(50.216)	(39.021)
Pre-treatment Outcome Mean	812.899	
Infant Mortality Rate	0.107	0.044
	(0.117)	(0.162)
Pre-treatment Outcome Mean	5.845	

Notes: The table reports event-study estimates of the effect of Blue Cross plan entry on maternal and infant mortality. The maternal mortality rate is measured as maternal deaths per 100,000 live births, and the infant mortality rate is measured as infant deaths per 100 births. The Average Pre column reports the average of the event-study coefficients for event years -5 through -2, with event year -1 omitted as the reference period. The Average Post column reports the average of the event-study coefficients for event years 0 through 9. Pre-treatment outcome means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Figure 1: U.S. Birth Rate and Blue Cross Enrollment

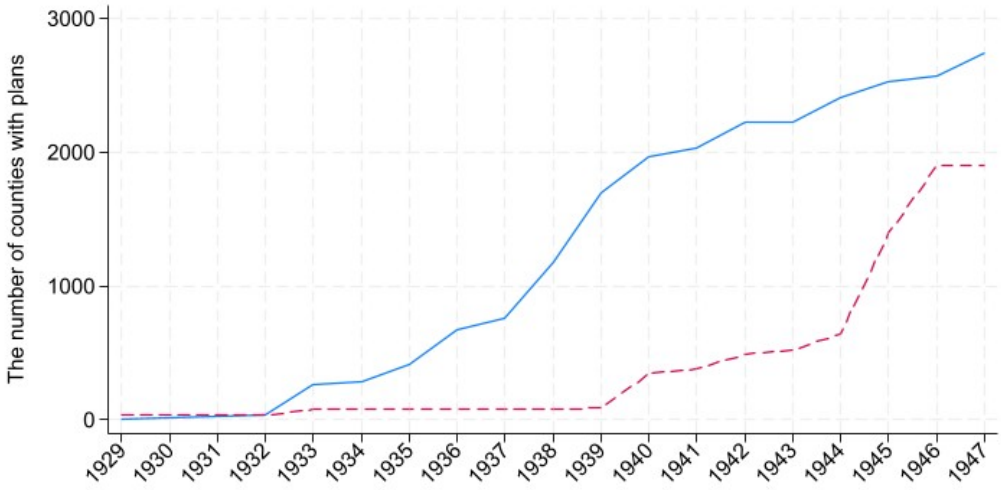


Notes: The solid line plots the U.S. birth rate, measured as births per 100 women ages 15–44. The dashed line plots total Blue Cross enrollment, measured in millions of enrollees. The light shaded region denotes World War II, and the darker shaded region denotes the Baby Boom period beginning in 1946.

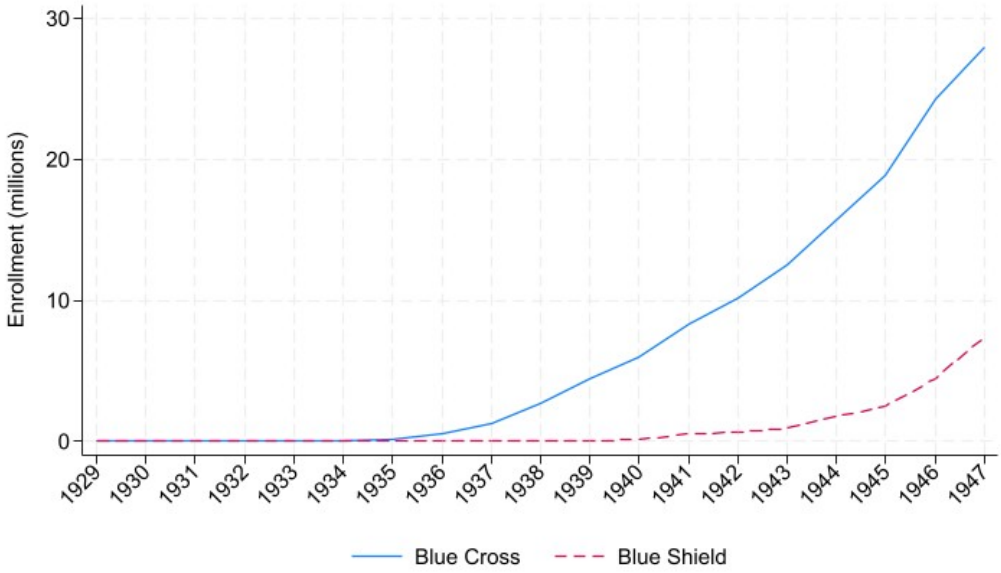
Sources: National Center for Health Statistics; Reed (1947); Health Insurance Institute (1963).

Figure 2: The Expansion of Blue Cross and Blue Shield

Panel A. Number of Counties with Blue Cross and Blue Shield Plans



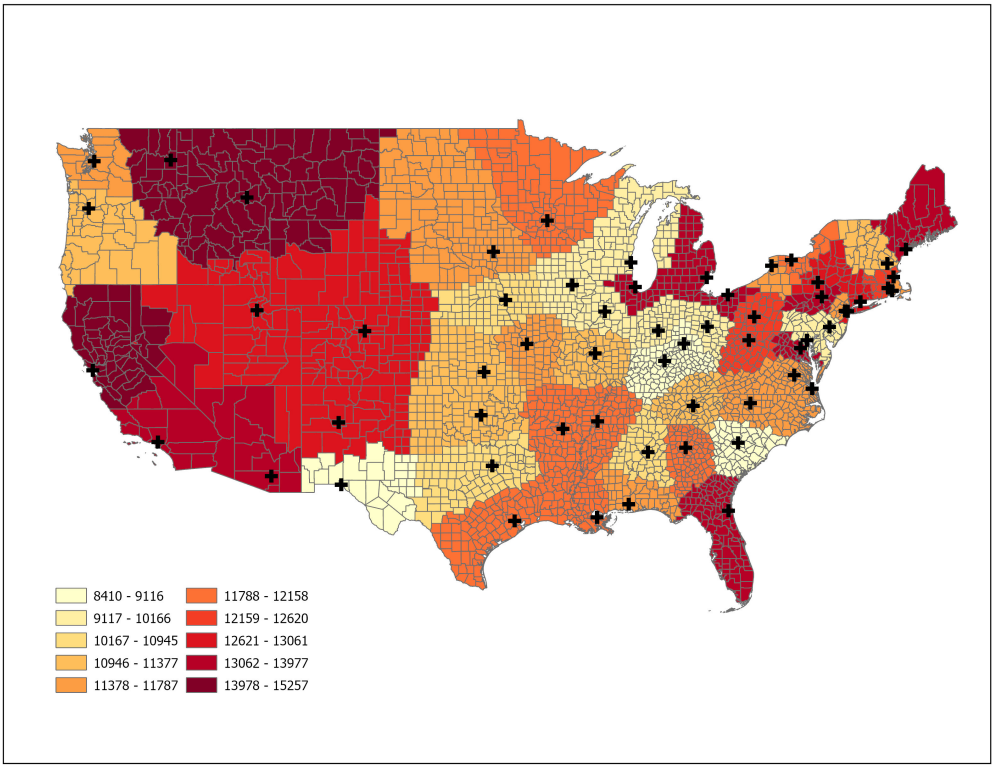
Panel B. Blue Cross and Blue Shield Enrollment



Notes: Panel A plots the cumulative number of U.S. counties in which Blue Cross and Blue Shield plans were available from 1929 to 1947. Panel B plots total enrollment in Blue Cross and Blue Shield plans over the same period, measured in millions of enrollees. Blue Cross plans provided hospital-service coverage, while Blue Shield plans provided coverage for physician services.

Source: Reed [1947].

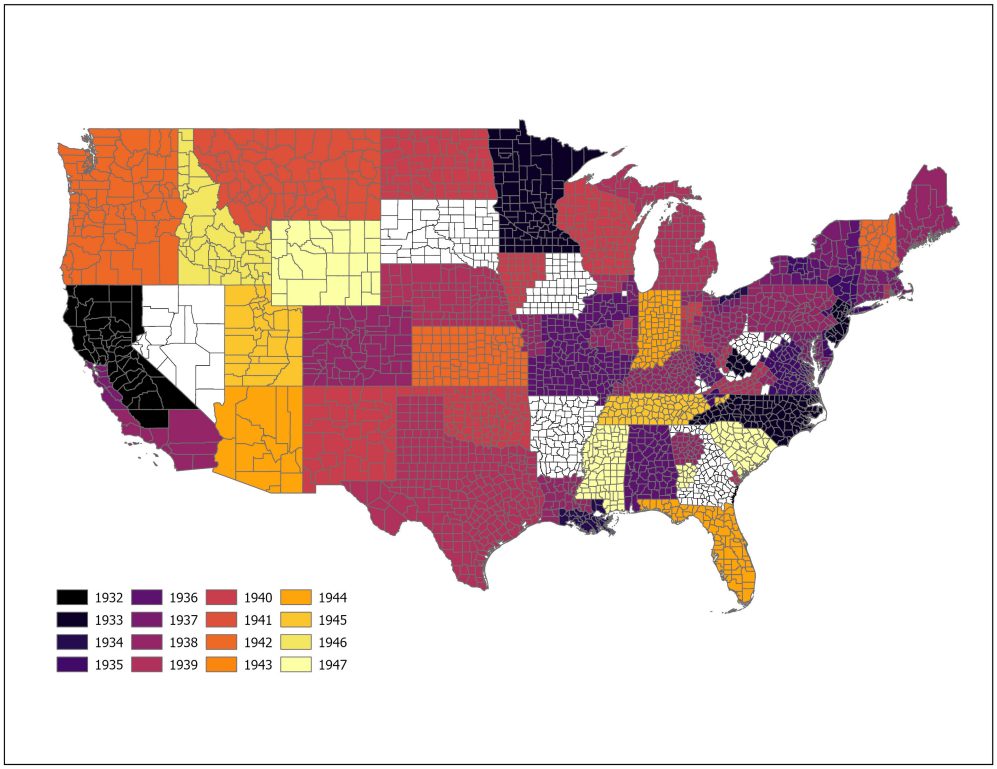
Figure 3: Geographic Distribution of Minimum Medical Care Costs, 1935



Notes: The map shows the geographic distribution of minimum medical service costs across U.S. counties in 1935. The measure represents the annual cost of a standardized bundle of minimum medical services for a four-person family, based on expected medical care needs over a lifetime. Because costs are observed for only 59 cities, each county is assigned the value of the geographically nearest city. Darker shading indicates higher medical service costs, and crosses mark the 59 cities for which costs are directly observed.

Source: Stecker [1937].

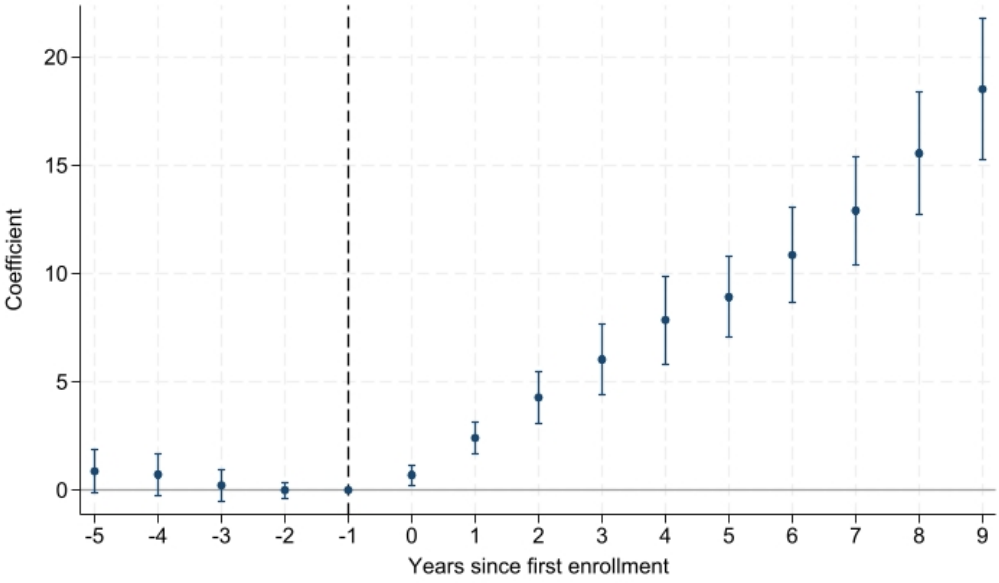
Figure 4: Timing of Blue Cross Hospital Plan Entry Across Counties



Notes: The map shows the first year in which Blue Cross hospital plan coverage became available in each U.S. county. Counties are shaded according to the year of initial Blue Cross entry, with colors corresponding to entry years from 1932 to 1947. White counties had no Blue Cross hospital plan coverage by 1947.

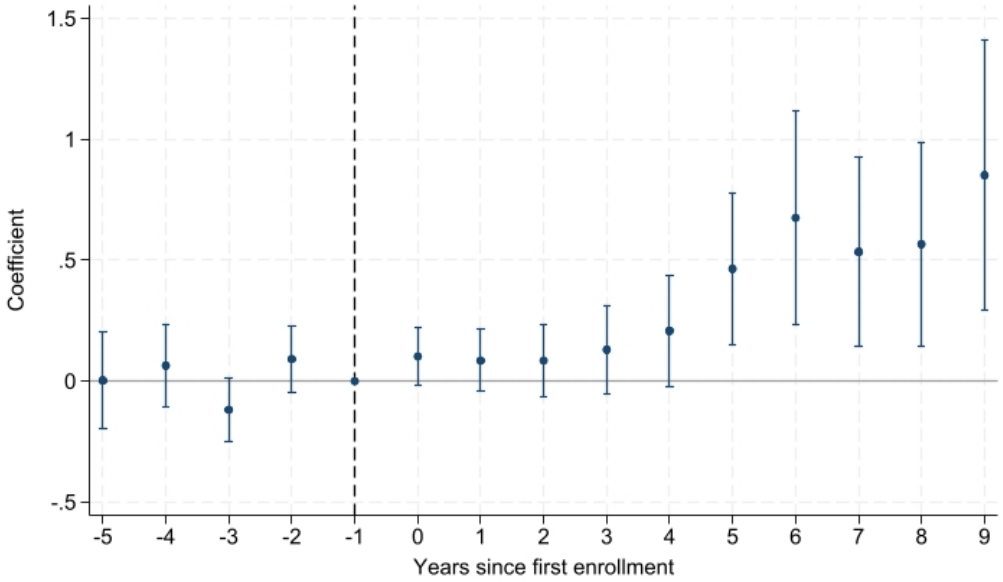
Source: Reed [1947].

Figure 5: The Effect of Blue Cross Hospital Plans on Enrollment Share



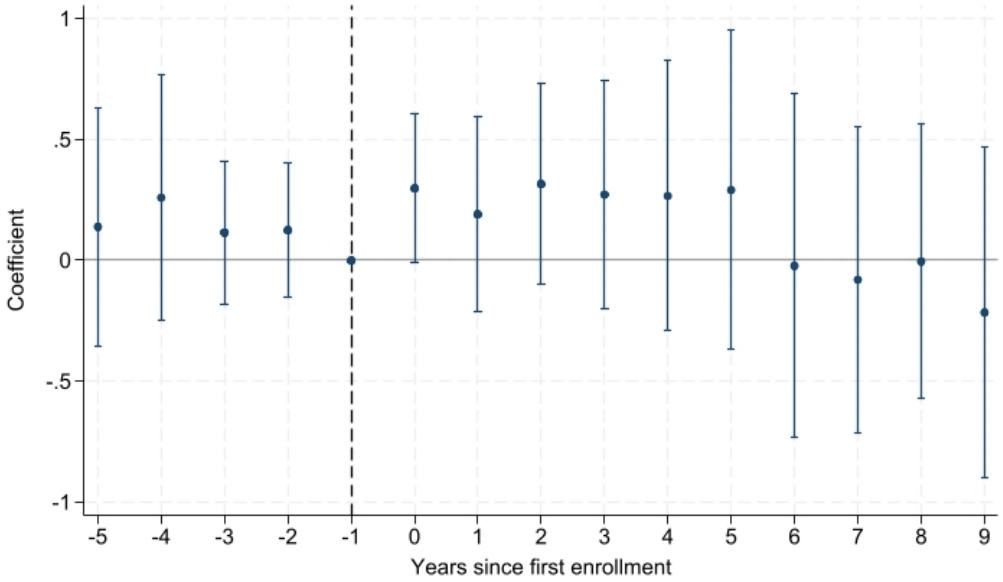
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on Blue Cross enrollment share. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Enrollment share is measured on a 0–100 percentage scale. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure 6: The Effect of Blue Cross Hospital Plans on Hospital Births per 100 Women aged 15–44



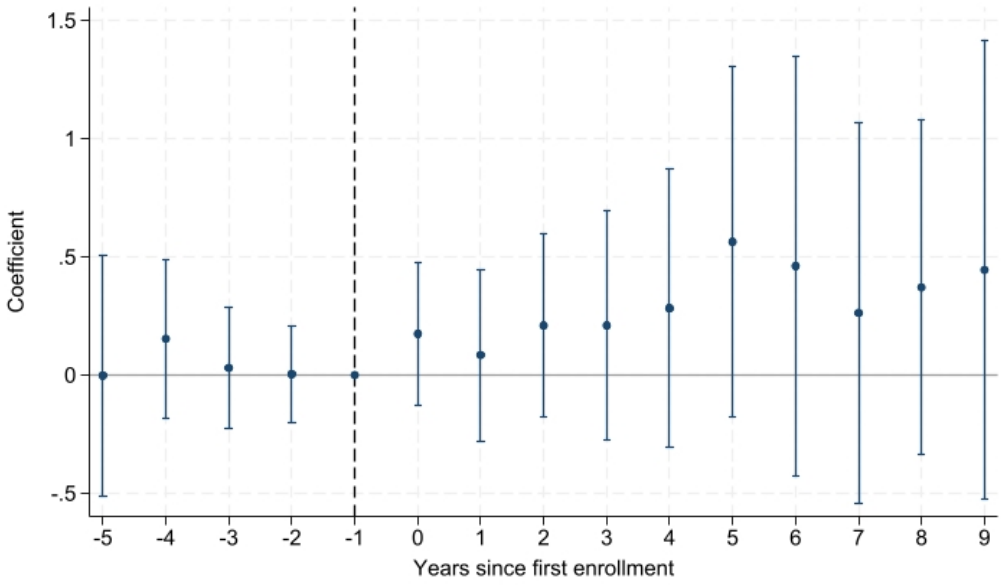
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the hospital birth rate. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The hospital birth rate is measured as hospital births per 100 women aged 15–44. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure 7: The Effect of Blue Cross Hospital Plans on Non-Hospital Births per 100 Women aged 15–44



Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the non-hospital birth rate. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period.The non-hospital birth rate is defined as total births minus hospital births, divided by the number of women aged 15–44 and multiplied by 100. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

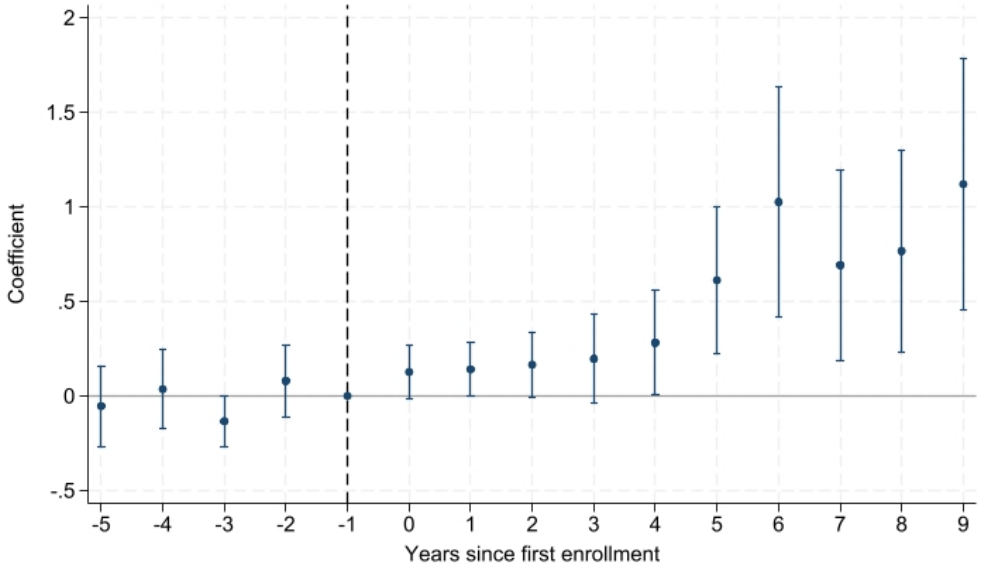
Figure 8: The Effect of Blue Cross Hospital Plans on Births per 100 Women aged 15–44



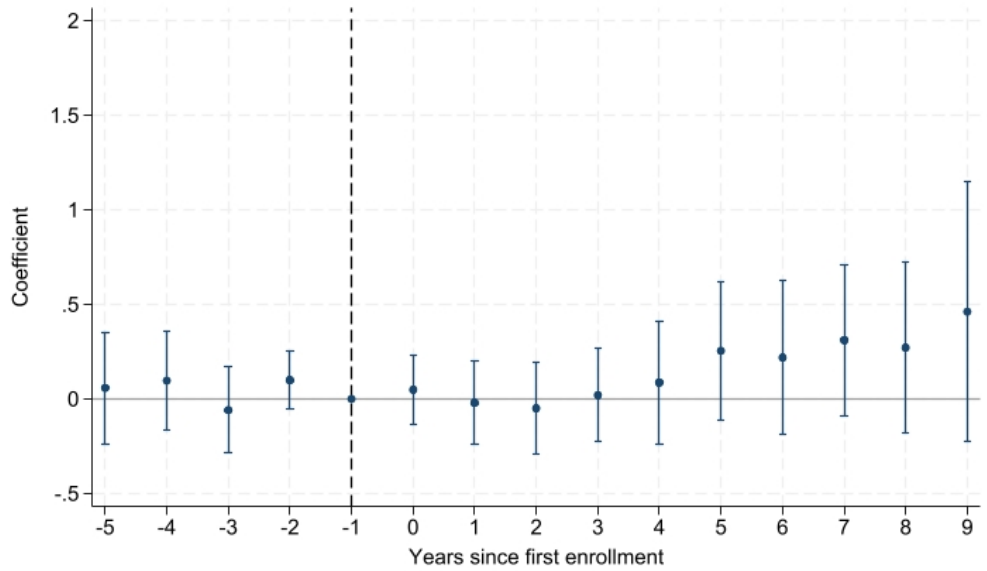
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the total birth rate. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The birth rate is measured as total births per 100 women ages 15–44. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure 9: Heterogeneous Effects of Blue Cross Hospital Plans on Hospital Births per 100 Women aged 15–44 by Baseline Medical Costs

Panel A: High Baseline Medical Costs



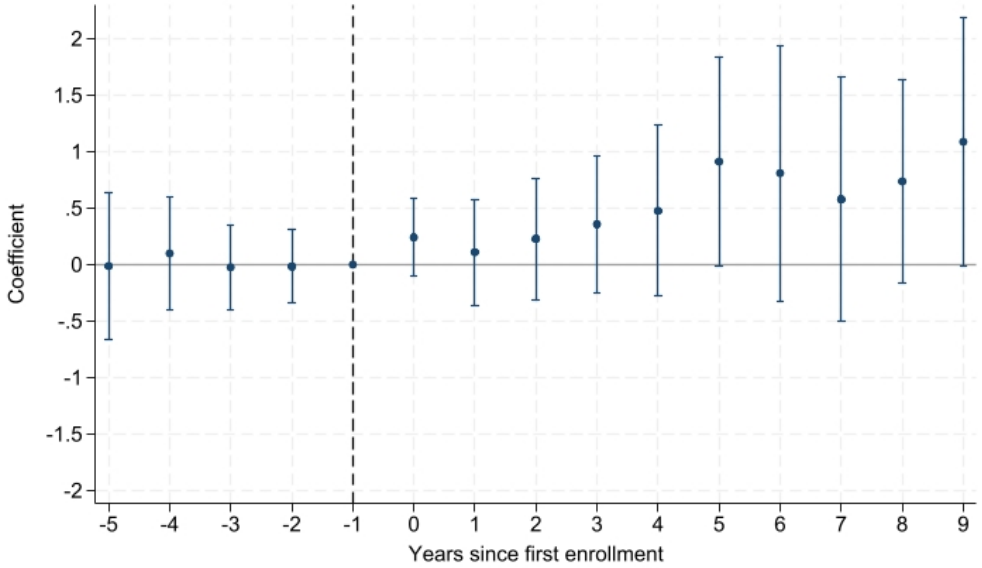
Panel B: Low Baseline Medical Costs



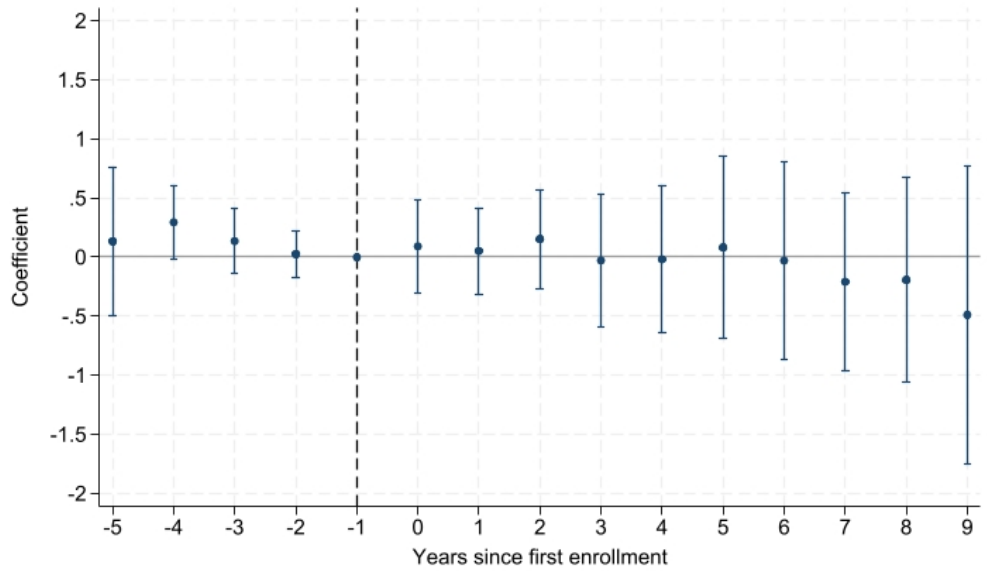
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the hospital birth rate separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The hospital birth rate is measured as hospital births per 100 women aged 15–44. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure 10: Heterogeneous Effects of Blue Cross Hospital Plans on Births per 100 Women aged 15–44 by Baseline Medical Costs

Panel A: High Baseline Medical Costs

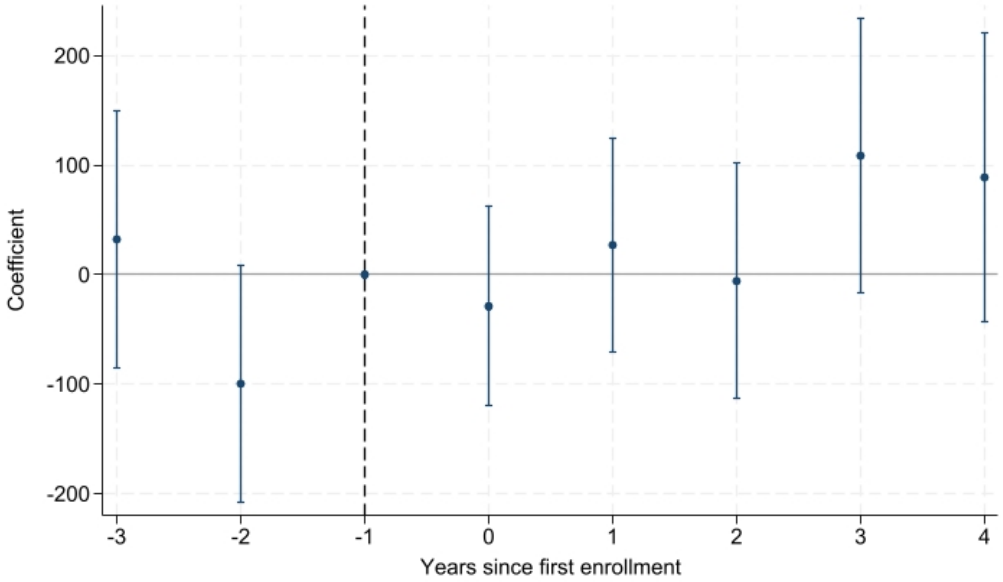


Panel B: Low Baseline Medical Costs



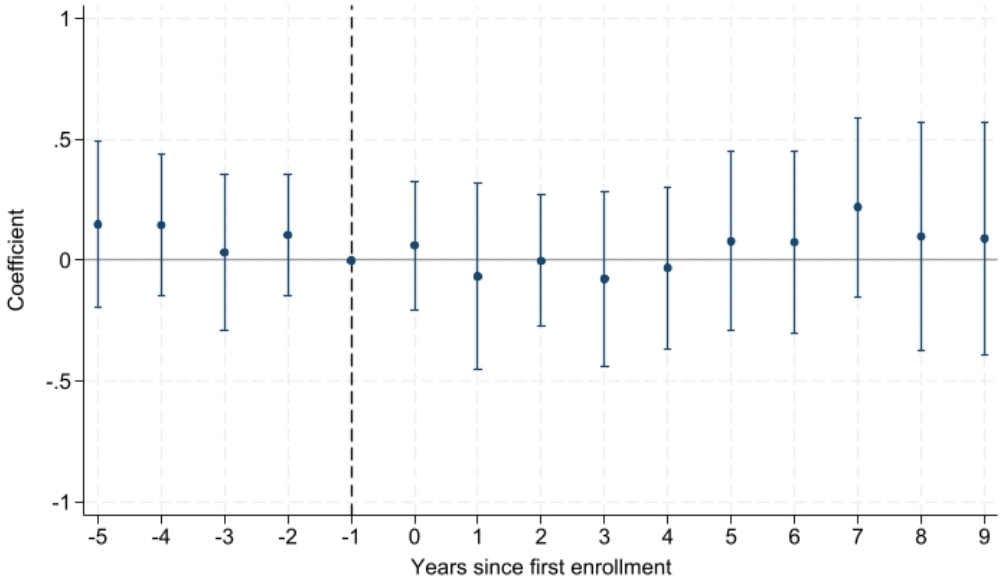
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the total birth rate separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The birth rate is measured as total births per 100 women aged 15–44. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure 11: The Effect of Blue Cross Hospital Plans on Maternal Mortality per 100,000 Births



Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the maternal mortality rate. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The maternal mortality rate is measured as maternal deaths per 100,000 live births. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure 12: The Effect of Blue Cross Hospital Plans on Infant Mortality per 100 Births



Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the infant mortality rate. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The infant mortality rate is measured as infant deaths per 100 live births. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

A Additional Tables and Figures

Table A1: Descriptive Statistics

	All Counties		Treated by 1947		Main Analysis Cohorts 1932–1938	
	Mean	SD	Mean	SD	Mean	SD
Panel A. Fertility and Mortality						
Birth Rate	9.23	2.77	9.22	2.81	9.19	3.30
Infant Mortality Rate	5.22	2.77	5.23	2.73	5.42	2.56
Hospital Birth Rate	2.35	3.62	2.40	3.64	2.36	3.50
Panel B. Blue Cross Enrollment						
Blue Cross Enrollment Share	2.65	7.94	2.94	8.30	4.38	7.69
Panel C. County Characteristics						
Retail Sales per Capita	577	328	584	326	566	325
Share Black	10.79	17.97	10.30	17.47	11.41	17.40
Share Urban	23.04	25.30	23.60	25.45	25.19	26.90
Share Foreign-Born	4.08	5.08	4.18	5.19	4.15	5.53
Has a Hospital	0.61	0.48	0.61	0.48	0.63	0.48
Panel D. Hospital Capacity and Utilization						
Hospitals per Capita	0.004	0.006	0.004	0.006	0.003	0.005
Bassinets per 100 Women	0.13	0.18	0.13	0.17	0.12	0.16
Beds per Capita	0.59	1.82	0.59	1.78	0.73	2.15
Average Daily Census per Capita	0.48	1.74	0.49	1.70	0.63	2.07

Notes: The table reports means and standard deviations for the county-year sample from 1927 to 1947. Counties treated by 1947 are counties in which Blue Cross enrollment began by the end of the sample period. The main analysis cohorts consist of counties in which Blue Cross enrollment began between 1932 and 1938; variation in the timing of entry across these cohorts provides the treatment variation used in the main empirical analysis. Blue Cross enrollment share is measured on a 0–100 percentage scale. Birth and hospital birth rates are measured as births per 100 women aged 15–44. The infant mortality rate is measured as infant deaths per 100 births. Retail sales per capita are measured in dollars. Shares of Black, urban, and foreign-born populations are measured on a 0–100 percentage scale. Has a Hospital is an indicator equal to one if the county has at least one hospital. Bassinets per 100 Women is measured per 100 women aged 15–44. Average Daily Census measures the average number of patients occupying hospital beds on a given day. Hospitals per Capita, Beds per Capita, and Average Daily Census per Capita are scaled by county population.

Table A2: The Effect of Blue Cross Hospital Plans on Enrollment: County-Level Estimates

	Average Pre	Average Post
Enrollment Share	0.005	7.518***
	(0.02)	(0.968)

Notes: The table summarizes county-level event-study estimates of the effect of Blue Cross hospital plan entry on Blue Cross enrollment share. The Average Pre column reports the average of the event-study coefficients for event years -5 through -2, with event year -1, the year immediately before entry, omitted as the reference period. The Average Post column reports the average of the event-study coefficients for event years 0 through 9. Enrollment share is measured on a 0–100 percentage scale. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A3: The Effect of Blue Cross Hospital Plans on Birth Rates and Birth Counts by Hospital Availability

	Has a Hospital	No Hospital	Difference
Panel A. Birth Rate			
Average Pre	0.098	0.033	
	(0.123)	(0.271)	
Average Post	0.385	0.074	0.311
	(0.339)	(0.268)	(0.288)
Pre-treatment Outcome Mean	8.585	9.378	
Panel B. Birth Counts			
Average Pre	33.464	1.441	
	(30.372)	(9.086)	
Average Post	404.348***	1.990	402.357***
	(111.887)	(8.805)	(110.936)
Pre-treatment Outcome Mean	764.736	281.152	

Notes: The table reports event-study estimates of the effect of Blue Cross hospital plan entry separately for counties with and without a hospital at baseline. The Average Pre estimates average the event-study coefficients for event years -5 through -2, with event year -1, the year immediately before entry, omitted as the reference period. The Average Post estimates average the event-study coefficients for event years 0 through 9. In Panel A, the outcome is the birth rate, measured as births per 100 women aged 15–44. In Panel B, the outcome is the total number of births in a county-year. The Difference column reports the difference in average post-treatment effects between counties with and without a hospital (Has a Hospital minus No Hospital). Pre-treatment outcome means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A4: The Effect of Blue Cross Hospital Plans on Birth Counts

	Average Pre	Average Post
Hospital Births	-89.704*	321.658**
	(49.11)	(127.825)
Pre-treatment Outcome Mean	138.936	
Non-Hospital Births	72.534***	-94.227**
	(21.937)	(38.017)
Pre-treatment Outcome Mean	406.915	
Total Births	29.63	296.878***
	(30.868)	(101.348)
Pre-treatment Outcome Mean	545.426	

- Notes: The table summarizes event-study estimates of the effect of Blue Cross hospital plan entry on county-level birth counts. The Average Pre column reports the average of the event-study coefficients for event years -5 through -2, with event year -1, the year immediately before entry, omitted as the reference period. The Average Post column reports the average of the event-study coefficients for event years 0 through 9. Hospital births are the number of births occurring in hospitals, non-hospital births are calculated as total births minus hospital births, and total births are the total number of births in the county-year. Pre-treatment outcome means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A5: The Effect of Blue Cross Hospital Plans by Baseline Medical Costs: Additional Outcomes

	High Baseline Medical Costs	Low Baseline Medical Costs	Difference
Panel A. Hospital Birth Counts			
Average Pre	-133.122*	-26.108	–
	(71.691)	(26.683)	
Average Post	526.946**	71.742	455.203**
	(203.379)	(67.141)	(203.255)
Pre-treatment Outcome Mean	140.995	137.060	–
Panel B. Non-Hospital Birth Rate			
Average Pre	0.112	0.255	–
	(0.268)	(0.161)	
Average Post	0.181	0.033	0.147
	(0.348)	(0.233)	(0.323)
Pre-treatment Outcome Mean	8.154	7.671	–
Panel C. Non-Hospital Birth Counts			
Average Pre	98.711***	54.916	–
	(36.198)	(17.824)	
Average Post	-137.964**	-46.666	-91.297
	(53.649)	(31.364)	(58.494)
Pre-treatment Outcome Mean	400.580	416.704	–
Panel D. Total Birth Counts			
Average Pre	20.517	47.035	–
	(41.012)	(23.532)	
Average Post	499.693***	55.283	444.409***
	(157.178)	(58.339)	(165.210)
Pre-treatment Outcome Mean	536.874	559.373	–

Notes: The table reports event-study estimates of the effect of Blue Cross hospital plan entry separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. The Average Pre estimates average the event-study coefficients for event years -5 through -2, with event year -1, the year immediately before entry, omitted as the reference period. The Average Post estimates average the event-study coefficients for event years 0 through 9. In Panel A, the outcome is the number of hospital births in a county-year. In Panel B, the non-hospital birth rate measures births occurring outside hospitals per 100 women ages 15–44 and is constructed as the difference between the total birth rate and the hospital birth rate. In Panels C and D, the outcomes are the number of non-hospital births and total births, respectively, in a county-year. The Difference column reports the difference in average post-treatment effects between high- and low-cost counties (High minus Low). Pre-treatment outcome means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A6: The Effect of Blue Cross Hospital Plans on Additional Mortality Outcomes

	Average Pre	Average Post
Panel A: Infant Deaths		
Infant Deaths	6.362***	0.246
	(2.265)	(1.767)
Pre-treatment Outcome Mean	32.315	
Panel B: Maternal Mortality Rate		
White	0.320	48.033
	(52.316)	(63.181)
Pre-treatment Outcome Mean	857.107	
Black	247.695	-121.634
	(149.542)	(200.583)
Pre-treatment Outcome Mean	1320.682	

Notes: The table summarizes event-study estimates of the effect of Blue Cross hospital plan entry on additional mortality outcomes. Panel A reports the number of infant deaths at the county-year level. The Average Pre estimate averages event-study coefficients for event years -5 through -2, with event year -1, the year immediately before entry, omitted as the reference period; the Average Post estimate averages coefficients for event years 0 through 9. Panel B reports maternal mortality rates separately for White and Black mothers, measured as maternal deaths per 100,000 live births. For maternal mortality, the Average Pre estimate averages coefficients for event years -3 and -2, with event year -1 omitted as the reference period, and the Average Post estimate averages coefficients for event years 0 through 4. Pre-treatment outcome means are calculated using observations from the corresponding pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A7: The Effect of Blue Cross Hospital Plans on Hospital Capacity

	Average Pre	Average Post	Pre-treatment Mean
Panel A: Bassinets			
Bassinets per 100 Women	0.002	0.001	0.097
	(0.003)	(0.005)	
Bassinets	0.255	6.854**	9.977
	(1.240)	(2.602)	
Panel B: Hospital Beds			
Beds per Capita	-0.033**	0.073***	0.462
	(0.016)	(0.026)	
Beds	-31.933	145.038**	211.334
	(27.392)	(55.740)	
Panel C: General Hospitals			
Has a General Hospital	-0.001	-0.008	0.546
	(0.012)	(0.022)	
General Hospitals per Capita	-0.0002	0.0002	0.004
	(0.0001)	(0.0003)	
General Hospitals	0.043	0.051	1.060
	(0.048)	(0.047)	

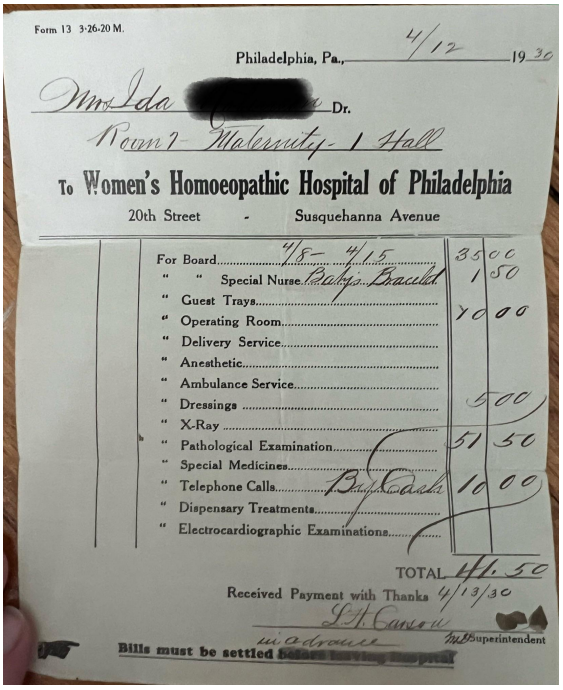
Notes: The table summarizes event-study estimates of the effect of Blue Cross hospital plan entry on hospital capacity. The Average Pre column reports the average of the pre-treatment event-study coefficients, excluding event year -1, the year immediately before entry, which is omitted as the reference period. The Average Post column reports the average of the post-treatment event-study coefficients. In Panel A, bassinets per 100 women measures the number of hospital bassinets per 100 women aged 15–44, while Bassinets reports the total number of bassinets in the county-year. In Panel B, Beds per Capita measures hospital beds relative to population, while Beds reports the total number of hospital beds in the county-year. In Panel C, Has a General Hospital is an indicator for the presence of at least one general hospital, General Hospitals per Capita measures the number of general hospitals relative to population, and General Hospitals reports the total number of general hospitals in the county-year. Pre-treatment means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A8: The Effect of Blue Cross Hospital Plans on Hospital Utilization and Mortality

	Average Pre	Average Post	Pre-treatment Mean
Panel A: Hospital Utilization			
Average Daily Census per Capita	-0.023*	0.068***	0.354
	(0.014)	(0.024)	
Average Daily Census	-45.767*	121.474**	169.014
	(21.128)	(47.568)	
Panel B: Hospital Mortality			
Mortality Rate	0.013	0.003	1.009
	(0.016)	(0.022)	
Deaths	-17.075	33.218	324.267
	(30.451)	(33.066)	

Notes: The table summarizes event-study estimates of the effect of Blue Cross hospital plan entry on hospital utilization and hospital mortality. The Average Pre column reports the average of the pre-treatment event-study coefficients, excluding event year -1, the year immediately before entry, which is omitted as the reference period. The Average Post column reports the average of the post-treatment event-study coefficients. In Panel A, Average Daily Census measures the average number of patients hospitalized on a given day, while Average Daily Census per Capita scales this measure by county population. In Panel B, Mortality Rate is calculated as the number of deaths divided by county population, while Deaths reports the total number of deaths in the county-year. Pre-treatment means are calculated using observations from the pre-treatment period. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Figure A1: Historical Receipts for Hospital Deliveries



Form 13 3-26-20 M.

Philadelphia, Pa., 4/12 1930

Mrs Ida [redacted] Dr.

Room 7 Maternity - 1 Hall

To Women's Homoeopathic Hospital of Philadelphia

20th Street - Susquehanna Avenue

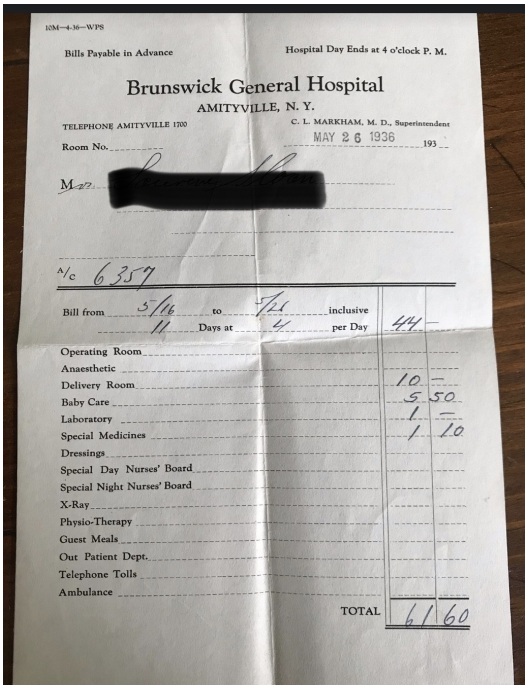
For Board 4/8 - 4/15		35 00
" " Special Nurse Baby's Bracelet		1 50
" Guest Trays		
" Operating Room		10 00
" Delivery Service		
" Anesthetic		
" Ambulance Service		
" Dressings		5 00
" X-Ray		
" Pathological Examination		51 50
" Special Medicines		
" Telephone Calls Bal Cash		10 00
" Dispensary Treatments		
" Electrocardiographic Examinations		
TOTAL		41.50

Received Payment with Thanks 4/13/30

L H Carson

in advance Superintendent

Bills must be settled before leaving Hospital



10M—4-36—WPS

Bills Payable in Advance

Hospital Day Ends at 4 o'clock P. M.

Brunswick General Hospital

AMITYVILLE, N. Y.

TELEPHONE AMITYVILLE 1700

C. L. MARKHAM, M. D., Superintendent

Room No. MAY 26 1936 193

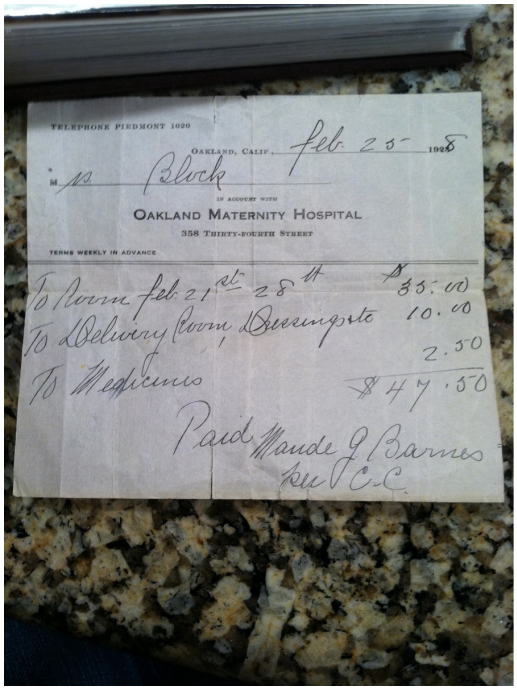
Mrs. [redacted]

A/c 6357

Bill from 5/16 to 5/21 inclusive

11 Days at 4 per Day 44 —

Operating Room	
Anaesthetic	
Delivery Room	10 —
Baby Care	5 50
Laboratory	1 —
Special Medicines	1 10
Dressings	
Special Day Nurses' Board	
Special Night Nurses' Board	
X-Ray	
Physio-Therapy	
Guest Meals	
Out Patient Dept.	
Telephone Tolls	
Ambulance	
TOTAL	61 60



TELEPHONE PIEDMONT 1020

OAKLAND, CALIF. feb 25 1928

Mrs Block

IN ACCOUNT WITH

OAKLAND MATERNITY HOSPITAL

358 THIRTY-FOURTH STREET

TERMS WEEKLY IN ADVANCE

To Room feb 21st 28th $35.00

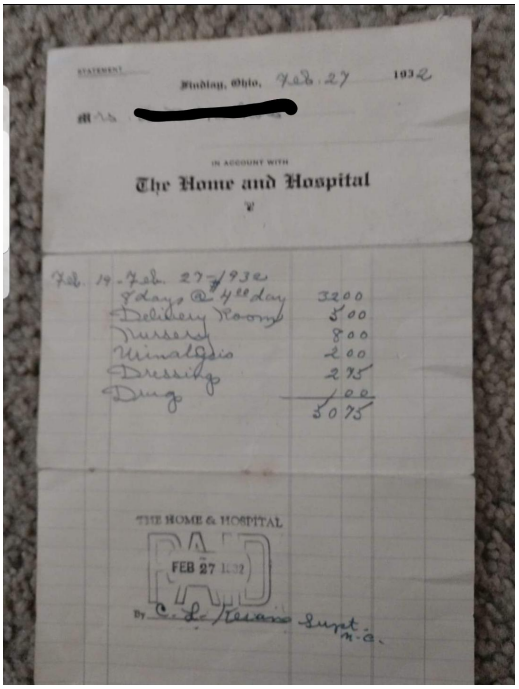
To Delivery Room, Duerngate 10.00

To Medicines 2.50

$47.50

Paid Maude J Barnes

per C.C.



STATEMENT

Findlay, Ohio, Feb. 27 1932

Mrs. [redacted]

IN ACCOUNT WITH

The Home and Hospital

Feb. 19 - Feb 27 - 1932

8 Days @ 4.00 Day	32 00
Delivery Room	5 00
Nursery	8 00
Minalgio	2 00
Dressing	2 75
Drug	1 00
	50 75

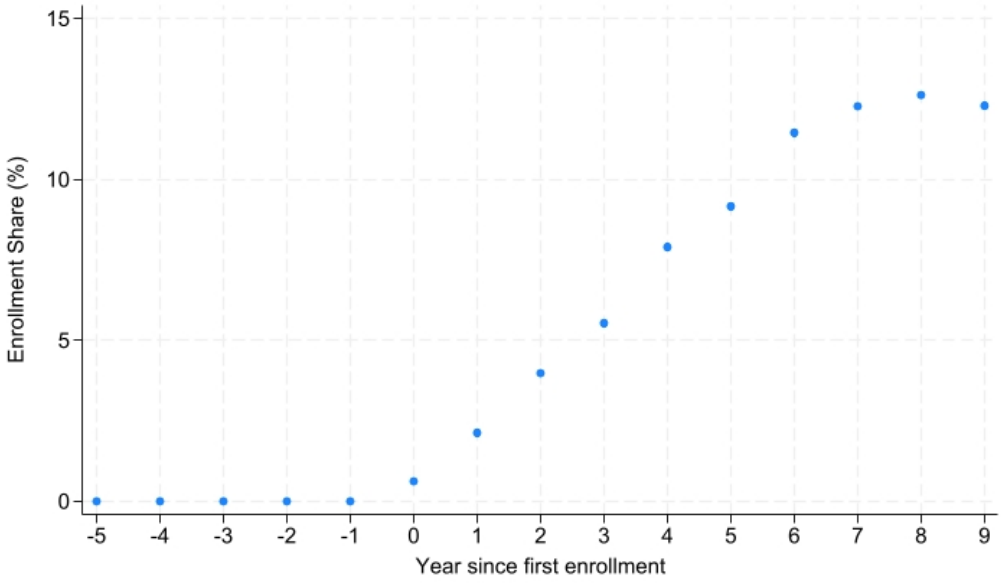
THE HOME & HOSPITAL

PAID

FEB 27 1932

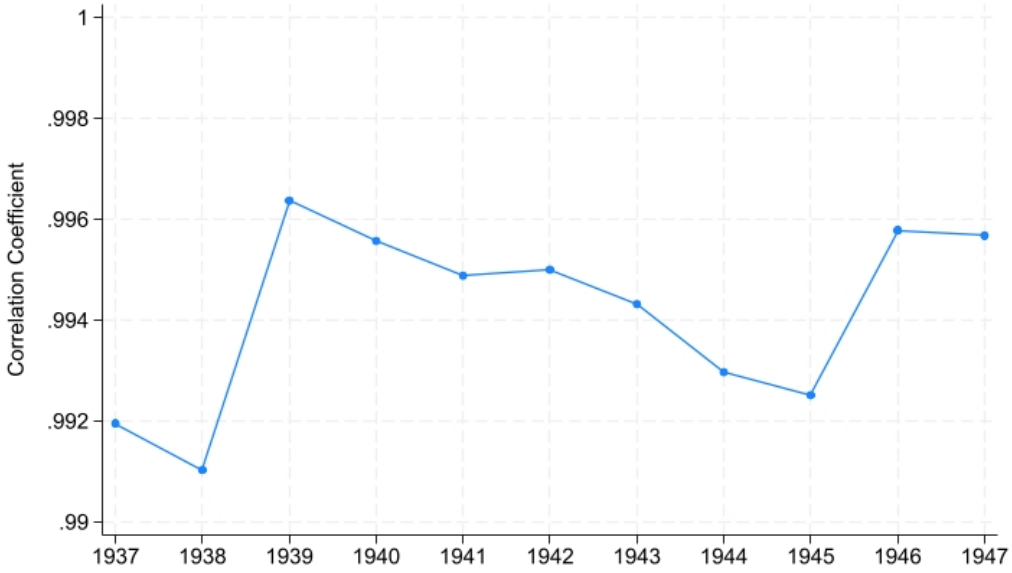
By C. L. Reeves Supt. M. C.

Figure A2: Blue Cross Enrollment Growth Following the First Year of Enrollment



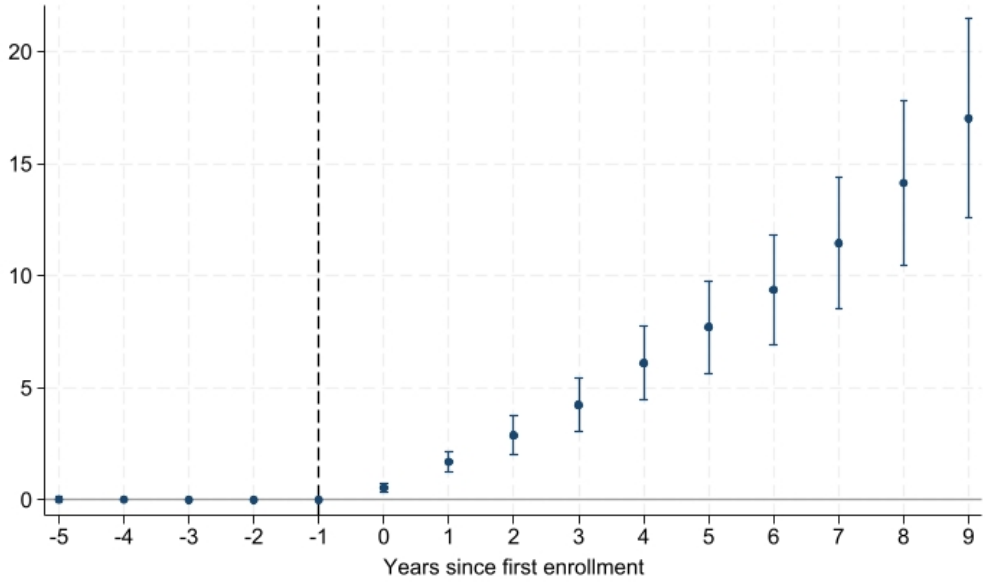
Notes: The figure plots average Blue Cross enrollment share by year relative to the first year of Blue Cross enrollment. Event year 0 denotes the first year of enrollment, while negative event years denote years prior to enrollment and positive event years denote years following enrollment. Enrollment share is measured on a 0–100 percentage scale.

Figure A3: Correlation Between Births by Residence and Births by Occurrence



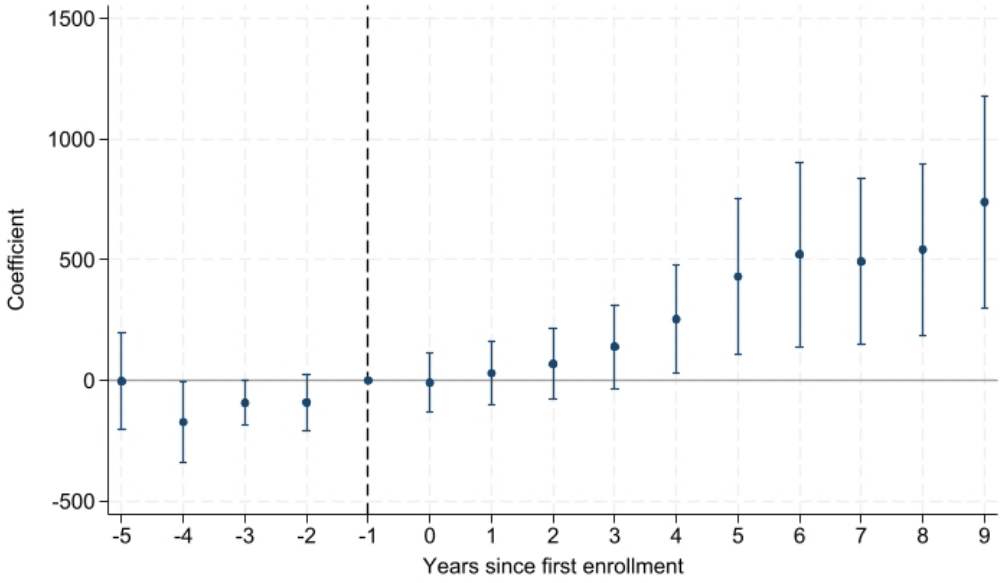
Notes: The figure plots the annual correlation between county-level births measured by place of residence and births measured by place of occurrence from 1937 to 1947. Each point represents the correlation coefficient across counties in a given year. Correlation coefficients closer to one indicate a stronger correspondence between the two measures.

Figure A4: The Effect of Blue Cross Hospital Plans on Enrollment Share: County-Level Estimates



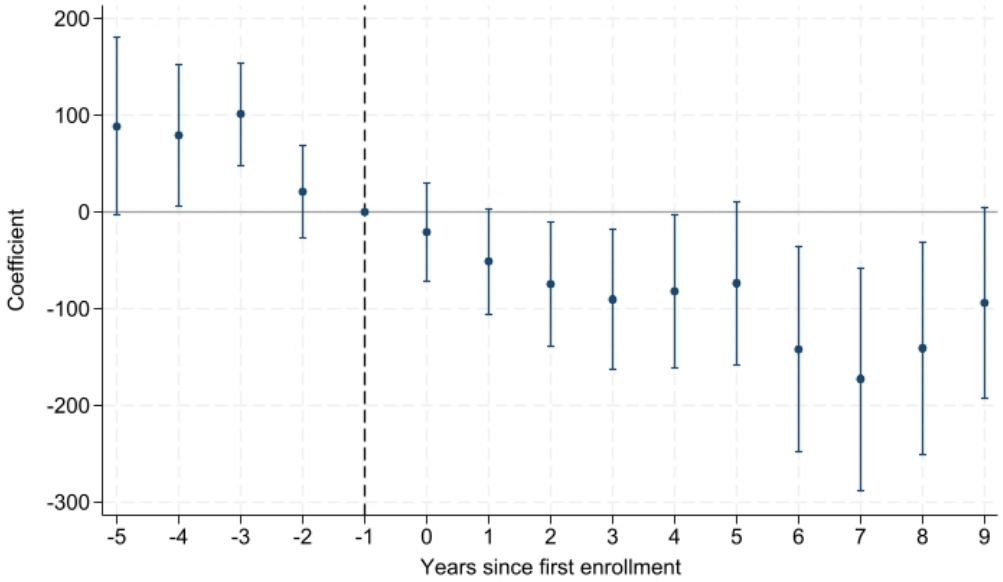
Notes: The figure plots county-level event-study estimates of the effect of Blue Cross hospital plan entry on Blue Cross enrollment share. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Enrollment share is measured on a 0–100 percentage scale. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A5: The Effect of Blue Cross Hospital Plans on Hospital Birth Counts



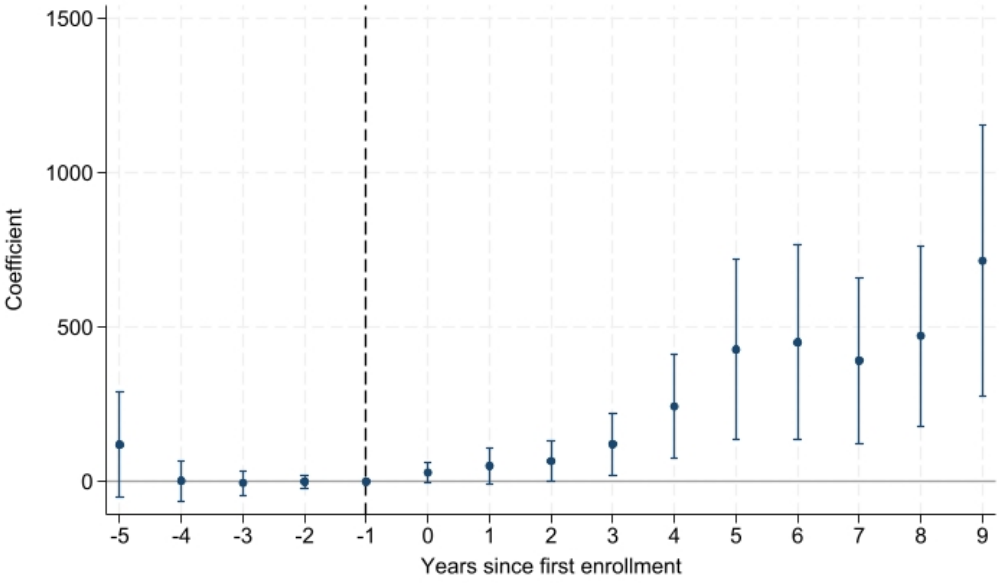
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the number of hospital births at the county-year level. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A6: The Effect of Blue Cross Hospital Plans on Non-Hospital Birth Counts



Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the number of non-hospital births at the county-year level. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Non-hospital births are calculated as total births minus hospital births. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

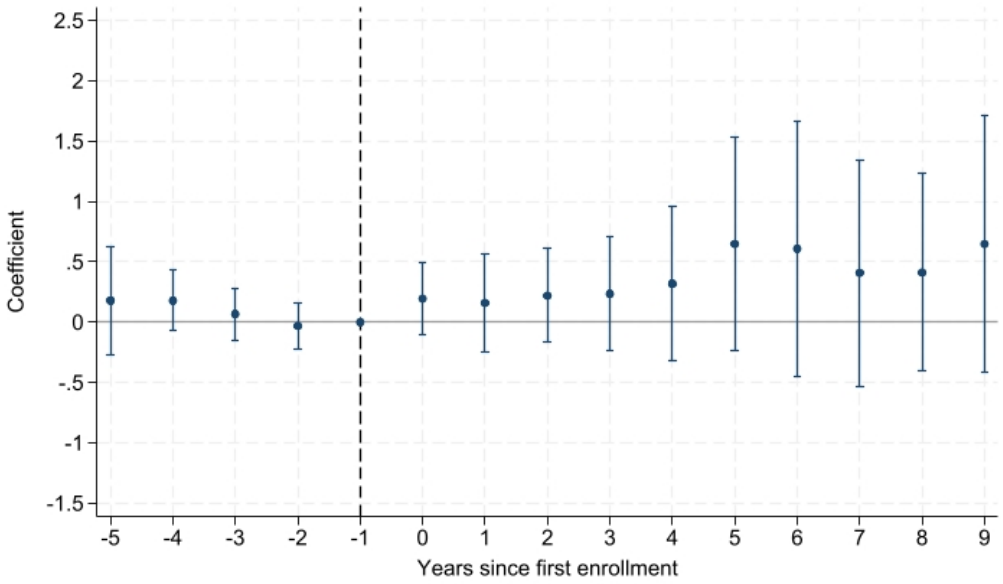
Figure A7: The Effect of Blue Cross Hospital Plans on Total Birth Counts



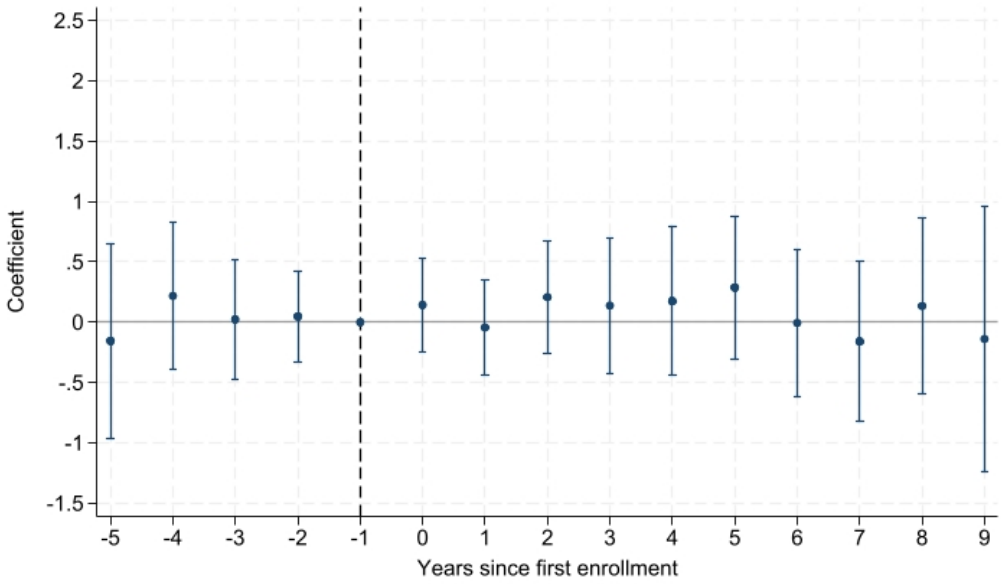
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the total number of births at the county-year level. Event time is measured relative to the first year of Blue Cross entry, with event year -1, the year immediately before entry, omitted as the reference period. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A8: The Effect of Blue Cross Hospital Plans on Births per 100 Women aged 15–44, by Hospital Availability

Panel A. Has a Hospital



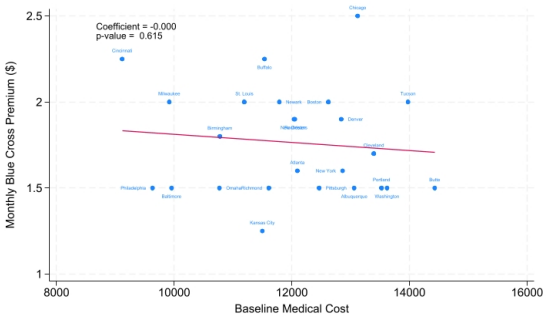
Panel B. No Hospital



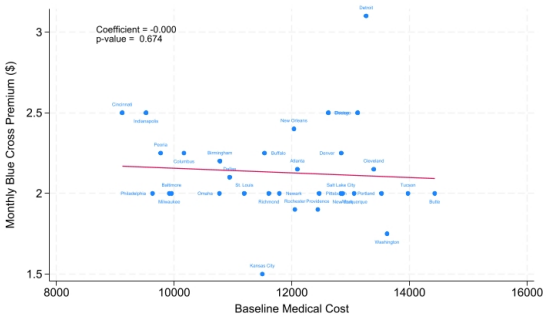
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the birth rate separately for counties with and without a hospital at baseline. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The birth rate is measured as total births per 100 women ages 15–44. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A9: Baseline Medical Costs and Monthly Blue Cross Premiums

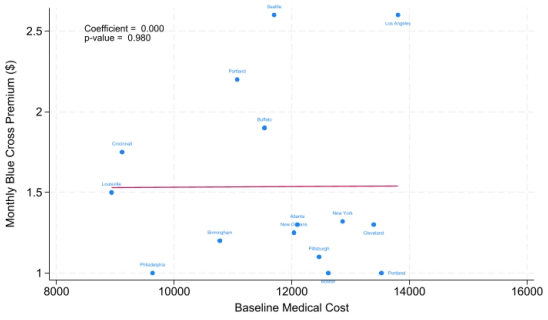
Panel A. Semiprivate, Two-Person Plan



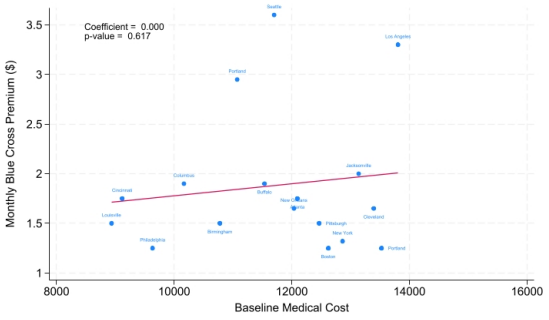
Panel B. Semiprivate, Family Plan



Panel C. Ward, Two-Person Plan



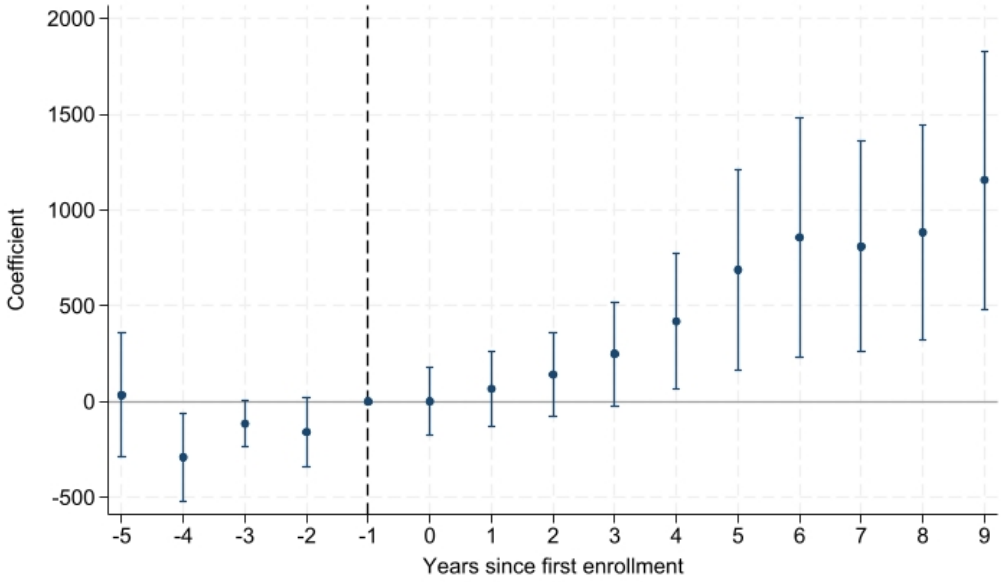
Panel D. Ward, Family Plan



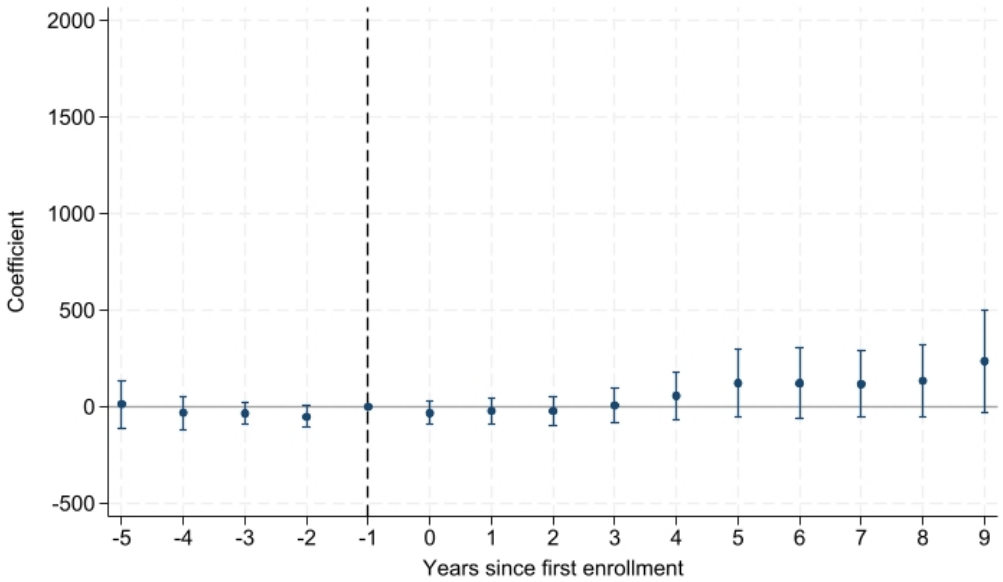
Notes: Each panel plots city-level monthly Blue Cross premiums against baseline medical service costs. Baseline medical costs are measured using the 1935 cost of a standardized bundle of minimum medical services for a four-person family. Panels A and B report premiums for semiprivate-room coverage under two-person and family plans, respectively; Panels C and D report premiums for ward coverage under two-person and family plans. The solid line shows the fitted linear relationship between baseline medical costs and monthly premiums. The estimated regression coefficient and corresponding p-value are reported in the upper-left corner of each panel.

Figure A10: The Effect of Blue Cross Hospital Plans on Hospital Birth Counts by Baseline Medical Costs

Panel A. High Baseline Medical Costs



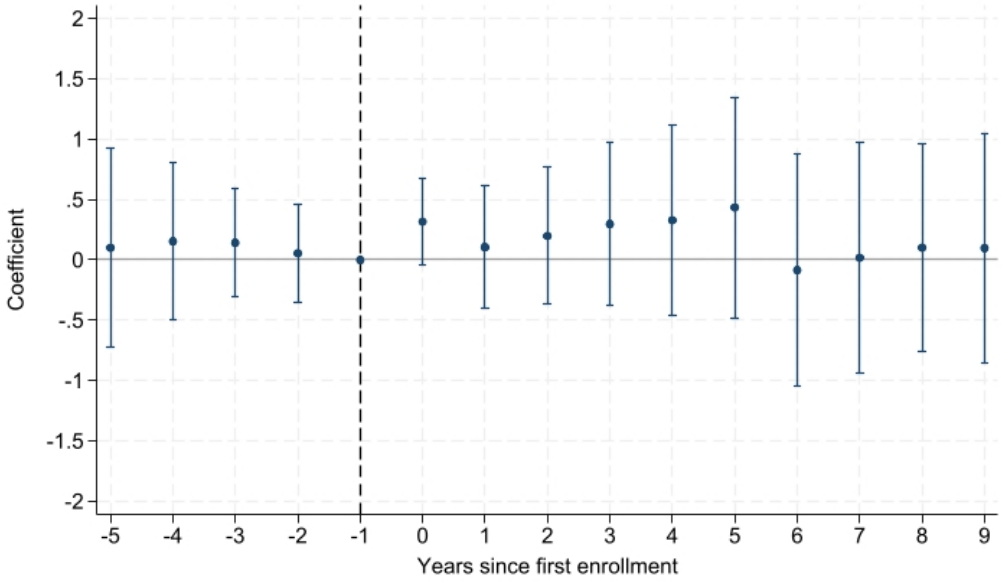
Panel B. Low Baseline Medical Costs



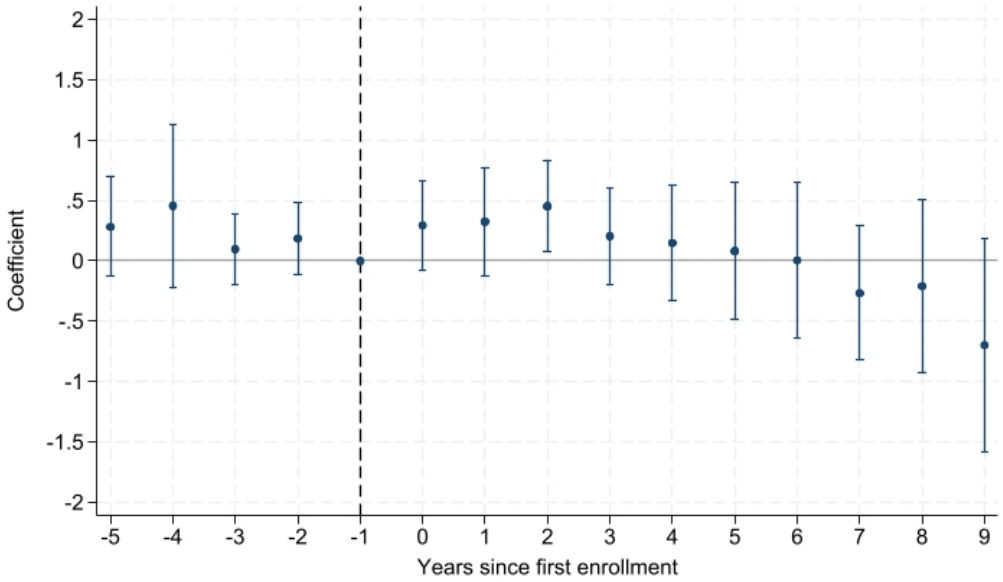
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on hospital birth counts separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Hospital birth counts are measured as the total number of hospital births in a county-year. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A11: The Effect of Blue Cross Hospital Plans on Non-Hospital Births per 100 Women aged 15–44 by Baseline Medical Costs

Panel A. High Baseline Medical Costs



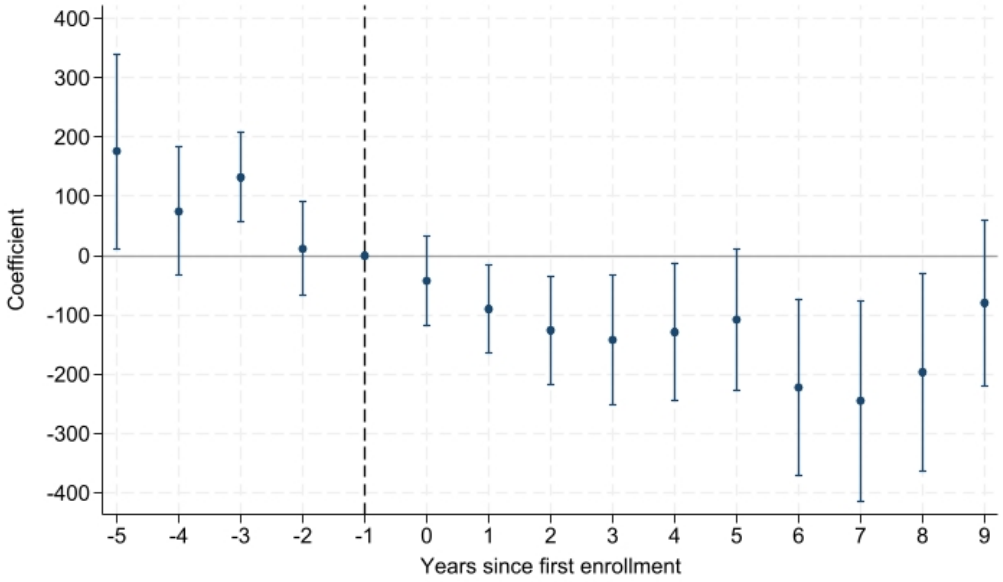
Panel B. Low Baseline Medical Costs



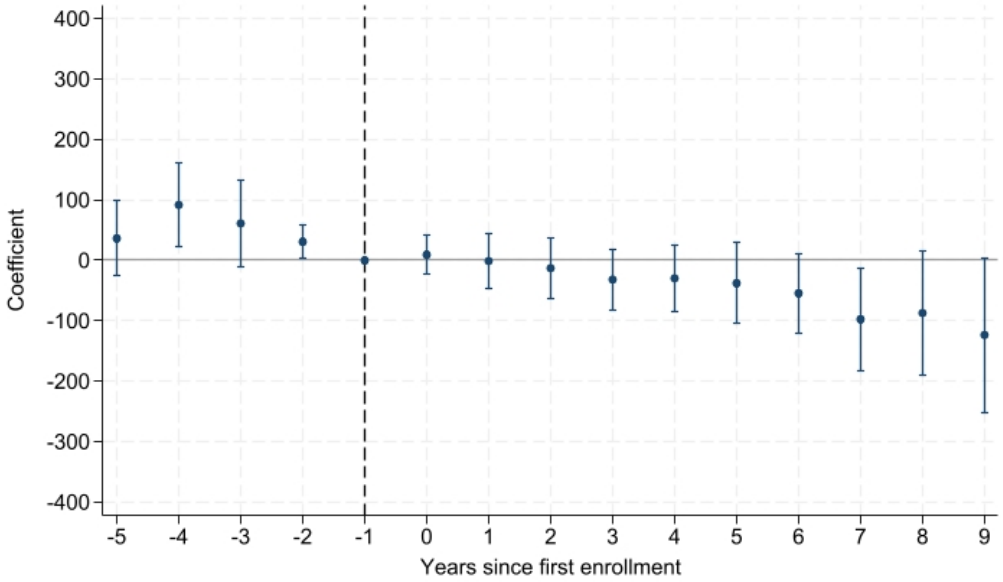
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the non-hospital birth rate separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. The non-hospital birth rate measures births occurring outside hospitals per 100 women ages 15–44 and is constructed as the difference between the total birth rate and the hospital birth rate. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A12: The Effect of Blue Cross Hospital Plans on Non-Hospital Birth Counts by Baseline Medical Costs

Panel A. High Baseline Medical Costs



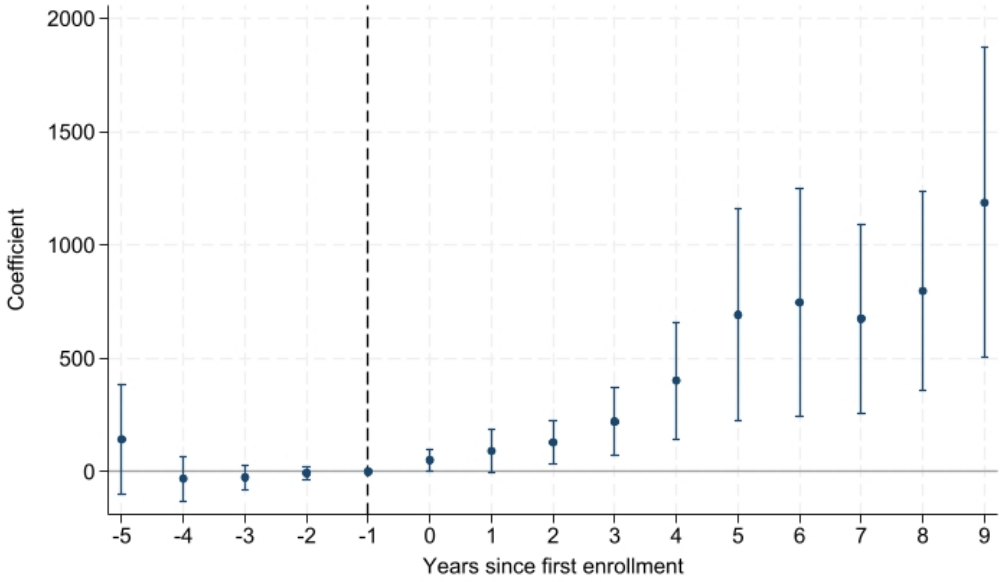
Panel B. Low Baseline Medical Costs



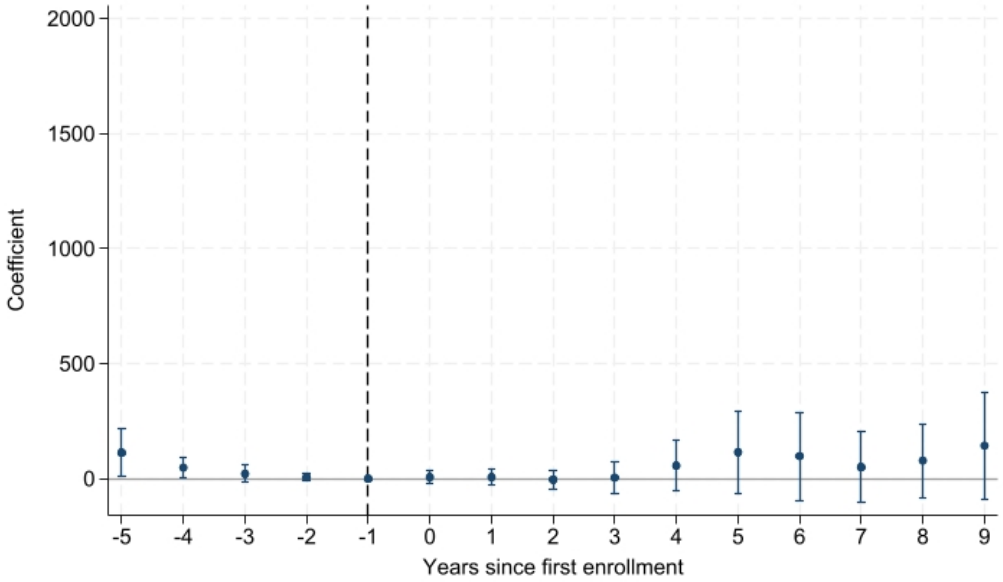
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on non-hospital birth counts separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. Event time is measured relative to the first year of Blue Cross entry, with event year -1, the year immediately before entry, omitted as the reference period. Non-hospital birth counts are calculated as total births minus hospital births at the county-year level. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A13: The Effect of Blue Cross Hospital Plans on Total Birth Counts by Baseline Medical Costs

Panel A. High Baseline Medical Costs



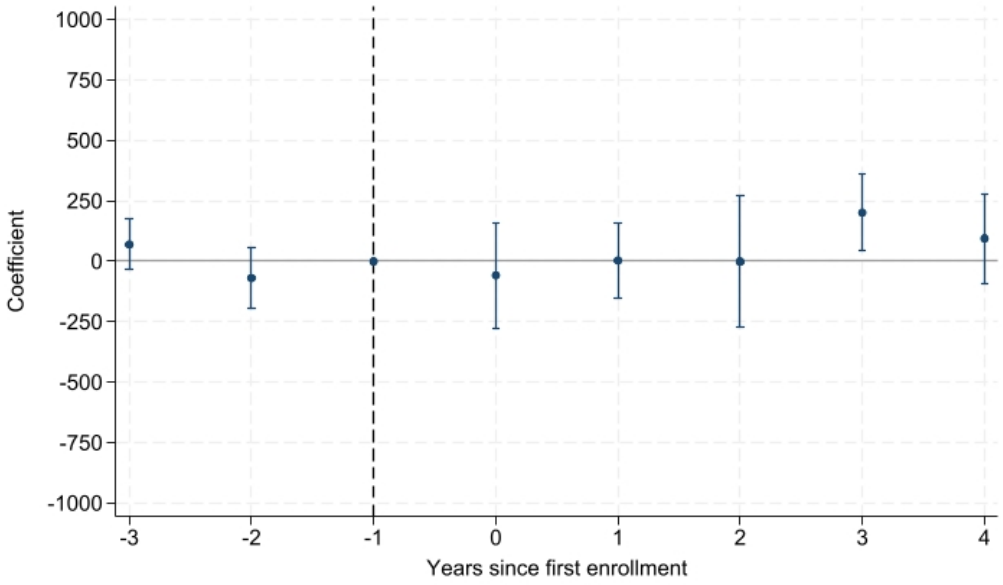
Panel B. Low Baseline Medical Costs



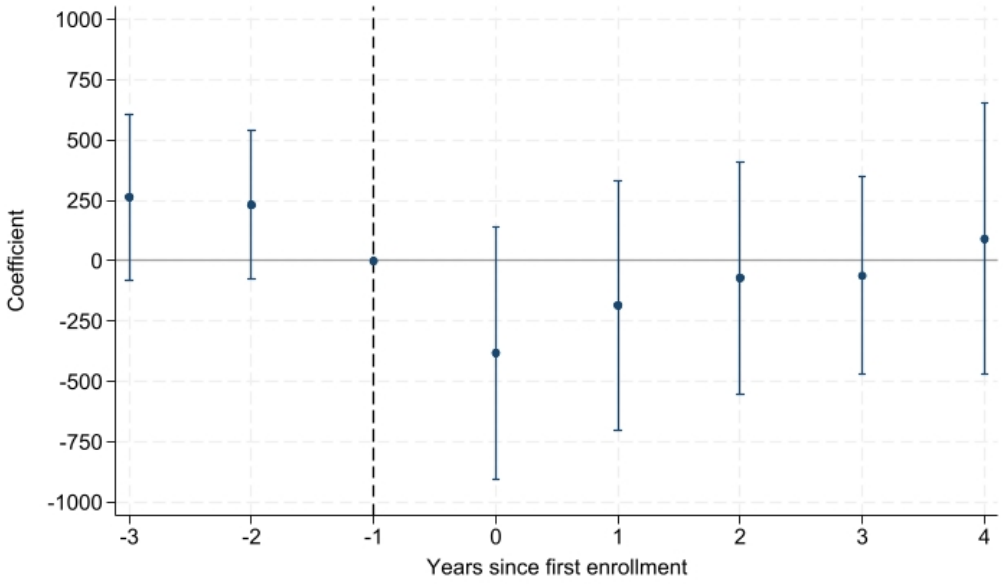
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on total birth counts separately for counties with high and low baseline medical costs. Counties are classified as high or low cost based on whether minimum medical service costs are above or below the sample mean. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Total birth counts are measured as the total number of births in a county-year. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A14: The Effect of Blue Cross Hospital Plans on Maternal Mortality Rates by Race

Panel A. White

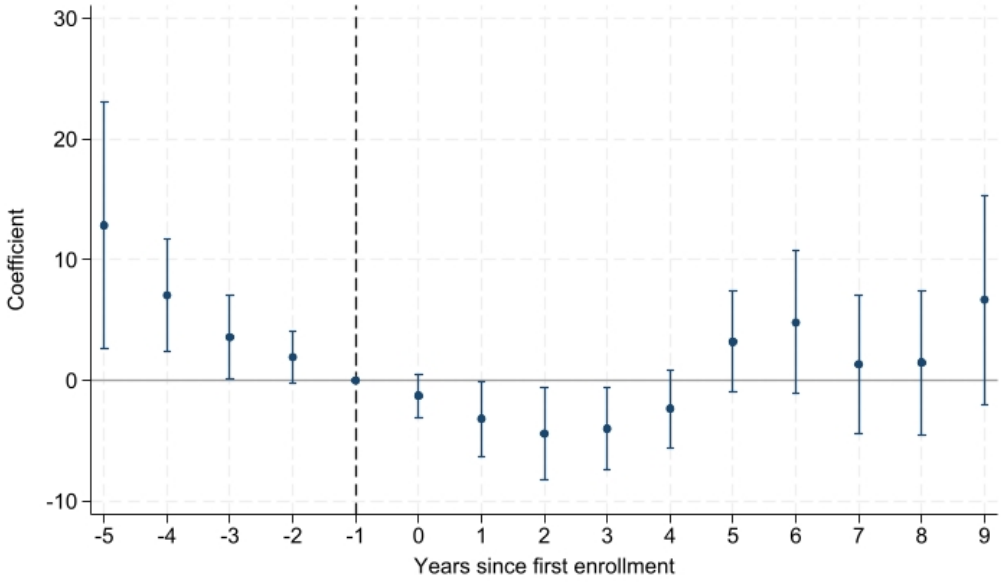


Panel B. Black



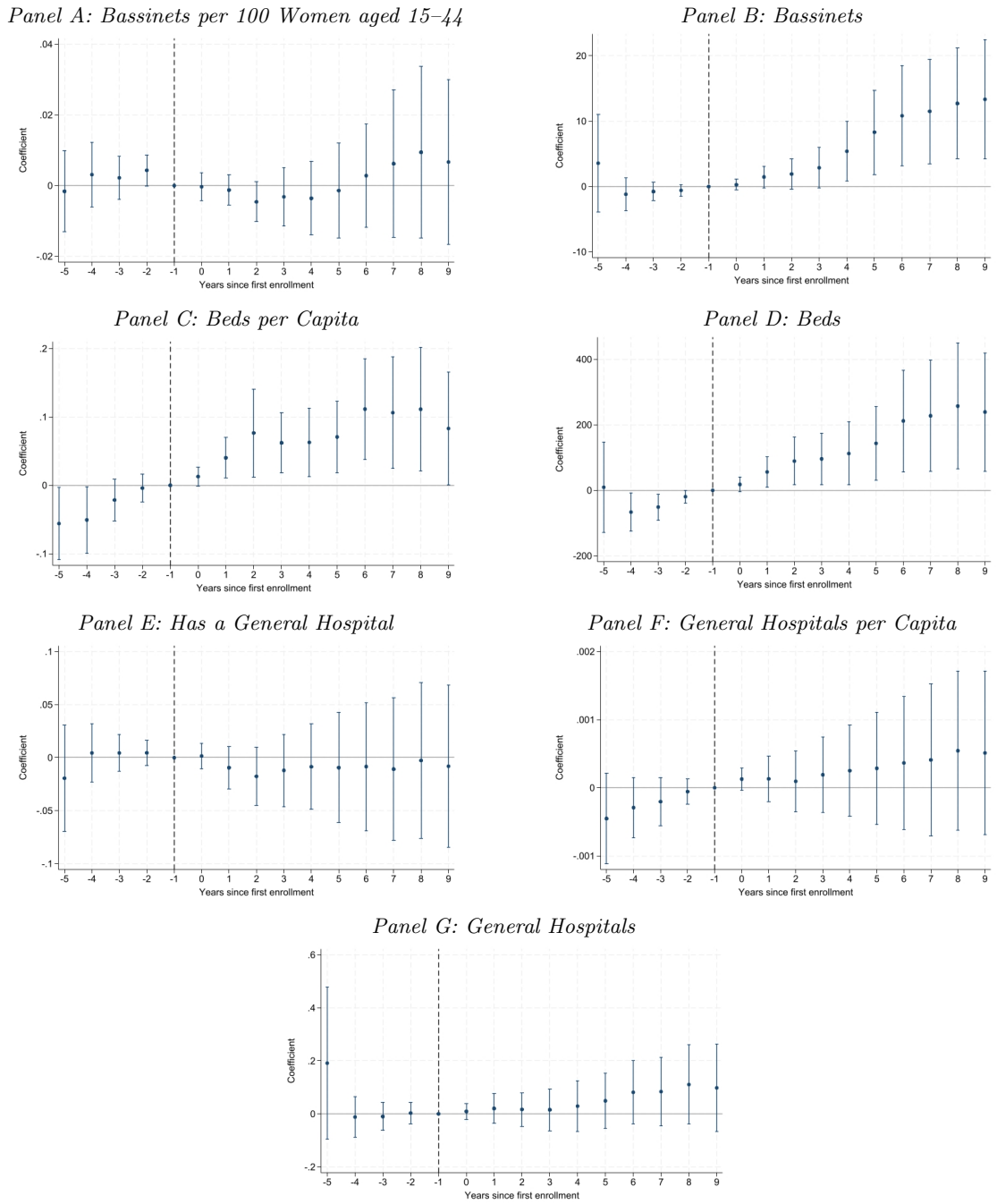
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on maternal mortality rates separately for White and Black mothers. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Maternal mortality rates are measured as maternal deaths per 100,000 live births. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A15: The Effect of Blue Cross Hospital Plans on Infant Deaths



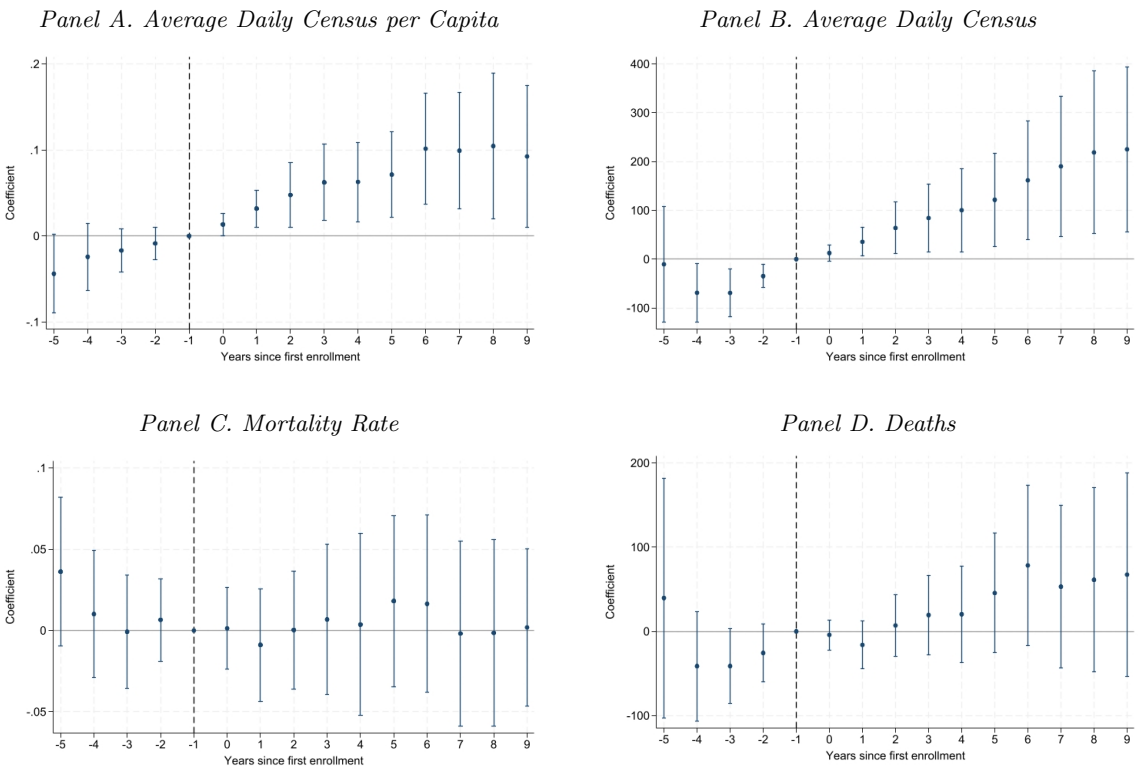
Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on the number of infant deaths at the county-year level. Event time is measured relative to the first year of Blue Cross entry, with event year -1, the year immediately before entry, omitted as the reference period. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A16: The Effect of Blue Cross Hospital Plans on Hospital Capacity



Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on measures of hospital capacity. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Panels A and B report the number of hospital bassinets, scaled per 100 women ages 15–44 and in levels, respectively. Panels C and D report hospital beds per capita and the total number of hospital beds. Panels E–G report an indicator for the presence of at least one general hospital, the number of general hospitals per capita, and the total number of general hospitals, respectively. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

Figure A17: The Effect of Blue Cross Hospital Plans on Hospital Utilization and Mortality



Notes: The figure plots event-study estimates of the effect of Blue Cross hospital plan entry on hospital utilization and mortality. Event time is measured relative to the first year of Blue Cross entry, with event year −1, the year immediately before entry, omitted as the reference period. Panels A and B report average daily census, scaled by county population and in levels, respectively. Average daily census measures the average number of patients hospitalized on a given day. Panel C reports the mortality rate, calculated as the number of deaths divided by county population. Panel D reports the total number of deaths in the county-year. Points indicate estimated coefficients, and vertical bars show 95 percent confidence intervals.

B Detailed Conceptual Framework

B.1 Household Problem

I develop a simple static framework in which households choose whether to attempt conception, while a live birth is realized probabilistically. This distinction separates the behavioral fertility decision from the live-birth outcome observed in the data.

Consider household i in period t. Let

$$a_{it} \in \{0, 1\} \tag{1}$$

denote whether the household attempts conception, where $a_{it} = 1$ indicates that the household chooses to try to conceive. Conditional on attempting conception, a live birth occurs with probability $p_{it} \in (0, 1)$. Let $\xi_{it} \in \{0, 1\}$ indicate whether an attempt results in a live birth:

$$\xi_{it} \sim \text{Bernoulli}(p_{it}) \tag{2}$$

The realized live-birth outcome is therefore

$$b_{it} = a_{it}\xi_{it} \tag{3}$$

Thus, $\Pr(b_{it} = 1 \mid a_{it} = 1) = p_{it}$ and $\Pr(b_{it} = 1 \mid a_{it} = 0) = 0$.

Households differ in their underlying propensity to attempt conception. Let ε_{it} denote an idiosyncratic utility shifter associated with attempting conception, observed by the household before the attempt decision, with

$$\varepsilon_{it} \sim F \tag{4}$$

where F is a continuously differentiable cumulative distribution function with density f. I assume that ε_{it} is independent of insurance status and of the biological realization ξ_{it}, conditional on the household's economic environment.

Let N_{it} denote the number of surviving children at the beginning of the period. Conditional on a live birth, let $z_{it} \in \{0, 1\}$ denote infant survival, where q_{it} is the probability that a live-born infant survives:

$$z_{it} \sim \text{Bernoulli}(q_{it}) \tag{5}$$

If the infant survives, the household has $N_{it} + 1$ surviving children; otherwise it remains at N_{it}

surviving children at the end of the period.

Household utility depends on consumption, the number of surviving children, and female non-market labor time. A live birth also imposes a maternal health cost. Conditional on the attempt decision and realized birth outcome, household utility is

$$u(c_{it}, N_{it} + b_{it}z_{it}, h_{it}) - b_{it}R(H_{it}) + a_{it}\varepsilon_{it} \tag{6}$$

where $u_c > 0$ and $u_N > 0$. The term $R(H_{it})$ captures the health cost associated with pregnancy and childbirth, where H_{it} denotes maternal health.

Insurance status is determined prior to the conception-attempt decision. Let $I_{it} \in \{0, 1\}$ denote insurance status and let Π_{it} denote premium expenditure over the period conditional on being insured. Actual premium expenditure is therefore $I_{it}\Pi_{it}$ and is incurred regardless of whether a birth subsequently occurs.

Conditional on conception-attempt choice $a \in \{0, 1\}$ and realized live-birth outcome $j \in \{0, 1\}$, define household value as

$$V_{it}^{a,j} = \max_{c_{it}, L_{it}, h_{it}} \{E_t \left[u(c_{it}, N_{it} + jz_{it}, h_{it})\right] - jR(H_{it}) + a\varepsilon_{it}\} \tag{7}$$

subject to

$$c_{it} = y_{it} + w(H_{it})L_{it} - I_{it}\Pi_{it} - jP_{it}(I_{it}, C_i) \tag{8}$$

and

$$L_{it} + h_{it} + \ell j = 1 \tag{9}$$

Here, y_{it} denotes non-wife labor household income, L_{it} female labor supply, h_{it} wife's non-market time, $w(H_{it})$ the wage as a function of maternal health, C_i the baseline uninsured cost of childbirth in the local market, $P_{it}(I_{it}, C_i)$ the out-of-pocket childbirth expense, and ℓ the time cost associated with childbirth.

Let $\lambda_{it}^{a,j} > 0$ denote the multiplier on the budget constraint conditional on (a, j). By the envelope theorem, $\lambda_{it}^{a,j}$ is the marginal value of household resources in that state. Because the attempt-specific utility shifter is additive, it affects the decision to attempt conception but does not alter the optimal allocation of consumption, labor supply, or non-market time conditional on a realized birth outcome.

The household chooses whether to attempt conception before the live-birth outcome is realized. Let W_{it}^{a} denote the household's expected value associated with conception-attempt choice a, evaluated before the live-birth outcome is realized. If the household does not attempt conception, then $b_{it} = 0$ with certainty and

$$W_{it}^{0} = V_{it}^{0,0} \tag{10}$$

If the household attempts conception, a live birth occurs with probability p_{it}, so

$$W_{it}^{1} = p_{it} V_{it}^{1,1} + (1 - p_{it}) V_{it}^{1,0} \tag{11}$$

Define the relative value of attempting conception as

$$\Delta_{it} \equiv W_{it}^{1} - W_{it}^{0} \tag{12}$$

Because the states $(a, j) = (1, 0)$ and $(a, j) = (0, 0)$ have identical budget and time constraints and differ only by the additive attempt-specific utility shifter,

$$V_{it}^{1,0} - V_{it}^{0,0} = \varepsilon_{it} \tag{13}$$

It follows that

$$\Delta_{it} = p_{it} \left(V_{it}^{1,1} - V_{it}^{1,0} \right) + \varepsilon_{it} \tag{14}$$

Define the systematic component of the relative value of attempting conception as

$$\overline{\Delta}_{it} \equiv p_{it} \left(V_{it}^{1,1} - V_{it}^{1,0} \right) \tag{15}$$

The household attempts conception when

$$a_{it}^{*} = \mathbf{1} \left\{ \overline{\Delta}_{it} + \varepsilon_{it} \geq 0 \right\} \tag{16}$$

Thus,

$$\Pr(a_{it}^{*} = 1) = 1 - F(-\overline{\Delta}_{it}) \tag{17}$$

Since a live birth occurs with probability p_{it} conditional on attempting conception,

$$\Pr(b_{it} = 1) = p_{it} \left[1 - F(-\overline{\Delta}_{it}) \right] \tag{18}$$

For a variable x that affects household value but does not directly affect p_{it},

$$\frac{\partial \Pr(b_{it} = 1)}{\partial x} = p_{it}^{2} f(-\overline{\Delta}_{it}) \frac{\partial \left(V_{it}^{1,1} - V_{it}^{1,0} \right)}{\partial x} \tag{19}$$

Hence, for households with positive density around the conception threshold, the direction of the

effect on realized live births is determined by the direction of the effect on the value of the live-birth state relative to the no-live-birth state, conditional on attempting conception. The following sections consider how insurance changes this relative value through three channels.

B.2 Financial Channel

The financial channel operates through the way insurance changes household resources across the live-birth and no-live-birth states. Let $C_i > 0$ denote the baseline uninsured cost of childbirth. Suppose insurance covers a fraction $\kappa \in (0,1)$ of this cost:

$$P_{it}(I_{it}, C_i) = (1 - \kappa I_{it})C_i \tag{20}$$

Insurance therefore reduces the out-of-pocket expense associated with a live birth by

$$P_{it}(0, C_i) - P_{it}(1, C_i) = \kappa C_i \tag{21}$$

This reduction is realized only in the live-birth state, whereas the premium $I_{it}\Pi_{it}$ is paid regardless of whether a live birth occurs.

Holding maternal health and infant survival fixed, the envelope theorem gives, conditional on attempting conception,

$$\left.\frac{\partial V_{it}^{1,j}}{\partial I_{it}}\right|_{\text{Financial}} = \lambda_{it}^{1,j}\left[-\Pi_{it} - j\frac{\partial P_{it}}{\partial I_{it}}\right], \qquad j \in \{0,1\} \tag{22}$$

Since $\partial P_{it}/\partial I_{it} = -\kappa C_i$,

$$\left.\frac{\partial V_{it}^{1,1}}{\partial I_{it}}\right|_{\text{Financial}} = \lambda_{it}^{1,1}(-\Pi_{it} + \kappa C_i) \tag{23}$$

$$\left.\frac{\partial V_{it}^{1,0}}{\partial I_{it}}\right|_{\text{Financial}} = -\lambda_{it}^{1,0}\Pi_{it} \tag{24}$$

The financial effect of insurance on the value of the live-birth state relative to the no-live-birth state is therefore

$$\left.\frac{\partial\left(V_{it}^{1,1} - V_{it}^{1,0}\right)}{\partial I_{it}}\right|_{\text{Financial}} = \lambda_{it}^{1,1}\kappa C_i - \Pi_{it}\left(\lambda_{it}^{1,1} - \lambda_{it}^{1,0}\right) \tag{25}$$

$$= \lambda_{it}^{1,1}(\kappa C_i - \Pi_{it}) + \Pi_{it}\lambda_{it}^{1,0} \tag{26}$$

Because $\lambda_{it}^{1,1} > 0$, $\lambda_{it}^{1,0} > 0$, and $\Pi_{it} \geq 0$, a sufficient condition for this effect to be positive is

$$\kappa C_i \geq \Pi_{it} \tag{27}$$

Under this condition, insurance raises the relative value of the live-birth state. Since $p_{it} > 0$ and is assumed not to depend on insurance,

$$\left.\frac{\partial \overline{\Delta}_{it}}{\partial I_{it}}\right|_{\text{Financial}} = p_{it}\left[\lambda_{it}^{1,1}\kappa C_i - \Pi_{it}\left(\lambda_{it}^{1,1} - \lambda_{it}^{1,0}\right)\right] > 0 \tag{28}$$

Using equation (19), the financial component of the effect on the probability of a realized live birth is

$$\left.\frac{\partial \Pr(b_{it}=1)}{\partial I_{it}}\right|_{\text{Financial}} = p_{it}^2 f(-\overline{\Delta}_{it})\left[\lambda_{it}^{1,1}\kappa C_i - \Pi_{it}\left(\lambda_{it}^{1,1} - \lambda_{it}^{1,0}\right)\right] > 0 \tag{29}$$

for households with positive density around the conception threshold. Thus, when condition (27) holds, insurance increases the incentive to attempt conception and the probability of a realized live birth.

B.2.1 Heterogeneity by Baseline Childbirth Costs

The financial channel also generates a prediction for heterogeneity across markets with different baseline childbirth costs. For a given coverage rate κ, equation (21) shows that insurance removes a larger dollar expense where childbirth is more costly.

Define the financial effect on the systematic value of attempting conception as

$$G(C_i) \equiv \left.\frac{\partial \overline{\Delta}_{it}}{\partial I_{it}}\right|_{\text{Financial}} = p_{it}\left[\lambda_{it}^{1,1}(C_i)\kappa C_i - \Pi_{it}\left(\lambda_{it}^{1,1}(C_i) - \lambda_{it}^{1,0}\right)\right] \tag{30}$$

Baseline childbirth costs enter the household budget only in the live-birth state, so, conditional on the premium, $\lambda_{it}^{1,0}$ does not depend on C_i. In the live-birth state, a higher C_i reduces household resources. Under concavity of the conditional value function in resources,

$$\frac{\partial \lambda_{it}^{1,1}(C_i)}{\partial C_i} \geq 0 \tag{31}$$

To see this, let $m_{it}^{1,1} = y_{it} - I_{it}\Pi_{it} - (1 - \kappa I_{it})C_i$ denote non-labor resources available in the live-birth state. Since $\lambda_{it}^{1,1} = \partial V_{it}^{1,1}/\partial m_{it}^{1,1}$, concavity implies $\partial^2 V_{it}^{1,1}/\partial (m_{it}^{1,1})^2 \leq 0$, while $\partial m_{it}^{1,1}/\partial C_i < 0$. Hence equation (31) follows.

Holding p_{it}, κ, and Π_{it} fixed with respect to C_i, differentiating equation (30) gives

$$\frac{\partial G(C_i)}{\partial C_i} = p_{it}\left[\kappa\lambda_{it}^{1,1}(C_i) + (\kappa C_i - \Pi_{it})\frac{\partial\lambda_{it}^{1,1}(C_i)}{\partial C_i}\right] \tag{32}$$

Under condition (27), the second term is nonnegative and the first is strictly positive. Therefore,

$$\frac{\partial G(C_i)}{\partial C_i} > 0 \tag{33}$$

Thus, under these conditions, insurance has a larger financial effect on the incentive to attempt conception where baseline childbirth costs are higher.

To translate this prediction into the realized live-birth outcome observed in the data, recall that

$$\left.\frac{\partial \Pr(b_{it}=1)}{\partial I_{it}}\right|_{\text{Financial}} = p_{it} f(-\overline{\Delta}_{it}) G(C_i) \tag{34}$$

The response of realized births therefore depends both on the effect of insurance on the incentive to attempt conception, $G(C_i)$, and on the share of households near the conception-attempt threshold. If this share is comparable across markets, the larger financial incentive in higher-cost markets translates into a larger increase in realized births.

B.3 Maternal Health Channel

The maternal-health channel operates through the effect of insurance on maternal health. Holding the financial and infant-survival channels fixed, suppose

$$H_{it} = H(I_{it}), \qquad H_I \equiv \frac{\partial H_{it}}{\partial I_{it}} > 0 \tag{35}$$

Maternal health affects household value through two components. Better maternal health reduces the health cost of pregnancy and childbirth,

$$R_H(H_{it}) < 0 \tag{36}$$

and raises female labor-market productivity,

$$w_H(H_{it}) > 0 \tag{37}$$

Let $L_{it}^{1,j}$ denote optimal female labor supply conditional on attempting conception and realized birth outcome j. By the envelope theorem,

$$\frac{\partial V_{it}^{1,j}}{\partial H_{it}} = -jR_H(H_{it}) + \lambda_{it}^{1,j} w_H(H_{it}) L_{it}^{1,j}, \qquad j \in \{0,1\} \tag{38}$$

Therefore,

$$\frac{\partial \left(V_{it}^{1,1} - V_{it}^{1,0}\right)}{\partial H_{it}} = -R_H(H_{it}) + w_H(H_{it}) \left[\lambda_{it}^{1,1} L_{it}^{1,1} - \lambda_{it}^{1,0} L_{it}^{1,0}\right] \tag{39}$$

The first component is positive because better maternal health reduces the health cost incurred in the live-birth state. The second component captures the labor-market effect. Although $w_H(H_{it}) > 0$, its sign is ambiguous because the value of the wage increase depends on labor supply and the marginal value of resources in the two birth states.

The maternal-health effect of insurance on the systematic value of attempting conception is therefore

$$\left.\frac{\partial \overline{\Delta}_{it}}{\partial I_{it}}\right|_{\text{Maternal}} = p_{it} \left\{-R_H(H_{it}) + w_H(H_{it}) \left[\lambda_{it}^{1,1} L_{it}^{1,1} - \lambda_{it}^{1,0} L_{it}^{1,0}\right]\right\} H_I \gtrless 0 \tag{40}$$

Using equation (19), the same sign carries through to the probability of a realized live birth:

$$\left.\frac{\partial \Pr(b_{it}=1)}{\partial I_{it}}\right|_{\text{Maternal}} = p_{it}^2 f(-\overline{\Delta}_{it}) \left\{-R_H(H_{it}) + w_H(H_{it}) \left[\lambda_{it}^{1,1} L_{it}^{1,1} - \lambda_{it}^{1,0} L_{it}^{1,0}\right]\right\} H_I \gtrless 0 \tag{41}$$

Thus, better maternal health lowers the health cost of childbirth, which can increase the incentive to attempt conception, but can also raise the opportunity cost of childbearing through improved labor-market productivity. The overall maternal-health effect on fertility is therefore theoretically ambiguous.

B.4 Infant Survival Channel

The infant-survival channel operates through the probability that a live-born infant survives. Suppose

$$q_{it} = q(I_{it}), \qquad q_I \equiv \frac{\partial q_{it}}{\partial I_{it}} > 0 \tag{42}$$

Conditional on attempting conception and realizing a live birth,

$$E_t\left[u(c_{it}^{1,1}, N_{it} + z_{it}, h_{it}^{1,1})\right] = q_{it} u(c_{it}^{1,1}, N_{it} + 1, h_{it}^{1,1}) \tag{43}$$

$$+ (1 - q_{it}) u(c_{it}^{1,1}, N_{it}, h_{it}^{1,1}) \tag{44}$$

By the envelope theorem,

$$\frac{\partial V_{it}^{1,1}}{\partial q_{it}} = u(c_{it}^{1,1}, N_{it}+1, h_{it}^{1,1}) - u(c_{it}^{1,1}, N_{it}, h_{it}^{1,1}) > 0 \tag{45}$$

where the inequality follows from $u_N > 0$. Conditional on attempting conception but realizing no live birth, infant survival is irrelevant, so $\partial V_{it}^{1,0}/\partial q_{it} = 0$. Hence,

$$\frac{\partial \left(V_{it}^{1,1} - V_{it}^{1,0}\right)}{\partial q_{it}} = u(c_{it}^{1,1}, N_{it}+1, h_{it}^{1,1}) - u(c_{it}^{1,1}, N_{it}, h_{it}^{1,1}) > 0 \tag{46}$$

The corresponding effect of insurance on the systematic value of attempting conception is

$$\left.\frac{\partial \overline{\Delta}_{it}}{\partial I_{it}}\right|_{\text{Infant}} = p_{it}\left[u(c_{it}^{1,1}, N_{it}+1, h_{it}^{1,1}) - u(c_{it}^{1,1}, N_{it}, h_{it}^{1,1})\right] q_I > 0 \tag{47}$$

Using equation (19),

$$\left.\frac{\partial \Pr(b_{it}=1)}{\partial I_{it}}\right|_{\text{Infant}} = p_{it}^2 f(-\overline{\Delta}_{it})\left[u(c_{it}^{1,1}, N_{it}+1, h_{it}^{1,1}) - u(c_{it}^{1,1}, N_{it}, h_{it}^{1,1})\right] q_I > 0 \tag{48}$$

Thus, if insurance increases infant survival, it raises the expected benefit of attempting conception and therefore increases the probability of a realized live birth.

B.5 Summary

The framework separates the household's behavioral fertility decision from the live-birth outcome observed in the data. Households choose whether to attempt conception according to

$$a_{it}^* = \mathbf{1}\left\{\overline{\Delta}_{it} + \varepsilon_{it} \geq 0\right\} \tag{49}$$

while a live birth occurs probabilistically conditional on attempting conception. The probability of a realized live birth is

$$\Pr(b_{it}=1) = p_{it}\left[1 - F(-\overline{\Delta}_{it})\right] \tag{50}$$

where

$$\overline{\Delta}_{it} = p_{it}\left(V_{it}^{1,1} - V_{it}^{1,0}\right) \tag{51}$$

Insurance affects this systematic value through three channels:

- *Financial channel:* Insurance requires households to pay a premium but reduces the out-of-pocket expense associated with childbirth in the live-birth state. Under the sufficient condition $\kappa C_i \geq \Pi_{it}$, insurance raises the incentive to attempt conception and the probability of a realized live birth. The financial effect is predicted to be larger where baseline childbirth costs

are higher, subject to the conditions discussed above.

- *Maternal-health channel:* Insurance can improve maternal health. Better maternal health lowers the health cost of childbirth but can also raise female labor-market productivity and the opportunity cost of childbearing. The overall effect on fertility is therefore theoretically ambiguous.

- *Infant-survival channel:* Insurance can increase the probability that a live-born infant survives. Because households value an additional surviving child, improved infant survival raises the expected value of attempting conception and predicts a positive fertility response.

These predictions guide the empirical mechanism analysis. Heterogeneity in the effects of Blue Cross by baseline medical costs provides evidence on the financial channel, while effects on maternal and infant mortality provide evidence on whether changes in maternal health or infant survival may account for the fertility response.

C Additional Data Construction

I construct several additional county-level control variables, following Thomasson and Treber [2008], to account for demographic and economic conditions that may be correlated with both the expansion of Blue Cross and fertility outcomes.

To control for county demographic characteristics, I include log total population and the shares of the population that are Black, urban, and foreign-born. Population data come from *Historical, Demographic, Economic, and Social Data: The United States, 1790–2002* (ICPSR 2896) [Haines and Inter-university Consortium for Political and Social Research, 2010]. I use observations from the 1920, 1930, 1940, and 1950 Censuses. For each census year, I calculate the Black, urban, and foreign-born population shares and linearly interpolate these shares between census years. I similarly interpolate total population between census years and use its logarithm as a measure of county size.

To capture county-level economic conditions, I use real retail sales per capita. Retail sales are observed in 1929, 1933, 1935, 1939, and 1948, and I linearly interpolate between observed years to construct annual values over the sample period. Data for 1929, 1933, 1935, and 1939 come from the *New Deal Studies*, ICPSR file 101199 [Fishback and Kantor, 2018]. The 1948 observation, which provides the endpoint for interpolation through 1947, comes from the *City and County Data Book Consolidated File, County Data 1947–1977*, ICPSR file 7736 [United States Bureau of the Census, 2008]. I adjust retail sales for inflation and divide by the interpolated county population described above to construct real retail sales per capita.