LOCALIZING WELFARE: EVIDENCE FROM TRIBAL TANF AND INFANT HEALTH OUTCOMES

by

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ABSTRACT

There is limited empirical evidence on how the localization of transfer program administration affects infant health outcomes. Tribal Temporary Assistance for Needy Families (TANF) allows federally recognized tribes to assume administrative control of TANF programs from state governments. Using linked birth and infant death vital statistics data and leveraging the staggered adoption of Tribal TANF, I estimate that the establishment of Tribal TANF is associated with a considerable decline the incidence of low and very low birthweights among potentially treated AIAN populations. These effects are consistent with improved access to TANF and increased program participation under tribal administration. These findings highlight the importance of administrative structure in shaping the effectiveness of transfer programs for disadvantaged populations.

CHAPTER ONE

INTRODUCTION

American Indian and Alaska Native (AIAN) communities experience some of the most severe economic and health disparities in the United States. Maternal and infant health outcomes reflect these conditions. AIAN mothers face maternal mortality rates more than twice the national average, and infant mortality among AIAN populations is roughly 61 percent higher than among white populations (Kozhimannil et al., 2020; Wong et al., 2014).

A large literature in economics and public health provides evidence that adverse prenatal conditions and birth outcomes have lasting consequences for human capital formation and long run economic outcomes (see Behrman & Rosenzweig, 2004; Black et al., 2007; Victora et al., 2008). Household resources are an important determinant of these conditions, suggesting that transfer programs targeting low-income families may improve infant health outcomes. However, the efficacy of these programs depends not only on the benefits, but how the program is administered and how large the barriers to access are (see Duflo, 2017; Herd & Moynihan, 2025).

The 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) replaced Aid to Families with Dependent Children (AFDC) with Temporary Assistance for Needy Families (TANF), reforming welfare in the United States. TANF introduced work requirements, time limits, and greater state discretion. It is widely associated with declines in welfare caseloads relative to AFDC . Research suggests that these reductions in caseloads, due to

stricter program requirements, are associated with worse infant health outcomes (Kaestner & Lee, 2005; Leonard & Mas, 2008).

Unlike most federal welfare programs, TANF allows federally recognized tribes to administer their own programs, known as Tribal TANF, rather than participating in state-administered systems. Tribal TANF provides tribes the autonomy to develop more culturally relevant programming, reduces barriers in accessing TANF, and has more flexibility in restrictions compared to state TANF[1] (Hillabrant et al., 2003). Early evidence suggests that Tribal TANF programs reduced barriers to accessing TANF (Brown et al., 2001), with caseloads increasing following program adoption, reversing the broader national trend observed under state-administered TANF.

The differences between state and Tribal TANF highlight a broader question about the role of governance in shaping policy effectiveness. A large literature studies the impacts of transfer programs, but there is little analysis on how the level of administration affects outcomes. Tribal TANF represents a rare institutional setting in which the administration of a federal transfer program shifts from state governments to tribal governments, allowing for a direct comparison of administrative regimes within the same policy framework. It also provides a setting to evaluate whether increasing tribal sovereignty in program administration can improve outcomes for historically underserved populations.

The paper analyzes how prenatal exposure to Tribal TANF impacts infant health outcomes using restricted cohort linked birth-death vital statistics data from 1995-2020 combined with

[1] See Table 1 for detailed differences between state and Tribal TANF.

geographic information linking births to reservation areas. The data is the full set of individual birth and death certificates in the United States, containing detailed parental demographics and infant health outcomes. Although the data contain identifiers for AIAN parents, they do not allow for identification of tribal members or TANF recipients. Heterogeneity in the time Tribal TANF programs begin is exploited to compare infant health outcomes for Native American reservations that did and did not implement Tribal TANF. To address concerns about treatment endogeneity and improve balance in the panel, matched samples of reservations using pre-treatment covariates are constructed. Results suggest that adoption of Tribal TANF led to a decrease in the incidence of low and very low birthweights but are inconclusive on the impacts on infant mortality rates.

These findings are consistent with increased program access and participation under tribal administration and highlight the importance of administrative structure in shaping the effectiveness of transfer programs. More broadly, the results provide evidence that shifting program administration to tribal governments may be an effective mechanism for improving outcomes in tribal communities.

CHAPTER TWO

BACKGROUND

Tribal TANF

Temporary Assistance for Needy Families (TANF) is a federal conditional transfer program within the United States available to households with children under the age of eighteen or women in their third trimester of pregnancy. In 1996, the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) replaced the AFDC program with TANF, intending to stop permanent dependency of welfare (Moseley, 1996). TANF introduced work requirements, imposed a lifetime benefit limit of 60 months, and required states to maintain spending equal to 75 percent[2] of their 1994 AFDC expenditures, known as the Maintenance of Effort (MOE) requirement. (PRWORA, 1996). Eligibility for TANF is conditioned on earnings limits, work requirements, and has a lifetime benefit limit. The federal government has bounds on the conditions for eligibility and leaves the prerogative to set the exact constraints to individual states, such as the maximum time someone can receive TANF or participate in job training programs. TANF block grants[3] are apportioned to states with broad discretion in how to allocate the money to meet any of the four goals of TANF: provide assistance to needy families, end dependance on government benefits, reduce out-of-wedlock pregnancies, and encourage the formation and maintenance of two-parent families (PRWORA, 1996). From the inception of TANF most states have been gradually shifting TANF program spending from cash transfers to

[2] States that do not meet the minimum workforce participation rate (see Table 1) have a MOE requirement of 80% of 1994 AFDC expenditures (PRWORA, 1996).
[3] TANF block grants are based on the maximum annual federal contribution to a state's ADFC, job training, and emergency programs between 1992-1995.

other programs like education or work activities[4] (Arkin, 2025).

PRWORA also allowed federally recognized tribes to administer their own TANF programs, known as Tribal TANF. Tribal TANF programs receive a share of the state's federal TANF block grant and have similar discretion as states in determining how funds are allocated. Tribal TANF programs are also subject to fewer and more flexible federal restrictions than state TANF programs. Key differences between the programs are described in Table 1. Case studies of early Tribal TANF programs reported that most tribes kept similar restrictions as their state, such as maximum time limits of 60 months, but expanded the allowable work activities and heavily invested into job training programs (Brown et al., 2001). In 2002, over twenty percent of Tribal TANF recipients were engaged in work activities that would not be accepted by the state TANF program (Fagnoni et al., 2002). These program refinements reflect the persistent unemployment experienced on Native American reservations.

There are no official funding sources to assist in the costs of developing a Tribal TANF program, which has been cited as the main barrier to starting a Tribal TANF program (Hillabrant et al., 2003; Kauffman, 2002). To start a Tribal TANF program, tribal leaders must first submit a Letter of Intent to Health and Human Services (HHS). This letter contains the geographic Service Delivery Area (SDA) and population(s) that the program will administer to (*How to Become a Tribal TANF Program*, 2023). Once that is approved, the tribe and state must agree on how many individuals within the defined SDA and population base were receiving AFDC assistance from the state in 1994. This determines the proportion of the state's federal TANF block grant that is given to the Tribal TANF program (PRWORA, 1996). Few states collected information on

[4] How Tribal TANF programs allocate their resources is not publicly disclosed, so it is unknown if they also exhibit this behavior.

Table 1. Key Differences Between Federal Rules for State and Tribal TANF

Federal TANF Rule	State TANF	Tribal TANF
Required to contribute MOE funds	Yes	No
Access to TANF Contingency Fund	Yes	No[5]
Max percentage of block grant that can be spent on administrative costs	15%	35% in first year, 30% in second, and 25% in all subsequent years.
Min Work Participation Rate (WPR)	50% and 90% WPR for 1 and 2 parent families, respectively	Can be negotiated by tribes
Time limit on receiving TANF benefits	≤ 60 months (with federal funds), except for families with hardship exceptions	Can be negotiated by tribes[6]
Allowable work activities for WPR	Any of the 12 federally defined work activities	Tribes can also include culturally relevant and substance activities[7]
Time limit on vocational education	≤ 12 months	No
Required to condition TANF on cooperation and assignment of child support	Yes	No
Can provide benefits to individuals with drug-related felonies	No, but state can pass legislation to allow it	Yes

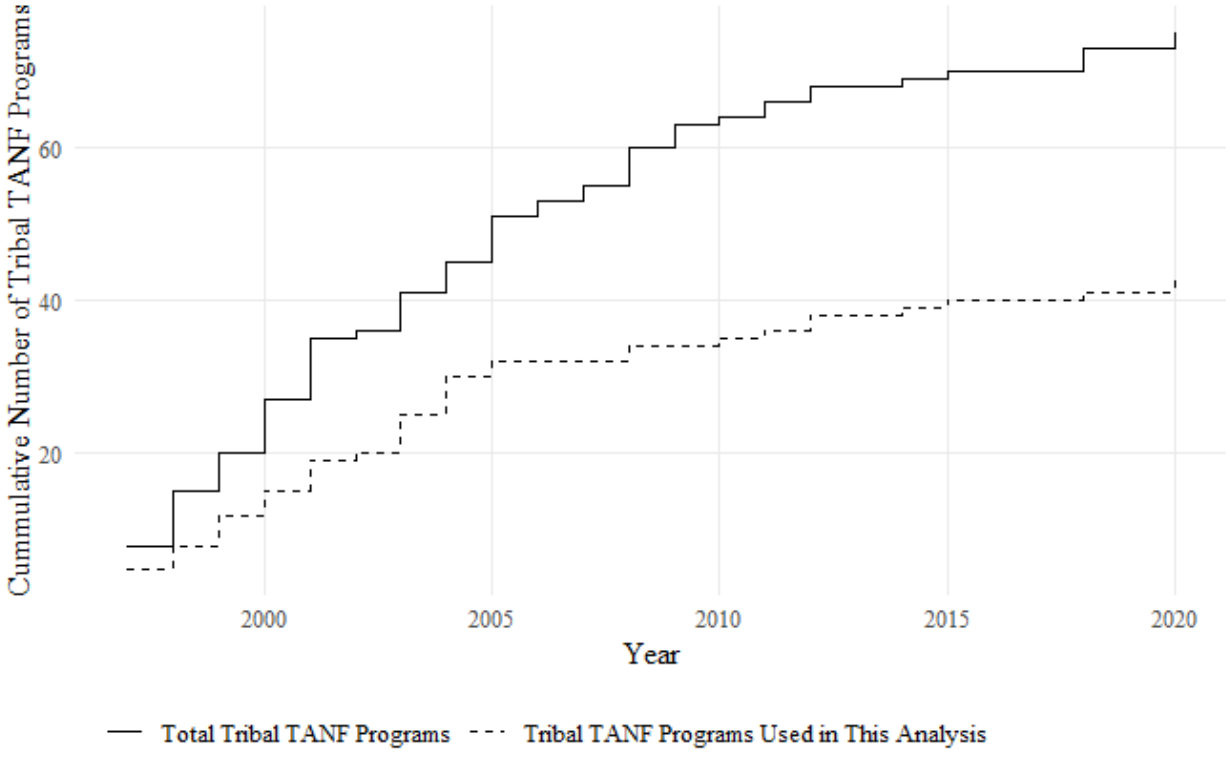
Notes: All information from the Center on Budget and Policy Priorities' Policy Basics: Tribal TANF (2022).

[5] In practice, these funds have been made available to Tribal TANF programs during the 2008 and COVID recessions, but this requires federal legislation (Policy Basics, 2022).
[6] Tribal members have access to the Bureau of Indian Affairs' general assistance program, which provides payments equivalent to TANF if an individual has timed out of TANF. Therefore, the state's time limit is not a binding constraint, and there should be little to no impact of Tribal TANF's flexibility on time limits.
[7] 13 of the 23 Tribal TANF programs in 2002 included additional work activities beyond what is defined in PRWORA (Fagnoni et al., 2002).

tribal affiliation of AFDC recipients which often causes difficulties in determining this exact number. In some instances, disagreements between states and tribes on AFDC caseload counts had to be mediated by HHS (Hillabrant et al., 2003). Most Tribal TANF programs were established before 2005, though program adoption has continued to expand steadily since its inception (see Figure 1). As of 2022, nearly half of all Federally Recognized Tribes are served by one of the 75 Tribal TANF programs (Policy Basics, 2022).

Tribal populations reported many barriers to accessing both AFDC and TANF, incentivizing the development of a Tribal TANF program. Early programs all noted that there were few, if any, state TANF offices within reservations. The lack of reliable transportation on

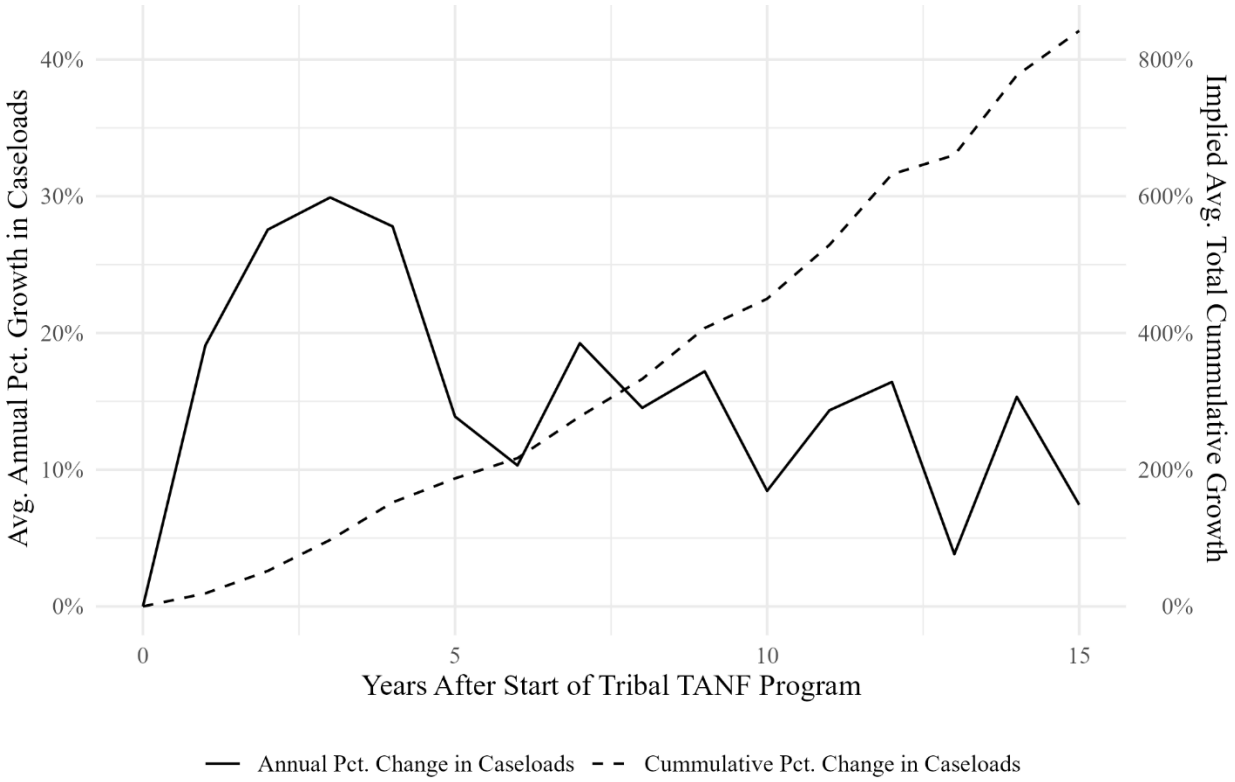
Figure 1: Growth in Tribal TANF Programs from 1996-2020



Notes: The analysis in this paper excludes Alaskan Tribal TANF Programs (7) and all Tribal TANF within counties with another Tribal TANF program (25).

reservations made it difficult for tribal members to commute to TANF offices to complete the paperwork to receive TANF (Hillabrant et al., 2003). The Navajo Nation, the largest reservation by land size, established several satellite Tribal TANF offices and allowed caseworkers to travel outside of the office to address this issue (Brown et al., 2001). Additionally, some tribal members reported perceived discrimination from state TANF administrators and indicated that eligibility determinations did not adequately account for limited employment opportunities on reservations, at times resulting in the termination of benefits (Hillabrant et al., 2003). Tribal TANF programs placed offices on reservations to make access easier and had the flexibility to tailor the

Figure 2. Average Growth in Annual Tribal TANF Caseloads After 2008



Notes: This analysis is from Tribal TANF caseload data available from The Administration For Children and Families from 2008-2020. 73 Tribal TANF programs are represented in this graph. The average total cummulative growth in caseloads is implied from the average growth in caseloads from program inception. This is only an estimate due to missing caseload data from prior to 2008.

requirements and programming to best meet the cultural and economic needs of their service population. Tribal TANF plausibly reduces the administrative burden on accessing TANF, which has been shown to increase uptake in other welfare programs (see Duflo, 2017; Herd & Moynihan, 2025). This is consistent with the observed caseload count, as shown in Figure 2. On average, caseloads for Tribal TANF programs have doubled within five years of the program starting. This trend is the opposite of what was observed for state TANF programs, where caseloads declined over a similar period (Monahan et al., 2024).

States also have incentives to support the continuation of Tribal TANF programs once they are established. For a state to receive its full TANF block grant, 50% of families within a state must engage in work activities[8] (PRWORA, 1996). There are often very few employment opportunities on Native American reservations, which leads to persistently high unemployment rates (Scott, 2002). Transferring these caseloads to Tribal TANF programs removes them from the state's work participation calculations, which can improve the state's compliance with federal requirements. Additionally, a state's mandated MOE contribution is proportionately scaled down by the size of the federal grant given to Tribal TANF programs, and the state is not required to provide any funding to the Tribal TANF program. In practice, states will give Tribal TANF programs a percentage of the MOE they were previously obligated to spend[9] (Hahn et al., 2016). Due to this, states are incentivized to promote and maintain Tribal TANF programs. For example, when the Central Council of Tlingit & Haida Indian Tribes of Alaska Tribal TANF program was going to retrocede to the state due to lack of funds, Alaska increased their MOE contributions to

[8] Tribes can negotiate lower minimum work participation rates (WPR), with the average Tribal TANF WPR in 2022 being 34% (Policy Basics, 2022).
[9] 54 of 70 Tribal TANF programs in 2015 received some MOE funds from the state(s) they are in (Approved Tribal TANF Grants, 2015)

the program to prevent failure. The TANF block grant also increased for the White Mountain Apache Tribal TANF program after higher than planned caseloads led to the potential of retroceding to the state (Hillabrant et al., 2003). States also often share their TANF reporting systems and train Tribal TANF employees on how to complete mandatory quarterly reports to HHS, which is commonly cited as the main difficulty of maintaining a Tribal TANF program[10] (Hahn et al., 2016).

Expected Effects of Tribal TANF on Infant Health

Infant mortality and birthweight are commonly used as measures of infant health within the public health and economics literature. Birthweight, in particular, is widely employed as an indicator of early life health endowments and fetal conditions (see Almond et al., 2005; Currie, 2009). Infants with lower birthweights are at elevated risk of mortality, morbidity, and adverse long-term outcomes (Almond et al., 2005; McCormick, 1985), making birthweight a central outcome in both economics and epidemiology. To assess at-risk birthweights, the World Health Organization classifies births below 2,500 grams and 1,500 grams as low and very low birthweights, respectively.

Despite their widespread use, both infant mortality and mean birthweight present limitations as empirical measures. Infant mortality is a relatively rare outcome: in 2023, in the United States it occurred in 5.6 of every 1000 births (Murphy et al., 2024). This can limit statistical power and obscure meaningful changes in underlying health, particularly in smaller samples (Swanson et al., 2019). Mean birthweight, by contrast, aggregates outcomes across the

[10] The ACF-196T details what type of programs Tribal TANF programs allocate their money to. State versions of these forms are publicly available, but not for Tribal TANF programs.

entire sample and may mask important changes in the lower tail, where health risks are most severe (McIntire et al., 1999). Additionally, across all population groups nationally, birthweight has been declining, but there is no clear medical consensus as to why. There is a parallel trend of declining gestation length due to an increase in scheduled births (Zhang et al., 2010). However, research suggests this is not the only mechanism (Morisaki et al., 2013).

For these reasons, a complementary strand of literature emphasizes low and very low birthweights as more informative indicators of infant health. These measures isolate the lower tail of the birthweight distribution, where risks of mortality and morbidity are sharply elevated. This focus is especially relevant in the context of means-tested programs such as TANF, as lower-income populations have been shown to experience higher rates of low birthweight outcomes (Jardine et al., 2021; Martinson & Reichman, 2016). Consequently, low and very low birthweights provide a more sensitive and policy-relevant measure of the margins along which such programs are likely to operate.

A large biomedical literature documents the relationship between maternal health and behaviors and infant health outcomes. Mechanically, low birthweight is primarily caused by intrauterine growth restriction (IUGR) or lower gestational periods (Morisaki et al., 2013; Saleem et al., 2011). This literature provides evidence that birthweight, and consequently infant mortality, is influenced more by intrauterine conditions than by genetic factors (Clausson et al., 2000; Demerth et al., 2007; Jardine et al., 2021; Robinson et al., 2000). There is broad consensus within the medical literature that low and very low birth weights are leading indicators of infant mortality (Jana et al., 2023; McCormick, 1985; McIntire et al., 1999; Onishi et al., 2024; Shrimpton, 2003), so both are commonly used as metrics of infant health.

The economics literature also consistently finds a relationship between prenatal conditions and infant health outcomes. More pollution exposure, higher maternal stress, parental job loss, and lower socio-economic status during pregnancy have all been associated with a negative impact on birth outcomes (Camacho, 2008; Currie, 2009; Currie & Schmieder, 2009; Currie & Walker, 2011; Kennedy-Moulton et al., 2025; Lindo, 2011). Almond & Mazumder (2011) show that even relatively small changes to maternal behavior, such as fasting during Ramadan, are associated with lower birthweights. Taken together, this literature suggests that policies affecting material conditions during pregnancy, including transfer programs, may play an important role in shaping birth outcomes.

TANF is a conditional transfer program that is only available to families under a state-specified income threshold. The low-income families TANF serves experience, on average, higher rates of infant mortality and lower birthweights (Aizer & Currie, 2014; Collins et al., 2009; Kennedy-Moulton et al., 2025). Nutritional welfare programs targeting these populations like Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) and Food Stamps are associated with higher birthweights (Almond et al., 2011; Hoynes et al., 2011). However, research on PRWORA, the 1996 welfare reform bill, finds evidence that lower caseloads and binding time limits with TANF resulted in worse infant health outcomes than under AFDC (Kaestner & Lee, 2005; Leonard & Mas, 2008). Geographic barriers to access, in the form of local office closures, for SNAP and Social Security Disability Insurance have been associated with lower local participation (Bitler et al., 2025; Deshpande & Li, 2019). Programs that relax restrictions and lower bureaucratic frictions, like Tribal TANF, have been shown to increase participation, which could mitigate the negative effects to infant health seen from TANF

(Duflo, 2017; Herd & Moynihan, 2025).

Economic conditions on many Native American reservations differ substantially from those in the broader United States, particularly with respect to poverty and labor market opportunities. Transfer programs within developing countries have broadly been found to improve infant health outcomes. Mexico's PROGRESA program gave low-income families a cash payment provided that the family participated in a preventative health and nutrition program. Due to budget constraints, the initial rollout was randomly staggered across villages. Gertler (2004) finds that children in families receiving PROGRESA were taller, less anemic, and had less illness. However, the effects cannot be clearly decomposed between the cash payments or the mandatory health programs. Based on PROGRESA, Uruguay's PANES program was an unconditional[11] cash transfer program to households under a predefined predicted income threshold. Comparing barely eligible and barely ineligible households, Amarante et al. (2016) find the program increased birthweights by 20%. Both Latin American transfer programs suggest that increasing welfare recipients among low-income families can improve birth outcomes.

Research on the direct impact of exogenous increases in income on AIAN health has been done in the context of reservation casino profit sharing. Akee et al. (2010) find that an additional $4000[12] in annual household income is associated with one more year of education and reduces the chances of committing minor crime by 22%. These results also estimate that the poorest households exhibit the largest effects. Further research finds evidence of a negative relationship

[11] The PANES program was initially intended to be conditional on similar activities as PROGRESA, but these conditions were not defined or enforced until the last months of the program (Amarante et al., 2016)
[12] The 1996-2020 average state TANF benefit for a household of three with no income is $438. Data for Tribal TANF cash benefits is not publicly available, but it is suggested that early Tribal TANF programs mirrored state programs in cash benefits (Kauffman, 2002)

between casino cash transfers and the mortality of AIAN individuals on Medicaid (Akee & Simeonova, 2024). These studies provide evidence that cash payments made to AIAN communities may improve outcomes, but the impact on infant health remains unclear.

Both the medical and economics literature provide evidence that the intrauterine experience can markedly affect birth outcomes. Further, studies of transfer programs suggest that increasing resources available to low-income families during pregnancy can improve infant health outcomes. Early reports indicate that Tribal TANF increases access to TANF for the served population, which these studies suggest could lead to improvements in infant health outcomes (Hahn et al., 2016; Hillabrant et al., 2003).

CHAPTER THREE

DATA AND EMPIRICAL FRAMEWORK

Data

The goal of this analysis is to identify the effect of participation in a Tribal TANF program on infant health and marital outcomes. Infant health outcomes are measured using the Birth-Cohort Linked Birth/Infant Death dataset from the National Vital Statistics System (NVSS) from 1995-2020. County is the finest geographic identifier in this dataset, so all variables are aggregated to the county-year level[13].

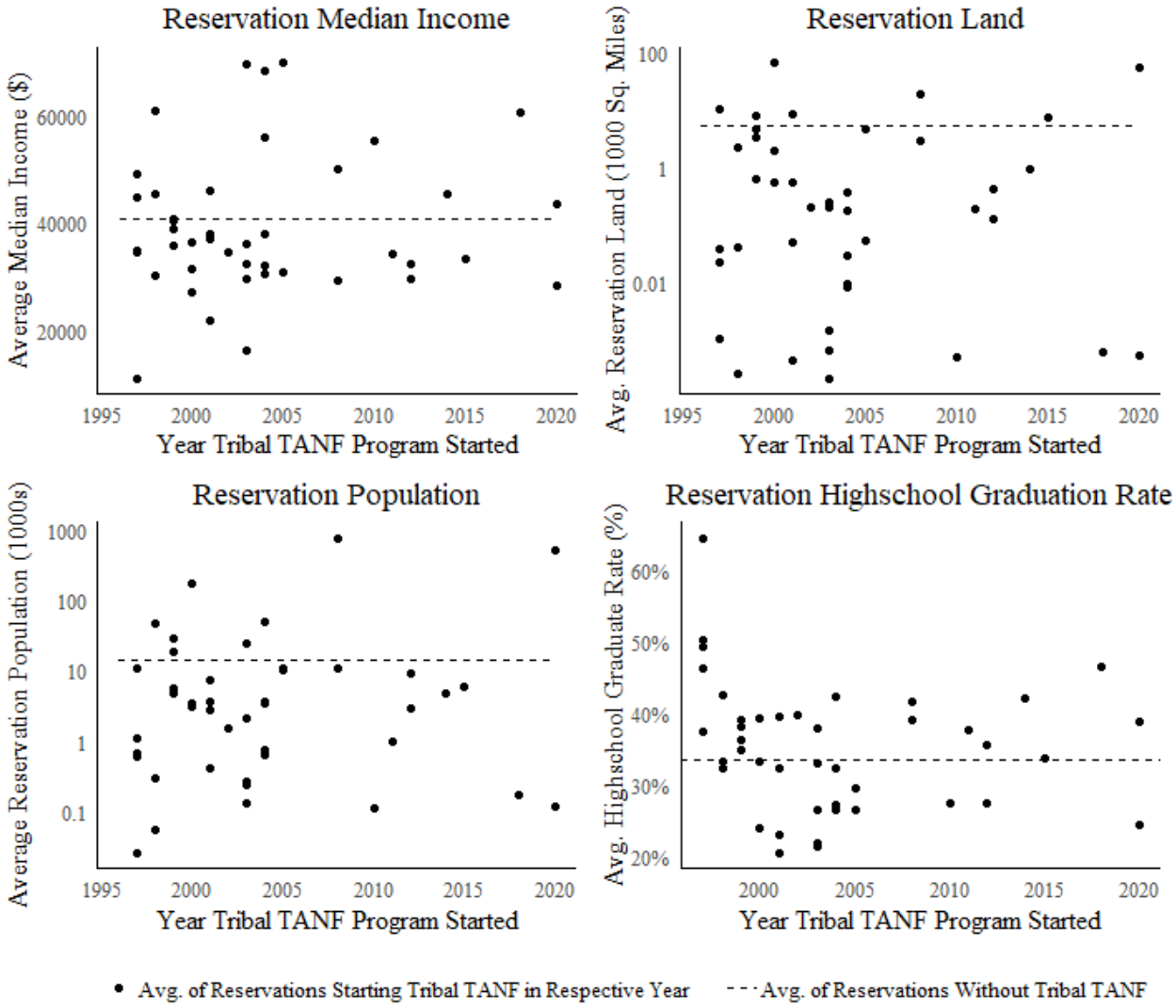
The primary dataset is the US Vital Statistics Birth-Cohort Linked Birth/Infant Death data. This contains information from every birth certificate and linked death record, if death was within the first year of life, in the US. The data includes information on birthweight, county of residence at birth, parental race, maternal marital status, parental education level, plurality, and birth order.

Tribal TANF program start dates, shown in Figure 1, were compiled from two Health and Human Services (HHS) sources: a federal grant report covering programs initiated prior to 2015, and Tribal TANF caseload data for programs initiated after 2015. The 2015 report also documents the SDA for all Tribal TANF programs active at that time[14]. In 2015, 84% of Tribal TANF SDAs used counties as their program boundaries, while most remaining programs only serve individuals living on the reservation.

[13] City identifiers are included on the birth certificate if the population is greater than 100,000. These urban centers rarely overlap with Native American Reservations and are not used in this analysis.
[14] 6 of 76 Tribal TANF programs started after 2015, and four of those six are included in this analysis.

For Tribal TANF programs initiated after 2015, the SDA is assumed to include all counties overlapping the reservation. Due to limitations in the NVSS data, identification of Tribal TANF is defined at the county level for all reservations, including for reservations with

Figure 3. Comparisons of Timing of Tribal TANF Programs By Descriptive Statistics



Notes: Data for reservation population, median income, and highschool graduation averages from ACS 5-Year Avg. 2009-2020. Reservation land size derived from U.S. Census Reservation GIS data. Each point represents the average of the ACS 5-Year Avg. from 2009-2020 relative the year their Tribal TANF program was started.

SDAs only within the reservation boundaries[15]. US Census Bureau reservation and county GIS data are used to determine all counties overlapping each reservation[16]. Counties with more than one reservation that has a Tribal TANF program, as well as Alaska Native Tribal TANF programs, are excluded from this analysis[17]. Figure 1 shows the difference in program start years between excluded and included Tribal TANF programs.

Alaskan boroughs (county equivalent) are geographically very large and all Alaska Native Tribal TANF programs are consortiums serving many dispersed tribes. Both make identification more difficult. Counties with more than one Tribal TANF program typically occur in regions with many small reservations, such as California or Washington. In other cases, such as Nevada and Arizona, counties are geographically large and overlap with multiple reservations.

Reservation, county, and state characteristics are also used as covariates in the matching procedure. Reservation and county characteristics are drawn from the 1990 and 2000 Decennial US Census and the 2009-2019 5-year average American Community Survey estimates. State specific TANF regulations are obtained from the Urban Institute's Welfare Rules Databook[18].

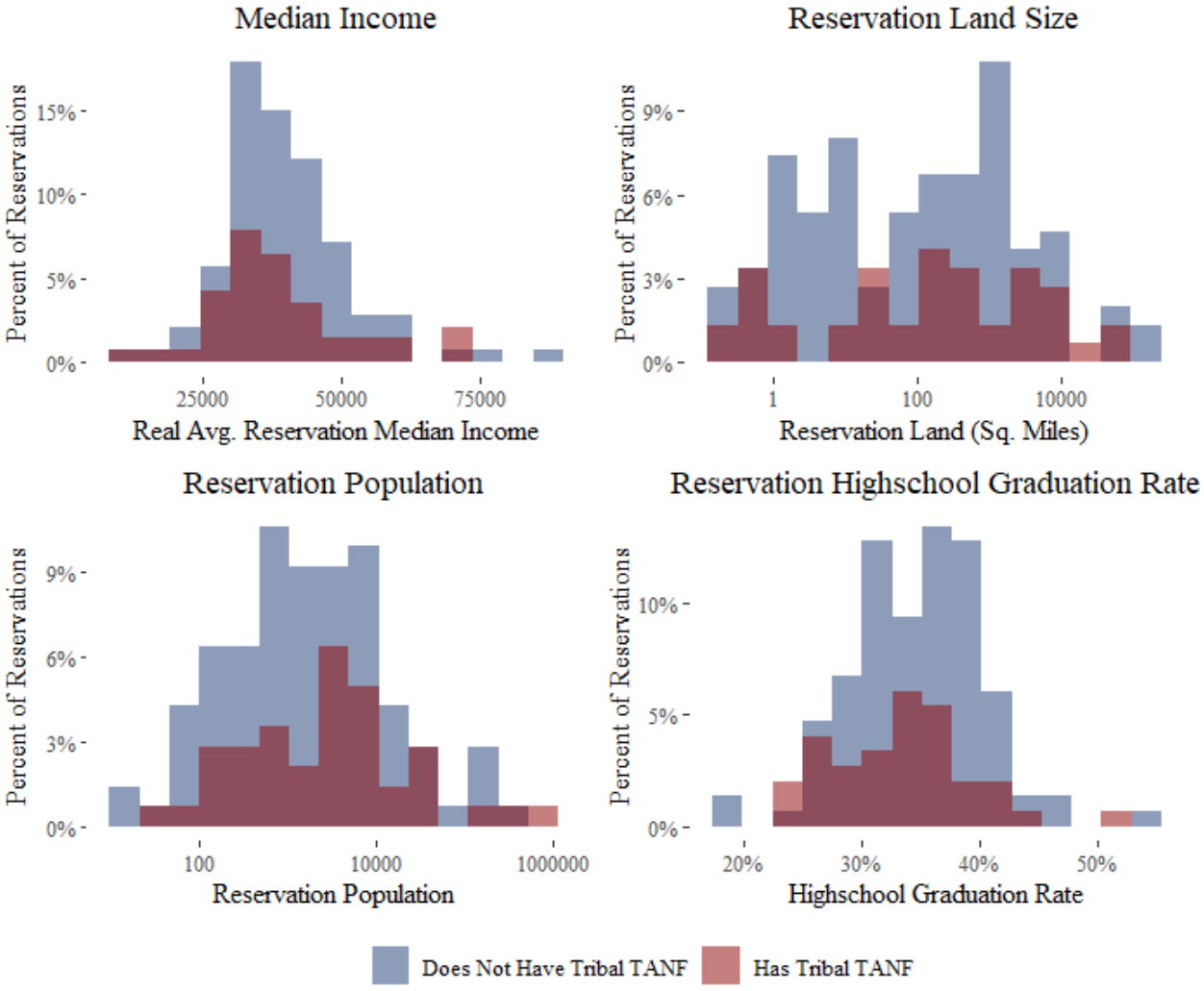
Figure 3 shows the trends in reservation average population, land size, median income, and high school graduation rate by the year Tribal TANF was adopted within the sample against the average of programs that only have state TANF. These descriptive trends do not suggest

[15] For Tribal TANF programs only available within reservation borders or those with an SDA that is unavailable, all counties that the reservation overlaps with are considered to be treated.
[16] Counties with more than one reservation were not excluded, to increase the sample size of reservations. This will increase the number of individuals coded as eligible for Tribal TANF that are not, which should attenuate any estimated treatment effects.
[17] Of the 168 counties within the contiguous United States identified as overlapping with a reservation with a Tribal TANF program, thirty-three had more than one program. Programs with at least one county not overlapping another treated country are not excluded.
[18] See Appendix A for which state TANF rules panel data was collected.

strong temporal selection into Tribal TANF adoption based on these characteristics[19]. Similarly, Figure 4 suggests that reservation size, population, education levels, and median income are not strongly correlated with Tribal TANF adoption.

All infants with a mother or father that fully or partially identified as AIAN and resided

Figure 4. Comparisons of Distributions of Reservation Descriptive Statistics



Notes: Data for reservation population, median income, and highschool graduation averages from ACS 5-Year Avg. 2009-2020. Reservation land size derived from U.S. Census Reservation GIS data.

[19] See Appendix B for estimates of the impact of Tribal TANF timing on the outcomes reported in Figure 3. All estimates are small in magnitude and insignificant.

within the SDA of a Tribal TANF program are coded as treated[20]. This definition may include individuals who are not eligible for Tribal TANF, either because they are not members of the administering tribe or because they reside within the county but outside the SDA. In both cases, measurement errors in treatment assignments will attenuate estimated treatment effects. The sample is restricted to singleton births (pregnancy of a single infant) and mothers between 15 and 39[21].

For robustness, additional restrictions on the sample are imposed which could better reflect the composition of TANF recipients. From state reported demographics from 2001-2020 93.4% of adult state TANF recipients did not have more than a high school education and 87.1% were unmarried. For primigravida, TANF is only available in their third trimester, while women with children could receive benefits for their total pregnancy. Imposing these restrictions could reduce attenuation but also restrict the sample size.

Several data limitations may lead to attenuation of the estimated treatment effects. The data do not contain information on income or household size, preventing direct identification of TANF-eligible households. Only race, not tribal status or affiliation, is present in the data, preventing identification of eligibility for Tribal TANF. Finally, the finest geographical level is county, which does not allow for accurate mapping of treatment when the Tribal TANF program SDA is not defined by county boundaries, such as within a reservation. These limitations likely

[20] Tribal TANF program eligibility ranges from all households with members of any tribes living in eligible counties to only households with tribal members living on reservation. If the parents do not cohabitate and only the father is a tribal member, the child could be eligible for tribal membership, making the mother eligible for Tribal TANF. Tribal membership usually depends on blood quantum levels and/or lineal descent (Fletcher, 2012). If tribal membership is predicated on blood quantum levels, assuming the child is always eligible when only the mother or father identifies as AIAN would be incorrect and lead to attenuation in results.

[21] Births with more than one infant or with mothers over 40 or under 15 have higher rates of infant mortality and lower birthweights on average (Fretts et al., 1995; Saavedra, 2020).

result in individuals being incorrectly classified as treated, which would bias estimated treatment effects toward zero.

Matching and Descriptive Statistics

Native American reservations differ substantially from most other regions of the United States in their institutional structure and economic conditions. They are quasi-sovereign from the Federal government creating unique legal situations. Relative to national averages, reservations experience higher poverty and unemployment rates as well as higher infant mortality and lower birthweight (Beyer, 2022; Elder et al., 2016).

Due to these conditions, a natural counterfactual for reservations that adopt Tribal TANF is reservations with state TANF. However, the decision to start a Tribal TANF program may be endogenous. More populous reservations may face lower per capita startup costs, which could lower the barriers to starting a Tribal TANF program. Residents of larger reservations may face greater travel distances to state TANF offices, which increases potential benefits of administering TANF locally. Reservations with higher median income or education levels may have smaller populations eligible for TANF. As shown in Figure 3, there is little evidence that adoption timing is correlated with these observable characteristics. To address additional endogeneity concerns, a matching design was used to achieve better balance between and reduce bias from observed covariates in the treatment and control groups (Stuart, 2010).

Several matching approaches are implemented as robustness checks, and there is further discussion on the differences in matched controls and results in Appendix C. The preferred matching design is Mahalanobis distance matching. The Mahalanobis distance, $\boldsymbol{D_{tc}}$, between treated, $\boldsymbol{x_t}$, and control, $\boldsymbol{x_c}$, pre-treatment covariate vectors is defined as:

$$\boldsymbol{D_{tc}} = \sqrt{(\boldsymbol{x_t} - \boldsymbol{x_c})^T S^{-1} (\boldsymbol{x_t} - \boldsymbol{x_c})}$$

where S^{-1} is the inverse of the covariance matrix of the covariates. This is effectively the Euclidean distance between decorrelated and standardized covariate vectors (Gu & Rosenbaum, 1993). Mahalanobis distance matching does not require specifying a treatment assignment model and is invariant to correlated or differently scaled variables. However, it is sensitive to the variables selected, so an optimization procedure is used to select both the set of covariates and the number of matched controls for each reservation [22].

Covariates used in the Mahalanobis distance calculation include reservation and county characteristic data from the 1990 and 2000 decennial census and the 2009-2020 five-year American Community Survey estimates. Reservation population is available at the reservation level. Percentage of households in poverty and education level are calculated for the American Indian/Alaska Native population within each county. Data for a state's TANF eligibility earnings cutoff for a household of three were collected from the Urban Institute's Welfare Rules Database. These variables are averaged across all years the reservation did not have a Tribal TANF program.

Each treated reservation is matched to the thirteen untreated reservations with the smallest Mahalanobis distances, with replacement[23]. This approach restricts the control group to reservations that are most similar to reservations with Tribal TANF on observed characteristics. Figure 5 shows which reservations are and are not identified as controls using this methodology.

[22] The optimization metric used was the average pre-treatment standardized mean difference (SMD) added to the standard deviation of the SMD across all covariates reported in Table 2.
[23] Due to replacement, some reservations without Tribal TANF are used as matched controls for more than one treated reservation. To account for this, these reservations are weighted more heavily within the empirical specification proportional to the number of matched control groups each is in.

Table 2 reports population-weighted pre-treatment descriptive statistics for infant health outcomes and maternal characteristics on the full sample, the matched sample, treated reservations, their matched counterparts. Column 1 shows the descriptive statistics for all reservations without a Tribal TANF program prior to 2004 and prior to the start of the Tribal TANF program otherwise. Column 2 reports the descriptive statistics for treated reservations and their respective matched controls before the start of their Tribal TANF program. Column 3 reports the descriptive statistics for only reservations with a Tribal TANF program and column 4 reports the descriptive statistics for the matched reservations without Tribal TANF. Prior to implementation, treated reservations, on average, had lower infant mortality, similar rates of low and very low birth weight, and higher birthweights than the untreated reservations. Maternal characteristics show similar trends with mothers on treated reservations having more prenatal

Figure 5. Reservation Counties Used for Identification

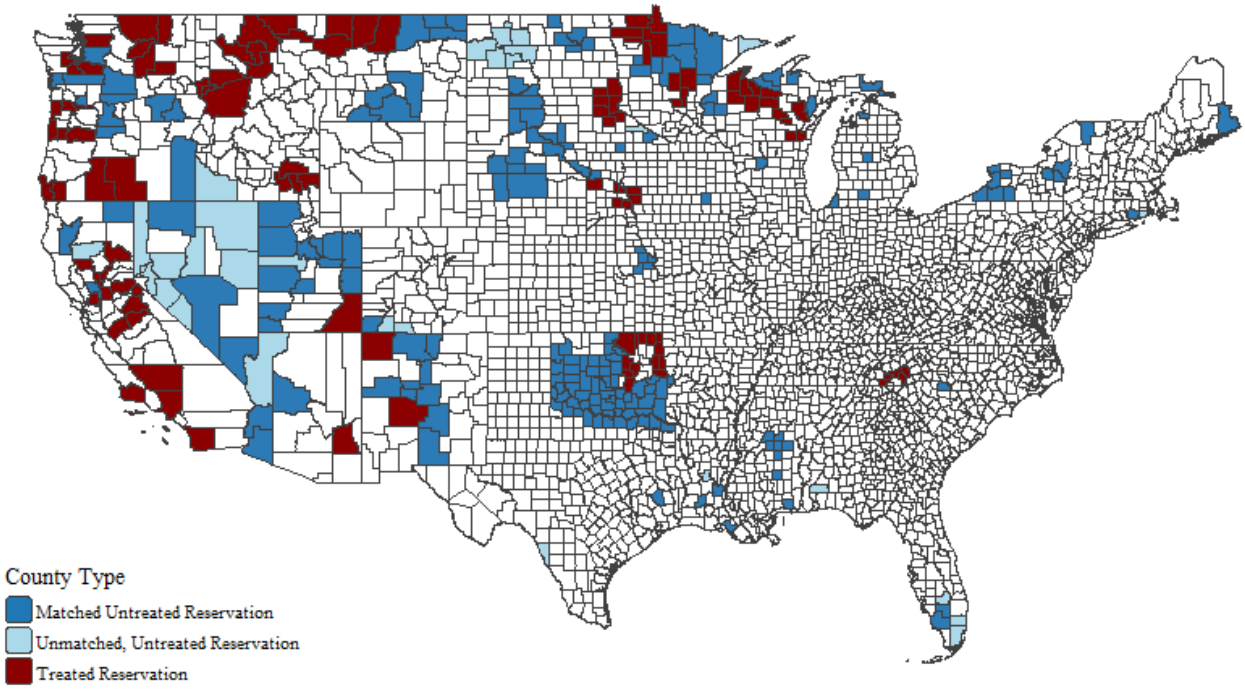


Table 2. Descriptive Statistics of AIAN Birth Outcomes and Parental Demographics on Treated and Matched Reservations Before the Implementation of Tribal TANF

Variable	Full Sample (1)	Matched Sample (2)	Treated (3)	Control (4)	SMD (5)
IMR (per 1000)	7.7	7.7	7.1	7.8	-0.26
	(11.7)	(1.1)	(2.7)	(1.1)	
Birth Weight (g)	3396.5	3382.9	3389.1	3382.1	0.13
	(97.1)	(24.7)	(53.0)	(23.6)	
Low BW (per 1000)	54.3	55.6	55.7	55.6	0.02
	(29.8)	(3.6)	(7.5)	(3.7)	
Very Low BW (per 1000)	9.5	9.6	9.5	9.6	-0.02
	(12.3)	(1.1)	(3.1)	(1.2)	
Gestation (weeks)	38.9	38.8	38.8	38.8	-0.09
	(0.4)	(0.2)	(0.2)	(0.2)	
Moderate Preterm (per 1000)	87.4	86.3	86.6	86.2	0.03
	(46.5)	(7.6)	(12.3)	(8.0)	
Very Preterm (per 1000)	9.8	9.5	9.3	9.5	-0.07
	(15.4)	(1.5)	(3.1)	(1.6)	
Extremely Preterm (per 1000)	4.8	5.1	4.7	5.2	-0.21
	(8.7)	(0.6)	(2.3)	(0.7)	
Neonatal Mortality (per 1000)	3.7	3.8	3.6	3.9	-0.15
	(8.2)	(0.5)	(2.0)	(0.5)	
Mother Age	24.6	24.6	24.7	24.6	0.11
	(1.5)	(0.5)	(0.7)	(0.6)	
Pct. Mothers with Education Post-HS	0.30	0.33	0.31	0.33	-0.23
	(0.10)	(0.06)	(0.05)	(0.07)	
Married (per 1000)	425.9	451.4	454.5	451.1	0.03
	(156)	(95)	(128)	(93)	
Num Prenatal Visits	10.0	10.2	10.2	10.2	0.07
	(1.4)	(0.7)	(1.0)	(0.7)	
Pct. Tobacco During Pregnancy	0.21	0.22	0.20	0.22	-0.19
	(0.15)	(0.04)	(0.11)	(0.04)	
Pct. Births in Medical Center	0.995	0.996	0.995	0.996	-0.13
	(0.01)	(0.00)	(0.00)	(0.00)	
Mother's Children	2.28	2.21	2.21	2.21	-0.01
	(0.29)	(0.15)	(0.17)	(0.16)	
Previous Fetal Deaths	0.37	0.36	0.34	0.36	-0.19
	(0.17)	(0.04)	(0.12)	(0.04)	
N	190,069	168,445	80,140	88,305	

Notes: Standard deviations are shown in parentheses. SMD = Standard Mean Difference, IMR = Infant Mortality Rate, BW = Birth Weight. Sample sizes, *N*, correspond to the number of unique births with parents that identify as fully or partially Native American on the birth certificate. The sample size does not reflect the weighting of untreated reservations that are used as controls for more than one treated reservation. The sample period for control groups is before the matched treated reservation has implemented Tribal TANF, respectively. The sample period for the full sample is prior to the average sample program start year, 2005. Standard mean difference is the difference between the average of the treatment and control groups (treated-control) divided by their combined standard deviation.

Source: All results derived from the Cohort Linked Infant Birth-Death data from the NCHS National Vital Statistics System.

visits, smoking less during pregnancy, having fewer children, and completing more pregnancies to term. For most covariates, the matched subsample of reservations more closely resembles treated reservations than the full sample reservations. In all instances the variance of the matched reservations is much smaller than that of the full sample. Additionally, the standardized mean difference (SMD)[24], as reported in column 5, is under 0.25 for all covariates but infant mortality, which is very close at -0.26. Absolute SMD values below 0.25 are generally considered indicative of acceptable balance between treatment and control groups (Baker et al., 2026). Overall, the Mahalanobis matching technique has improved pre-treatment balance within the panel.

Empirical Specification

The preferred empirical approach is the two-stage difference-in-differences estimator proposed by Gardner (2022). This estimator addresses bias in traditional two-way fixed effects models that arises under staggered treatment adoption with heterogeneous treatment effects. In the first stage, (1), group and time fixed effects are estimated using only untreated observations ($D_{cy} = 0$). These estimated coefficients are then used in the second stage, (2), to residualize outcomes in the full sample, which allows for an estimation of the average treatment effect.

Tribal TANF is only available to low-income families that are within the population served by the program, typically official members of the tribe. The infant health data does not observe income, tribal membership or status, or assistance program usage. Tribal TANF membership is assumed if either parent is a resident of the county that the Tribal TANF program

[24] The standardized mean difference is a common metric to assess balance within the panel. It is the difference of the sample means (i.e. columns 1 and 2) divided by the combined standard deviations (Baker et al., 2026; Stuart, 2010)

serves and identify as AIAN on the birth certificate. This will result in individuals who are not eligible for Tribal TANF being considered as receiving the treatment, attenuating any estimates.

Let $Outcome_{cy}$ denote the average infant health outcome (e.g., infant mortality, birthweight) for births to American Indian/Alaska Native parents in county c in year y. D_{cy} is an indicator equal to one if a Tribal TANF program is active in county c in year y. The preferred regression model is:

$$Outcome_{cy} = County_c + Year_y + Year * State_s + Match_m + \varepsilon_{cy},\ D_{cy} = 0 \qquad (1)$$

$$Outcome_{cy} - \widehat{County}_c - \widehat{Match}_m - \widehat{Year}_y - \widehat{Year * State}_s = \propto + \beta D_{cy} + \mu_{cy},\ D_{cy} = 0{,}1 \qquad (2)$$

where $County_c$ fixed effects control for any systematic differences in infant health outcomes between counties and $Year_y$ fixed effects control for national temporal changes in infant health. $Match_m$ denotes matched-group specific fixed effects, linking the reservation with Tribal TANF with its matched controls. The coefficient of interest, β, captures the average treatment effect of Tribal TANF adoption on infant health outcomes among treated counties.

To account for unobserved state policies that may influence birth outcomes, the preferred specification includes state-specific linear time trends. Results without these trends are also reported[25]. The regressions are weighted by the number of births in each county-year and by the weights implied by the matching algorithm. For low incidence binary outcome variables, such as infant mortality or low birthweight, counties with few births can exhibit extreme values. Weighting by births reduces the influence of these extreme observations while retaining information from smaller counties. The standard errors are clustered at the reservation level.

[25] Recent literature has shown that unit specific linear time trends impose a function form that can introduce bias (Baker et al., 2026). All results are shown with and without the state-year time trends.

CHAPTER FOUR

RESULTS

Impacts on Infant Health Outcomes

Estimates of the impact of Tribal TANF programs on infant health outcomes are reported in Table 3, with the top panel reporting estimates with state linear trends and the bottom without. Estimates with the state linear trends are larger in magnitude than those without and generally have more significance. While year fixed effects will account for any national trends in the dependent variable, state-specific trends allow each state to follow different trends. However, these trends impose a functional form in how state trends differ, which can introduce bias, so both estimates are reported (Baker et al., 2026).

To assess robustness of the results with respect to the matching algorithm, columns 1 and 2 report estimates with different numbers of untreated reservations matched to each treated reservation. The point estimates and standard errors are relatively stable across columns 1-3, indicating that results are robust to the specifics of the matching technique.

To address issues with identification of individuals receiving Tribal TANF, estimates of subsets of the data are also included in columns 4-7. The data is restricted to unmarried women and women with no education beyond high school so that it is more representative of the population that receives TANF[26]. Additionally, the data is restricted to a stricter definition of race, only keeping infants with a parent identifying Alaska Native/American Indian as their only

[26] From 2001-2020 93.4% of adult state TANF recipients did not have more than a high school education and 87.1% were unmarried.

race[27]. These individuals are more likely to be tribal members, and therefore within the population Tribal TANF programs serve. Each of these subsets reduces the number of underlying individuals observed, which increases the variance within the sample.

The primary outcomes of interest are low and very low birthweight. While infant

Table 3. Two-Stage Least Squares Estimates of the Effect of Tribal TANF on American Indian Infant Health Outcomes Within Native American Reservations

	Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
With State Linear Time Trends	Infant Mortality (per 1000)	-1.3 (1.4)	-1.4 (1.4)	-3.3 (2.3)	-2.4 (2.8)	-2.4 (1.4)	-5.7 (3.6)	-1.1 (1.2)
	Birth Weight (g)	10.6 (5.7)	9.4 (6.0)	20.9* (10.2)	13.2 (9.4)	11.6 (8.4)	18.0 (15.2)	4.9 (7.9)
	Low Birth Weight (per 1000)	-8.2*** (1.8)	-7.9*** (1.8)	-7.1** (2.7)	-6.1** (2.2)	-11.6*** (3.0)	-6.6 (3.8)	-4.1 (2.2)
	Very Low Birth Weight (per 1000)	-4.1* (1.9)	-4.1* (1.9)	-3.7 (2.5)	-2.9 (2.1)	-7.2** (2.3)	-7.9* (3.5)	-4.1 (2.8)
Without State Linear Time Trends	Infant Mortality (per 1000)	-0.9 (0.7)	-1.3 (0.7)	-0.9 (1.0)	-1.1 (0.9)	-2.8* (1.1)	-3.7 (2.2)	-0.7 (0.8)
	Birth Weight (g)	2.4 (5.1)	3.9 (4.9)	6.5 (7.1)	-2.3 (6.2)	7.7 (6.1)	3.7 (10.4)	-3.4 (6.0)
	Low Birth Weight (per 1000)	-3.8* (1.6)	-4.3** (1.6)	-2.5 (2.0)	-2.1 (2.0)	-7.8*** (2.4)	-2.1 (3.5)	-2.5 (1.9)
	Very Low Birth Weight (per 1000)	-1.2 (1.0)	-1.5 (1.0)	-1.7 (1.4)	-0.7 (1.1)	-3.4** (1.3)	-3.9 (2.1)	-0.9 (1.5)
County-Year Observations		6149	6907	6622	6712	6753	6126	6712
Unique Births		501050	543541	319013	328159	341767	130316	365391
Number Matched Controls		5	13	13	13	13	13	13
Restrict to Unmarried				X			X	
Restrict HS Grad or Less					X		X	
Restrict 1+ Previous Births						X	X	
Restrict Race only Full AI/NA								X

Notes: Standard errors are clustered at the reservation level. Each cell represents a separate regression where treated reservations are compared to control reservations determined through Mahalanobis matching. Regressions differ by number of matched control reservations per treated, the inclusion of linear state time trends, and sub setting the population of mothers by education level and marriage status. Standard errors are clustered at the Reservation level and reported in parenthesis. Low birth weight (< 2500g) and very low birth weight (< 1500g) are defined by the WHO. *** $p < .001$, ** $p < 0.01$, * $p < 0.05$.

[27] Since 2003, parents can identify with more than one race on their birth certificate.

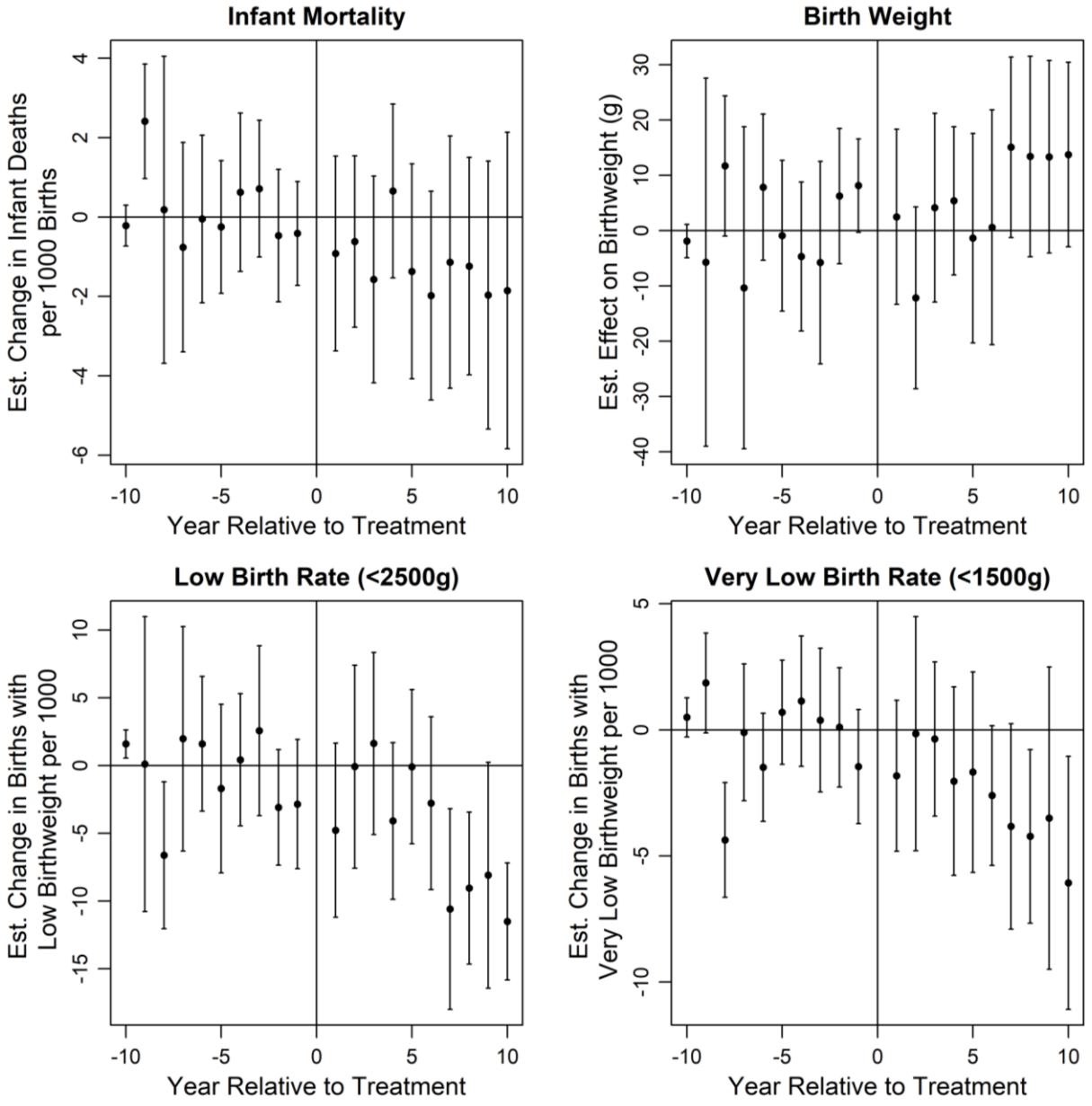
mortality and birthweight are common and important metrics of infant health, both present limitations in this empirical context. Infant mortality is a low frequency event, with an average of 5.6 deaths per 1,000 births in the United States in 2023 (Murphy et al., 2024). This reduces statistical power and makes it difficult to detect any treatment effects. As a result, even meaningful improvements in underlying infant health may not translate into detectable changes in mortality rates. Mean birthweight, by contrast, aggregates outcomes across the entire population, so it can be insensitive to changes concentrated in the lower tail. Policy effects that primarily reduce the incidence of adverse birth outcomes may be attenuated or obscured when using average birthweight, especially in the presence of broader secular trends. Low and very low birthweight provide more informative and targeted measures in this setting. These outcomes capture clinically meaningful variation in the lower tail of the birthweight distribution, where risks of mortality and morbidity are sharply elevated (McCormick, 1985). These metrics serve as leading indicators of infant health and are more closely aligned with the mechanisms through which Tribal TANF is likely to operate, such as improvements in maternal resources and prenatal conditions.

The preferred empirical specification is reported in column 2 and is the specification used in Figures 6 and 7. These results estimate that Tribal TANF results in around 4 fewer infants with very low birth weights and 8 fewer with low birth weights for every thousand births. Compared to the averages before Tribal TANF, this is a 14% and 43% reduction in the incidence of low and very low birth weights, respectively. This is in line with the estimates of the impacts of the PANES program in Uruguay, of a 20% reduction in the incidence of low birthweight (Amarante et al., 2016). State time trends do not shift the pre-treatment trends within the event studies of

low and very low birth weights, as shown in Figures 6 and 7. However, the state time trends do effectively shift the post-treatment estimates down while preserving the underlying trends.

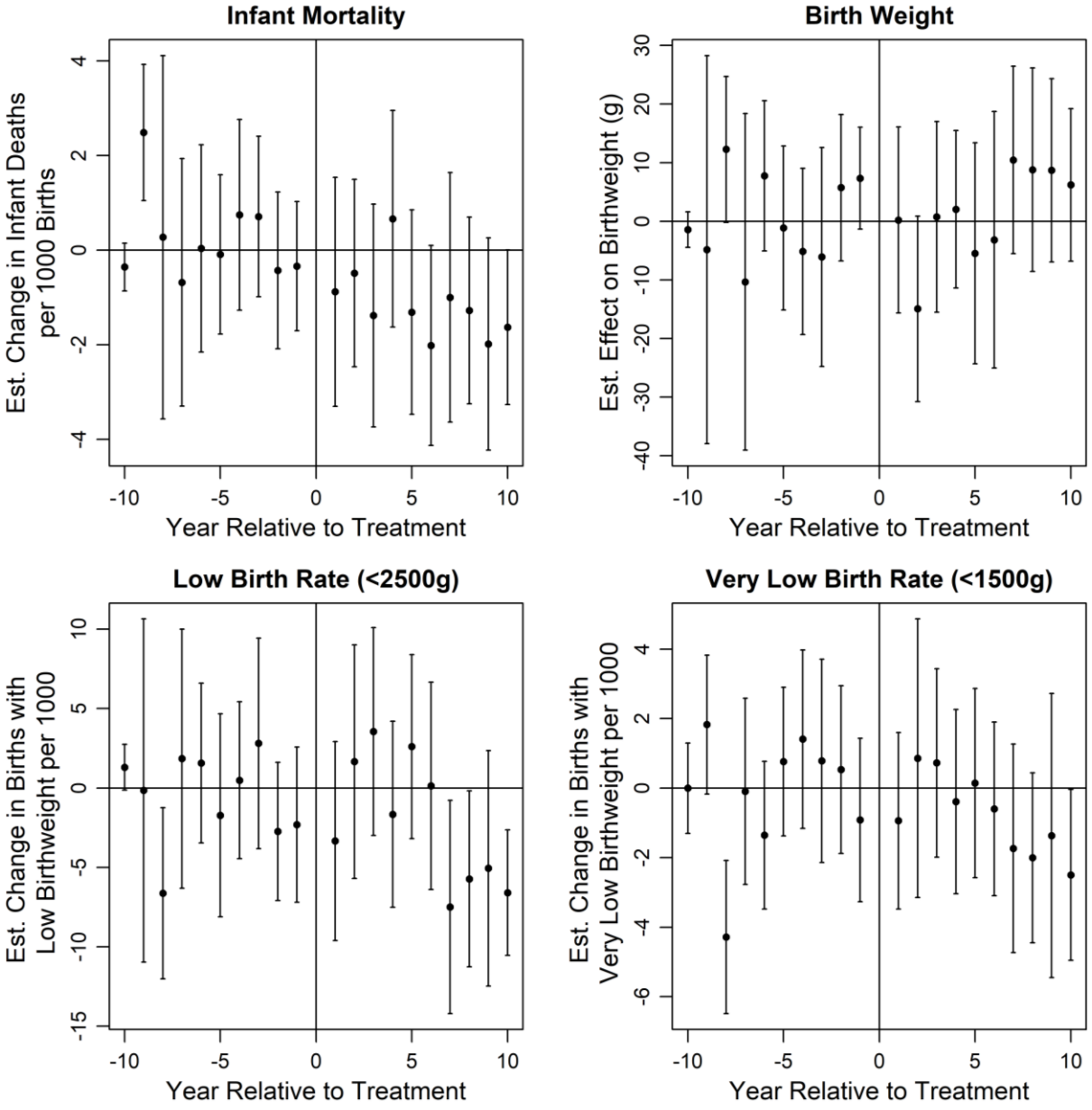
Figures 6 and 7 suggest that the treatment effects of Tribal TANF are largest after five years of having the program. This is consistent with the increase in caseloads for each program

Figure 6. Impact of Tribal TANF on AIAN Infant Health Outcomes By Year Relative to Treatment With State Time Trends



shown in Figure 2, which shows that on average the largest increase in caseloads occurs within the first five years of the program. Additionally, many tribes reported difficulties initially with administrative tasks (Hillabrant et al., 2003), which may be alleviated over time as employees

Figure 7. Impact of Tribal TANF on AIAN Infant Health Outcomes By Year Relative to Treatment Without State Time Trends



gain institutional knowledge.

Despite these indications of a decrease in low and very low birthweights, there is not an obvious increase in birthweight within the sample. It is expected that untreated individuals in the sample who are coded as treated would follow the national trend of decreasing birth weights, which could offset any change in birthweights due to Tribal TANF. Binary variables, like low and very low birth weight, would not be as impacted by these trends, which may explain these differences.

All estimated signs reported in the top panel of Table 2 suggest that Tribal TANF improves health outcomes. Infant mortality, low birth weight, and very low birth weight estimates are all negative, and birthweight estimates are positive. However, there are no significant estimates of the impact of Tribal TANF on infant mortality and very limited evidence that is has any effect on birth weight. The event studies for infant mortality in Figures 6 and 7 show a suggestive trend that Tribal TANF reduces infant mortality. Nine of the ten the post-treatment estimates are negative and trending downward. Additionally, the estimates are robust to state time trends, although the additional trends decrease the significance.

Mechanisms

Mechanically, Tribal TANF can impact birthweight through preventing intrauterine reduction from maternal behaviors and environments or through extending gestation length. To assess the mechanism through which Tribal TANF helped, additional dependent variables were estimated and reported in Table 4.

Gestation length is estimated to increase with Tribal TANF, significantly without state

Table 4. Tribal TANF Effects on Additional Outcomes

Dependant Variable	With State Time Trend	Without State Time Trend
Gestation Weeks	0.03 (0.05)	0.15** (0.05)
Moderate Preterm Births (per 1000)	3.73 (5.12)	-0.13 (5.27)
Very Preterm Births (per 1000)	-2.12 (1.60)	-0.64 (0.90)
Extreme Preterm Births (per 1000)	-3.04** (1.11)	-0.45 (0.66)
Neonatal Mortatality Rate (per 1000)	-1.58 (0.98)	-0.71 (0.68)
Mother's Age	-0.03 (0.13)	0.00 (0.15)
Pct. Mothers With Post-HS Eduction	-0.01 (0.01)	0.01 (0.02)
Married Mothers (per 1000)	-10.16 (13.27)	1.42 (15.17)
Prenatal Visits	-0.21 (0.16)	-0.16 (0.15)
Pct. Mothers Smoke During Pregnancy	0.08* (0.03)	0.03 (0.02)
Pct. Deliveries in Medical Facility	-0.00 (0.00)	-0.00 (0.00)
Number of Children	0.03 (0.03)	-0.06 (0.03)
Number of Fetal Deaths	-0.03 (0.02)	-0.01 (0.02)

Notes: Each cell represents a seperate Two-Stage Least Squares estimate of the effect of Tribal TANF on dependant variables, with a specification equivalent to Table 3 column 2. Moderate, very, and extremely preterm births are defined by the WHO as less than 37, 32, and 28 weeks of gestation, respectively. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

time trends, and insignificantly with state time trends. This is the only significant observed mechanism through which Tribal TANF improves infant health outcomes. Surprisingly, the estimates show that there is an increase in the percentage of mothers who smoke during pregnancy, which is associated with lower birthweights (Abrevaya, 2006). There also appears to be an insignificant decrease in prenatal visits, which may indicate that Tribal TANF does not improve prenatal care or access. This is consistent with the early TANF literature (Kaestner & Lee, 2005). These results also suggest that Tribal TANF does not have an effect on mother's age, education level[28], number of children, or fetal deaths.

Increased access to food or better nutrition is a potential mechanism for how Tribal TANF can improve infant outcomes but is not observed in the data. There is an association within the medical literature between poor nutrition and worse birth outcomes (Lechtig et al., 1975; Victora et al., 2008), and the economics literature has found that nutrition based welfare programs, like WIC and food stamps, led to improved birth outcomes (Almond et al., 2011; Hoynes et al., 2011). Proximity to state TANF offices and lack of access to reliable transportation were commonly cited as reasons many Tribal TANF programs saw higher caseloads relative to estimates from AFDC. Additionally, Native American reservations are often food deserts[29], requiring consistent transportation to access food (Chodur et al., 2016). Many Tribal TANF programs provide transportation assistance, which could be increasing nutritional availability (Fagnoni et al., 2002).

[28] Tribal TANF programs often have job education programming for recipients (Hahn et al., 2016). The Vital Statistics measure only includes formal educational pathways, so do not reflect these programs.
[29] Research finds that food deserts do not drive nutritional inequality nationally (Allcott et al., 2019). However, this finding was due to low-income individuals in food deserts commuting to grocery stores. To the extent that transportation had been found to be a binding constraint on accessing state TANF on Native American reservations, this finding may not extend to these individuals.

Robustness

Additional matching techniques were used to ensure that results are not solely a product of the Mahalanobis matching used in this analysis. These are propensity score matching, inverse propensity score weighting, and coarse exact matching (CES). The results from these models and

Table 5. Two-Stage Least Squares Estimates of the Effect of Tribal TANF on Infant Health Outcomes With Subpopulations and Placebo Populations

	Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
With State Linear Time Trends	Infant Mortality (per 1000)	-1.6	-2.5	-1.9	-2.8	1.5*	2.3***	1.2
		(1.5)	(2.2)	(1.6)	(2.2)	(0.6)	(0.4)	(0.8)
	Birth Weight (g)	9.4	10.8	10.7	10.5	7.1	-32.2**	-17.8
		(6.5)	(8.2)	(6.6)	(7.9)	(7.6)	(11.4)	(10.5)
	Low Birth Weight (per 1000)	-8.3***	-5.9**	-8.3***	-10.0***	-3.5	7.1***	4.0
		(2.0)	(2.2)	(1.8)	(2.6)	(1.9)	(1.8)	(3.0)
	Very Low Birth Weight (per 1000)	-4.5*	-1.5	-5.8***	-4.6	-3.0*	1.1*	-0.2
		(2.2)	(2.0)	(1.0)	(2.8)	(1.4)	(0.4)	(0.8)
Without State Linear Time Trends	Infant Mortality (per 1000)	-1.4	-0.5	-1.5*	-2.3*	0.9	0.2	-0.7
		(0.7)	(0.9)	(0.8)	(1.0)	(0.6)	(0.4)	(0.5)
	Birth Weight (g)	3.0	5.4	4.7	4.9	1.9	-21.2*	-7.7
		(5.1)	(6.7)	(5.5)	(5.6)	(7.7)	(9.6)	(8.6)
	Low Birth Weight (per 1000)	-4.3**	-4.1	-5.0**	-5.1*	-2.6	1.3	-0.5
		(1.6)	(2.1)	(1.7)	(2.1)	(2.0)	(1.2)	(1.5)
	Very Low Birth Weight (per 1000)	-1.7	-1.8	-2.4**	-1.7	-1.2	-0.2	-1.3*
		(1.1)	(1.5)	(0.9)	(1.4)	(0.9)	(0.5)	(0.6)
County-Year Observations		6582	6482	6832	6907		7242	
Unique Births		493436	468551	516747	543541		1543173	
Exclude Oklahoma		X						
Exclude California			X					
Exclude Navajo Nation				X				
Start Tribal TANF < 2004					X			
Start Tribal TANF >= 2004						X		
Exclude AIAN							X	X
Exclude White								X

Notes: Standard errors are clustered at the reservation level. Each cell in columns 1-3 represent a seperate regression. Columns 4-5 & 6-7 report interacted speciications with each column being the total estimated impact for each subgroup. All regressions use an empirical specification equivalent to Table 3 column 2. Regressions differ by populations included or excluded. Columns 6 & 7 only include mothers that have a highschool education or less, are unmarried, and have at least one previous child. This is to best align the placebo population with the TANF population, and the sample size is large enough to retain sufficient power. All models used the same treated and control counties as shown in Figure 4, with the relevant filtering. Columns 1-5 only include AIAN populations. Low birth weight (< 2500g) and very low birthweight (< 1500g) are defined by the WHO. *** $p < .001$, ** $p < 0.01$, * $p < 0.05$.

additional description of the methodologies are described in Appendix C. As described in Table A.1, the results from these models are consistent with the main results presented in Table 2, providing evidence that the estimates from this analysis are due to bias within the matching algorithm.

To further explore issues of heterogeneity with the sample of reservations that started Tribal TANF programs, further analysis was explored. Columns 1-3 of Table 5 show results from the preferred specification excluding all treated reservations in Oklahoma, California, and the Navajo reservation, respectively. These represent the largest AIAN populations within the dataset. Due to population weighting in the regression model, these populations have more influence on the results. Results from this heterogeneity analysis show that these populations are large enough to influence the results, but similar trends as before are still observed without them. Californian reservations appear to have experienced a larger reduction in the incidence of low and very low birthweights than the rest of the sample, while the Navajo Nation experienced a smaller reduction. Estimates without Oklahoma Tribal TANF programs are close to those from the full population.

The TANF block grant has never been increased, so the real value to Tribal TANF programs has eroded over time ,which may limit the efficacy of later programs. Additionally, programs that expect the highest return to starting Tribal TANF would also be expected to adopt earlier. Due to this, there may be heterogeneity in treatment effect across the time Tribal TANF programs started. Columns 4 & 5 in Table 5 show the differential impacts between programs that

started earlier and later, respectively[30]. There appears to be heterogeneity in treatment effect between earlier and later programs. Earlier Tribal TANF programs saw larger and more significant improvements in infant health than later programs. Later adoption of Tribal TANF is associated with increased infant mortality, significantly with linear state time trends. Attenuation in program impacts is consistent with an eroding block grant as well as early programs anticipating the largest benefits. As seen in Figures 6 & 7, the impacts of Tribal TANF on low and very low birthweight appear to increase over time, so the later Tribal TANF programs may just not have been established for long enough to see the improvements in birth outcomes that the earlier programs experienced.

Finally, the results found in this analysis could just be picking up local efforts to improve these outcomes for all races. To evaluate this, the same analysis was conducted with the non-AIAN populations within the counties identified in the matching specification. To better match the population of TANF recipients, this sample was restricted to births with mothers with a high school education or less, at least one previous child, and who are unmarried[31]. Columns 6 & 7 report estimates for all non-AIAN individuals and all non-AIAN, non-white individuals[32]. These results indicate that non-AIAN populations in the same counties saw worsening infant health outcomes or improvements of smaller magnitudes than the AIAN populations. This suggests that the estimates of the impact of Tribal TANF are not driven by simultaneous, unrelated local efforts.

[30] The median Tribal TANF program was established in 2003, which was used as the cutoff between "early" and "late".
[31] These are the same population subsets as reported in column 6 of Table 3. The non-AIAN sample is large enough that these restrictions can be imposed while still retaining sufficient power.
[32] Within this analysis, "white" is defined as both parents listing white as their only race.

CHAPTER FIVE

CONCLUSION

This paper studies the impact of Tribal Temporary Assistance for Needy (TANF) on infant health outcomes. Since 1996, Federally Recognized Tribes can establish their own Tribal TANF program, which shifts the administration and execution of TANF from the state to the tribe. This change localizes programming, reducing cultural and geographical barriers to access TANF for tribal communities.

Reservations that started a Tribal TANF program are matched on pretreatment descriptive covariates with counterfactual reservations that do not have Tribal TANF. Using matched birth-cohort infant birth-death vital statistics data, this analysis estimates that Tribal TANF programs are associated with a 14% reduction in the incidence of low birthweight and a 42% reduction in very low birthweight. There is also an estimated reduction in neonatal mortality and extreme preterm births, both of which are closely linked to low birthweight (Anderson & Smith, 2002). These results are robust to alternative matching strategies, are not observed in placebo populations, and are not driven by a high-population AIAN areas.

The results are consistent with increased program access and participation under tribal administration. In contrast to the broader decline in caseloads following the transition from AFDC to TANF, Tribal TANF programs exhibit increases in participation, suggesting that local administration can mitigate barriers that limit Tribal participation in state-administered TANF.

These results have implications beyond TANF. Many federal programs serving low-income populations remain state-administered and may not adequately address the unique conditions within tribal communities. These findings suggest that the transfer of welfare

administration to tribal governments may play an important role in improving early-life health conditions in Native communities. The results contribute to a growing literature showing that program design and local governance structures can shape the effectiveness of social welfare programs. Understanding how tribal administration alters program access, incentives, and service delivery remains a key area for future research and may have implications for the design of other place-based or tribally administered social programs.

REFERENCES

Abrevaya, J. (2006). Estimating the effect of smoking on birth outcomes using a matched panel data approach. Journal of Applied Econometrics, 21(4), 489–519. https://doi.org/10.1002/jae.851

Aizer, A., & Currie, J. (2014). The intergenerational transmission of inequality: Maternal disadvantage and health at birth. Science, 344(6186), 856–861. https://doi.org/10.1126/science.1251872

Akee, R. K. Q., Copeland, W. E., Keeler, G., Angold, A., & Costello, E. J. (2010). Parents' Incomes and Children's Outcomes: A Quasi-experiment Using Transfer Payments from Casino Profits. American Economic Journal: Applied Economics, 2(1), 86–115. https://doi.org/10.1257/app.2.1.86

Akee, R., & Simeonova, E. (2024). Economic Development, Unearned Income and Mortality: Evidence from Tribal Casinos (Retirement and Disability Research Center Nos. NB22-05). NBER. https://www.nber.org/programs-projects/projects-and-centers/retirement-and-disability-research-center/center-papers/nb22-05

Allcott, H., Diamond, R., Dubé, J.-P., Handbury, J., Rahkovsky, I., & Schnell, M. (2019). Food Deserts and the Causes of Nutritional Inequality*. The Quarterly Journal of Economics, 134(4), 1793–1844. https://doi.org/10.1093/qje/qjz015

Almond, D., Chay, K. Y., & Lee, D. S. (2005). The Costs of Low Birth Weight. The Quarterly Journal of Economics, 120(3), 1031–1083. https://doi.org/10.1093/qje/120.3.1031

Almond, D., Hoynes, H. W., & Schanzenbach, D. W. (2011). Inside the War on Poverty: The Impact of Food Stamps on Birth Outcomes. The Review of Economics and Statistics, 93(2), 387–403. https://doi.org/10.1162/REST_a_00089

Almond, D., & Mazumder, B. (2011). Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy. American Economic Journal: Applied Economics, 3(4), 56–85. https://doi.org/10.1257/app.3.4.56

Amarante, V., Manacorda, M., Miguel, E., & Vigorito, A. (2016). Do Cash Transfers Improve Birth Outcomes? Evidence from Matched Vital Statistics, Program, and Social Security Data. American Economic Journal: Economic Policy, 8(2), 1–43. https://doi.org/10.1257/pol.20140344

Anderson, R., & Smith, B. (2002). QuickStats: Leading Causes of Neonatal and Postneonatal Deaths—United States (53(17); National Vital Statistics Reports). U.S. Centers for Disease Control and Prevention. https://www.cdc.gov/mmwr/preview/mmwrhtml/mm5438a8.htm?utm_source=chatgpt.com

Approved Tribal TANF Grants. (2015). Administration for Children & Families. https://acf.gov/sites/default/files/documents/ofa/appvd_tfags_fy_2015_revised_12_15_2014.pdf

Arkin, J. (2025). TEMPORARY ASSISTANCE FOR NEEDY FAMILIES: Enhanced Reporting Could Improve HHS Oversight of State Spending (GAO-25-107235). U.S. Government Accountability Office. https://files.gao.gov/reports/GAO-25-107235/index.html

Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A., & Sant'Anna, P. H. C. (2026). Difference-in-Differences Designs: A Practitioner's Guide. Journal of Economic Literature. https://doi.org/10.1257/jel.20251650

Behrman, J. R., & Rosenzweig, M. R. (2004). Returns to Birthweight. The Review of Economics and Statistics, 86(2), 586–601.

Beyer, D. (2022). Native American Communities Continue to Face Barriers to Opportunity that Stifle Economic Mobility—Native American Communities Continue to Face Barriers to Opportunity that Stifle Economic Mobility—United States Joint Economic Committee. Joint Economic Committee. https://www.jec.senate.gov/public/index.cfm/democrats/2022/5/native-american-communities-continue-to-face-barriers-to-opportunity-that-stifle-economic-mobility

Bitler, M., Cook, J. B., East, C. N., Porter, S. R., & Tiehen, L. (2025). The Intersection of Place and Need: How Lack of Enrollment Offices Deters Participation in the Safety Net (Working Paper No. 34529). National Bureau of Economic Research. https://doi.org/10.3386/w34529

Black, S. E., Devereux, P. J., & Salvanes, K. G. (2007). From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes*. The Quarterly Journal of Economics, 122(1), 409–439. https://doi.org/10.1162/qjec.122.1.409

Brown, E., Whitaker, L., Springwater, M., Cornell, S., Jorgensen, M., Hale, M., & Nagle, A. (2001). Welfare, Work, and American Indians: The Impact of Welfare Reform. Buder Center for American Indian Studies Research. https://openscholarship.wustl.edu/buder_research/11

Camacho, A. (2008). Stress and Birth Weight: Evidence from Terrorist Attacks. American Economic Review, 98(2), 511–515. https://doi.org/10.1257/aer.98.2.511

Chodur, G. M., Shen, Y., Kodish, S., Oddo, V. M., Antiporta, D. A., Jock, B., & Jones-Smith, J. C. (2016). Food Environments around American Indian Reservations: A Mixed Methods Study. PLOS ONE, 11(8), e0161132. https://doi.org/10.1371/journal.pone.0161132

Clausson, B., Lichtenstein, P., & Cnattingius, S. (2000). Genetic influence on birthweight and gestational length determined by studies in offspring of twins. BJOG: An International

Journal of Obstetrics & Gynaecology, 107(3), 375–381. https://doi.org/10.1111/j.1471-0528.2000.tb13234.x

Collins, J. W., Wambach, J., David, R. J., & Rankin, K. M. (2009). Women's lifelong exposure to neighborhood poverty and low birth weight: A population-based study. Maternal and Child Health Journal, 13(3), 326–333. https://doi.org/10.1007/s10995-008-0354-0

Currie, J. (2009). Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. Journal of Economic Literature, 47(1), 87–122. https://doi.org/10.1257/jel.47.1.87

Currie, J., & Schmieder, J. F. (2009). Fetal Exposures to Toxic Releases and Infant Health. American Economic Review, 99(2), 177–183. https://doi.org/10.1257/aer.99.2.177

Currie, J., & Walker, R. (2011). Traffic Congestion and Infant Health: Evidence from E-ZPass. American Economic Journal: Applied Economics, 3(1), 65–90. https://doi.org/10.1257/app.3.1.65

Demerth, E. W., Choh, A. C., Czerwinski, S. A., Lee, M., Sun, S. S., Chumlea, WM. C., Duren, D., Sherwood, R. J., Blangero, J., Towne, B., & Siervogul, R. M. (2007). Genetic and Environmental Influences on Infant Weight and Weight Change: The Fels Longitudinal Study. American Journal of Human Biology : The Official Journal of the Human Biology Council, 19(5), 692–702. https://doi.org/10.1002/ajhb.20660

Deshpande, M., & Li, Y. (2019). Who Is Screened Out? Application Costs and the Targeting of Disability Programs. American Economic Journal: Economic Policy, 11(4), 213–248. https://doi.org/10.1257/pol.20180076

Duflo, E. (2017). The Economist as Plumber. American Economic Review, 107(5), 1–26. https://doi.org/10.1257/aer.p20171153

Elder, T. E., Goddeeris, J. H., & Haider, S. J. (2016). Racial and ethnic infant mortality gaps and the role of socio-economic status. Labour Economics, Health and the Labour Market, 43, 42–54. https://doi.org/10.1016/j.labeco.2016.04.001

Fagnoni, C., Mrena, C., & Larin, K. (2002). Welfare Reform: Tribal TANF Allows Flexibility to Tailor Programs, but Conditions on Reservations Make It Difficult to Move Recipients into Jobs (Report to Congressional Requesters GAO-02-768). U. S. Government Accountability Office. https://www.gao.gov/products/gao-02-768

Fletcher, M. L. M. (2012). Tribal Membership and Indian Nationhood. American Indian Law Review, 37(1), 1–18.

Fretts, R. C., Schmittdiel, J., McLean, F. H., Usher, R. H., & Goldman, M. B. (1995). Increased Maternal Age and the Risk of Fetal Death. New England Journal of Medicine, 333(15), 953–957. https://doi.org/10.1056/NEJM199510123331501

Gardner, J. (2022). Two-stage differences in differences (arXiv:2207.05943). arXiv. https://doi.org/10.48550/arXiv.2207.05943

Gertler, P. (2004). Do Conditional Cash Transfers Improve Child Health? Evidence from PROGRESA′s Control Randomized Experiment. American Economic Review, 94(2), 336–341. https://doi.org/10.1257/0002828041302109

Gu, X. S., & Rosenbaum, P. R. (1993). Comparison of Multivariate Matching Methods: Structures, Distances, and Algorithms. Journal of Computational and Graphical Statistics, 2(4), 405–420. https://doi.org/10.1080/10618600.1993.10474623

Hahn, H., Healy, O., Hillabrant, W., & Narducci, C. (2016). A Descriptive Study of Tribal Temporary Assistance for Needy Families (TANF) Programs. Urban Institute. https://www.urban.org/research/publication/descriptive-study-tribal-temporary-assistance-needy-families-tanf-programs

Herd, P., & Moynihan, D. (2025). Administrative Burdens in the Social Safety Net. Journal of Economic Perspectives, 39(1), 129–150. https://doi.org/10.1257/jep.20231394

Hillabrant, W., Rhoades, M., & Pindus, N. (2003). Operating TANF: Opportunities and Challenges for Tribes and Tribal Consortia (MPR Nos. 8550–921). Mathematica Policy Research, Inc. http://aspe.hhs.gov/reports/operating-tanf-opportunities-challenges-tribes-tribal-consortia-1

How to Become a Tribal TANF Program. (2023, June 30). Office of Family Assistance. https://acf.gov/ofa/programs/tribal/policy/how-become-tribal-tanf-program

Hoynes, H., Page, M., & Stevens, A. H. (2011). Can targeted transfers improve birth outcomes?: Evidence from the introduction of the WIC program. Journal of Public Economics, 95(7), 813–827. https://doi.org/10.1016/j.jpubeco.2010.12.006

Iacus, S. M., King, G., & Porro, G. (2012). Causal Inference without Balance Checking: Coarsened Exact Matching. Political Analysis, 20(1), 1–24.

Jardine, J., Walker, K., Gurol-Urganci, I., Webster, K., Muller, P., Hawdon, J., Khalil, A., Harris, T., van der Meulen, J., & National Maternity and Perinatal Audit Project Team. (2021). Adverse pregnancy outcomes attributable to socioeconomic and ethnic inequalities in England: A national cohort study. Lancet, 398(10314), 1905–1912. https://doi.org/10.1016/S0140-6736(21)01595-6

Kaestner, R., & Lee, W. C. (2005). The effect of welfare reform on prenatal care and birth weight. Health Economics, 14(5), 497–511. https://doi.org/10.1002/hec.921

Kauffman, J. A. (2002). Welfare Reform and American Indian Tribes: Critical Decisions for the Future of Indian Families. Kaiser Family Foundation. https://eric.ed.gov/?id=ED475038

Kennedy-Moulton, K., Miller, S., Persson, P., Rossin-Slater, M., Wherry, L. R., & Aldana, G. (2025). Maternal and Infant Health Inequality: New Evidence from Linked Administrative Data. The Review of Economics and Statistics, 1–32. https://doi.org/10.1162/REST.a.1633

King, G., & Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. Political Analysis, 27(4), 435–454.

Kozhimannil, K. B., Interrante, J. D., Tofte, A. N., & Admon, L. K. (2020). Severe Maternal Morbidity and Mortality Among Indigenous Women in the United States. Obstetrics and Gynecology, 135(2), 294–300. https://doi.org/10.1097/AOG.0000000000003647

Lechtig, A., Yarbrough, C., Delgado, H., Habicht, J., Martorell, R., & Klein, R. (1975). Influence of maternal nutrition on birth weight. The American Journal of Clinical Nutrition, 28(11), 1223–1233. https://doi.org/10.1093/ajcn/28.11.1223

Leonard, J., & Mas, A. (2008). Welfare reform, time limits, and infant health. Journal of Health Economics, 27(6), 1551–1566. https://doi.org/10.1016/j.jhealeco.2008.05.013

Lindo, J. M. (2011). Parental job loss and infant health. Journal of Health Economics, 30(5), 869–879. https://doi.org/10.1016/j.jhealeco.2011.06.008

Lively, C. P. (2021). COVID-19 in the Navajo Nation Without Access to Running Water: The lasting effects of Settler Colonialism. Voices in Bioethics, 7. https://doi.org/10.7916/vib.v7i.7889

Martinson, M. L., & Reichman, N. E. (2016). Socioeconomic Inequalities in Low Birth Weight in the United States, the United Kingdom, Canada, and Australia. American Journal of Public Health, 106(4), 748–754. https://doi.org/10.2105/AJPH.2015.303007

McCormick, M. C. (1985). The Contribution of Low Birth Weight to Infant Mortality and Childhood Morbidity. New England Journal of Medicine, 312(2), 82–90. https://doi.org/10.1056/NEJM198501103120204

McIntire, D. D., Bloom, S. L., Casey, B. M., & Leveno, K. J. (1999). Birth Weight in Relation to Morbidity and Mortality among Newborn Infants. New England Journal of Medicine, 340(16), 1234–1238. https://doi.org/10.1056/NEJM199904223401603

Medford, A., & Akee, R. (2025, September 9). Social and Economic Changes in American Indian Reservations: A Databook of the US Census and the American Community Survey, Third Edition 1990-2020. Ash Center. https://ash.harvard.edu/resources/social-and-economic-changes-in-american-indian-reservations-a-databook-of-the-us-census-and-the-american-community-survey-third-edition/

Monahan, E., Wiegand, E., Goerge, B., Geoghegan, R., & Delgado, H. (2024). Patterns and trends in Temporary Assistance for Needy Families (TANF) participation: Analysis of

longitudinal Federal TANF participation in 28 states. Chapin Hall at the University of Chicago. https://www.chapinhall.org/research/overall-tanf-caseload-declined-between-2010-and-2022/

Morisaki, N., Esplin, M. S., Varner, M. W., Henry, E., & Oken, E. (2013). Declines in Birth weight and Fetal Growth Independent of Gestational Length. Obstetrics and Gynecology, 121(1), 51–58. https://doi.org/10.1097/aog.0b013e318278d014

Moseley, P. (1996). SUMMARY OF WELFARE REFORMS MADE BY PUBLIC LAW 104-193 THE PERSONAL RESPONSIBILITY AND WORK OPPORTUNITY RECONCILIATION ACT AND ASSOCIATED LEGISLATION (WPRT Nos. 104–15). Ways and Means Committee. https://www.govinfo.gov/content/pkg/CPRT-104WPRT27305/html/CPRT-104WPRT27305.htm

Murphy, S., Kochanek, K., Xu, J., & Arias, E. (2024). Mortality in the United States, 2023 (No. 521; NCHS Data Brief). U.S. Centers for Disease Control and Prevention. https://doi.org/10.15620/cdc/170564

Personal Responsibility and Work Opportunity Reconciliation Act of 1996, Pub. L. Nos. 104–193 (1996). https://www.congress.gov/bill/104th-congress/house-bill/3734/text

Policy Basics: Tribal TANF. (2022). Center on Budget and Policy Priorities. https://www.cbpp.org/research/income-security/tribal-tanf

Robinson, J. S., Moore, V. M., Owens, J. A., & McMillen, I. C. (2000). Origins of fetal growth restriction. European Journal of Obstetrics, Gynecology, and Reproductive Biology, 92(1), 13–19. https://doi.org/10.1016/s0301-2115(00)00421-8

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. Biometrika, 70(1), 41–55. https://doi.org/10.2307/2335942

Saavedra, M. (2020). Birth weight and infant health for multiple births. Journal of Health Economics, 69, 102255. https://doi.org/10.1016/j.jhealeco.2019.102255

Saleem, T., Sajjad, N., Fatima, S., Habib, N., Ali, S. R., & Qadir, M. (2011). Intrauterine growth retardation—Small events, big consequences. Italian Journal of Pediatrics, 37, 41. https://doi.org/10.1186/1824-7288-37-41

Scott, W. (2002). Welfare Reform and American Indians: Critical Issues for Reauthorization (NHPF Issue Brief No. 778). National Health Policy Forum.

Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. Statistical Science, 25(1), 1–21.

Swanson, D. A., Kposowa, A., & Baker, J. (2019). Estimating the Underlying Infant Mortality Rates for Small Populations, Including those Reporting Zero Infant Deaths: A Case Study of Counties in California. Population Review, 58(2). https://muse.jhu.edu/pub/251/article/727959

Victora, C. G., Adair, L., Fall, C., Hallal, P. C., Martorell, R., Richter, L., & Sachdev, H. S. (2008). Maternal and child undernutrition: Consequences for adult health and human capital. The Lancet, 371(9609), 340–357. https://doi.org/10.1016/S0140-6736(07)61692-4

Wong, C. A., Gachupin, F. C., Holman, R. C., MacDorman, M. F., Cheek, J. E., Holve, S., & Singleton, R. J. (2014). American Indian and Alaska Native Infant and Pediatric Mortality, United States, 1999–2009. American Journal of Public Health, 104(Suppl 3), S320–S328. https://doi.org/10.2105/AJPH.2013.301598

APPENDICES

APPENDIX A

STATE TANF REGULATIONS

Table A1. State TANF Regulations

Regulation	Description
Job Search Required	If the state mandates that all individuals in the household over twenty-one to search for a job as a requirement of receiving TANF
Asset Limit	The maximum dollar value of assets that a household can hold is still eligible for TANF. Vehicles are either partially or wholly excluded from this calculation.
Has Asset Limit	If the state conditions TANF on an asset limit.
Maximum Earnings	The maximum annual earnings a household of three can earn and still be eligible for a TANF cash benefit
Lifetime Limit	The maximum number of months an individual can receive TANF benefits without a hardship exemption. Federal funds can only be used to fund TANF cash benefits for 60 months.
Has Lifetime Limit	If the state has a maximum number of months an individual can receive TANF benefits without a hardship exemption
Maximum TANF Cash Benefit	The maximum monthly TANF cash benefit that a household of three with no income can receive.

Source: Urban Institute's Welfare Rules Database, funded by HHS/ACF

APPENDIX B

ESTIMATED RELATIONSHIP BETWEEN TRIBAL TANF PROGRAM START DATE AND RESERVATION CHARACTERISTICS

Table B1. Estimated Relationship Between Tribal TANF Program Start Date and Reservation Characteristics

Characteristic	Estimate
Real Median Income	197 (321)
Log Reservation Land	-0.009 (0.09)
Log Reservation Population	0.03 (0.06)
High school Graduation Rate	-0.002 (0.002)

Notes: Standard errors are reported in parenthesis below estimates. Each cell represents a separate regression with the estimated impact of the year each Tribal TANF program started relative to 1997 (year of first Tribal TANF program) on each respective outcome. Regressions use data displayed in Figure 3. *** $p < .001$, ** $p < 0.01$, * $p < 0.05$.

APPENDIX C

ADDITIONAL MATCHING TECHNIQUES

Propensity Scores

To calculate reservation propensity scores, reservation and county characteristic data from the 1990 and 2000 decennial census, and the 2009-2020 5-year average ACS surveys were used. Population and median income are available at the reservation level. Percentage of households in poverty and education levels are specific to the American Indian/Alaska Native population within the county. State restrictions on availability and benefits for TANF from the Welfare Rules Database were included. These include whether a job search is required, if there is an asset limit, the maximum cash benefit for a household with no income and three individuals, and the lifetime limit (i.e., maximum number of months TANF is available). These variables were averaged across all years the reservation did not have a tribal TANF program. Propensity scores, as described in Rosenbaum & Rubin (1983), were then calculated using a probit model.

Propensity scores were used in two matching designs: closest neighbors and inverse propensity score weighting. In the closest neighbor design, all untreated reservations with propensity scores within 1% of the treated reservation are matched as counterfactuals. If no untreated reservation has a propensity score within 1%, then the untreated reservation with the most similar propensity score is matched. The dataset is then limited to only treated and matched control reservations. With inverse propensity score weighting all reservations are kept within the sample and observations are weighted within the regression, with weights calculated through:

$$Inverse\ Propensity\ Score = \frac{Treated}{Propensity\ Score} + \frac{1 - Treated}{1 - Propensity\ Score} \quad (1)$$

This gives more weight to reservations that were predicted to have a high probability of treatment, based on their covariates, and did not develop a Tribal TANF program, and vice versa.

Observable Characteristic Matching

Another method of identifying suitable control groups of untreated reservations is through Coarse Exact Matching (CEM) (Iacus et al., 2012). This allows for matching treated and control units on similar observable, continuous characteristics. The match variables are reservation population, percentage of population with a high school diploma, and the maximum earnings a household of three can have and still be eligible for the state's TANF. The pre-treatment average of each variable is divided into four bins, and treated reservations are matched with all untreated reservations that fall into the same bins[33].

Table C1. Two-Stage Least Squares Estimates of the Effect of Tribal TANF on American Indian Infant Health Outcomes Within Native American Reservations With Various Matching Regimes

	Outcome	Propensity Score (PS)	Inv. PS Weighting	Coarse Exact Match
With State Linear Time Trends	Infant Mortality (per 1000)	-0.6 (1.4)	-3.5 (2.1)	-1.6 (1.4)
	Birth Weight (g)	7.2 (6.5)	12.8* (5.5)	9.4 (6.3)
	Low Birth Weight (per 1000)	-9.8*** (1.9)	-8.4*** (2.1)	-5.1** (1.8)
	Very Low Birth Weight (per 1000)	-5.4* (2.4)	-3.9** (1.3)	-2.6 (1.8)
Without State Linear Time Trends	Infant Mortality (per 1000)	-1.2 (0.8)	-1.3 (0.7)	-0.4 (0.7)
	Birth Weight (g)	4.5 (5.5)	4.2 (5.3)	4.9 (5.1)
	Low Birth Weight (per 1000)	-4.3* (1.7)	-3.7 (2.1)	-4.3* (1.7)
	Very Low Birth Weight (per 1000)	-1.2 (1.2)	-1.4 (1.3)	-0.5 (1.1)
County-Year Observations		4394	7364	4880
Unique Births		348773	558523	408121

Notes: Standard errors are clustered at the reservation level. Each cell represents a separate regression where reservations that started Tribal TANF programs are matched with different methodology to reservations that did not, with an empirical specification equivalent to Table 3 column 2. Low birth weight (< 2500g) and very low birthweight (< 1500g) are defined by the WHO. *** $p < .001$, ** $p < 0.01$, * $p < 0.05$.

[33] The number of treated reservations that can have a match found for is very sensitive to the number of bins per variable. With four bins three reservations are unmatched, and twelve reservations are unmatched with five bins.

Discussion

Mahalanobis distance matching was chosen as the primary matching technique due to its abilities to match based on similarity to observable characteristics without assuming a functional form and incorporate all treated reservation options. Propensity scores, while widely used, rely on a specified functional form that may not best represent the data generating process. For this reason, simulation analysis has found that matching techniques using propensity scores often have poor balance within the panel (King & Nielsen, 2019). CEM is simple and has an obvious interpretation. However, this methodology relies on binning for continuous variables which impose arbitrary thresholds which the model is very sensitive to when there is a small sample of units. Due to this, a limited number of variables with few bins is used in this analysis, resulting in poor balance. Mahalanobis matching overcomes these issues, making it the preferred choice. As discussed earlier, it is sensitive to variable selection, so these additional matching techniques are used for robustness.