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Landon C. Echols
University of Pennsylvania

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Abstract

Revenue allocation plans (RAPs) are one way in which Native American tribal governments distribute their casino profits equally to every member of the tribe. This study matches tribes with approved RAPs to their respective “treatment” counties. These treatment counties are then matched and compared to control counties of similar geography and population through difference-in-difference analysis. Through this analysis, it is apparent that there are no effects of RAPs on unemployment rates in treatment counties – however, there seems to be a slight positive effect on employment-to-population ratios and labor force participation rates. This paper finds that the RAP in 22 counties (by proxy, tribes) studied do not follow the income effect. Instead, the study suggests that windfall (or non-labor) income on these tribes has a positive, yet small, effect on labor supply.

Keywords

income effect, labor supply, Native American economics, basic income, non-labor income

Disciplines

Labor Economics

JACKPOT! THE EMPLOYMENT EFFECTS OF GAMING REVENUE ALLOCATION
PLANS ON NATIVE AMERICAN TRIBES

By

Landon Echols

An Undergraduate Thesis submitted in partial fulfillment of the requirements for the
WHARTON RESEARCH SCHOLARS

Faculty Advisor:

Benjamin Lockwood

Assistant Professor, Business Economics and Public Policy

THE WHARTON SCHOOL, UNIVERSITY OF PENNSYLVANIA

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ABSTRACT

Revenue allocation plans (RAPs) are one way in which Native American tribal governments distribute their casino profits equally to every member of the tribe. This study matches tribes with approved RAPs to their respective “treatment” counties. These treatment counties are then matched and compared to control counties of similar geography and population through difference-in-difference analysis. Through this analysis, it is apparent that there are no effects of RAPs on unemployment rates in treatment counties – however, there seems to be a slight positive effect on employment-to-population ratios and labor force participation rates. This paper finds that the RAP in 22 counties (by proxy, tribes) studied do not follow the income effect. Instead, the study suggests that windfall (or non-labor) income on these tribes has a positive, yet small, effect on labor supply.

Keywords: income effect, labor supply, Native American economics, basic income, non-labor income

INTRODUCTION

Background: Gaming on Native American Reservations

Casinos and gaming institutions have become widely popular on Native American reservations within the past thirty years. How did these reservations become hubs for gambling? Through a series of court cases and regulatory battles, reservations received the right to host gaming institutions on native land.

Initially, *Bryan v. Itasaca County* (1976) revolved around a class action suit regarding a state's ability to collect taxes on tribal land. The final ruling held, unanimously, that Public Law 280, which reads that states can assume control over reservations, did not apply to civil matters but, rather, to only criminal matters. This landmark case gave tribes more autonomy over economic activity in their reservations, as the state retained criminal jurisdiction but could no longer dictate civil matters without Congressional consent. After this ruling, the question regarding whether gambling was a criminal or civil matter came to the forefront of the Native American gaming conversation.

Bryan v. Itasaca County opened up new questions regarding Native American reservations' autonomy, paving way for the historic *California v. Cabazon Band of Mission Indians* (1987) ruling. Therefore, the ruling lifted the restrictions states could place on Indian reservations regarding gaming and, thus, the Indian casino was born. A year later, President Reagan signed the Indian Gaming Regulatory Act, creating a regulatory framework, forming the National Indian Gaming Commission, and expanding gaming protections for Native American reservations country-wide (Akee, Spilde, and Taylor, 2015).

Native American casinos particularly thrive due to the uniqueness of gaming legality compared to most of the U.S. While Nevada and Louisiana are the only two U.S. states to

legalize commercial gambling statewide, Native American reservations generally have more lenience to open commercial gambling institutions to the public. The majority of states with Native American reservations allow for Indian gaming (Humphrey). State residents may then travel to reservations to gamble because “domestic” gaming is illegal, unavailable, or inconvenient (or far away).

Therefore, there is no coincidence that the gaming industry rapidly grew in a number of reservations. In 1996, less than ten years later, Native American casinos made \$4.5 billion from Class III gaming (and \$300 million on additional goods in casinos) - \$1.6 billion directly given back to tribes in the form of per capita payments (“National Gaming”).

Literature Review

Per capita payments through revenue allocation plans (RAPs) are a way of distributing casino profits to members of the respective tribe. In order for tribes to distribute per capita payments, they must submit a plan to and receive approval from the Bureau of Indian Affairs (BIA). These payments range in size and frequency – however, per capita payments are not conditioned based on labor supply of individuals. This way, the payment acts as a windfall, increasing the overall income of an individual without increasing wages. According to economic theory, this would result in an income effect, but not a substitution effect (Gamel, Balsan, and Vero, 2006). The income effect suggests that, once individuals receive per capita payments, they will reduce their labor supply because they can attain the same income as before (in time = -1) as they can now (in time = 0) with less work hours. However, this is not necessarily the case in practice – understanding and empirically testing the significance of this effect is a key aspect of this thesis.

Imbens, Rubin, and Sacerdote (2001) studied the effect of unearned income on labor earnings of lottery winners. The authors found in their study an MPE of 11% (the marginal propensity to reduce earnings per dollar of non-labor income), a significant but clearly not substantial decrease in earnings. This study builds on the income effect theory – although individuals do not considerably change their labor behavior, it is evident that a windfall, such as a lottery win, creates a reduction in labor supply.

Similarly, Sila and Sousa (2014) support the notion that unearned income imposes a negative, albeit small, effect on an individual's labor supply. In studying windfall gains from the European House Panel, the two find that the result is more people are more likely to drop out of the labor force entirely rather than reduce number of hours worked in favor of leisure. Although they found a slight positive effect in middle-aged adults seeking investment, most demographics as a whole reduced labor supply when receiving windfalls. There is a marginal fall in the utility of wealth, so overall future labor supply is also reduced. The study finds that windfalls particularly reduce labor when the windfalls are unanticipated – since these payments are part of tribal policy and approved by the BIA (“Tribal Revenue,” 2016), it is unlikely that the RAP per capita payments are unanticipated by their recipients. Therefore, this thesis, in congruence with the two aforementioned studies, expects there to be a small but notable reduction in labor supply on Native American tribes.

The income effect and windfalls discussion also has broader implications on the basic income debate. The designation of leisure as a normal or inferior good is essential in understanding individuals' labor decisions. If leisure is normal, then increased income should result in increased consumption of leisure. If leisure is inferior, there should be reduced consumption of the good. Gamel, Basan, and Vero (2005) conducted a survey and found that 2/3

of respondents do not view leisure as a normal good. This suggests that the majority of respondents, when receiving a windfall like those of RAPs in tribes, would actually decrease their leisure compared to work hours – a deviation from the properties of the income effect. The authors found some labor supply reduction, though – but this tended to be in those with less stable jobs or those leaving the labor force to pursue investment behavior, like attend college. There are also social factors such as non-income work benefits and preferences that can taper the reduction in labor supply. These social considerations are necessary to understand when implementing policy, but are not the focus of this thesis. The assignment of “inferior good” to leisure can have major implications on those receiving per capita payments and the presence (or lack thereof) is considered during the study. The fact that, from the results, employment-to-population ratio has a generally positive trend with RAPs suggests that people may consider leisure to be an inferior good within the particular tribes studied.

The unemployment rate reflects the number of people who have recently been out of work yet are actively seeking a job. However, this study is examining whether people reduce their labor supply or exit the labor force entirely due to windfalls via per capita payments. If people are receiving these payments, it’s unlikely that they will have a significant propensity to leave their current job and look for a new one – rather, it is more important to understand one’s propensity to willingly leave the workforce entirely due to windfall payments, without searching for a new job. The results show a very negligible effect on unemployment rates.

Through a difference-in-difference analysis, this study analyzes the effect of RAPs on unemployment rates, employment-to-population ratios, and labor force participation rates on 22 tribes by studying their respective counties by proxy. Although there is little effect on unemployment rates, there is an overall small positive effect on employment-to-population ratios

and labor force participation rates. This could be attributed to the idea proposed by Gamel, Basan, and Vero (2005) – leisure is perceived as an inferior good and, thus, income effect may not be present when receiving windfalls. Although there is not enough conclusive evidence to consider this true, it is an interesting lens to use when looking at the results of this study. Though there may be some limitations to the analysis, particularly due to the lack of tribe-specific data and using counties as proxies, the results show an interesting result which deviates from traditional thinking regarding income effect and non-labor income. Future research, including a better understanding of the type and amount of per capita payments, may be necessary in understanding the effect of RAPs to the fullest extent.

METHODOLOGY

Treatment Group

In this experiment, the treatment group consists of counties with large tribal populations.

First, the dataset, which consisted of all tribes (578), was narrowed down 120 tribes that received approval of their respective revenue allocation plans from the Bureau of Indian Affairs to distribute per capita payments as of 2009. This list was provided by request by William A. Taggart and Thaddieus W. Conner from *Indian Gaming and Tribal Revenue Allocation Plans: A Case of “Play to Pay,”* data originally retrieved via request from the Bureau of Indian Affairs. This also includes the dates in which the revenue allocation plan was approved, the first of which was 1993. All data are from datasets accessible online from the U.S. Census Bureau, the Bureau of Labor Statistics, and the Bureau of Indian Affairs.

Matching Tribes to Counties

There is a lack of historical data regarding employment and labor supply on Native American tribes dating back to 1990. In order to completely find and analyze population data, it

was imperative to match tribes to their respective counties. The tribes are matched to counties via the city in which the tribal seat of government is located, found from a dataset provided online by the Bureau of Indian Affairs. For example, the Comanche Nation of Oklahoma's seat of government is in Lawton, OK which is located within Comanche County borders. Therefore, the county included in the treatment group is Comanche County, OK.

Choosing Tribes to Include

Rather than a statistical analysis using a random sample, this paper focuses on the analysis of employment data for 22 major tribes. First, the dataset was reduced from 120 to 109 tribes – 11 RAP-approved tribes were not on the Bureau of Indian Affairs' official tribal directory. The choice to analyze specific tribes, rather than to randomly sample, is due to the fact that some tribal populations are too small to be actually reflected on county employment data. Thus, this paper does not intend to find a trend that applies to all RAP programs, since the sample is not random. Rather, this paper will focus specifically on the RAP's effect on 22 tribes, but will not attempt to extrapolate the findings to apply to all tribes. In order to truly understand the effect of RAPs on Native American employment, it is imperative that the effects of said programs can be interpreted from county data. Therefore, when narrowing the dataset to one that can translate into results in county-level analysis, the tribe had to fulfill two conditions.

Condition 1 (treatment): The tribal population must exceed 1,000 members as of 2010.

$$P_R > 1000$$

where $P_R = \text{population of reservation as of 2010 census}$.

Condition 2 (treatment): The tribal population must makeup at least 5% of the respective total county population.

$$\frac{P_R}{P_{TC}} \geq 0.05$$

where P_{TC} = *population of treatment county as of 2010 census*.

46 of 109 (42%) tribes fulfilled the first condition. Of the remaining 46 tribes, 25 (54%) had over 5% of the county population living within the tribes as of 2010. Further, three tribes were excluded due to inconclusive or inaccessible data. Therefore, this study analyzes the employment behavior on 22 major tribes that were approved for per capita payments, consist of over 1000 members, and represent at least 5% of their respective county's population. For example, as of 2010 census, Comanche Nation of Oklahoma has $P_R = 23,330 (> 1000)$ and has $P_{TC} = 124,098$, so $\frac{P_R}{P_{TC}} = 0.1880 (> 0.05)$. Therefore, this tribes meets both conditions and its county is included in the treatment group in this paper.

Control Group

A control group is used to control for outside macroeconomic, political, technological, or social factors that may influence the unemployment, employment, or labor force participation of the treatment group. Therefore, it is necessary to compare a treatment county's changes in labor supply with a comparable control county that does not have a major tribe that fulfills aforementioned conditions 1 (treatment) and 2 (treatment). In this paper, each treatment county is matched with a unique control county. This study identifies control counties using three narrowing conditions.

Condition 1 (control): The control county must share a border (land or water) with its matched treatment county.

Condition 2 (control): The control county must not be a treatment county.

Condition 3 (control): Within the pool of shared-border counties without major RAP-approved tribes, the control county must be the one closest in population to the treatment county's population.

Condition 4 (control): The control county must be unique.

For example, Comanche County, OK is matched with Grady County, OK because the two counties share a border (condition 1 [control]), Grady County is not already a treatment county (condition 2 [control]), Grady County is the shared-border county that closest in population to Comanche County's population (condition 3 [control]), and Grady County is not used as a control county for any other treatment county (condition 4 [control]).

Independent Variable

The independent variable is the presence of a significant tribe (meets conditions 1 [treatment] and 2 [treatment]) with an approved RAP. Therefore, the treatment group is the group of counties with the independent variable (the existence of a significant tribe with an approved RAP) while the control group is the group of counties that have an absence of this variable.

Dependent Variables

Unemployment

Unemployment rates per county through the years 1990-2010 are widely available through the Bureau of Labor Statistics.

$$\text{unemployment rate} = \frac{\text{number of unemployed persons}}{\text{labor force}}$$

$$\text{where labor force} = \text{employed} + \text{unemployed persons}$$

Employment-to-Population Ratio

The employment-to-population ratio in this study is

$$\text{employment} - \text{to} - \text{population ratio} = \frac{\text{number of employed persons}}{\text{working age population}}$$

where *working age population* = number of persons aged 15 – 64.

Employment-to-population ratio from 1990-2010 was not readily available. Therefore, this study used the number of employed persons from the aforementioned Bureau of Labor Statistics dataset divided by the estimated populations per county per year from the U.S. 1990 and 2000 censuses, using the age range 15-64.

Labor Force Participation Rate

The labor force participation rate used in this study is

$$\text{labor force participation rate} = \frac{\text{labor force}}{\text{working age population}}$$

where labor force = employed + unemployed persons.

Like the employment-to-population ratio, the labor force participation rate was not readily available – therefore, it was extrapolated by dividing the number of employed plus the number of unemployed persons by the county population estimates for ages 15-64 from the 1990 and 2000 censuses.

Difference-in-Difference Analysis

This study's findings will lie in the difference-in-difference analysis between the results of three dependent variables: unemployment rate, employment-to-population ratio, and labor force participation rate of treatment and control counties across time. In doing so, the dependent variable is isolated from other effects, such as macroeconomic or political changes, that may affect a given state. By using the difference-in-difference analysis approach (Lechner, 2011), the study is able to hold for confounding variables by comparing the treatment (or intervention) group, where the RAP was approved and, therefore, the “event” occurred, and the control group, where this event did not occur.

The analysis relies on the parallel trends assumption – if the event, RAP approval, did not occur, then the difference between the treatment and control counties for any given variable

would remain constant. Therefore, the larger the difference in difference (or spread), the larger the deviation from the “common trend” and, thus, the more significant the effect of the event. If the spread is negative, there is a negative effect of the event on the given dependent variable and, if positive, a positive effect. The difference-in-difference estimator isolates the effect from the RAP approval from time trends and individual characteristics.

DID Estimator

$$DV_{i,c,t} = \beta_0 + \beta_1 R_{it} + \beta_2 T_{it} + \beta_3 R_{it} T_{it} + \varepsilon_{it}$$

Where

DV_{i,c,t} = dependent variable (either unemployment rate, employment – to – population ratio, or labor force participation rate)

β₀ = DV when 1) county is control and 2) year is pre RAP approval

β₁ = change in DV when 1) county is control and 2) year is post RAP approval

β₂ = change in DV when 1) county is treatment and 2) year is pre RAP approval

β₃ = change in DV when 1) county is treatment and 2) year is post RAP approval

If county is treatment, T_{it} = 1. If control, T_{it} = 0.

If period is post RAP approval, R_{it} = 1. If period is pre RAP approval, R_{it} = 0.

	Before RAP approval	After RAP approval	Difference
Treatment county	$\beta_0 + \beta_2$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	
Control county	β_0	$\beta_0 + \beta_1$	
Difference	β_2	$\beta_2 + \beta_3$	$\beta_3 = S_{DV}$

Table 1. Difference-in-difference estimator rationale.

The difference-in-difference (or spread), S_{DV} , is found for every dependent variable – unemployment, employment-to-population ratio, and labor force participation rate.

Event “RAP approval” occurs at $t=0$. It is important to learn the difference-in-difference for various time frames to understand the short, mid, and long-term effects of the RAP approval. Thus, this study will examine the three-year spread S_3 (the difference between the dependent variable at time $t+1$ and $t-1$), the five-year spread S_5 (the difference between the dependent variable at time $t+2$ and $t-2$) and a seven-year spread S_7 (the difference between the dependent variable at time $t+3$ and $t-3$).

Analysis

$$U_T - U_C = U_D$$

Where, for any given year, U_T is the unemployment rate of the treatment county, U_C is the unemployment rate of the control county, and U_D is the unemployment rate difference.

$$E_T - E_C = E_D$$

Where, for any given year, E_T is the employment-to-population ratio of the treatment county, E_C is the employment-to-population ratio of the control county, and E_D is the employment-to-population ratio difference.

$$L_T - L_C = L_D$$

Where, for any given year, L_T is the labor force participation rate of the treatment county, L_C is the labor force participation rate of the control county, and L_D is the labor force participation rate difference for any given year.

U_D , E_D , and L_D are then be plotted on a graph at every given year ($t-3$ to $t+3$) to visually understand the effect of given event, RAP approval at time $t=0$ (see appendix). After the visual representation, a difference-in-difference will be taken for each individual reservation then as an average of all 22 reservations studied.

Difference-in-Differences (or Spreads)

There will be difference-in-difference estimates for a three-year spread (t-1 to t+1), five-year spread (t-2 to t+2), and seven-year spread (t-3 to t+3) for the three dependent variables. This allows for a more thorough analysis and understanding of whether there are short-term or long-term effects of the RAP approval across time or whether significant effects are absent entirely.

Unemployment

$$\text{three – year unemployment rate spread} = S_{U,3} = U_{D,t+1} - U_{D,t-1}$$

$$\text{five – year unemployment rate spread} = S_{U,5} = U_{D,t+2} - U_{D,t-2}$$

$$\text{seven – year unemployment rate spread} = S_{U,7} = U_{D,t+3} - U_{D,t-3}$$

where

if $S_U > 0$, then there is a positive effect of the RAP on unemployment.

if $S_U < 0$, then there is a negative effect of the RAP on unemployment.

if $S_U = 0$, then there is no effect of RAP on unemployment.

Employment-to-Population Ratio

$$\text{three – year employment – to – population ratio spread} = S_{E,3} = E_{D,t+1} - E_{D,t-1}$$

$$\text{five – year employment – to – population ratio spread} = S_{E,5} = E_{D,t+2} - E_{D,t-2}$$

$$\text{seven – year employment – to – population ratio spread} = S_{E,7} = E_{D,t+3} - E_{D,t-3}$$

where

if $S_E > 0$, then there is a positive effect of the RAP on employment.

If $S_E < 0$, then there is a negative effect of the RAP on employment.

If $S_E = 0$, then there is no effect of RAP on employment.

Labor Force Participation Rate DID

$$\text{three – year labor force participation rate spread} = S_{L,3} = L_{D,t+1} - L_{D,t-1}$$

$$\text{five – year labor force participation rate spread} = S_{L,5} = L_{D,t+2} - L_{D,t-2}$$

seven – year labor force participation rate spread = $S_{L,7} = L_{D,t+3} - L_{D,t-3}$

where

if $S_L > 0$, then there is a positive effect of the RAP on labor force participation.

If $S_L < 0$, then there is a negative effect of the RAP on labor force participation.

If $S_L = 0$, then there is no effect of RAP on labor force participation.

RESULTS AND ANALYSIS

Unemployment Rate

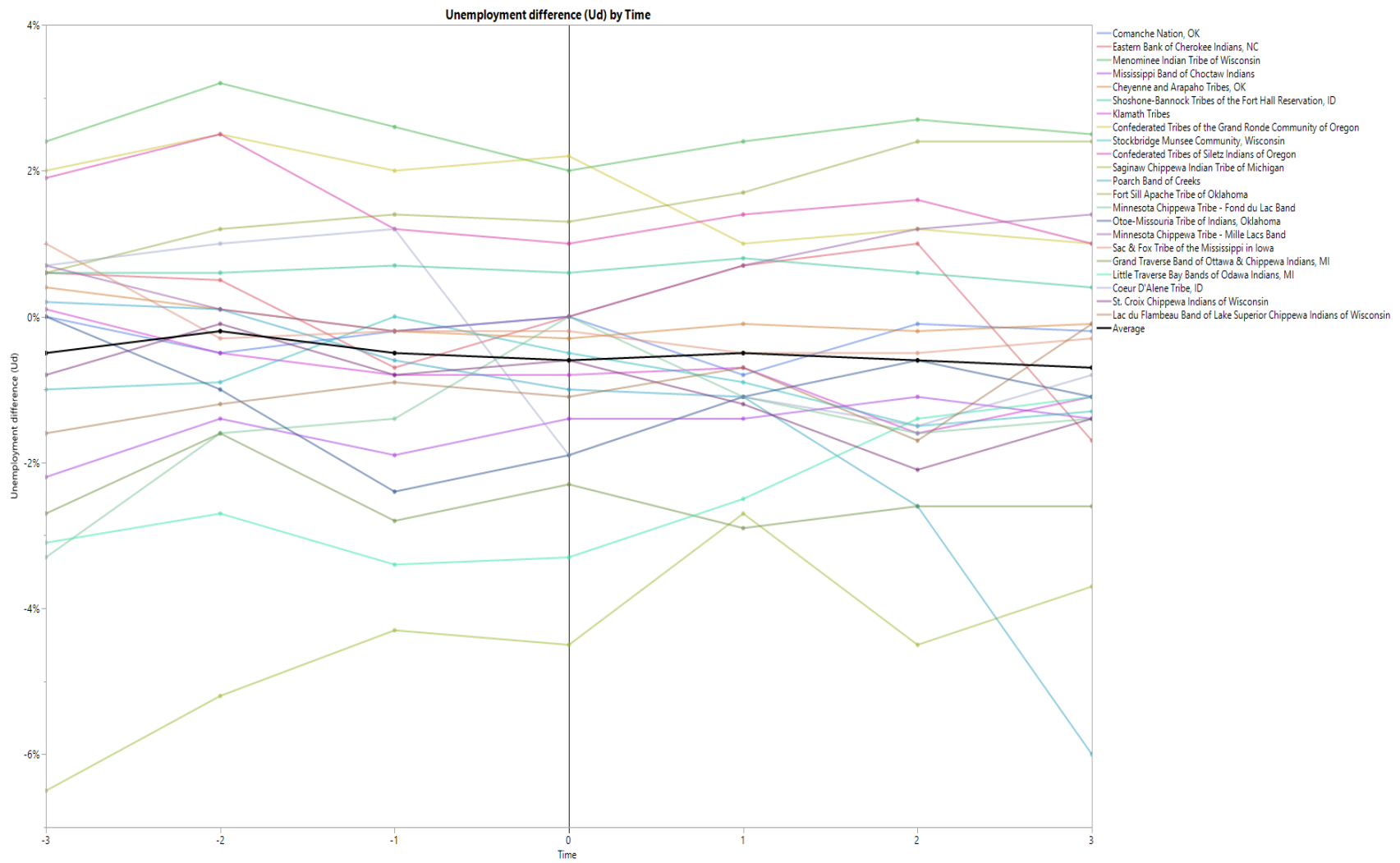


Figure 1. Unemployment rate difference (U_D) at time t=-3 to t=3 for all studied tribes with the average difference at each time period.

Tribe	$S_{U,3}$	$S_{U,5}$	$S_{U,7}$
Comanche Nation, OK	-0.6%	0.1%	-0.2%
Eastern Band of Cherokee Indians, NC	1.4%	0.5%	-2.3%
Menominee Indian Tribe of Wisconsin	-0.2%	-0.5%	0.1%
Mississippi Band of Choctaw Indians	0.5%	0.3%	0.8%
Cheyenne and Arapaho Tribes, OK	0.1%	-0.3%	-0.5%
Shoshone-Bannock Tribes of the Fort Hall Reservation, ID	0.1%	0.0%	-0.2%
Klamath Tribes, OR	0.1%	-1.1%	-1.2%
Confederated Tribes of the Grand Ronde Community of Oregon	-1.0%	-1.3%	-1.0%
Stockbridge Munsee Community, Wisconsin	-0.9%	-0.6%	-0.3%
Confederated Tribes of Siletz Indians of Oregon	0.2%	-0.9%	-0.9%
Saginaw Chippewa Indian Tribe of Michigan	1.6%	0.7%	2.8%
Poarch Band of Creeks, AL	-0.5%	-2.7%	-6.2%
Fort Sill Apache Tribe of Oklahoma	0.3%	1.2%	1.8%
Minnesota Chippewa Tribe - Fond du Lac Band	0.3%	0.0%	1.9%
Otoe-Missouria Tribe of Indians, Oklahoma	1.3%	0.4%	-1.1%
Minnesota Chippewa Tribe - Mille Lacs Band	0.9%	1.1%	0.7%
Sac & Fox Tribe of the Mississippi in Iowa	-0.3%	-0.2%	-1.3%
Grand Traverse Band of Ottawa & Chippewa Indians, MI	-0.1%	-1.0%	0.1%
Little Traverse Bay Bands of Odawa Indians, MI	0.9%	1.3%	2.0%
Coeur D'Alene Tribe, ID	-2.3%	-2.5%	-1.5%
St. Croix Chippewa Indians of Wisconsin	-0.4%	-2.0%	-0.6%
Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin	0.2%	-0.5%	1.5%
<i>Average</i>	0.1%	-0.4%	-0.3%

Table 2. Tribes with three-year, five-year, and seven-year spreads for unemployment rate differences.

The differences between the treatment and control county in the short-term ($S_{U,3}$), mid-term ($S_{U,5}$), and long-term ($S_{U,7}$) are relatively insignificant. Although there are a few differences that seem to be quite significant in treatment and control counties for tribes like Poarch Band of Creeks ($S_{U,7} = -6.2\%$), where there seems to be a strongly negative relationship between the RAP and the unemployment rate, this is offset by numerous tribes with relatively high differences like Saginaw Chippewa Indian Tribe of Michigan ($S_{U,7} = 2.8\%$), Minnesota

Chippewa Tribe - Fond du Lac Band ($S_{U,7} = 1.9\%$), and Little Traverse Bay Bands of Odawa Indians, MI ($S_{U,7} = 2.0\%$). Overall, 13, or 59.1%, of 22 treatment counties had a negative long term effect on unemployment relative to their control county.

It is unsurprising that the data reflects little significant effect of RAPs on unemployment rate. By the very definition of unemployment, it makes sense that per capita payments would not increase unemployment. According to the Bureau of Labor Statistics, unemployed individuals are those that have looked for work within the past four weeks and are available to work. It is unlikely that more (or less) people will be fired from or leaving their jobs in search of a new job.

However, one example of the potential for per capita payments to provoke unemployment would be if, due to the new windfall payment, people are more willing to leave their current job in search of one that is more fulfilling to them but may not pay as much as their old job. Therefore, people have more flexibility to move between jobs to find meaningful work with less of a focus on salary or pay – additionally, it can act as unemployment insurance, giving people more freedom to leave their current jobs in search of a new one (Gamel et al. 2005) This would, theoretically, increase frictional unemployment. However, there is little evidence of that occurring in these 22 tribes as a whole, but perhaps this could be playing a role in tribes with positive unemployment change.

Employment-to-Population Ratio

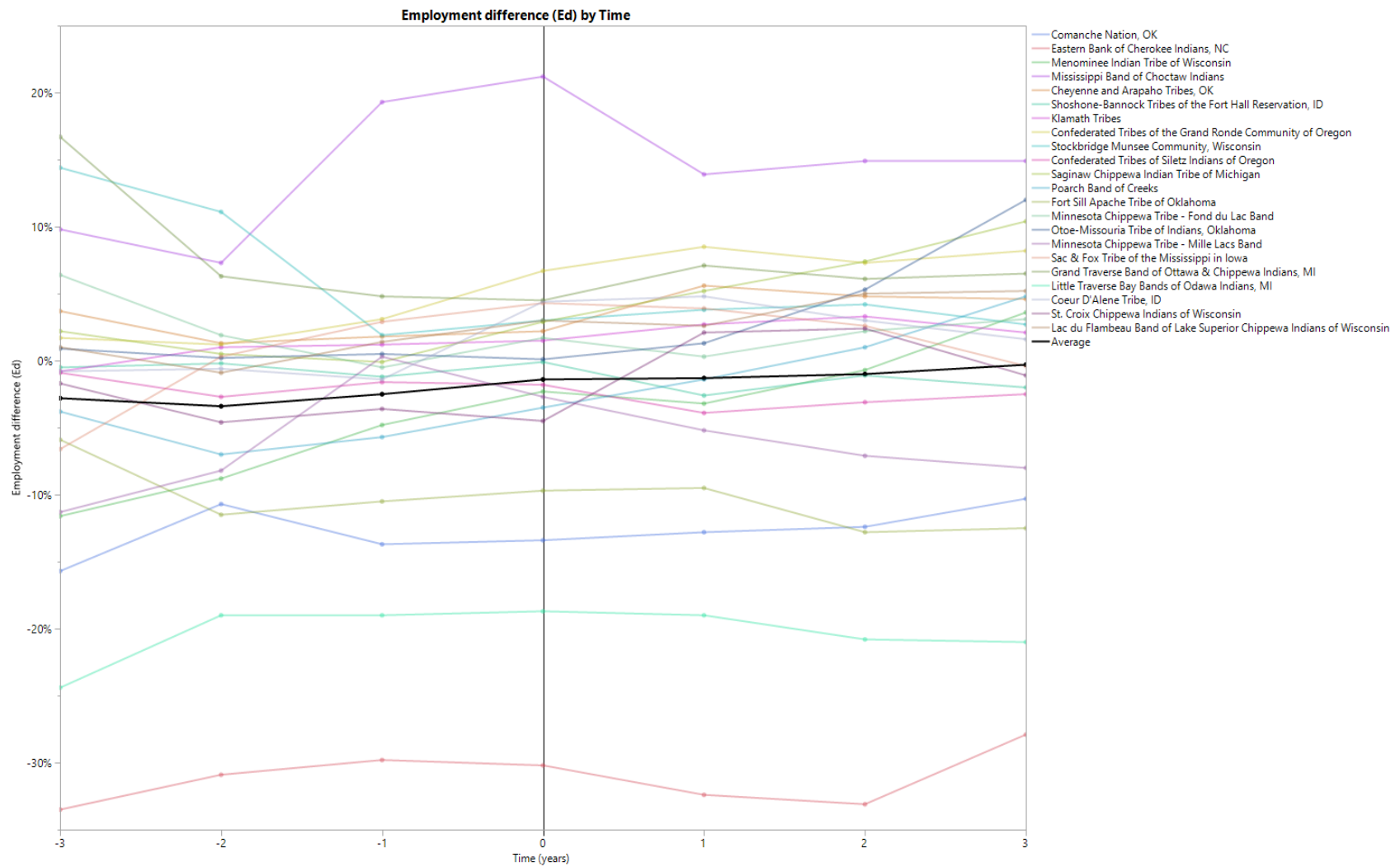


Figure 2. Employment-to-population ratio differences (E_D) at time $t=-3$ to $t=3$ for all studied tribes with the average difference at each time period.

Tribe	$S_{E,3}$	$S_{E,5}$	$S_{E,7}$
Comanche Nation, OK	0.89%	-1.65%	5.44%
Eastern Band of Cherokee Indians, NC	-2.68%	-2.17%	5.61%
Menominee Indian Tribe of Wisconsin	1.59%	8.12%	15.22%
Mississippi Band of Choctaw Indians	-5.37%	7.63%	5.10%
Cheyenne and Arapaho Tribes, OK	3.76%	3.53%	0.98%
Shoshone-Bannock Tribes of the Fort Hall Reservation, ID	-1.32%	-0.95%	-1.47%
Klamath Tribes, OR	1.52%	2.32%	2.93%
Confederated Tribes of the Grand Ronde Community of Oregon	5.43%	6.15%	6.46%
Stockbridge Munsee Community, Wisconsin	1.85%	-6.88%	-11.67%
Confederated Tribes of Siletz Indians of Oregon	-2.30%	-0.41%	-1.59%
Saginaw Chippewa Indian Tribe of Michigan	5.25%	6.90%	8.23%
Poarch Band of Creeks, AL	4.28%	8.04%	8.60%
Fort Sill Apache Tribe of Oklahoma	1.03%	-1.22%	-6.59%
Minnesota Chippewa Tribe - Fond du Lac Band	0.81%	0.32%	-3.33%
Otoe-Missouria Tribe of Indians, Oklahoma	0.80%	5.08%	11.16%
Minnesota Chippewa Tribe - Mille Lacs Band	-5.41%	1.09%	3.30%
Sac & Fox Tribe of the Mississippi in Iowa	0.96%	2.28%	6.23%
Grand Traverse Band of Ottawa & Chippewa Indians, MI	2.35%	-0.26%	-10.22%
Little Traverse Bay Bands of Odawa Indians, MI	0.05%	-1.80%	3.42%
Coeur D'Alene Tribe, ID	6.20%	3.65%	2.49%
St. Croix Chippewa Indians of Wisconsin	5.76%	7.02%	0.61%
Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin	1.26%	5.91%	4.19%
Average	1.21%	2.40%	2.50%

Table 3. Tribes with three-year, five-year, and seven-year spreads for employment-to-population ratio differences.

The differences observed the short-term ($S_{E,3}$), mid-term ($S_{E,5}$), and long-term ($S_{E,7}$) suggest a positive effect of RAPs on employment-to-population ratios in treatment counties and, thus, by proxy, tribes. The trend is generally positive and increases as time span increases from three to seven years. Although there are evident outliers, like Stockbridge Munsee Community, Wisconsin ($S_{E,7} = -11.67\%$) and Grand Traverse Band of Ottawa & Chippewa Indians, MI ($S_{E,7} = -10.22\%$), 16, or 72.7%, of the 22 treatment counties studied have had an increase in

employment relative to their respective control county. There are also strongly positive outliers as well, including Menominee Indian Tribe of Wisconsin ($S_{E,7} = 15.22\%$) and Otoe-Missouria Tribe of Indians, Oklahoma ($S_{E,7} = 11.16\%$), which could have skewed the data in a more positive direction. Although the long-term spread of ($S_{E,7} = 2.50\%$) reflects a slightly significant positive effect that RAP approval has had on employment in the 22 studied tribes as an aggregate, there is no significant underlying trend.

Although the analysis on unemployment differences seemed to align with traditional economic theory, the observed employment differences do not fall into that same line. As mentioned in the literature review, the per capita payments would induce the labor effect, since total income would shift upward but marginal income per hour worked would remain unchanged. It is apparent that there is no significant effect of RAP on employment in any systematic way. However, the increase in employment-to-population ratios overall, and in the specific treatment counties of tribes like Menominee Indian Tribe of Wisconsin ($S_{E,7} = 15.22\%$) and Otoe-Missouria Tribe of Indians, Oklahoma ($S_{E,7} = 11.16\%$) could be due to the perception of leisure as an inferior good. Gamel et al.'s (2005) study found over half (2/3) of respondents thought of leisure to be an inferior good – when one has more income, one will demand more of said good and, when one has less income, they will spend more. Counties with significant positive effects of RAP on employment may also be empowered by the windfall. The extra income could be used to invest in self-employment, which could drive people to enter the workforce as a self-employed individual and increase the employment-to-population ratio.

In treatment counties where employment-to-population ratio saw a decline, like Fort Sill Apache Tribe of Oklahoma ($S_{E,7} = -6.59\%$), there could be a substantial income effect from

the per capita payments as expanded upon by Imbens et al. (2001), as well as Sila and Sousa (2014).

Budget Constraint and the Income Effect of Per Capita Payments

An example of the income effect is presented below. Assume that an individual in Tribe A can work 160 hours a month for \$10 per hour. Then, Tribe A's RAP is approved by the Bureau of Indian Affairs and, from the profits of its tribal-run casino, distributes \$200 per month to every adult in the tribe as a per capita payment.

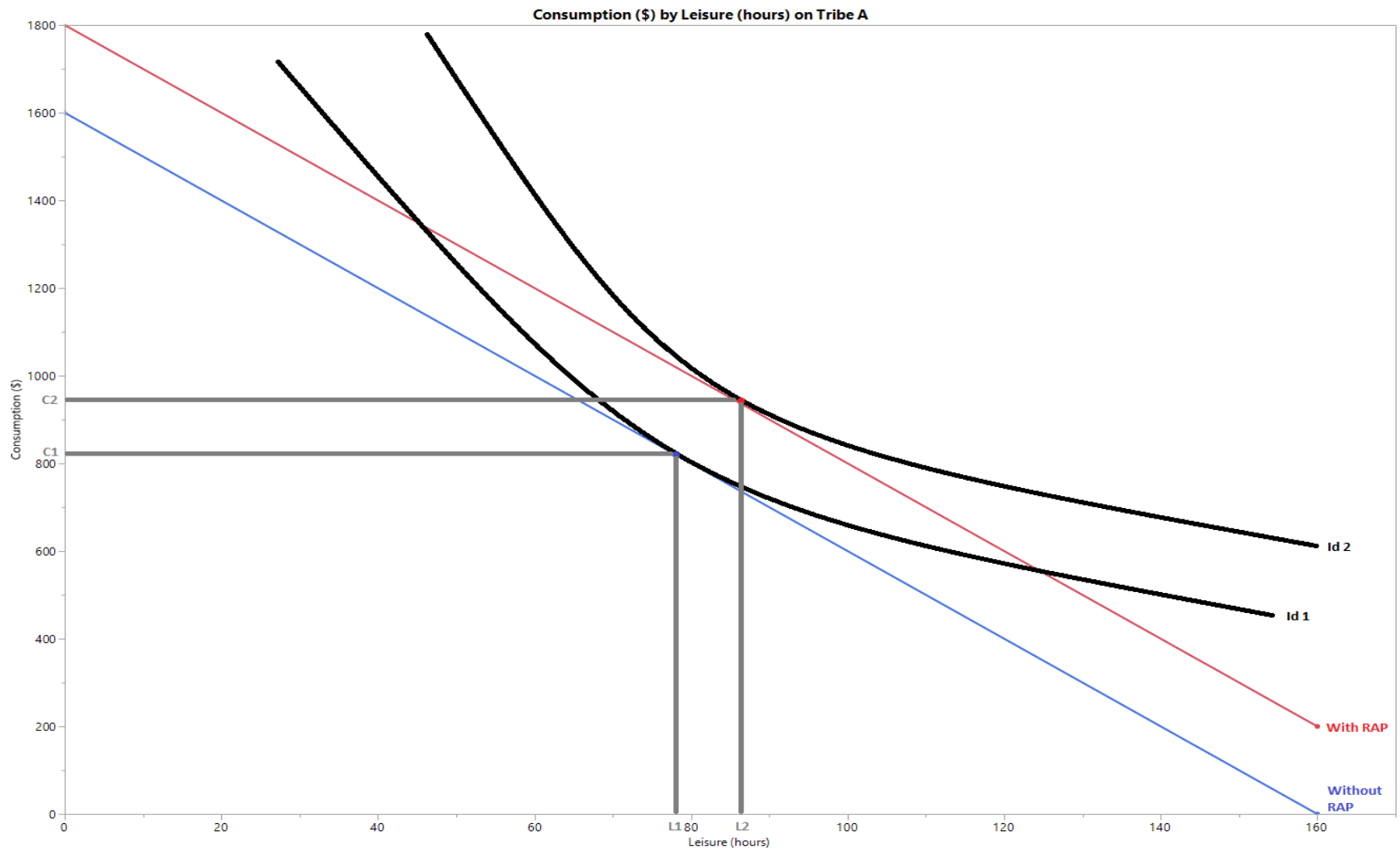


Figure 3. Example of income effect of per capita payments (due to RAP approval).

With the \$200 increase in income at every level of leisure, the indifference curve shifts from Id 1 to Id 2. The increase in leisure hours, from L1 to L2, reflects the income effect, where one can get the same (or, in this case, more) consumption than before the RAP approval while working less hours and, thus, consuming more leisure.

Another reason why employment difference between the treatment and control counties could be due to investment in human capital. The extra income that per capita payments provide could provide incentive for individuals to invest in education or vocational training, as those would have more income to support themselves and invest in tuition and living expenses while in school (Gamel et al. 2005) leaving the workforce temporarily with plans to return. Although this may be contributing to decreases in employment-to-population ratio differences, this does not seem to be significantly apparent.

Labor Force Participation Rate

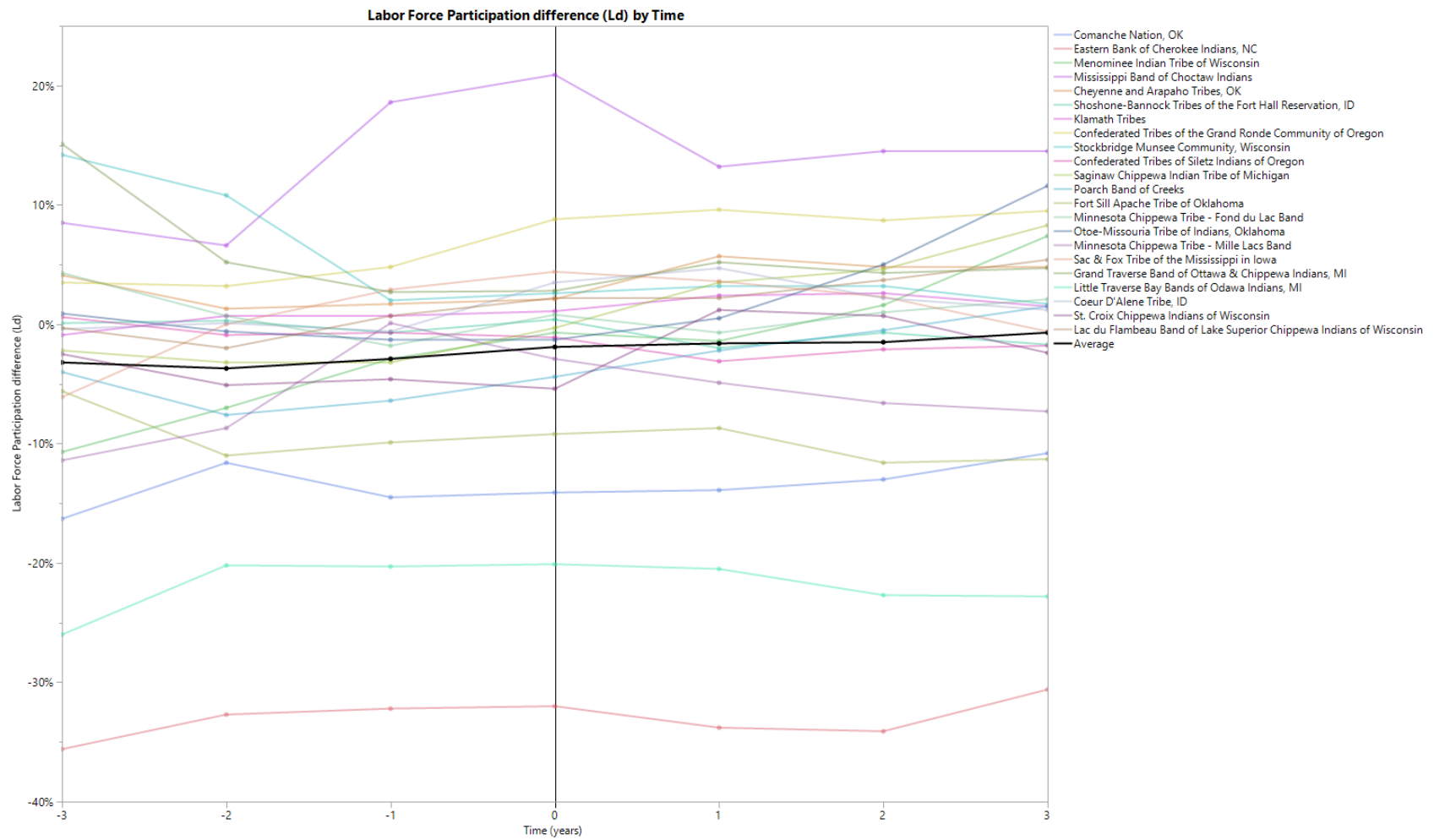


Figure 4. Labor force participation rate differences (L_D) at time $t=-3$ to $t=3$ for all studied tribes with the average difference at each time period.

Tribe	$S_{L,3}$	$S_{L,5}$	$S_{L,7}$
Comanche Nation, OK	0.56%	-1.39%	5.55%
Eastern Band of Cherokee Indians, NC	-1.63%	-1.38%	4.98%
Menominee Indian Tribe of Wisconsin	1.50%	8.63%	18.10%
Mississippi Band of Choctaw Indians	-5.43%	7.90%	5.94%
Cheyenne and Arapaho Tribes, OK	4.07%	3.48%	0.72%
Shoshone-Bannock Tribes of the Fort Hall Reservation, ID	-1.35%	-1.01%	-1.74%
Klamath Tribes, OR	1.74%	1.94%	2.40%
Confederated Tribes of the Grand Ronde Community of Oregon	4.80%	5.45%	6.04%
Stockbridge Munsee Community, Wisconsin	1.15%	-7.61%	-12.41%
Confederated Tribes of Siletz Indians of Oregon	-2.35%	-1.21%	-2.41%
Saginaw Chippewa Indian Tribe of Michigan	6.70%	7.86%	10.55%
Poarch Band of Creeks, AL	4.22%	7.01%	5.57%
Fort Sill Apache Tribe of Oklahoma	1.23%	-0.61%	-5.67%
Minnesota Chippewa Tribe - Fond du Lac Band	1.17%	0.26%	-2.24%
Otoe-Missouria Tribe of Indians, Oklahoma	1.84%	5.56%	10.73%
Minnesota Chippewa Tribe - Mille Lacs Band	-5.02%	2.03%	4.11%
Sac & Fox Tribe of the Mississippi in Iowa	0.72%	2.26%	5.42%
Grand Traverse Band of Ottawa & Chippewa Indians, MI	2.50%	-0.98%	-10.35%
Little Traverse Bay Bands of Odawa Indians, MI	-0.25%	-2.48%	3.23%
Coeur D'Alene Tribe, ID	5.26%	2.15%	1.58%
St. Croix Chippewa Indians of Wisconsin	5.80%	5.78%	0.13%
Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin	1.53%	5.70%	5.68%
Average	1.31%	2.24%	2.54%

Table 4. Tribes with three-year, five-year, and seven-year spreads labor force participation rate differences.

In terms of labor force participation, there is an overall aggregate average increasing trend in treatment counties relative to the control counties. Labor force participation and employment are very closely related, so it makes sense for the trends to be similar in nature. In fact, from earlier we found there was a negligible effect of RAPs on unemployment. Therefore, although some of the difference between labor force and employment trends could be due to small changes in unemployment, due to the insignificant effects of RAPs on unemployment,

employment-to-population ratio spreads and labor force participation spreads are extremely similar and closely interlinked in the short, mid, and long-terms.

CONCLUSION

Limitations and Other Considerations

Sampling

One primary limitation faced throughout the study is the fact that there was not enough data to execute a statistical analysis with a random sample. Due to the nature of matching, where tribes are matched to their respective counties, it was necessary for the tribe to be large enough so that the effects of the RAPs were visible at the county level. In order to do this, the study used conditions 1 and 2 (treatment) to create a data set that would be more visibly represented at the county level. However, because of this (and other inaccessible data issues), many of the tribes (98/120 or 81.7%) of the tribes could not be analyzed through the matching method and, thus, the study could not use a random sample. Due to this fact, the study focused primarily on the employment behavior and labor supply within the applicable 22 tribes to find a common pattern. However, this study does not attempt to extrapolate that pattern as one that can apply to all tribes with RAPs – rather, it is an examination, at face-value, of the studied 22 tribes.

Matching Tribes to Counties

As with many economic studies, it is very unlikely to control for all possible confounding variables. Due to the lack of tribal specific data, it was imperative to match tribes to their respective counties in order to study the effects of RAP approval on different dependent variables. This way, the treatment (matched) county could be paired to a respective control county (following conditions 1, 2, 3, and 4 (control)), similar in population and geography, to control for political, social, economic, and technological factors affecting the U.S. or the specific

state. In matching treatment to control counties with similar populations and geography, this paper attempts to match the treatment county with a control county with a similar trajectory. This matching process controls for all state and nation-wide macro changes, but events within the specific counties are difficult to control for. The control county does not perfectly control for external factors. There could be other factors such as intra-county political or economic changes as well as tribe-specific events that could have made a significant impact during the time period studied.

The presence of a confounding variable in either the treatment or control county would be in violation of the parallel trends assumption.

Population Estimates

Another limitation of the study is the use of population estimates, rather than actual numbers. The data from the U.S. Census Bureau, total county populations and working age populations, are based on estimates from the 1990 and 2000 censuses. Although census estimates are certainly not perfect, the estimates have vastly improved in accuracy. According to a working paper by Tammany J. Mulder and the census staff (2002), census estimates have become far more accurate through improved knowledge on and stabilization of population trends and, thus, the proximity of estimates to actual numbers is closer than ever. Although this study could be more accurate with actual, rather than estimated, population numbers, it is unlikely that the results would be significantly different.

Looking Forward

There are many important future steps that should be taken in order to understand the effect of RAPs on a more holistic and concrete level. First, it is important to gain more data on

tribes and reservations – using counties by proxy can be of use, but using actual tribal data would make the study more concrete.

Beyond further data retrieval, there are a few interesting further approaches that could expand on the understanding of RAP effects on labor supply. If tribal specific data could be obtained, it would be very interesting to prepare a difference-in-difference analysis between tribes with casinos and RAPs and tribes with casinos, but without RAPs. Additionally, another area of research could be learning more about whether the size, not just the presence, of per capita payments changes the effect the RAP may have on labor supply. Lastly, it would also be very interesting to pursue qualitative and/or case study research with specific tribes that have enacted per capita payments. It is very important to learn from those who are actually within the tribe and interact with these payments – this is a necessary step for this topic's future research.

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APPENDIX

Unemployment Rates Data

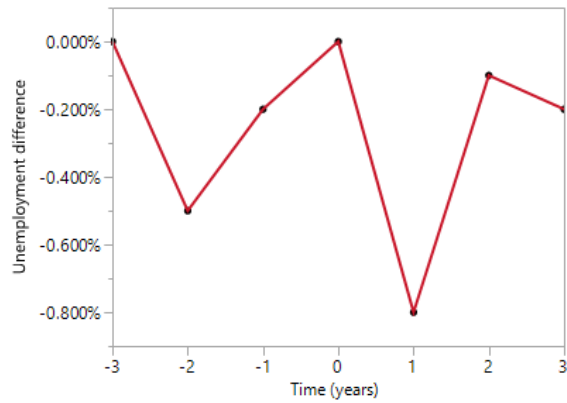


Figure 5. Comanche Nation, OK Ud.

Time	Comanche Nation, OK
-3	0.0%
-2	-0.5%
-1	-0.2%
0	0.0%
1	-0.8%
2	-0.1%
3	-0.2%

Table 5. Comanche Nation, OK Ud.

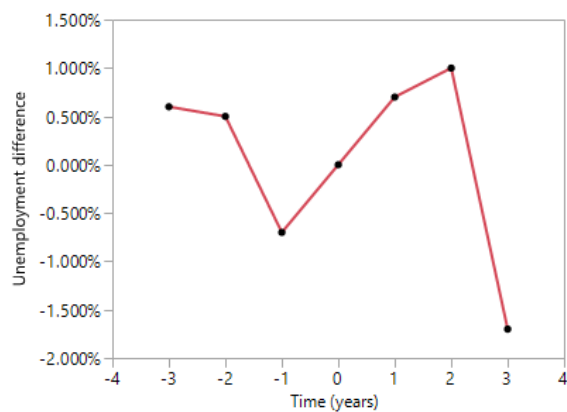


Figure 6. Eastern Band of Cherokee Indians, NC Ud.

Time	Eastern Band of Cherokee Indians, NC
-3	0.6%
-2	0.5%
-1	-0.7%
0	0.0%
1	0.7%
2	1.0%
3	-1.7%

Table 6. Eastern Band of Cherokee Indians, NC Ud.

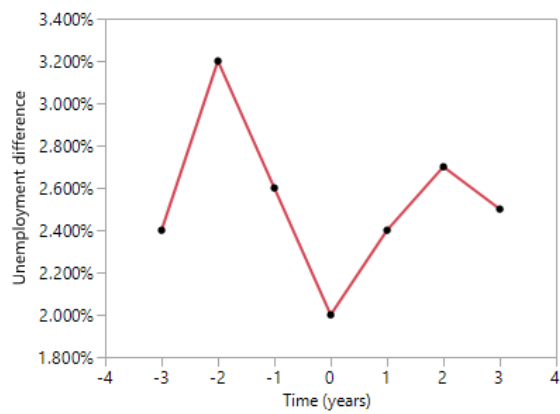


Figure 7. Menominee Indian Tribe of Wisconsin Ud.

Time	Menominee Indian Tribe of Wisconsin
-3	2.4%
-2	3.2%
-1	2.6%
0	2.0%
1	2.4%
2	2.7%
3	2.5%

Table 7. Menominee Indian Tribe of Wisconsin Ud.

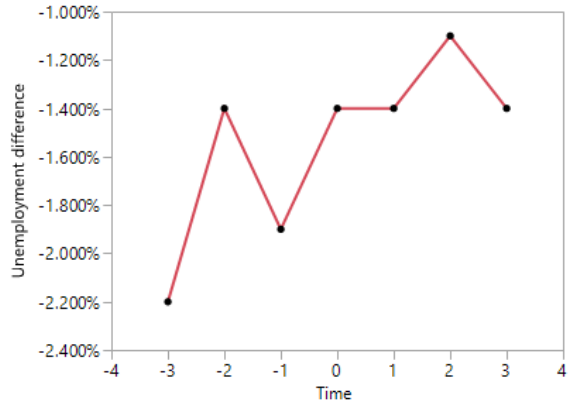


Figure 8. Mississippi Band of Choctaw Indians Ud.

Time	Mississippi Band of Choctaw Indians
-3	-2.2%
-2	-1.4%
-1	-1.9%
0	-1.4%
1	-1.4%
2	-1.1%
3	-1.4%

Table 8. Mississippi Band of Choctaw Indians Ud.

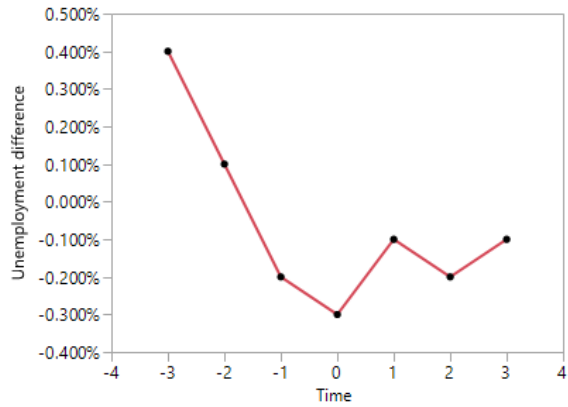


Figure 9. Cheyenne and Arapaho Tribes, OK Ud.

Time	Cheyenne and Arapaho Tribes, OK
-3	0.4%
-2	0.1%
-1	-0.2%
0	-0.3%
1	-0.1%
2	-0.2%
3	-0.1%

Table 9. Cheyenne and Arapaho Tribes, OK Ud.

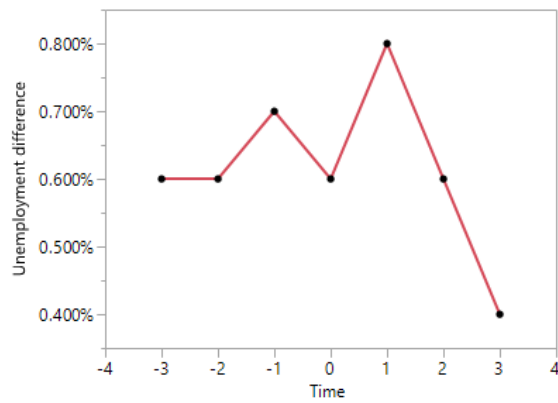


Figure 10. Shoshone-Bannock Tribes of the Fort Hall Reservation, ID Ud.

Time	Shoshone-Bannock Tribes of the Fort Hall Reservation, ID
-3	0.6%
-2	0.6%
-1	0.7%
0	0.6%
1	0.8%
2	0.6%
3	0.4%

Table 10. Shoshone-Bannock Tribes of the Fort Hall Reservation, ID Ud.

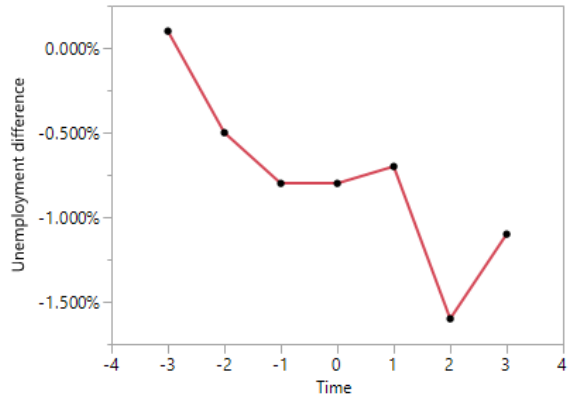


Figure 11. Klamath Tribes, OR Ud.

Time	Klamath Tribes
-3	0.1%
-2	-0.5%
-1	-0.8%
0	-0.8%
1	-0.7%
2	-1.6%
3	-1.1%

Table 11. Klamath Tribes, OR Ud.

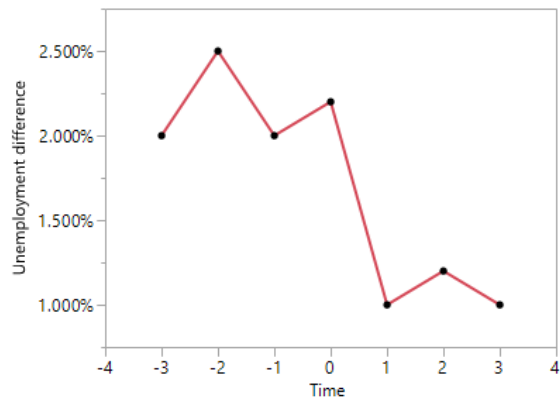


Figure 12. Confederated Tribes of the Grand Ronde Community of Oregon Ud.

Time	Confederated Tribes of the Grand Ronde Community of Oregon
-3	2.0%
-2	2.5%
-1	2.0%
0	2.2%
1	1.0%
2	1.2%
3	1.0%

Table 12. Confederated Tribes of the Grand Ronde Community of Oregon Ud.

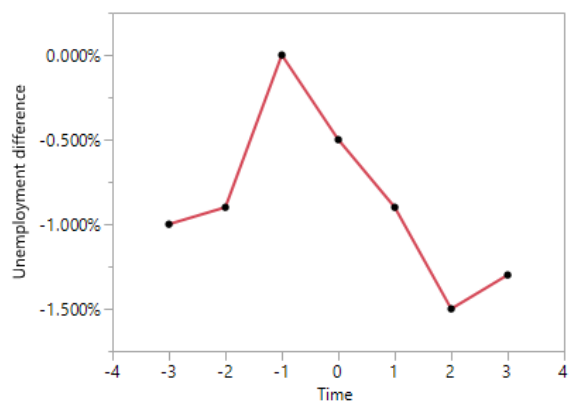


Figure 13. Stockbridge Munsee Community, Wisconsin Ud.

Time	Stockbridge Munsee Community, Wisconsin
-3	-1.0%
-2	-0.9%
-1	0.0%
0	-0.5%
1	-0.9%
2	-1.5%
3	-1.3%

Table 13. Stockbridge Munsee Community, Wisconsin Ud.

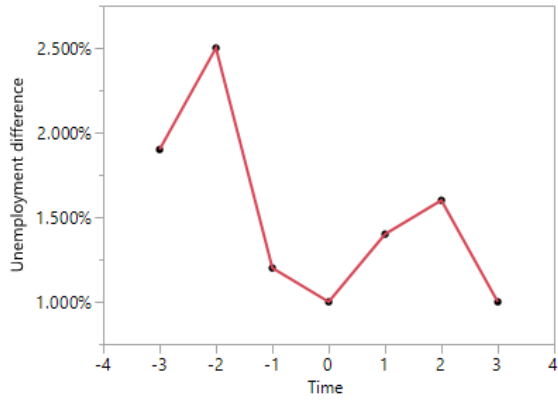


Figure 14. Confederated Tribes of Siletz Indians of Oregon Ud.

Time	Confederated Tribes of Siletz Indians of Oregon
-3	1.9%
-2	2.5%
-1	1.2%
0	1.0%
1	1.4%
2	1.6%
3	1.0%

Table 14. Confederated Tribes of Siletz Indians of Oregon Ud.

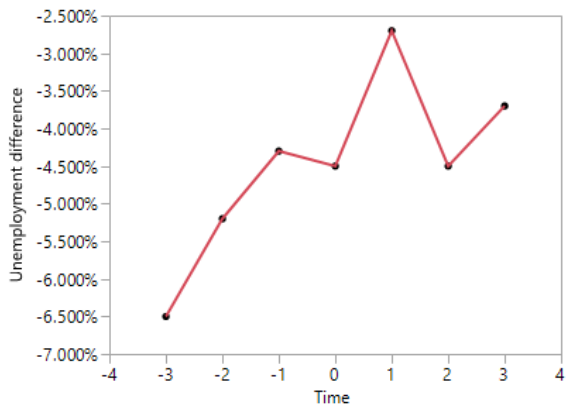


Figure 15. Saginaw Chippewa Indian Tribe of Michigan Ud.

Time	Saginaw Chippewa Indian Tribe of Michigan
-3	-6.5%
-2	-5.2%
-1	-4.3%
0	-4.5%
1	-2.7%
2	-4.5%
3	-3.7%

Table 15. Saginaw Chippewa Indian Tribe of Michigan Ud.

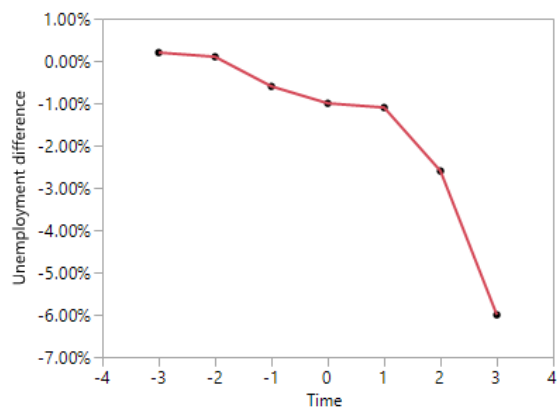


Figure 16. Poarch Band of Creek Indians, AL Ud.

Time	Poarch Band of Creeks
-3	0.2%
-2	0.1%
-1	-0.6%
0	-1.0%
1	-1.1%
2	-2.6%
3	-6.0%

Table 16. Poarch Band of Creeks, AL Ud.

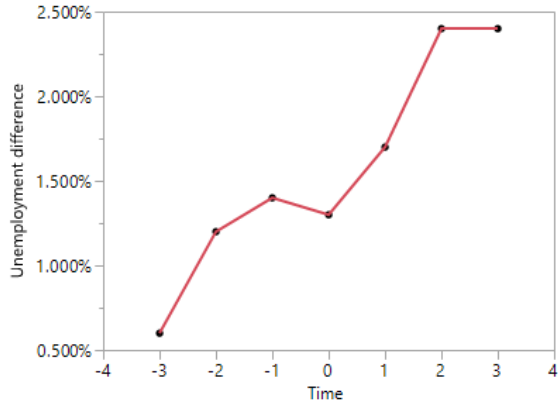


Figure 17. Fort Sill Apache Tribe of Oklahoma Ud.

Time	Fort Sill Apache Tribe of Oklahoma
-3	0.6%
-2	1.2%
-1	1.4%
0	1.3%
1	1.7%
2	2.4%
3	2.4%

Table 17. Fort Sill Apache Tribe of Oklahoma Ud.

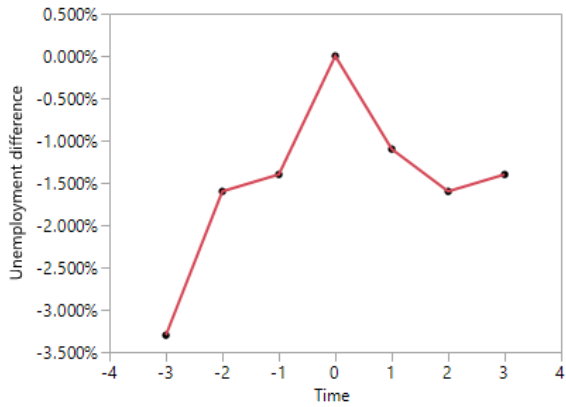


Figure 18. Minnesota Chippewa Tribe - Fond du Lac Band Ud.

Time	Minnesota Chippewa Tribe - Fond du Lac Band
-3	-3.3%
-2	-1.6%
-1	-1.4%
0	0.0%
1	-1.1%
2	-1.6%
3	-1.4%

Table 18. Minnesota Chippewa Tribe - Fond du Lac Band Ud.

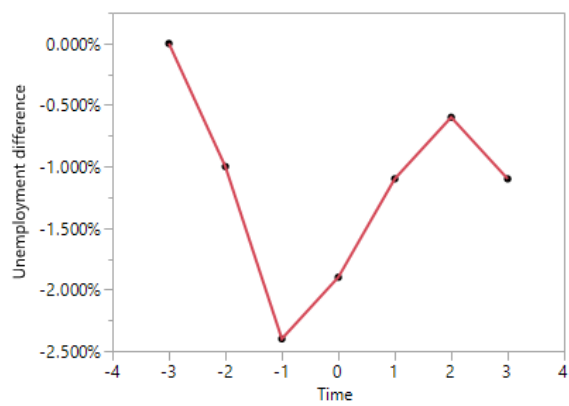


Figure 19. Otoe-Missouria Tribe of Indians, Oklahoma Ud.

Time	Otoe-Missouria Tribe of Indians, Oklahoma
-3	0.0%
-2	-1.0%
-1	-2.4%
0	-1.9%
1	-1.1%
2	-0.6%
3	-1.1%

Table 19. Otoe-Missouria Tribe of Indians, Oklahoma Ud.

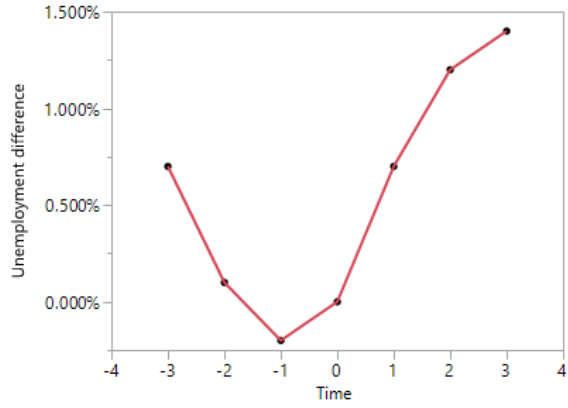


Figure 20. Minnesota Chippewa Tribe - Mille Lacs Band Ud.

Time	Minnesota Chippewa Tribe - Mille Lacs Band
-3	0.7%
-2	0.1%
-1	-0.2%
0	0.0%
1	0.7%
2	1.2%
3	1.4%

Table 20. Minnesota Chippewa Tribe - Mille Lacs Band Ud.

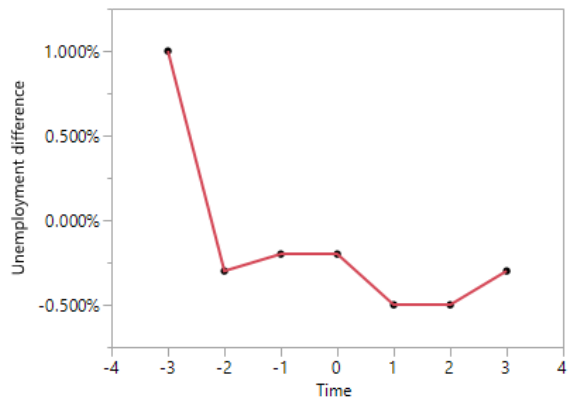


Figure 21. Sac & Fox Tribe of the Mississippi in Iowa Ud.

Time	Sac & Fox Tribe of the Mississippi in Iowa
-3	1.0%
-2	-0.3%
-1	-0.2%
0	-0.2%
1	-0.5%
2	-0.5%
3	-0.3%

Table 21. Sac & Fox Tribe of the Mississippi in Iowa Ud.

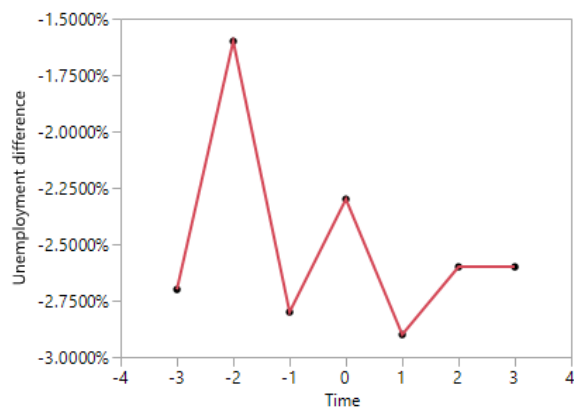


Figure 22. Grand Traverse Band of Ottawa & Chippewa Indians, MI Ud.

Time	Grand Traverse Band of Ottawa & Chippewa Indians, MI
-3	-2.7%
-2	-1.6%
-1	-2.8%
0	-2.3%
1	-2.9%
2	-2.6%
3	-2.6%

Table 22. Grand Traverse Band of Ottawa & Chippewa Indians, MI Ud.

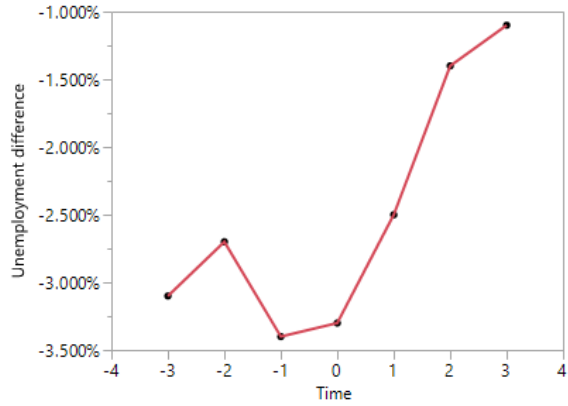


Figure 23. Little Traverse Bay Bands of Odawa Indians, MI Ud.

Time	Little Traverse Bay Bands of Odawa Indians, MI
-3	-3.1%
-2	-2.7%
-1	-3.4%
0	-3.3%
1	-2.5%
2	-1.4%
3	-1.1%

Table 23. Little Traverse Bay Bands of Odawa Indians, MI Ud.

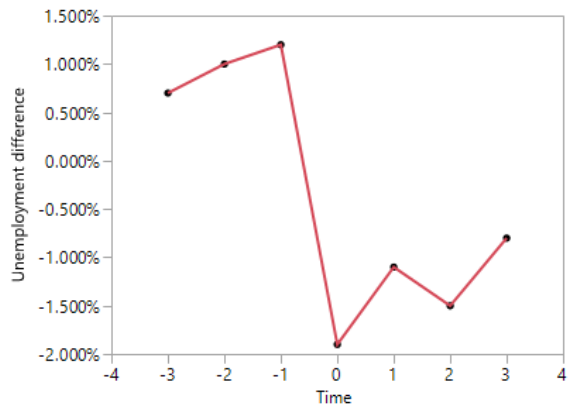


Figure 24. Coeur D'Alene Tribe, ID Ud.

Time	Coeur D'Alene Tribe, ID
-3	0.7%
-2	1.0%
-1	1.2%
0	-1.9%
1	-1.1%
2	-1.5%
3	-0.8%

Table 24. Coeur D'Alene Tribe, ID Ud.

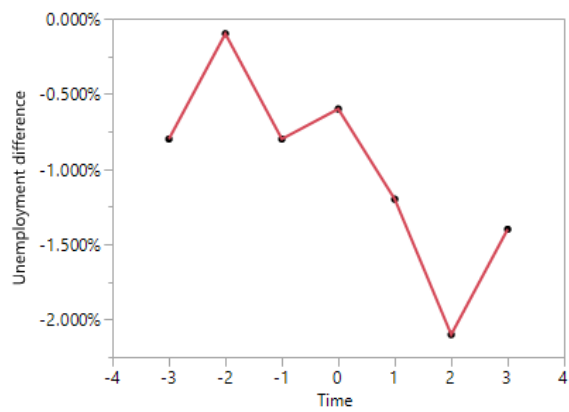


Figure 25. St. Croix Chippewa Indians of Wisconsin Ud.

Time	St. Croix Chippewa Indians of Wisconsin
-3	-0.8%
-2	-0.1%
-1	-0.8%
0	-0.6%
1	-1.2%
2	-2.1%
3	-1.4%

Table 25. St. Croix Chippewa Indians of Wisconsin Ud.

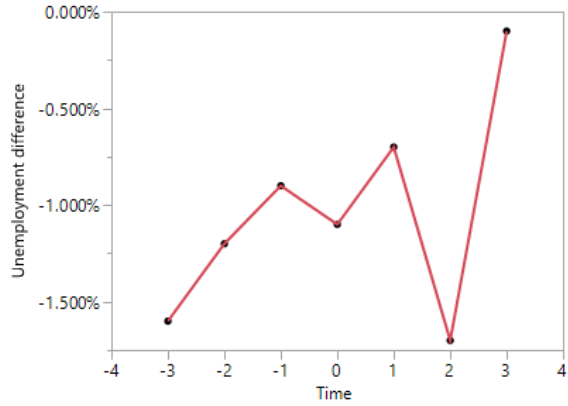


Figure 26. Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin Ud.

Time	Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin
-3	-1.6%
-2	-1.2%
-1	-0.9%
0	-1.1%
1	-0.7%
2	-1.7%
3	-0.1%

Table 26. Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin Ud.

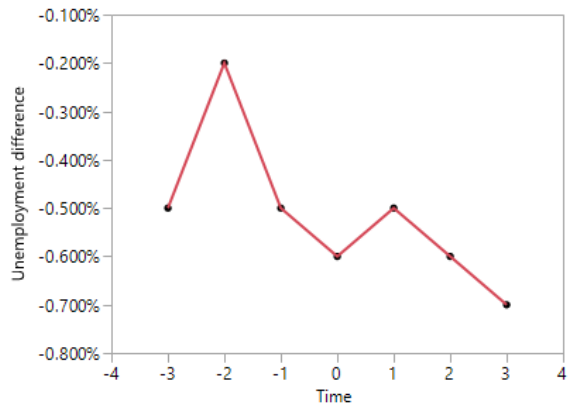


Figure 27. Average Ud.

Time	Average
-3	-0.5%
-2	-0.2%
-1	-0.5%
0	-0.6%
1	-0.5%
2	-0.6%
3	-0.7%

Table 27. Average Ud.

Employment-to-Population Ratios Data

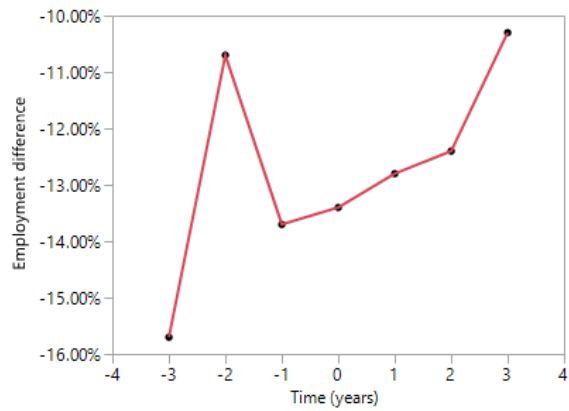


Figure 28. Comanche Nation, OK Ed.

Time	Comanche Nation, OK
-3	-15.7%
-2	-10.7%
-1	-13.7%
0	-13.4%
1	-12.8%
2	-12.4%
3	-10.3%

Table 28. Comanche Nation, OK Ed.

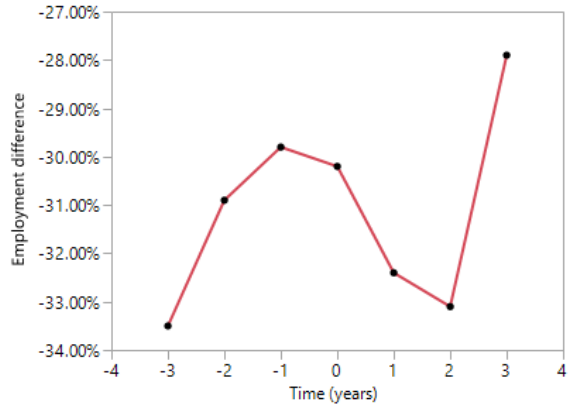


Figure 29. Eastern Bank of Cherokee Indians, NC Ed.

Time	Eastern Bank of Cherokee Indians, NC
-3	-33.5%
-2	-30.9%
-1	-29.8%
0	-30.2%
1	-32.4%
2	-33.1%
3	-27.9%

Table 29. Eastern Bank of Cherokee Indians, NC Ed.

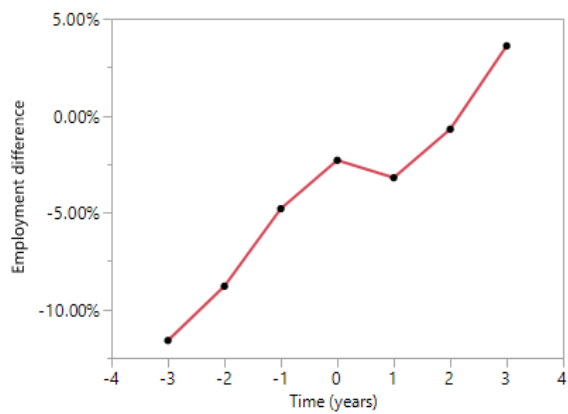


Figure 30. Menominee Indian Tribe of Wisconsin Ed.

Time	Menominee Indian Tribe of Wisconsin
-3	-11.6%
-2	-8.8%
-1	-4.8%
0	-2.3%
1	-3.2%
2	-0.7%
3	3.6%

Table 30. Menominee Indian Tribe of Wisconsin Ed.

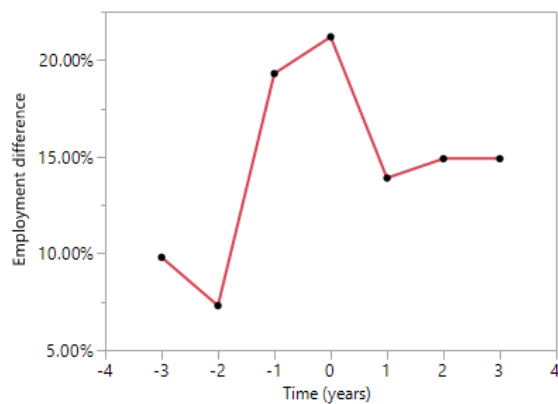


Figure 31. Mississippi Band of Choctaw Indians Ed.

Time	Mississippi Band of Choctaw Indians
-3	9.8%
-2	7.3%
-1	19.3%
0	21.2%
1	13.9%
2	14.9%
3	14.9%

Table 31. Mississippi Band of Choctaw Indians Ed.

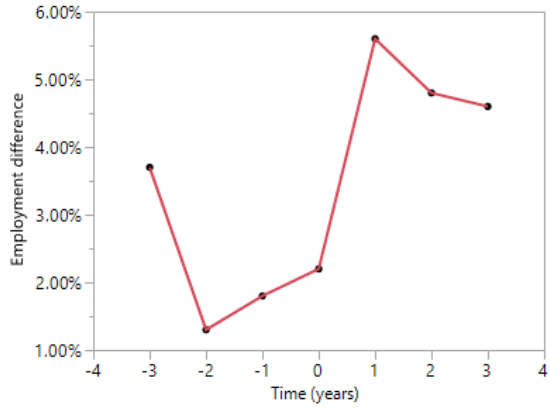


Figure 32. Cheyenne and Arapaho Tribes, OK Ed.

Time	Cheyenne and Arapaho Tribes, OK
-3	3.7%
-2	1.3%
-1	1.8%
0	2.2%
1	5.6%
2	4.8%
3	4.6%

Table 32. Cheyenne and Arapaho Tribes, OK Ed.

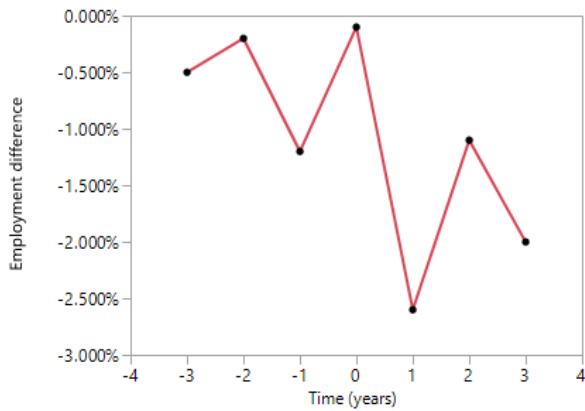


Figure 33. Shoshone-Bannock Tribes of the Fort Hall Reservation, ID Ed.

Time	Shoshone-Bannock Tribes of the Fort Hall Reservation, ID
-3	-0.5%
-2	-0.2%
-1	-1.2%
0	-0.1%
1	-2.6%
2	-1.1%
3	-2.0%

Table 33. Shoshone-Bannock Tribes of the Fort Hall Reservation, ID Ed.

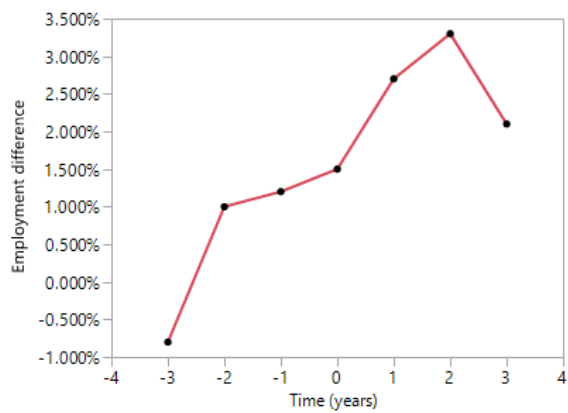


Figure 34. Klamath Tribes, OR Ed.

Time	Klamath Tribes
-3	-0.8%
-2	1.0%
-1	1.2%
0	1.5%
1	2.7%
2	3.3%
3	2.1%

Table 34. Klamath Tribes, OR Ed.

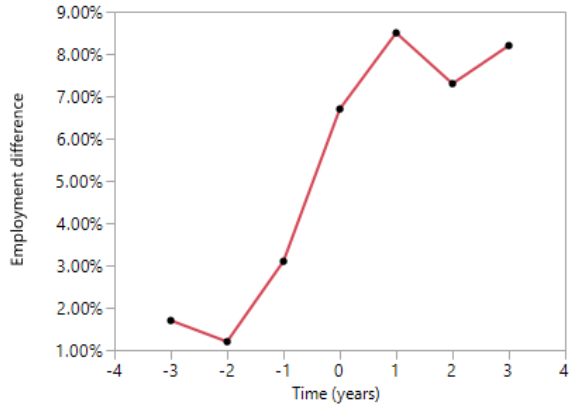


Figure 35. Confederated Tribes of the Grand Ronde Community of Oregon Ed.

Time	Confederated Tribes of the Grand Ronde Community of Oregon
-3	1.7%
-2	1.2%
-1	3.1%
0	6.7%
1	8.5%
2	7.3%
3	8.2%

Table 35. Confederated Tribes of the Grand Ronde Community of Oregon Ed.

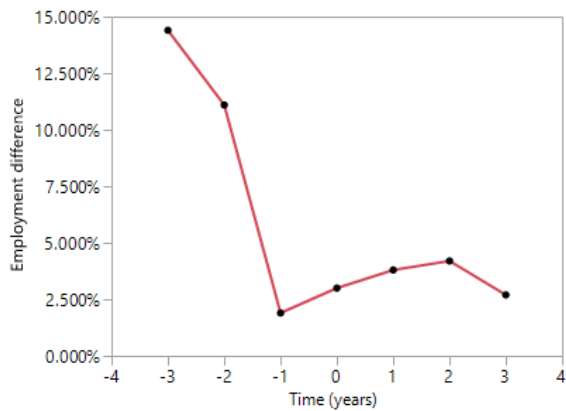


Figure 36. Stockbridge Munsee Community, Wisconsin Ed.

Time	Stockbridge Munsee Community, Wisconsin
-3	14.4%
-2	11.1%
-1	1.9%
0	3.0%
1	3.8%
2	4.2%
3	2.7%

Table 36. Stockbridge Munsee Community, Wisconsin Ed.

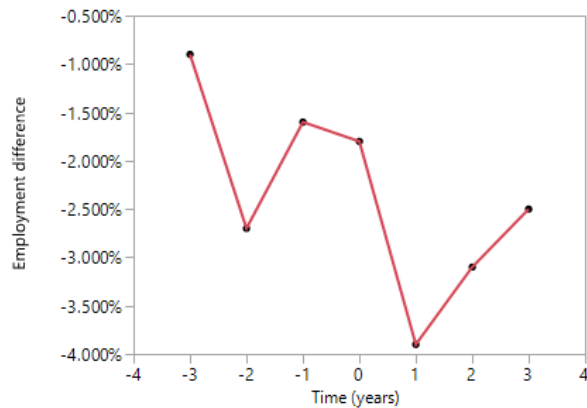


Figure 37. Confederated Tribes of Siletz Indians of Oregon Ed.

Time	Confederated Tribes of Siletz Indians of Oregon
-3	-0.9%
-2	-2.7%
-1	-1.6%
0	-1.8%
1	-3.9%
2	-3.1%
3	-2.5%

Table 37. Confederated Tribes of Siletz Indians of Oregon Ed.

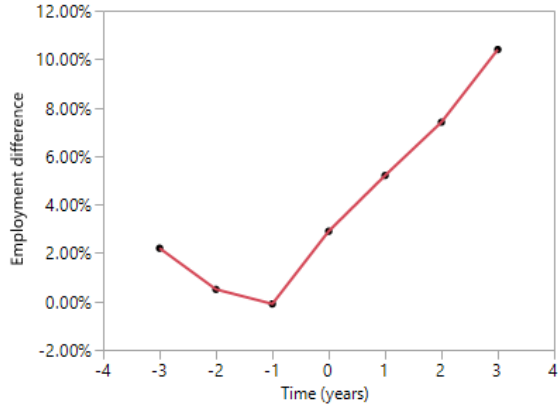


Figure 38. Saginaw Chippewa Indian Tribe of Michigan Ed.

Time	Saginaw Chippewa Indian Tribe of Michigan
-3	2.2%
-2	0.5%
-1	-0.1%
0	2.9%
1	5.2%
2	7.4%
3	10.4%

Table 38. Saginaw Chippewa Indian Tribe of Michigan Ed.

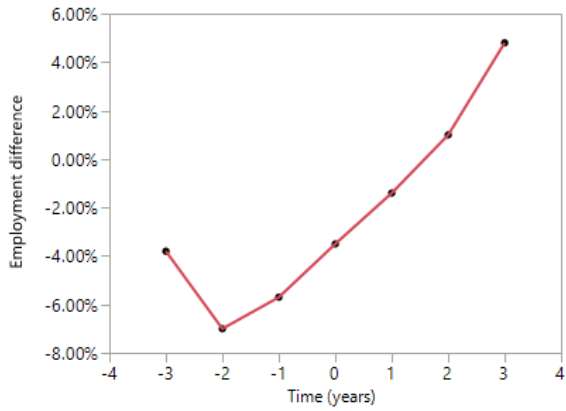


Figure 39. Poarch Band of Creeks Ed.

Time	Poarch Band of Creeks
-3	-3.8%
-2	-7.0%
-1	-5.7%
0	-3.5%
1	-1.4%
2	1.0%
3	4.8%

Table 39. Poarch Band of Creeks Ed.

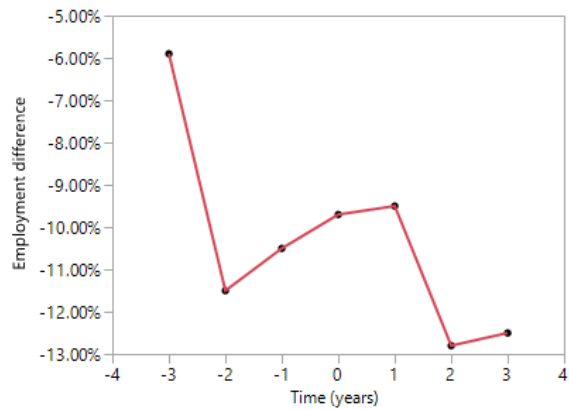


Figure 40. Fort Sill Apache Tribe of Oklahoma Ed.

Time	Fort Sill Apache Tribe of Oklahoma
-3	-5.9%
-2	-11.5%
-1	-10.5%
0	-9.7%
1	-9.5%
2	-12.8%
3	-12.5%

Table 40. Fort Sill Apache Tribe of Oklahoma Ed.

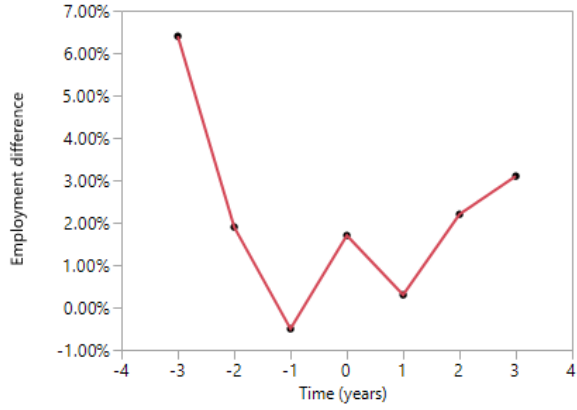


Figure 41. Minnesota Chippewa Tribe - Fond du Lac Band Ed.

Time	Minnesota Chippewa Tribe - Fond du Lac Band
-3	6.4%
-2	1.9%
-1	-0.5%
0	1.7%
1	0.3%
2	2.2%
3	3.1%

Table 41. Minnesota Chippewa Tribe - Fond du Lac Band Ed.

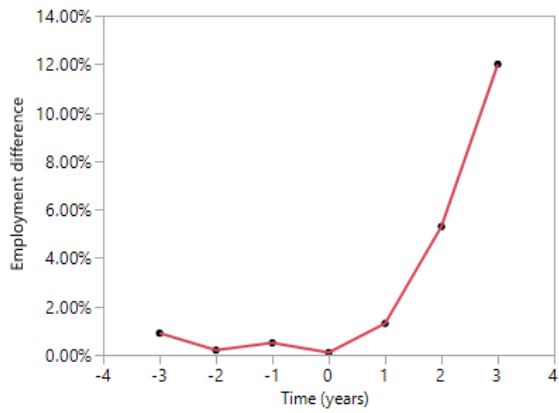


Figure 42. Otoe-Missouria Tribe of Indians, Oklahoma Ed.

Time	Otoe-Missouria Tribe of Indians, Oklahoma
-3	0.9%
-2	0.2%
-1	0.5%
0	0.1%
1	1.3%
2	5.3%
3	12.0%

Table 42. Otoe-Missouria Tribe of Indians, Oklahoma Ed.

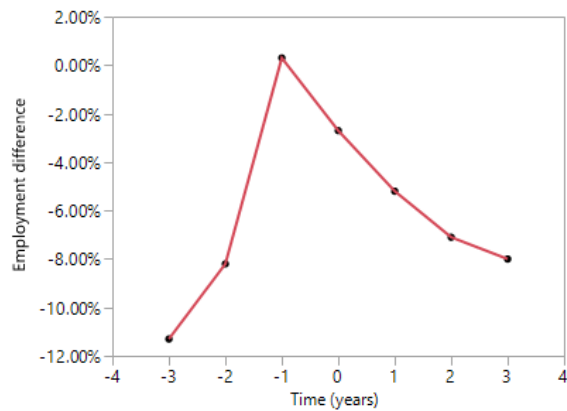


Figure 43. Minnesota Chippewa Tribe - Mille Lacs Band Ed.

Time	Minnesota Chippewa Tribe - Mille Lacs Band
-3	-11.3%
-2	-8.2%
-1	0.3%
0	-2.7%
1	-5.2%
2	-7.1%
3	-8.0%

Table 43. Minnesota Chippewa Tribe - Mille Lacs Band Ed.

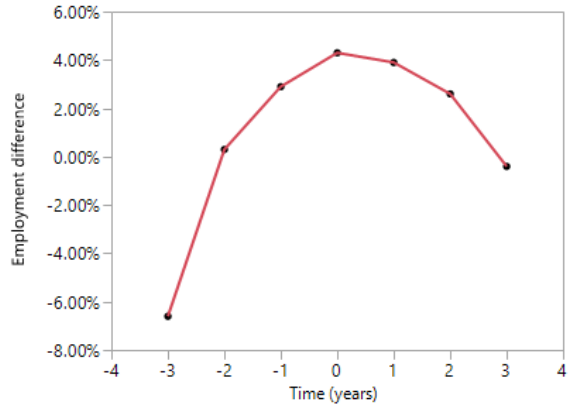


Figure 44. Sac & Fox Tribe of the Mississippi in Iowa Ed.

Time	Sac & Fox Tribe of the Mississippi in Iowa
-3	-6.6%
-2	0.3%
-1	2.9%
0	4.3%
1	3.9%
2	2.6%
3	-0.4%

Table 44. Sac & Fox Tribe of the Mississippi in Iowa Ed.

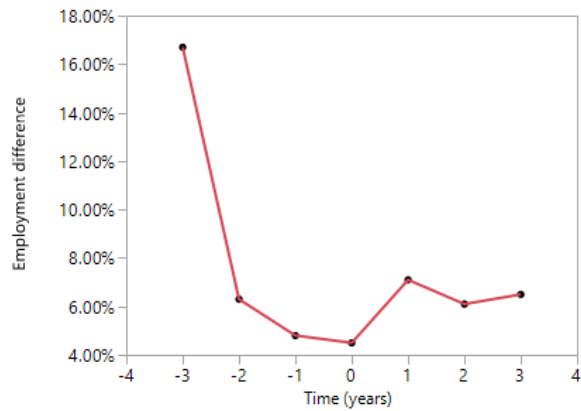


Figure 45. Grand Traverse Band of Ottawa & Chippewa Indians, MI Ed.

Time	Grand Traverse Band of Ottawa & Chippewa Indians, MI
-3	16.7%
-2	6.3%
-1	4.8%
0	4.5%
1	7.1%
2	6.1%
3	6.5%

Table 45. Grand Traverse Band of Ottawa & Chippewa Indians, MI Ed.

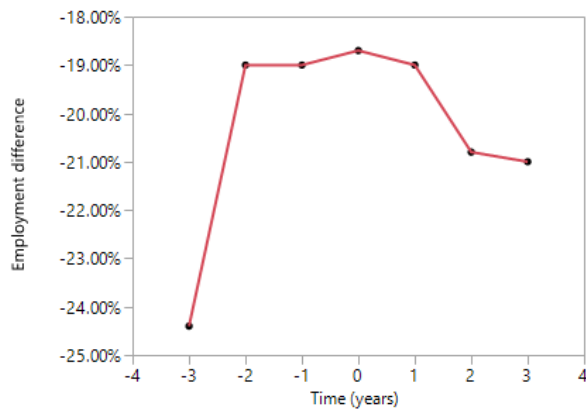


Figure 46. Little Traverse Bay Bands of Odawa Indians, MI Ed.

Time	Little Traverse Bay Bands of Odawa Indians, MI
-3	-24.4%
-2	-19.0%
-1	-19.0%
0	-18.7%
1	-19.0%
2	-20.8%
3	-21.0%

Table 46. Little Traverse Bay Bands of Odawa Indians, MI Ed.

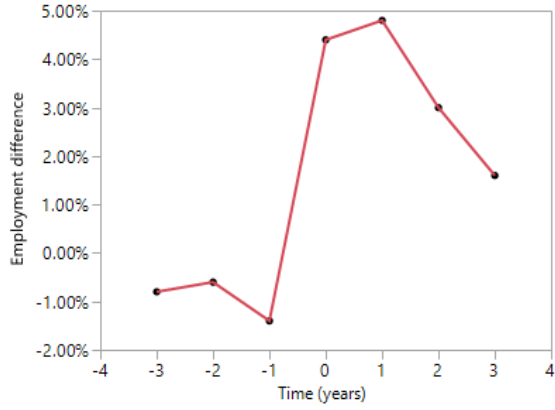


Figure 47. Coeur D'Alene Tribe, ID Ed.

Time	Coeur D'Alene Tribe, ID
-3	-0.8%
-2	-0.6%
-1	-1.4%
0	4.4%
1	4.8%
2	3.0%
3	1.6%

Table 47. Coeur D'Alene Tribe, ID Ed.

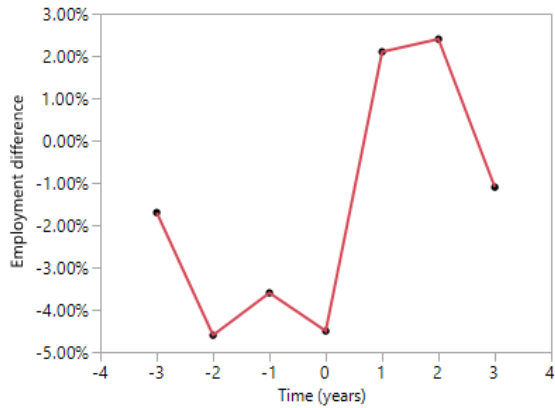


Figure 48. St. Croix Chippewa Indians of Wisconsin Ed.

Time	St. Croix Chippewa Indians of Wisconsin
-3	-1.7%
-2	-4.6%
-1	-3.6%
0	-4.5%
1	2.1%
2	2.4%
3	-1.1%

Table 48. St. Croix Chippewa Indians of Wisconsin Ed.

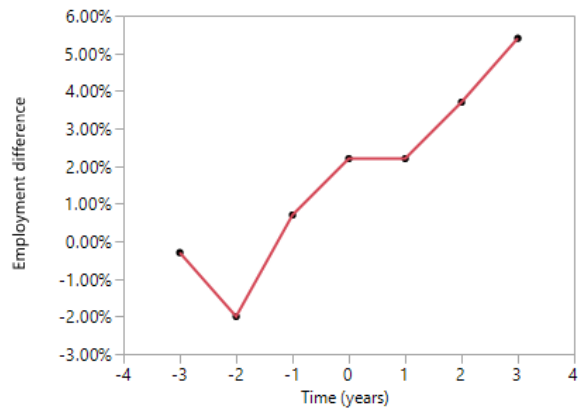


Figure 49. Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin Ed.

Time	Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin
-3	1.0%
-2	-0.9%
-1	1.4%
0	3.0%
1	2.6%
2	5.0%
3	5.2%

Table 49. Lac du Flambeau Band of Lake Superior Chippewa Indians of Wisconsin Ed.

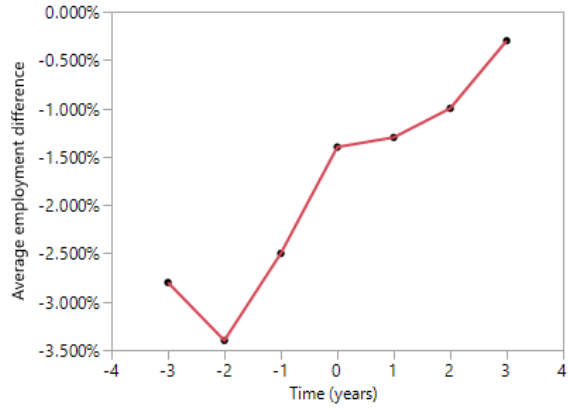


Figure 50. Average Ed.

Time	Average
-3	-2.8%
-2	-3.4%
-1	-2.5%
0	-1.4%
1	-1.3%
2	-1.0%
3	-0.3%

Table 50. Average Ed.