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THE IMPACT OF RIGHT-TO-WORK ON STATE ECONOMIC DEVELOPMENT: EVIDENCE FROM IDAHO

by

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Abstract

This paper presents new evidence on the impact of Right-To-Work (RTW) on state economic growth. It investigates manufacturing employment growth in Idaho following that state's adoption of RTW in 1986. Idaho is the most recent state to adopt RTW, and the only state to have adopted RTW within the last 25 years. Using a county-level analysis and comparisons based on alternative treatment and control groups, this study finds that manufacturing employment growth was significantly greater in Idaho than in the control groups. Medium-sized rural counties appear to have received the greatest benefit from the adoption of RTW.

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I. INTRODUCTION

Right-To-Work (RTW) is one of the most hotly contested and controversial policy issues in American labor relations. In 1947, the Taft-Hartley Act confirmed to states the right to prohibit "membership in a labor organization as a condition of employment." Since then, numerous statewide campaigns have engaged the issue, with the result that 21 states are currently "right-to-work" states. Despite the fact that only two states have adopted RTW since 1963 (Louisiana in 1976 and Idaho in 1986), the issue remains politically active. In the 1990's, RTW proponents advanced serious campaigns in New Hampshire, New Mexico, Montana, and Colorado. Maryland, Rhode Island, Pennsylvania, and Oregon also saw active campaigns on the issue. Oklahoma has scheduled a statewide referendum on RTW for September 2001.

An important research question is whether RTW impacts state economic development. A large literature has explored this issue, which is summarized in several surveys (Moore and Newman, 1985; Moore, 1998, and Tannenwald, 1997). The general consensus of the surveys is that there exists a statistically significant correlation between RTW and economic development.[1] However, most of this research consists of cross-sectional analyses. As Wheat (1988) and others have shown, there are serious difficulties associated with disentangling the individual impact of

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[1] For example, Moore (1998, p. 464) writes, "A little more than a decade ago, Professor Newman and I ended our review of the RTW literature with the conclusion that the better studies 'suggest that the effects of RTW laws are more symbolic than real' (Moore and Newman, 1985, p. 583). More recent evidence indicates that this conclusion was premature. RTW laws definitely appear to promote free riding and to lower union organizing efforts and successes, at least in the short-run. Although inconclusive, the accumulating evidence indicates that RTW laws reduce the long-run extent of unionization by 5 to 8 percent. *RTW laws are also positively correlated with long-run industrial development* [italics added]. The proponents of RTW laws may have been correct. RTW laws may have modestly reduced the growth of unions and promoted industrial development in the long run."

RTW from other sources of growth.[2] There remains uncertainty concerning the degree to which RTW proxies for other factors.

For this reason, the recent study by Thomas Holmes (1998) in the *Journal of Political Economy* is particularly noteworthy. Holmes studied differences in manufacturing employment growth from 1947-1992 for counties located in close proximity to borders between RTW and non-RTW states. He found abrupt and significant increases in manufacturing employment growth as one crossed the border from a non-RTW state to a RTW state. Given that his analysis includes counties that shared similar climate, geography, and labor force characteristics, it provides clear evidence that RTW, or state policies closely correlated with RTW, have a significant impact on industrial activity.

This paper makes two contributions to the RTW literature. First, it extends Holmes' analysis (albeit with significant differences) to the case of Idaho. Idaho adopted RTW in 1986, making it the most recent state to enact RTW, and the first other than Louisiana (1976) to adopt RTW since 1963 (see Table 1).[3] Holmes did not include Idaho in his analysis. Thus, this study brings new data to the study of the impact of RTW on manufacturing employment growth. As the only state to adopt RTW in the last twenty-five years, Idaho has particular policy relevance for states considering changing their RTW status today. Second, this is the first paper to investigate the county-level impact of RTW according to the rural-urban character of the

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[2] Illuminating in this respect is the exchange between Moore, Dunlevy and Newman (1986) and Carroll (1986).

[3] Louisiana is not well-suited for study of this issue because (i) it has no borders with non-RTW states, and (ii) it has changed its RTW status several times. Louisiana adopted RTW in 1954, then repealed it in 1956, replacing it with an agricultural RTW law instead. Louisiana again passed RTW in 1976.

impacted counties. These results should be of particular importance to those interested in how RTW may affect rural economic development.

The paper proceeds as follows: Section 2 briefly explains the methods and data employed by this study. Section 3 reports and discusses the empirical results. Section 4 concludes.

II. DATA AND ESTIMATION METHODS

Overview. Holmes examined (i) manufacturing employment share (1992) and (ii) manufacturing employment growth (1947-92) for counties located within 100 miles of a RTW/non-RTW border.[4] Counties were grouped into 8 groups, depending on how far (0-25 miles, 25-50 miles, 50-75 miles, and 75-100 miles) and on which side of a RTW/non-RTW border they were located. In the jargon of the experimental method, the counties on the RTW side of the border were the "treatment" observations, and the counties on the non-RTW side were the "control" observations. Given their geographical proximity, with corresponding similarities in climate, geography, and labor force characteristics, differences in economic outcomes between the treatment and control counties were attributed to RTW.

Holmes found that manufacturing employment shares were virtually the same for counties located 75-100 miles on either side of the border. However, the shares increased (decreased) significantly as one approached the border from the RTW (non-RTW) side, resulting in an abrupt change at the border. In contrast, Holmes found that manufacturing employment growth rates were generally higher for all counties on the RTW side of the border, regardless of their respective distance from the border.

[4] Strictly speaking, Holmes examined counties whose population centroids were located within 100 miles of a RTW/non-RTW border.

Unfortunately, a direct extension of his methodology to the case of Idaho is impractical because of the small number of counties that would be included in such an analysis. For example, only 24 counties lie within 25 miles on either side of Idaho's border with its non-RTW neighbors (Oregon, Washington, and Montana). As a result, this study expands the treatment and control groups. It does so in two ways. First, it includes counties that are located further from the border. Second, it expands the control group to include counties from neighboring RTW states (Nevada, Utah, and Wyoming). If the adoption of RTW in Idaho enabled Idaho's manufacturing sector to grow faster than its non-RTW neighbors, it should also have enabled Idaho's manufacturing sector to grow faster than its RTW neighbors, where RTW had already been long in place.

Of course, expansion of the treatment and control groups comes at a cost. In particular, the assumption that all other factors are held constant between treatment and control counties is less defensible as the geographical distance between these groups of counties is expanded. This study compensates by including socio-economic explanatory variables in order capture differences in growth-related factors between counties.

A further difference between this study and Holmes' study is that we only examine manufacturing employment growth, and not manufacturing shares of employment. We do this because Holmes found little difference in manufacturing shares for counties located more than 75 miles from a RTW/non-RTW border. Since our study expands treatment and control groups to include counties that are located further from the border, it seems best to focus on manufacturing employment growth rates, for which distance from a border does not seem to play a major role. Despite, these differences, this study attempts to replicate the "spirit" of Holmes' experimental analysis. The remainder of this section elaborates on the details of our analysis.

Treatment and Control Groups. This study develops four alternative treatment and control group data sets. The first two data sets employ counties belonging to *BEA Economic Areas* that either include or are contiguous to Idaho's border. The latter two data sets employ counties belonging to *states* that either include or are contiguous to Idaho's borders. The four data sets are:

1. Data Set One: Counties in BEA Economic Areas that contain or abut a border between Idaho and a non-RTW state.
2. Data Set Two: Counties in BEA Economic Areas that contain or abut a border between Idaho and any other state, including both non-RTW and RTW states.
3. Data Set Three: Counties in states that abut a border between Idaho and a non-RTW state.
4. Data Set Four: Counties in states that abut a border between Idaho and any other state, including both non-RTW and RTW states.

For each data set, treatment observations consist of counties from Idaho; control observations consist of counties located outside of Idaho. The respective treatment and control groups are defined more precisely in Table 2.

The collections of counties known as Economic Areas are defined by the Bureau of Economic Analysis (BEA) to represent counties that share important economic relationships.

> "Each economic area consists of one or more economic nodes - metropolitan areas or similar areas that serve as center of economic activity – and the surrounding counties that are economically related to the nodes. The main factor used in determining the economic relationships among counties is commuting patterns, so each economic area includes, as far as possible, the place of work and the place of residence of its labor force (Johnson, 1995)."

As Figure 1 shows, Economic Areas are generally smaller than states. This means that we can choose a set of Economic Areas such that the corresponding counties will be closer to Idaho's borders than if we selected all counties from the respective states. Further, counties from contiguous Economic Areas are likely to share key economic characteristics. As a result, empirical analyses based on Economic Areas are more likely to hold other factors constant (particularly unobservable determinants of manufacturing employment growth). Evidence of this is provided below.

Variables. The dependent variable in our analysis is manufacturing employment growth rate (*MEGR)*, calculated from 1986-1996. 1986 is chosen as the initial period because that is the year that Idaho adopted RTW. 1996 is chosen as the concluding year of the period because that was the last year for which data was available.

A complication immediately arises when using county-level data because some counties had no manufacturing employment in 1986. To address this problem we follow Holmes (1998) in calculating *MEGR* as

(1) $$MEGR_i = \frac{ME_{i,1996} - ME_{i,1986}}{0.5 * (ME_{i,1996} + ME_{i,1986})} \in [-2,2]$$

where $ME_{i,t}$ represents the level of manufacturing employment for county i at time t. $MEGR_i \times 100$ can be interpreted as the percentage change in manufacturing employment from the average of 1986 and 1996 manufacturing employment in county i.

$MEGR_i$ ranges between –2 and 2, taking the extreme values when manufacturing employment is zero in either the terminal or initial period. While the bounded nature of the dependent variable implies that the error terms will be heteroscedastic, it has the advantage that it allows us to use all the observations. The problem of heteroscedasticity is taken up below.

The independent variables used in this study are chosen because they had been identified as important variables in previous RTW research.[5] They can be broadly categorized into (i) input and (ii) demographic and geographic characteristics. Means and standard deviations of all of the independent variables are reported in Table 3.

Input measures used in this study are unemployment rate and educational attainment rates. For unemployment rate we use county unemployment rate in 1980 (*URATE80*) since the measure was only available from the decennial census. As such, *URATE80* should be interpreted as a (noisy) measure of persistent, long-run unemployment in the county. The parameter estimate on this variable is expected to have a positive sign, as a higher unemployment rate proxies for a relatively low wage rate.

To measure education, we use the share of population over 25 years of age with a Bachelor's degree in 1980 (*SHRCOL80*) and the share of population over 25 years of age with a high school or equivalent education in 1980 (*SHRHS80*). Both of these variables are expected to produce positive parameter estimates as a more highly educated workforce is expected to lead to more rapid economic growth.

The first of the demographic variables we employ is a measure of population growth in the county from 1980 to 1986 (*POP8086*), the period immediately prior to the adoption of RTW. This variable is interpreted to measure the existence of economic trends in effect as of 1986. It is expected that the existence of rapid population/economic growth in the period immediately prior to 1986 should harbinger continued economic expansion in the period after 1986. As a result, a positive coefficient is expected for the variable *POP8086*. Another demographic variable is

[5] In particular, we relied on Coughlin et. al., (1987); Schmenner, et. al., (1991); and Woodward and Glickman (1991).

share of population in 1980 self-identified as black (*SHRBLK80*). This variable is included as a control for differences in the demographics of counties. There is no expectation about the sign of its coefficient.

Three variables are included to control for differing industry compositions across counties. These are the percent of 1986 total employment in the mining sector (*SHRMIN86*), the percent of 1986 total employment in the transportation, communication, and public utilities sector (*SHRTCU86*), and the percent of 1986 total employment in the trade (wholesale and retail) sector (*SHRTRA86*). Again, there are no expectations concerning the signs of these coefficients.

An innovation of this study is that we investigate the differential impact that RTW may have on counties according to their degree of "rural-ness." To do this, we utilize a series of dummy variables, based on Beale codes, indicating the urban-rural character of a county. Beale codes describe the geographical character of a county as one of ten types. The county Beale code ranges from the central county of an urban area with population over one million (Beale Code = 0, *BEALE_0 = 1*) to a rural county that is not adjacent to a metropolitan area with an urban population of 2,500 or less (Beale Code = 9, *BEALE_9 = 1*) (Butler and Beale, 1994).

Counties with a 1983 Beale code between 4 and 9 are classified as "rural." Those with a value of 4, 6, or 8 are rural counties that are adjacent to a metropolitan area, while those with values of 5, 7, or 9 are not adjacent to a metropolitan area. There is no expectation attached to the parameter estimates associated with these dummy variables. They are included to control for differences in county size and relative location to a metropolitan area.

<u>Estimation Technique</u>. Our empirical analysis uses least squares to estimate the equation

$$\begin{aligned} MEGR_i &= \boldsymbol{b}_0 + \boldsymbol{b}_1 IDAHO_i + \boldsymbol{b}_2 URATE80_i + \boldsymbol{b}_3 SHRCOL80_i + \boldsymbol{b}_4 SHRHS80_i \\ &+ \boldsymbol{b}_5 SHRBLK80_i + \boldsymbol{b}_6 POP8086_i + \boldsymbol{b}_7 SHRMIN86_i + \boldsymbol{b}_8 SHRTCU86_i \\ &+ \boldsymbol{b}_9 SHRTRA86_i + \sum_j \left(\boldsymbol{b} \times Beale\ Code\ dummy\ variable\right)_j + \boldsymbol{e}_i\ , \end{aligned} \tag{2}$$

where the specific set of included Beale Code dummy variables differs across regressions, and e_i is a random error term. Of particular interest is the coefficient on the dummy variable *IDAHO*. It measures whether Idaho's *MEGR* is higher than its respective control groups after controlling for the influence of other variables.

As discussed above, the bounded nature of the dependent variable introduces heteroscedasticity. In addition, there are well-founded concerns about the independence of the error term across observations. Moulton (1990) emphasizes that using micro-level observations when a policy or treatment is applied at a higher order of aggregation (such as occurs when county-level data is used to estimate the impact of a state-level policy) can cause standard errors to be significantly biased. He shows that even mild degrees of positive correlation across grouped observations can lead to standard errors that are biased by three hundred percent or more.

This study uses robust cluster estimation to address the combined problems of heteroscedasticity and group correlation. As in standard robust estimation, OLS is used to produce the coefficient estimates. However, OLS estimates of the coefficients' standard errors will be biased in the presence of heteroscedasticity and group correlation. Robust cluster estimation produces consistent estimates of these standard errors.[6]

<u>Data Sources</u>. One of the best public sources of data on employment at the county level is the County Business Patterns (CBP) data available from the United State Census Bureau. *MEGR* is calculated from employment data from this source, as are the variables related to industry shares, *SHRMIN86*, *SHRTCU86*, and *SHRTRA86*.

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[6] Further details on robust cluster estimation can be found in the STATA Reference manual.

A common problem with the CBP is that information is occasionally suppressed to protect the confidentiality of firms. This problem becomes more acute in counties with relatively small employment levels. Many of the counties used in this study fall into this category. A common approach in the literature is to impute a value for observations where information is missing or non-disclosed. That is the approach followed here as well.[7]

As indicated previously, the Beale code dummy variables are obtained from the United States Department of Agriculture (Butler and Beale, 1994). The remainder of the independent variables, *URATE80*, *SHRHS80*, *SHRCOL80*, *POP8086*, *SHRBLK80* are taken from the data compact disk *USA Counties, 1998* from the United States Census Bureau.

III. EMPIRICAL RESULTS

Descriptive Statistics of Variables by Treatment and Control Groups. The means in Table 3 reveal that each of the treatment and control groups are distinctly rural in character. Beale codes 7 and 9 are far and away the most heavily represented county types. As would be expected from a sample of western, predominantly rural counties, the college-educated and black shares of the population are relatively small. The agriculture and wholesale and retail trade sectors predominate.

For our purposes, the most important feature of Table 3 is that it allows comparison between the respective treatment and control groups. The differences in means across individual variables are relatively small; all lie within a standard deviation of each other. While not a formal test, this provides evidence that the attempt to construct groups with similar economic

[7] Imputed values were calculated using statewide averages for each employment size class adjusted by industry.

characteristics was successful. The presumed statistical framework of "treatment" and "control" groups is not farfetched.

Estimates of RTW on *MEGR* by Data Set. Simple, difference-in-difference (DID) estimates are reported in Table 4. Alternatively, these can be thought of as estimating the coefficient on the dummy variable *IDAHO* in equation (2) when no control variables are included in the estimation. They provide the first evidence concerning the impact of RTW on the respective counties' manufacturing employment growth rates (*MEGR*).

The DID estimates are positive for each of the four data sets. In Data Set 1, constructed to consist of counties in BEA Economic Areas that contain or abut a border between Idaho and a non-RTW state, manufacturing employment grew thirty percentage points more in Idaho than in the corresponding non-RTW counties. The DID estimates for the other data sets are smaller, but still large in economic terms. The smallest estimate, 0.1036 for Data Set 4, implies that manufacturing employment growth was almost 50 percent larger in Idaho compared to its control counties (0.3284 versus 0.2248).

Table 5 investigates whether these large differences persist after controlling for the influence of other variables. Looking first at the control variables, we see that the respective coefficients generally conform to expectations. Increased unemployment (*URATE80*), greater educational attainment (*SHRCOL80* and *SHRHS80*) and higher population growth rates (*POP8086*) are in all cases save one positively (though usually not significantly) associated with *MEGR*. Interestingly, the R^2 for the regression using Data Set 1 is considerably larger than that for Data Sets 2 through 4. This is consistent with our expectation that the counties in Data Set 1 are characterized by the greatest similarity by virtue of their geographic proximity.

For all four data sets, the estimated coefficient on the *IDAHO* dummy variable remains positive after controlling for the other variables. It is statistically significant at the 1 percent level for three of the four data sets. The inclusion of the control variables reduces the size of the estimated RTW impact for Data Set 1, but increases it for the other three data sets relative to uncontrolled estimates in Table 4. The estimated coefficients imply that manufacturing employment grew 14 to 27 percentage points more in Idaho than its respective control groups. A comparison with Table 4 confirms that this implies that manufacturing employment growth was at least 70 percent larger in Idaho after controlling for the influence of other variables.

As Holmes (1998) discusses, RTW is predicted to especially impact the manufacturing sector because union activity is most concentrated there. By strengthening the economic position of the employer vis-à-vis the union, RTW makes investment in manufacturing industry more attractive. Our results do not specifically link the exceptional growth of manufacturing in Idaho to RTW. However, the fact that this is the predicted impact of RTW, in combination with the lack of a viable alternative hypothesis, provides compelling evidence that RTW significantly impacted Idaho's economic development.

<u>Estimates of RTW's Impact on Idaho's Rural Economic Development</u>. Table 6 repeats the analysis of Table 5 except that the observations are restricted to rural counties (counties having Beale Codes between 4 and 9). The results are very similar.[8] This isn't surprising since the great majority of counties in our original analysis are rural counties. Between 85 and 90 percent of Data Sets 2 through 4 are rural counties. 97 percent of the counties in Data Set 1 are rural.

[8] The identical slope coefficients in Column 1 of Tables 5 and 6 is not a mistake. Both the treatment and control group for Data Set 1 had a single, non-rural observation that was controlled

The final three tables categorize the rural counties in the respective data sets into three groups. Ranging from smallest (most rural) to largest (least rural/most urban), these groups are (i) counties having urban populations of 2,499 or less (Beale Codes 8 and 9); (ii) counties having urban populations between 2,500 and 19,999 (Beale codes 6 and 7); and (iii) counties having urban populations larger than 20,000 (Beale codes 4 and 5). Disaggregating the rural counties into these groups serves two, related purposes. First, it allows us to determine whether our preceding finding that *MEGR* were higher in Idaho following RTW is robust across county-types. Second, it allows us to determine whether RTW differentially benefits some county-types more than others.

A number of observations can be made by comparing the results from Tables 7, 8, and 9. First, small sample sizes are characteristic of all the data sets. One result is that some of the coefficients for the respective control variables demonstrate substantial instability (e.g., the coefficient for *SHRBLK80*). Second, the R^2's for the Data Set I regressions are considerably larger than the R^2's for the other data sets in Tables 7 and 9 (the most and least rural, respectively). The R^2's are similar across data sets in Table 8. Even disaggregated into county-types, we see that the counties in Data Set 1 appear to be characterized by greater homogeneity.

Another observation is that disaggregating the rural sample by county-type results in generally higher R^2's. The R^2's in Table 7 are similar to those for the larger sample of all rural counties in Table 6, but those in Tables 8 and 9 are distinctly higher. Since the regressions in Table 6 included Beale Code dummy variables, this is evidence that county-type interacts in a complex fashion with the other variables in the equation to "explain" manufacturing employment growth. It encourages the notion that degree of rural-ness matters for economic development.

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by a unique Beale Code dummy variable. As a result, removing these singletons from the data

Turning now to our main interest, we see that the coefficient for *IDAHO* is positive in 10 out of 12 regressions across all three tables. Only for the most rural of rural counties, those with populations less than 2,400, do we obtain negative estimated impacts of RTW (see Table 7). Most of the estimates are insignificant. Table 8 is the exception, where three of the four coefficient estimates are significant (positive) at the 5 percent level. We interpret these results as generally demonstrating the robustness of the previous results concerning the positive impact of RTW on manufacturing employment growth. Admittedly, the results from Table 7 present a muddled picture. We shall have more to say about them below.

Of the three county-types represented in Tables 7 through 9, it appears that mid-sized rural counties--those with urban populations between 2,500 and 20,000—are the most impacted by RTW. The estimated impacts range from 0.2089 to 0.3577 (cf. Table 8). The smallest estimated impact, and the only insignificant coefficient for the mid-sized rural counties, occurs in the regression using Data Set 1. As a group, these estimates are substantially larger than those for the other rural county-types.

The most urban of the rural counties—those with urban populations larger than 20,000—also show evidence of a positive impact from RTW. However, as already indicated, the estimated impacts are substantially smaller than those for mid-sized rural counties. The estimates range from 0.0560 to 0.1187. None of the corresponding coefficients are significant.

The results for the most rural category of counties—those with urban populations less than 2,500—are conflicting. On the one hand, two of the four estimated impacts are negative, with one (the estimate in the Data Set 3 regression) being large in absolute value and bordering on significance. On the other hand, the estimated impact in the regression for Data Set

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set affected the intercept, but not the slope coefficients of the regression equation.

1--which is generally preferred over the other data sets--is positive, though with a relatively large standard error.

IV. CONCLUSION

This study finds evidence that Idaho's manufacturing sector grew significantly faster than those of neighboring states following the enactment of RTW in Idaho. The similarity of these findings to those reported by Holmes (1998) provide further support to the claim that RTW is correlated with state economic development. Idaho is the only state in the last twenty-five years to have enacted RTW. As such, it provides the most recent example of what states might be able to expect should they adopt RTW today.

An innovation of this study is that it provides evidence that RTW has differential impacts by county-type. Mid-sized rural counties appear to receive the greatest impact. Larger-sized rural counties receive a smaller impact. The impact on the most rural of rural counties, those with urban populations less than 2,500 is indeterminate. Taken together, they suggest that RTW can play an important role in rural economic development, with the most substantial impacts being experienced by mid-sized rural counties.

FIGURE 1
Economic Areas Containing or Contiguous to Idaho Borders

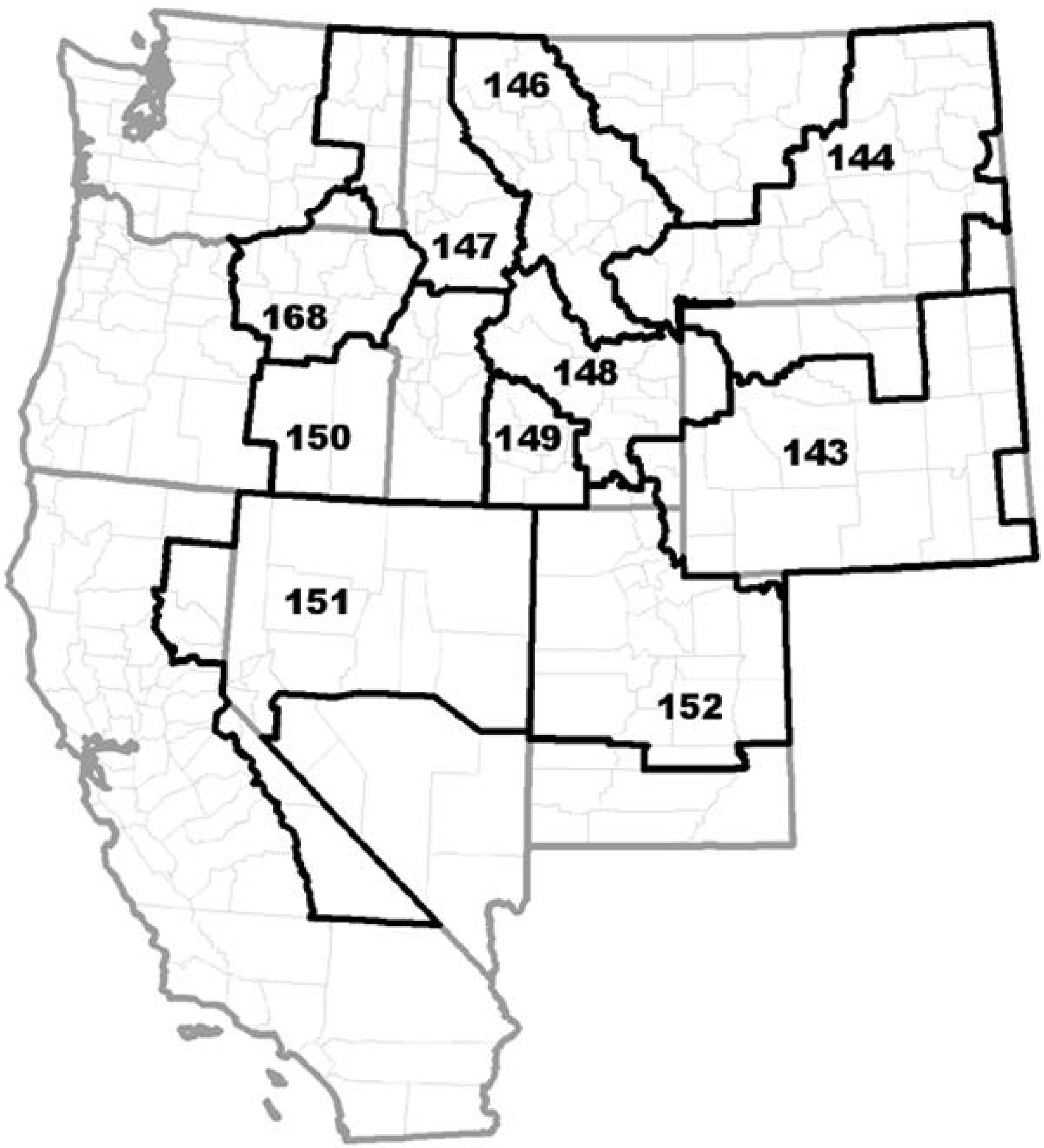

FIGURE 2
Idaho and Border States

TABLE 1
States with RTW Laws by Year of Adoption (Descending Order)

STATE	YEAR OF ADOPTION
Idaho	1986
Louisiana	1976
Wyoming	1963
Kansas	1958
Utah	1955
Mississippi	1954
South Carolina	1954
Alabama	1953
Nevada	1951
Arizona	1947
Arkansas	1947
Georgia	1947
Iowa	1947
North Carolina	1947
North Dakota	1947
Tennessee	1947
Texas	1947
Virginia	1947
South Dakota*	1946
Nebraska*	1946
Florida*	1944

* Florida, Nebraska, and South Dakota each had constitutional amendments prohibiting union shops prior to passage of the Taft-Hartley Act in 1947.

TABLE 2
Description of Treatment and Control Groups for Data Sets One Through Four

DATA SET	TREATMENT OBSERVATIONS	CONTROL OBSERVATIONS
	Counties located in:	***Counties located in:***
ONE	(i) Idaho; and (ii) Economic Areas 150, 147, or 148.	(i) Oregon, Washington, or Montana; and (ii) Economic Areas 150, 168, 147, or 146.
TWO	Idaho.	(i) Oregon, Washington, Montana, Wyoming, Utah, or Nevada; and (ii) Economic Areas 150, 168, 147, 146, 144, 143, 152, or 151.
THREE	Idaho.	Oregon, Washington, or Montana.
FOUR	Idaho.	Oregon, Washington, Montana, Wyoming, Utah, or Nevada.

NOTE: Geographic areas (BEA Economic Areas and states) are represented in Figures 1 and 2.

TABLE 3
Variable Means and Standard Deviations

VARIABLE	TREATMENT GROUPS		CONTROL GROUPS			
	Data Set 1	*Data Sets 2, 3, and 4*	*Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 4*
URATE80 *(1980 Unemployment rate)*	10.0344 (4.5684)	8.9636 (4.3285)	9.0667 (3.8236)	6.2711 (3.5026)	7.9130 (3.7206)	7.0505 (3.4429)
SHRCOL80 *(Share of 1980 population over age 25 with a Bachelor's degree)*	0.1385 (.0467)	0.1391 (0.0485)	0.1526 (0.0610)	0.1494 (0.5373)	0.1460 (0.0496)	0.1465 (0.0501)
SHRHS80 *(Share of 1980 population over age 25 with high school or equivalent education)*	0.3729 (0.0347)	0.3722 (0.0367)	0.3946 (0.0426)	0.3934 (0.0398)	0.3890 (0.0356)	0.3917 (0.0375)
POP8086 *(1980-1986 population growth)*	1.0382 (0.1057)	1.0364 (0.0982)	1.0037 (0.0668)	1.0537 (0.1337)	1.0125 (0.0700)	1.0524 (0.1355)
SHRBLK80 *(Share of 1980 population self-identified as black)*	0.0022 (0.0066)	0.0017 (0.0057)	0.0022 (0.0038)	0.0027 (0.0053)	0.0037 (0.0091)	0.0043 (0.0112)
SHRMIN86 *(Share of 1986 total employment in mining)*	0.0521 (0.1341)	0.0476 (0.1224)	0.0298 (0.0607)	0.0770 (0.1209)	0.0235 (0.0565)	0.0534 (0.1085)
SHRTCU86 *(Share of 1986 total employment in transportation and public utilities)*	0.0647 (0.0473)	0.0696 (0.0543)	0.0655 (0.0766)	0.0754 (0.0717)	0.0683 (0.0589)	0.0693 (0.0609)

TABLE 3 (continued)
Variable Means and Standard Deviations

VARIABLE	TREATMENT GROUPS		CONTROL GROUPS			
	Data Set 1	*Data Sets 2, 3, and 4*	*Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 4*
SHRTRA86 *(Share of 1986 total employment in wholesale and retail trade)*	0.3247 (0.1074)	0.3308 (0.0986)	0.3339 (0.0928)	0.3360 (0.1024)	0.3485 (0.1021)	0.3364 (0.1019)
BEALE_0 *(Dummy variable for 1983 Beale Code = 0)*	0	0	0	0	0.0153 (0.1231)	0.0100 (0.09975)
BEALE_1 *(Dummy variable for 1983 Beale Code = 1)*	0	0	0	0	0.0382 (0.1923)	0.0250 (0.1565)
BEALE_2 *(Dummy variable for 1983 Beale Code = 2)*	0	0	0.0278 (0.1667)	0.0331 (0.1795)	0.0229 (0.1502)	0.0350 (0.1842)
BEALE_3 *(Dummy variable for 1983 Beale Code = 3)*	0.0312 (0.1767)	0.0227 (0.1507)	0	0.0331 (0.1795)	0.0840 (0.2784)	0.0700 (0.2558)
BEALE_4 *(Dummy variable for 1983 Beale Code = 4)*	0.0625 (0.2459)	0.0455 (0.2107)	0.0278 (0.1667)	0.0248 (0.1561)	0.0534 (0.2258)	0.0450 (0.2078)
BEALE_5 *(Dummy variable for 1983 Beale Code = 5)*	0.0937 (0.2961)	0.0909 (0.2908)	0.1667 (0.3780)	0.0826 (0.2765)	0.1145 (0.3196)	0.0900 (0.2869)

TABLE 3 (continued)
Variable Means and Standard Deviations

VARIABLE	TREATMENT GROUPS		CONTROL GROUPS			
	Data Set 1	*Data Sets 2, 3, and 4*	*Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 4*
BEALE_6 ***(Dummy variable for 1983 Beale Code = 6)***	0.0625 (0.2459)	0.0455 (0.2107)	0.0556 (0.2323)	0.0992 (0.3001)	0.0687 (0.2539)	0.0900 (0.2869)
BEALE_7 ***(Dummy variable for 1983 Beale Code = 7)***	0.4375 (0.5040)	0.4773 (0.5053)	0.3333 (0.4781)	0.3554 (0.4806)	0.2672 (0.4442)	0.3100 (0.4637)
BEALE_8 ***(Dummy variable for 1983 Beale Code = 8)***	0.0312 (0.1767)	0.0227 (0.1507)	0.0556 (0.2323)	0.0826 (0.2765)	0.0687 (0.2539)	0.0700 (0.2558)
BEALE_9 ***(Dummy variable for 1983 Beale Code = 9)***	0.2812 (0.4568)	0.2955 (0.4615)	0.3333 (0.4781)	0.2893 (0.4553)	0.2672 (0.4442)	0.2550 (0.4370)
Number of Observations	32	44	36	121	131	200

TABLE 4
Simple (Uncontrolled) Difference-In-Difference Estimates Of The Impact Of RTW in Idaho

DATA SET	GROUP	MEAN MANUFACTURING EMPLOYMENT GROWTH RATE (1986-1996)	SIMPLE DIFFERENCE-IN-DIFFERENCE ESTIMATE
Data Set 1	***Treatment (n = 32)***	0.3784	0.3085
	Control (n = 36)	0.0699	
Data Set 2	***Treatment (n = 44)***	0.3284	0.1107
	Control (n = 121)	0.2177	
Data Set 3	***Treatment (n = 44)***	0.3284	0.1289
	Control (n = 131)	0.1995	
Data Set 4	***Treatment (n = 44)***	0.3284	0.1036
	Control (n = 200)	0.2248	

NOTE: Data sets and treatment and control groups are defined in Table 2.

TABLE 5
Regression Estimates of the Impact of RTW on Idaho

VARIABLE	COEFFICIENT ESTIMATES *Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 4*
Constant	-2.7412 (3.4752)	-2.2035 (0.8167)	-2.8725 (1.2815)	-1.8440 (0.5741)
IDAHO	0.2011 (0.1330) [0.1368]	0.2697 (0.0646) [0.0001]	0.1428 (0.0373) [0.0002]	0.2013 (0.0230) [0.0000]
URATE80	0.0219 (0.0081)	0.0053 (0.0179)	-0.0030 (0.0111)	0.0073 (0.0119)
SHRCOL80	1.6299 (3.2998)	4.1064 (1.6768)	0.8593 (0.9663)	2.2972 (1.2027)
SHRHS80	0.4956 (4.7417)	1.4457 (1.7482)	1.3875 (1.2394)	0.5105 (1.4358)
SHRBLK80	19.7374 (8.6537)	4.1759 (7.3167)	4.5963 (5.2706)	-1.7546 (3.9705)
POP8086	1.3338 (1.0502)	0.6217 (0.2012)	1.5087 (0.9768)	0.7980 (0.1643)
SHRMIN86	1.4036 (0.2685)	1.4232 (0.3564)	1.1492 (0.6650)	1.0574 (0.4334)
SHRTCU86	2.4202 (2.7737)	2.1189 (0.8689)	2.3959 (1.0260)	1.8033 (0.8698)
SHRTRA86	1.5958 (0.6467)	1.1057 (0.5858)	1.4487 (0.2769)	1.3703 (0.4153)
n	68	165	175	244
R^2	0.4976	0.1694	0.2021	0.1457

NOTE: The dependent variable for each regression is *MEGR*, defined in equation (1). Beale Code dummy variables are included but the results are not reported. Standard errors are calculated using robust cluster estimation and reported in parentheses. The *p*-value associated with the test that $b_{IDAHO} = 0$ is reported in brackets.

TABLE 6
Regression Estimates of the Impact of RTW on Idaho
(Rural Counties Only)

VARIABLE	**COEFFICIENT ESTIMATES** *Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 4*
Constant	-2.5897 (3.4846)	-2.2322 (0.8112)	-2.7092 (1.4648)	-1.8279 (0.6246)
IDAHO	0.2011 (0.1310) [0.1313]	0.2692 (0.0683) [0.0001]	0.1284 (0.0422) [0.0028]	0.2068 (0.0251) [0.0000]
URATE80	0.0219 (0.0079)	0.0051 (0.0175)	-0.0041 (0.0133)	0.0048 (0.0131)
SHRCOL80	1.6299 (3.2502)	4.2051 (1.7178)	0.8322 (1.1298)	2.8717 (1.2045)
SHRHS80	0.4956 (4.6704)	1.5498 (1.7449)	1.6480 (1.4852)	0.9588 (1.5464)
SHRBLK80	19.7374 (8.5236)	2.8632 (7.8813)	19.2775 (4.3974)	-10.5233 (12.5785)
POP8086	1.3338 (1.0344)	0.6077 (0.2016)	1.5447 (0.9706)	0.7049 (0.1572)
SHRMIN86	1.4036 (0.2645)	1.4506 (0.3475)	1.1194 (0.6687)	1.0786 (0.4346)
SHRTCU86	2.4202 (2.7319)	2.1564 (0.8370)	2.4308 (1.0260)	1.6742 (0.8406)
SHRTRA86	1.5958 (0.6369)	1.1585 (0.5785)	1.3605 (0.2737)	1.3270 (0.5143)
n	66	156	153	215
R^2	0.4976	0.1671	0.2099	0.1491

NOTE: The dependent variable for each regression is *MEGR*, defined in equation (1). Beale Code dummy variables are included but the results are not reported. Standard errors are calculated using robust cluster estimation and reported in parentheses. The *p*-value associated with the test that $b_{IDAHO} = 0$ is reported in brackets.

TABLE 7
Regression Estimates of the Impact of RTW on Idaho
(Rural Counties with Urban Population of 2,499 or Less Only)

VARIABLE	**COEFFICIENT ESTIMATES**			
	Data Set 1	***Data Set 2***	***Data Set 3***	***Data Set 4***
Constant	-2.6790 (1.9206)	0.0359 (1.3278)	-1.5485 (1.8049)	0.7606 (0.9255)
IDAHO	0.2385 (0.6155) [0.7042]	-0.0175 (0.1956) [0.9291]	-0.2756 (0.1396) [0.0541]	0.0853 (0.2020) [0.6741]
URATE80	0.0352 (0.0499)	0.0154 (0.0341)	0.0081 (0.0334)	0.0009 (0.0266)
SHRCOL80	-3.2086 (5.3239)	1.1884 (2.3064)	-2.0074 (2.3036)	0.0492 (2.3000)
SHRHS80	0.1132 (7.1284)	-4.6711 (2.9794)	-3.8888 (2.0539)	-4.5826 (1.8021)
SHRBLK80	47.6019 (123.4302)	17.9214 (85.3506)	15.4691 (66.9894)	-1.6781 (65.6619)
POP8086	1.0259 (1.2389)	1.0345 (0.7053)	2.6535 (1.3035)	0.7035 (0.3503)
SHRMIN86	1.9785 (0.9451)	1.9586 (0.6188)	1.3938 (0.4719)	1.3000 (0.3714)
SHRTCU86	3.5106 (2.6817)	1.9161 (1.1679)	3.1039 (1.4631)	1.2703 (1.2437)
SHRTRA86	2.5202 (2.2177)	1.6954 (0.8265)	1.7519 (0.6347)	1.2765 (0.7976)
n	24	59	58	79
R^2	0.4718	0.1562	0.2312	0.1141

NOTE: The dependent variable for each regression is *MEGR*, defined in equation (1). Beale Code dummy variables are included but the results are not reported. Standard errors are calculated using robust cluster estimation and reported in parentheses. The *p*-value associated with the test that $b_{IDAHO} = 0$ is reported in brackets.

TABLE 8
Regression Estimates of the Impact of RTW on Idaho
(Rural Counties with Urban Population Between 2,500 and 19,999 Only)

VARIABLE	COEFFICIENT ESTIMATES			
	Data Set 1	***Data Set 2***	***Data Set 3***	***Data Set 4***
Constant	-2.0675 (3.7175)	-3.9978 (1.0844)	-5.5409 (2.3069)	-4.1280 (1.2171)
IDAHO	0.2089 (0.2779) [0.4610]	0.3394 (0.0983) [0.0010]	0.3577 (0.1431) [0.0153]	0.2845 (0.1244) [0.0245]
URATE80	0.0006 (0.0124)	0.0060 (0.0158)	-0.0084 (0.0108)	0.0171 (0.0155)
SHRCOL80	2.0519 (3.2374)	7.9473 (2.0106)	3.9219 (2.5052)	6.9040 (1.9132)
SHRHS80	0.6876 (5.3423)	5.4777 (2.0592)	7.8852 (3.2834)	4.9393 (3.1279)
SHRBLK80	28.1692 (9.4170)	5.9790 (5.9314)	7.6454 (8.1857)	-11.2539 (8.1961)
POP8086	1.6086 (1.2976)	0.4285 (0.2128)	1.4543 (0.7678)	0.6816 (0.3294)
SHRMIN86	0.5444 (0.6950)	0.4493 (0.8089)	0.5255 (0.5067)	0.4764 (0.7277)
SHRTCU86	-5.3704 (3.7175)	4.1327 (0.7354)	2.2359 (0.4620)	3.7609 (0.7429)
SHRTRA86	-0.3154 (0.3403)	0.3321 (0.7081)	0.9378 (0.9523)	1.0389 (0.5988)
n	30	78	67	103
R^2	0.3794	0.4011	0.3691	0.3885

NOTE: The dependent variable for each regression is *MEGR*, defined in equation (1). Beale Code dummy variables are included but the results are not reported. Standard errors are calculated using robust cluster estimation and reported in parentheses. The *p*-value associated with the test that $b_{IDAHO} = 0$ is reported in brackets.

TABLE 9
Regression Estimates of the Impact of RTW on Idaho
(Rural Counties with Urban Population of 20,000 or More)

VARIABLE	COEFFICIENT ESTIMATES			
	Data Set 1	***Data Set 2***	***Data Set 3***	***Data Set 4***
Constant	-1.2443 (1.2241)	-1.8389 (1.6271))	-1.5661 (1.6300)	-1.5222 (1.0913)
IDAHO	0.0741 (0.4165) [0.8752]	0.1187 (0.1424) [0.4261]	0.0560 (0.1366) [0.6867]	0.0703 (0.1109) [0.5324]
URATE80	-0.0485 (0.0926)	-0.0999 (0.0874)	-0.0047 (0.0179)	-0.0107 (0.0231)
SHRCOL80	-2.6953 (7.1291)	-3.2349 (1.5762)	0.8044 (2.7165)	0.3716 (2.2191)
SHRHS80	-1.3488 (15.4882)	-2.5819 (3.4751)	-0.4711 (2.7034)	-0.4451 (1.9172)
SHRBLK80	-10.2033 (23.3969)	-7.7969 (11.0172)	5.8321 (17.0772)	2.4195 (7.3971)
POP8086	1.4052 (5.0612)	2.9992 (1.1744)	1.4846 (0.4484)	1.4073 (0.6112)
SHRMIN86	-28.6745 (21.0388)	2.9040 (0.9295)	2.1292 (4.0796)	3.2368 (0.5660)
SHRTCU86	0.3305 (10.8106)	-2.1068 (4.0460)	-4.9009 (2.4164)	-3.5419 (2.9024)
SHRTRA86	4.8701 (0.9382)	4.4318 (0.8014)	1.9738 (1.7090)	2.1926 (1.3807)
n	12	19	28	33
R^2	0.9155	0.8115	0.6960	0.6658

NOTE: The dependent variable for each regression is *MEGR*, defined in equation (1). Beale Code dummy variables are included but the results are not reported. Standard errors are calculated using robust cluster estimation and reported in parentheses. The *p*-value associated with the test that $b_{IDAHO} = 0$ is reported in brackets.

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