Effects of Statewide Merit-Based Financial Aid Programs on Job Characteristics

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Abstract

A large number of states have implemented merit-based financial aid programs, beginning in the early 1990s, with the stated intention of increasing number of skilled workers in the state workforce (Georgia Student Finance Commission, 2020). While the affects of such programs on educational attainment has been evaluated (e.g. Dynarski 2000, Cornell Mustard, Sridhar 2006) less attention has been payed to potential effects of such programs on state workforce characteristics. This paper finds no correlation between the adoption of merit-based financial aid and the number of people who work in state. This paper finds some evidence that the skill level of the workforce decreases after the adoption of merit scholarship programs, but also finds evidence that this relationship may not be causal.

1 Introduction

Prior to the 1990s, most financial aid for college students was based on students' needs, and what merit-aid existed was generally handed out by individual universities trying to attract high-achieving students (Sjoquist Winters, 2014). However in 1993, Georgia rolled out the Helping Outstanding Students Educationally (HOPE) program, which covered the majority of tuition at in-state public and private community colleges and universities for students who achieved a high school 3.0 GPA and maintained a 3.0 GPA during college (Georgia Student Finance Commission, 2020). From the early 1990s to early 2000s, over two dozen states have begun similar statewide merit-based scholarship programs. Among the stated goals of the Georgia HOPE Scholarship is that it will lead to a more skilled work force in Georgia, (Georgia Student Finance Commission, 2020) and the other, similar programs have similar goals (Cornwell, Mustard, Sridhar, 2006). Thus, it is important to evaluate whether these policies lead people to work in skilled jobs in the states that provide the scholarships, to determine whether or not the policies are meeting their stated goals.

This paper will investigate whether statewide merit-based financial aid programs deliver the public and private benefits they were designed for, by investigating whether young people exposed to such programs are more likely to work in jobs that require post-secondary education, are more likely to work in more productive industries, or are more likely to work in their home states.

All the merit-based scholarship programs are similar in that awards are granted at the state level rather than by individual universities, and that awards are based on merit rather than financial need; these programs, however, vary widely in terms of the numbers of students granted awards and the size of the awards, so looking at outcomes across all states that adopt such programs will not be a good test of their effectiveness. Sjoquist and Winters (2014) provide data on the per-student spending of each scholarship programs in 2010, shown in Table I. They designate the nine largest

State	Year begin	Year end	Avg spending per in-state college student	% in-state college students receiving funding
Alaska	1999	NA	$43.88	4.46%
Arkansas	1991	NA	$55.45	1.63%
California	2001	NA	$254.00	3.56%
Florida*	1997	NA	$580.50	24.25%
Georgia*	1993	NA	$1,191.08	30.71%
Idaho	2001	NA	$54.41	9.07%
Illinois	1999	2004	Unavailable	Unavailable
Kentucky	1999	NA	$493.25	35.71%
Louisiana*	1998	NA	$708.57	23.23%
Maryland	2002	2005	Unavailable	Unavailable
Michigan	2000	2008	$181.06	0.20%
Mississippi	1997	NA	$138.11	18.72%
Missouri	1998	NA	$136.89	6.64%
Nevada*	2000	NA	$326.88	25.55%
New Jersey	1997	NA	$35.79	1.15%
New Mexico*	1997	NA	$494.67	20.71%
New York	1997	NA	$494.67	1.90%
North Dakota	1994	NA	$22.96	0.38%
Oklahoma	1996	NA	$58.33	11.89%
South Carolina*	1998	NA	$887.69	18.35%
South Dakota	2004	NA	$100.71	9.26%
Tennessee*	2003	NA	$919.57	26.86%
Utah	1999	NA	$18.26	0.73%
Washington	1999	NA	$9.94	0.15%
West Virginia*	2002	2006	$484.78	9.81%

Table 1: State Merit-Based Financial Aid Programs (Sjoquist Winters 2014)
*Sjoquist Winters - designated strong program (Sjoquist Winters 2014)

programs as "strong merit-based financial aid programs."

State merit scholarship programs generally advertised themselves as not only intended to make higher education more affordable for talented students, but also as a way of creating a more skilled state workforce, producing public benefits that produce gains for those with college education and those without, alike. Past evaluations of these programs have shown some indicators of success, finding that more people in states with merit scholarship programs were more likely to seek additional education after high school (Dynarski 2000), and were more likely to attend college in-state (Cornell Mustard, Sridhar 2006). In addition, Sjoquist and Winters (2014) found that students exposed to such scholarship programs were more likely to stay in-state after college.

However, there are reasons to be skeptical that these programs actually help develop a more skilled workforce. Hu (2008) found that students receiving state merit scholarships were less likely to major in STEM fields, possibly because it is harder to meet the GPA thresholds such scholarships require in those fields; this is cause for concern as STEM majors more likely than students in other fields to work in skilled jobs, and tend to work in jobs that provide more public benefits (Winters 2014). In addition, the Sjoquist and Winters (2014) finding that beneficiaries of state merit aid were more likely to remain in-state relied in large part on ACS data from 2000-2010. Since ACS data from 2000-2005 has since been shown to be flawed (Spielmen et al. 2014) and because some merit scholarship programs only began in the mid-200s (and thus would have mostly funded people who did not join the workforce until the late 2000s), it is worth revisiting this work with more recent ACS data.

This paper aims to make a new contribution to the evaluation of state merit scholarship programs by evaluating whether they lead to people becoming more skilled and productive workers, and will revisit the Sjoquist and Winters conclusion that these programs make people more likely to stay in-state using more recent Decennial Census and ACS data and a slightly different research design.

2 Data

Using Decennial Census data from 1990, 2000, and 2010, and ACS data from 2018, it is possible to construct what is essentially an intent-to-treat group comprised of people born in states that adopted merit-based financial aid policies in years where they would be exposed to those policies when they finish high school. Control groups can be constructed from people in states that do not have merit-based scholarships, and from people born too early to be exposed to them before such policies came into effect in the states that have them. This paper will consider those exposed to strong merit aid programs as treated, while omitting states with smaller programs from the analysis, as they would be inappropriate as control states. To test the robustness of this result to the inclusion of all fifty states, treatment will also be considered as a continuous variable, with its magnitude given alternately by the average spending per student, or the number of students reached.

People who were exactly eighteen in the years the policies were adopted will be omitted, as eighteen-year-olds more so than other ages are sometimes people who are still in high school and sometimes people who have started college. Following Sjoquist and Winters (2014), this paper will limit the sample studied to people between the ages of 24 and 30; this will eliminate most college students, who are not relevant as this paper is evaluating post-college location and career choices, and will also limit the study to people whose career and location choices are most likely to be affected by merit-based financial aid policies, if effects exist.

The data does not say in which state each person attended high school or college, if they did so. Thus, everyone from a birth cohort exposed to a merit-based aid policy will be considered a part of the intent-to-treat group, even if they attend school out-of-state and are not actually exposed to the policy. In addition, since merit-aid policies likely affect people's decisions on whether or not to seek post-secondary education, it would not be appropriate to limit the sample to only those who actually attend school after high school. Thus, every person born in a strong merit-aid state in a year that would allow them to receive merit-aid upon graduating high school will be considered a part of the treatment group. Since the treatment group will contain many people who did not actually receive financial aid through these programs, the results of this paper will likely underestimate the effects of these programs on the chosen outcome variables.

3 Outcome Variables

3.1 Skilled Jobs

To evaluate whether people exposed to state merit scholarship programs become skilled workers, it is first necessary to define what a skilled worker is. Since this paper is evaluating programs that focus on education as workforce training, it makes most sense to use a variable that captures the education level required by each occupation. In other papers that evaluate the educational requirements of jobs, researchers use whether or not the majority of workers in a job have historically attained a certain level of education as a threshold for whether or not that level of education is needed for the job (Vedder, Denhart, Robe, 2013; Abel Deitz, 2014). This paper will use the same standard to evaluate which occupations require post-secondary education, utilizing the edscor90 variable contained the ACS and Decennial Census data, which indicates "the percentage of people in the respondent's occupational category who had completed one or more years of college" in the year 1990. Occupations with scores over 50 will be considered skilled for purposes of this paper. As a robustness check, edscor90 can also be used as an individual level outcome variable; when regressed on a treatment variable, a positive coefficient would indicate that the policies have increased the overall skill level of the workforce.

3.2 Worker Retention

People who are working in the state in which they were born can be considered to be retained. Note that this paper will consider the number of people who work in their state of birth, rather than those who live in their state of birth, using the pwstate2 variable from the Decennial Census and ACS data. Thus, those who commute across state boundaries for work will be considered retained only if they work in their home state, even if they do not live there; those who are not in the labor force will not be considered. This is because the stated intention of many merit scholarship programs is to increase the education level of the state workforce.

4 Methodology

Measuring the effects of merit scholarship programs typical difference-in-differences model with treatment and control groups is difficult, due to the many differences between the existing programs. It is unlikely to be true that a program that reaches less than one percent of students has similar effects to one that reaches over a quarter. On the other hand, it is unlikely to be the case that program effects are strictly proportional to their expenses or reach, due to year-to-year, state-to-state, and school to school differences in costs of attending school and program funding. As such, this paper will follow Sjoquist in Winters (2014) in dividing programs into "strong" and "weak" categories. This paper will depart from Sjoquist and Winters by constructing binary treatment variables for both strong and weak programs, and using both as separate treatment variables in difference-in-differences regressions. The first regression estimated will be as follows:

$$y_{ist} = a_t + a_s \beta ST_{st} + BWT_{st} + \epsilon_{ist} \text{ (1)}$$

Where a_s is state fixed effects, a_t is time fixed effects, ST_{st} the treatment variable for strong programs, WT_{ist} is the treatment variable for weak programs, and ϵ_{ist} is the error term. The regression will be weighted using the individual weights included in the Decennial Census and American Community Survey, with standard error clustered by state.

Next, this regression will be re-run with controls for individual characteristics which may affect the outcome variables - race and sex. Dummy variables can be constructed that indicate whether or not each person is white, black, latino, native american, another race, and female, and these indicators can be included in the difference-in-differences regression model estimated as control. This model will be as follows:

$$y_{ist} = a_t + a_s \beta ST_{st} + BWT_{st} + CX_{ist} + \epsilon_{ist} \text{ (2)}$$

Where X_{ist} is the vector of control variables, and all other variables are the same is equation (1) above. Clustering and weighting, too, will be the same.

To test the robustness of results obtained via this method, this paper will also model the treatment variable as a continuous variable, with its magnitude given alternately by the share of full-time students funded through each program and the natural logarithm of average cost of the program per full-time student (across all students statewide, not only funded students). Results of these regressions are in the appendix.

A number of state characteristics influence which states adopt merit scholarship programs. In this case, the data allows for the construction of several pre-treatment characteristic variables which could conceivably affect the outcomes of interest. The relevant pre-treatment characteristics of each state that can be constructed from the available data are the percentage of people born in state who work in that state as adults, the percentage of the labor force working in skilled jobs, the mean edscor90 of the state workforce, the mean value added per employee, the percentage of the population that is working-age (defined as 25-65), the percentage of the population with any post-secondary education, the median income, the unemployment rate, the labor-force participation rate, and the party of the governor in 1990.

Heckman and Hotz (1989) show that difference-in-differences estimates are most accurate when comparison groups have similar pre-treatment characteristics, and, as shown in Table 2, this criterion is not met when all states are used, as the states that adopt merit scholarship programs differ from states that do not in important ways. Several of the pre-treatment characteristics, in terms of the variables described previously, are significantly different between states that adopt merit scholarship programs and those that do not. It appears that states that adopt merit scholarship programs have larger numbers of workers leaving the state, more skilled economies, more immigrants, and lower labor force participation rates. Thus, in addition to regressions using all fifty states, this paper will utilize propensity-score matching to attempt to account for the differences between states that do and do not adopt merit scholarship programs. To accomplish this, first a model will be estimated to predict each state's propensity to adopt a merit-scholarship program. For this purpose, no distinction will be made between strong and weak programs - programs will be modelled as a single binary variable. A probit regression model will be estimated as follows:

$$P = CX_{ist} + \epsilon_{ist} \text{ (5)}$$

Where P is the estimated probability (propensity score) that a state will adopt a merit scholarship program, and X_{ist} is a vector of pre-treatment characteristics (all those listed in Table 2). By using only states with propensity scores between .50 and .95, statistically significant differences in pre-treatment characteristics between states with programs and those without can be eliminated, as shown in table two. New regression models will be estimated using only those states. These models will be estimated as follows:

$$y_{ist} = a_t + a_s\beta ST_{st} + BWT_{st} + \epsilon_{ist} \text{ (6)}$$

$$y_{ist} = a_t + a_s\beta ST_{st} + BWT_{st} + CX_{ist} + \epsilon_{ist} \text{ (7)}$$

State Characteristic	Correlation With Treatment (All-States)	Correlation With Treatment (Propensity-Matched States)
% of birth cohort working in-state	-3.5970*	1.9033
% of workers in skilled jobs	6.0966*	2.2122
Mean edscor90	0.0178	0.0189
% of population that is working age	0.7461	3.9632
% of population with any college	-0.3220	-0.9578
% of workers who are immigrants	6.2428***	2.1345
Median income	0.0001	0.0000
Unemployment rate	18.359	6.7186
Labor-force participation rate	-4.8169*	0.5471

Table 2: Pre-Treatment Characteristics
* Statistically significant at 10% level
** Statistically significant at 5% level
*** Statistically significant at 1% level

Where a_t is year fixed effects a_s is time fixed effects, and ST_{st} and BWT_{st} are the strong and weak binary treatment variables, respectively.

Finally, due to the nature of the policies being considered, it will necessarily take several years after the passage of each policy for any difference to be made, as students take years to actually acquire the schooling the programs encourage them to attempt. Thus, one last model will be estimated, that accounts for this fact, by testing for effect heterogeneity based on whether a policy has been in effect for a decade or not. This last model will be estimated as follows:

$$y_{ist} = a_t + a_s\beta ST_{st} + BWT_{st} + CD_{st} + \alpha ST_{st} * D_{st} + \gamma WT_{st} * D_{st} + CX_{ist} + \epsilon_{ist} \quad (8)$$

Where D_{st} indicates whether or not a policy has been in effect for a decade or not, and all other variables are the same as above. This model will be estimated for all fifty states and for the propensity matched group.

5 Limitations

This research design is limited by the fact that state of birth is an imperfect proxy for exposure to merit-based financial aid policies, as not everyone born in a state applies to colleges and universities in that state. Some will move out of the state as children, some will not finish high school, some will decide not to apply to colleges and universities, and some will apply only to out-of-state schools. As such, there will be a significant amount of what can be considered noncompliance within the intent-to-treat group. Since there is unlikely to be as much noncompliance in the control group, the results will likely understate the effects and significance of the impact of the policies. If the policies have a

Outcome Variable	Treatment Coefficient (Strong Program)	Treatment Coefficient (Weak Program)	r^2
Skilled Job	-0.0049	-0.0046	0.0193
Edscor90	-1.0541***	-0.4961***	0.0293
Works In Home State	0.0188	0.0467	0.0338

Table 3: 50-State No Controls Besides FE Regression Results

* Statistically significant at 10% level

** Statistically significant at 5% level

*** Statistically significant at 1% level

Outcome Variable	Treatment Coefficient (Strong Program)	Treatment Coefficent (Weak Program)	r^2
Skilled Job	-0.0012	-0.0062*	0.0778
Edscor90	-0.7649***	-0.6475***	0.1213
Works In Home State	0.0188	0.0490	0.0706

Table 4: 50-State Regression Results, with Age, Race, and Sex controls

* Statistically significant at 10% level

** Statistically significant at 5% level

*** Statistically significant at 1% level

small but real impact, it will be difficult to isolate and evaluate their effects, and this research design may fail to identify differences where small but real effects exist. However, other evaluations of state merit scholarships use Decennial Census and ACS data and find significant results (Sjoquist Winters, 2014). As such, this research design, despite its limitations, is consistent with previous standards of research on these programs, and should be capable of identifying effects if they are large enough to stand out in an oversized treatment group.

6 Results and Discussion

As shown in Table 3, the size of merit aid policies do not have any apparent significant effects on whether or not people choose to work in-state, and these results are robust to all the different methods of regression used (see the appendix for results of robustness checks). Due to the limitations of the data and methodology used, these results do not necessarily mean that state merit scholarship policies do not actually affect the outcome variables, just that the effects are likely too small to be significant in a data set that includes many non-complyers. It is worth noting that Sjoquist and Win-

Outcome Variable	Strong Treatment Coefficient (without controls)	Strong Treatment Coefficient (with age, race, and sex controls)
Skilled Job	-0.0154**	0.0003
r^2	0.0353	0.0761
Edscor90	-1.6618***	-0.4268*
r^2	0.0337	0.1218
Works In Home State	0.0121	0.0067
r^2	0.0224	0.0727
Outcome Variable	Weak Treatment Coefficient (without controls)	Weak Treatment Coefficient (with age, race, and sex controls)
Skilled Job	-0.0194***	-0.0089
r^2	0.0353	0.0761
Edscor90	-1.1316***	-0.3290
r^2	0.0337	0.1218
Works In Home State	-0.0358*	-0.0400*
r^2	0.0224	0.0727

Table 5: Propensity Score Matched Regression Results (FE Controls Only)

* Statistically significant at 10% level

** Statistically significant at 5% level

*** Statistically significant at 1% level

Outcome Variable	Strong Policy Coefficient	Five-Year* Strong Policy Coefficient	Decade*Strong Policy Coefficient
Edscor90 (50-State Regression)	-0.0914*	-0.7400	-0.2875
Edscor90 (Propensity-Score Matched Regression)	-1.3020***	-1.0522	-1.0203**

Outcome Variable	Weak Policy Coefficient	Five-Year* Weak Policy Coefficient	Decade*Weak Policy Coefficient
Edscor90 (50-State Regression)	-0.0911	-3.4221***	-0.3983
Edscor90 (Propensity-Score Matched Regression)	-0.9804**	-3.7714***	-0.3964

Table 6: Effect Heterogeneity Regression Results II

ters (2014) find that strong merit scholarship programs led to a 2-3% increase in people choosing to remain in-state using a different selection of ACS and Census years and a different research design.

Merit scholarships do appear, at least at first glance, to have a negative effect on the skill-level of the jobs taken by those exposed to them. This result is present in each model estimated. When the likelihood that a person obtains a skilled job (considered as a binary outcome) is used to measure this outcome, this effect loses its significance depending on whether which treatment variable, control variable, and states are used, indicating that the negative results in other models may be more indicative of demographic or other trends in states that adopt policies, rather than true causal effects of the policies. When edscor90 is used to measure this outcome, however, the negative is significant no matter which model is used.

It is plausible that this negative effect is the result of merit scholarship programs disincentivizing STEM degrees. Since STEM students tend to obtain the most highly skilled jobs, a migration away from STEM degrees could plausibly result in a reduction in average skill level of workers; however, since programs only push students away from STEM majors, not out of school entirely, the number of people receiving post-secondary education and obtaining jobs typically done by people with such education would not be reduced at the same time. This may be the phenomenon at play.

However, it is also possible that shortcomings of the research design led to a false negative result. The regressions above control for fixed-effects, and do not capture time-variant effects. If there were a trend present in treatment states toward fewer skilled jobs, this could cause a negative and significant result on the treatment variable, without the treatment itself actually having caused the change. Since such a trend may actually motivate the commencement of merit scholarship programs, this too seems plausible. The effect heterogeneity results do not show effects increasing over time, which would be expected of a program that funds college students, who tend to spend several years in school. It would be strange if the effects of the policies did not grow over time as more students affected by the policy join the workforce. However, that may not be the case if the effects seen are not caused by the policies. Thus, an event study was conducted to investigate time-variant trends in treatment states.

7 Event Study

To investigate time-variant trends in skilled jobs in treatment states, the following model was estimated:

$$y_{ist} = a_t + a_s \beta T_{st} + \epsilon_{ist} \text{ (7)}$$

Where a_t is time fixed effects, a_s is state fixed effects, and T_{st} is a vector of variables indicating the amount of time before or after the beginning of treatment for each strong treatment state. Plotting the coefficients of these variables shows the trend of the skill level of the workforce in merit aid states, as opposed to non-aid states.

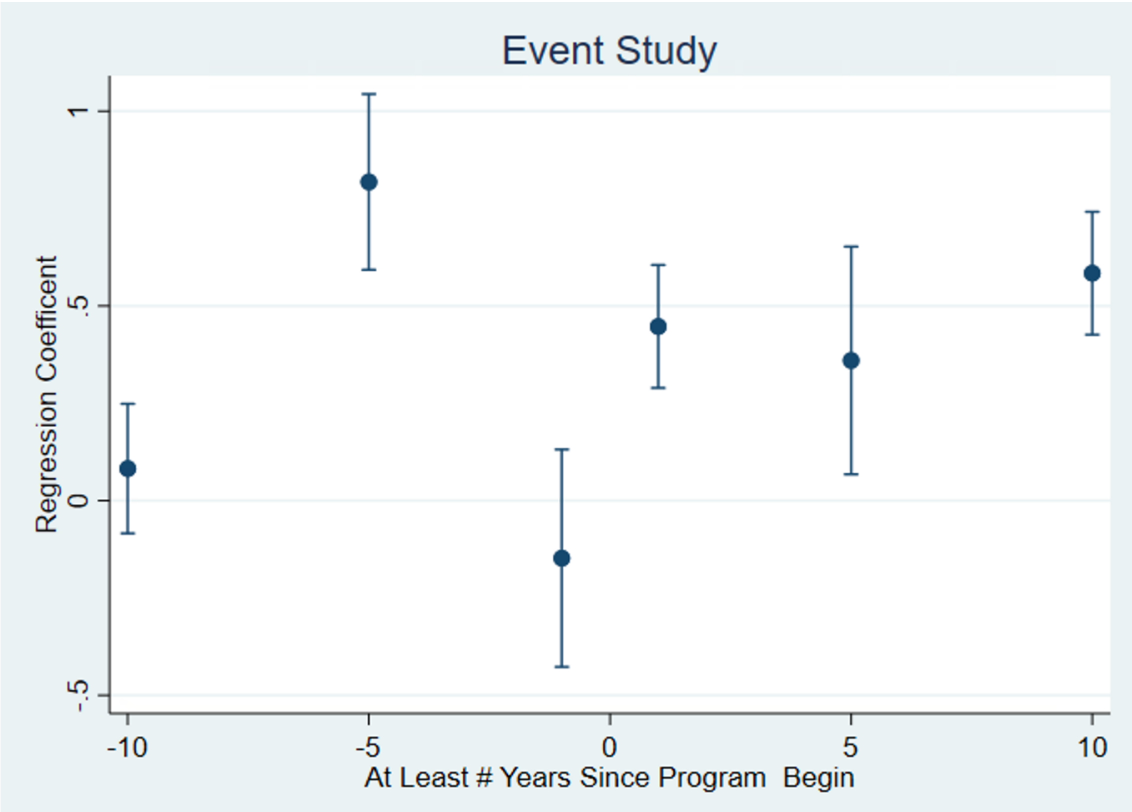

Figure 1: Event Study

As shown in Figure 1, the even study seems to show a spike in workforce skill level in treatment states five to ten years before program adoption, and a slight smaller increase after adoption. If there were truly a negative effect on skill level, there would be no pre-treatment effects, and a post treatment decline. Thus, it seems unlikely adopting merit scholarship programs caused workforce skill levels to drop.

Instead, given what is know about the pre-treatment characteristics of states that adopt programs, another hypothesis may make explain these trends. States that adopt merit scholarship programs tend to have higher shares of workers in skilled shops than other states, but low labor force participation rates. Such a situation may be caused by large losses of low-skilled jobs, a phenomenon that did occur throughout the 1990s and 2000s (BLS 2000; Hernandez 2018), as a relative lack of low skill jobs would provide an incentive for workers to seek more skilled jobs. It makes sense that a state, faced with such a situation, would adopt a merit scholarship program to help workers who were formerly working in unskilled jobs find new employment opportunities. However, merit scholarship programs may have been passed alongside other programs intended to help former low-skilled workers find jobs, as well as other economic forces bringing low-skilled jobs to states that had low-skilled labor reserves.

If these are the true causes of the decline in skill level of jobs attained post-treatment, then the skill level of the average job each person attained in merit scholarship states states may well have gone down after program adoption, but not have been caused by merit scholarship programs or caught in state fixed effects. This would be more consistent with the spike in the relationship between program states and job skill level five years prior to program adoption shown in the event study table. If the negative result is due to state trends that coincide with program adoption, then it would be expected that this result would not persist when examining only similar states and accounting for changes in individual characteristics would eliminate this result, which is what the propensity score matched regression with demographic controls does. Significantly, this regression shows no statistically significant effects on job-skill measures. Thus, tentatively, the paper concludes that the negative relationship between merit scholarship programs and the skill level of the jobs acquired by state residents is not causal.

8 Conclusion

This paper is intended to evaluate state merit-based scholarship programs in terms of their intended effects, namely, building a more educated and skilled state workforce. Due to the limitations of the data, it cannot be concluded with certainty that there is no causal effect of merit scholarship programs on people's location choices or attainment of skilled jobs. Evaluating merit scholarship programs would likely be more fruitful with data that identified in-state high school students who met the eligibility criteria for the programs, before and after the programs, and/or data with detailed information on work history and location. In the end, there are many in the workforce who are certain to attend college, or certain not to, regardless of aid policies. Similarly, the jobs available to new workers - and the skill level of such jobs - will likely vary more in some industries but not others if the education level of workers changes. Data that included more detailed information about workers high school locations, grades, and work history may shown that merit scholarship programs made differences for some portion some people or industries. Such data is not publicly available, though, and the ACS and Census data does not show that merit scholarship programs made significant differences to state-wide economies.

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10 Appendix: Robustness Checks

Outcome Variable	Treatment Coefficient (Program spending per student)	Treatment Coefficient (Share of students funded)
Skilled Job	-0.0030***	-0.0164
r^2	0.0205	0.0193
Edscor90	-0.2980***	-3.536***
r^2	0.0306	0.0293
Works In Home State	0.0042	0.0502
r^2	0.0240	0.0333

Table 7: 50-State No Controls Besides FE Regression Results, alternate treatment variables

* Statistically significant at 10% level

** Statistically significant at 5% level

*** Statistically significant at 1% level

Outcome Variable	Treatment Coefficient (Program Spending per Student)	Treatment Coefficent (Share of Students Funded)
Skilled Job	-0.0025**	-0.0021
r^2	0.0826	0.0778
Edscor90	0.2670***	-2.4276***
r^2	0.1302	0.1213
Works In Home State	0.0038	0.0486
r^2	0.0612	0.0701

Table 8: 50-State Regression Results, with Age, Race, and Sex controls, Alternate Treatment Variables

* Statistically significant at 10% level

** Statistically significant at 5% level

*** Statistically significant at 1% level