Los Angeles County Economic Development Corporation
444 S. Flower St., 37th Floor
Los Angeles, CA 90071
(213) 622-4300

November 13, 2019

RE: Potential Issues with "Do State Corporate Tax Incentives Create Jobs? Quasi-experimental Evidence from the Entertainment Industry" for CFC Use

Pictured are the results of the time series model utilized in the paper, most of the methodological issues can be seen from this.

Table 3. Impact of Motion Picture Incentive (MPI) Programs and Other Factors on the Annual Change in Motion Picture Industry Employment in High-expenditure States.

Variables	New York	Louisiana	Georgia	Connecticut	Massachusetts
Internal factors					
Change in own-state tax expenditures	−0.049 (0.030)	1.108 (0.420)*	0.507 (0.197)*	0.176 (0.098)	0.144 (0.036)**
Change in own-state motion picture industry wages	−0.718 (0.253)*	−0.780 (0.281)*	−0.509 (0.292)	−0.424 (0.266)	0.885 (0.652)
Competitive factors					
Change in MPI tax expenditures, New York	–	−0.444 (0.162)*	0.121 (0.097)	0.209 (0.069)*	0.209 (0.057)**
Change in MPI tax expenditures, Louisiana	−0.058 (0.157)	–	0.077 (0.352)	−0.617 (0.348)	−0.252 (0.237)
Change in MPI tax expenditures, Georgia	−0.073 (0.062)	0.051 (0.287)	–	0.408 (0.174)*	0.092 (0.142)
Change in MPI tax expenditures, Connecticut	−0.011 (0.034)	0.108 (0.181)	−0.166 (0.115)	–	−0.166 (0.060)*
Change in MPI tax expenditures, Massachusetts	−0.016 (0.027)	0.052 (0.079)	0.057 (0.054)	−0.170 (0.063)*	–
Change in MPI tax expenditures, other U.S. states	−0.016 (0.010)	0.151 (0.065)*	−0.021 (0.048)	0.048 (0.038)	0.004 (0.026)
Change in MPI tax expenditures, Canada	0.048 (0.040)	−0.228 (0.187)	0.063 (0.123)	0.042 (0.102)	−0.087 (0.072)
Controls					
Change in U.S. motion picture industry employment	0.550 (0.275)	−1.692 (1.109)	1.444 (0.969)	1.030 (1.141)	−0.626 (0.625)
Change in own-state private-sector employment	1.419 (0.881)	−5.119 (5.725)	−0.735 (3.082)	−1.562 (4.733)	2.047 (3.310)
Employment trends					
Pre-MPI program trend (β_1)	−0.442 (0.512)	−9.570 (2.889)**	−1.736 (4.001)	−3.504 (4.231)	−1.604 (2.476)
Initial MPI program impact (β_2)	27.754 (12.429)	24.528 (34.617)	−37.963 (23.243)	90.803 (20.787)**	14.068 (14.611)
Subsequent program impact (β_3)	−2.01 (1.665)	10.878 (4.018)**	8.337 (8.915)	−7.221 (7.631)	0.477 (4.513)
Model information					
Number of observations	26	27	24	22	24
F-score	4.67**	3.13*	6.28**	14.78***	11.68***
R^2	.835	.758	.891	.960	.938

Note: Cell entries are Prais–Winsten regression coefficients; standard errors appear in parentheses. Sensitivity checks are detailed in the Online Supplement.
*$p < .05$.
**$p < .01$.
***$p < .001$.

In the case of each of the five states considered, the paper fits a model which uses 13 explanatory variables. While it is possible that the dynamics of employment impacts are so complex that this is necessary, it is not reasonable to use so many different variables for so little data. In the worst case, the model for Connecticut, there are 13 variables for only 22 points of data. This leaves a model that is so overdetermined it achieves an R^2 value of .96. R^2 is a measure of how much of the variance of the response variable, in this case motion picture industry employment, can be explained by the model. In the case of a perfect fit, the model would have an R^2 value of 1. So, in the model for Connecticut we are to believe that 96% of all the changes in the state's employment is determined by the variables chosen by the author. This is extremely unlikely. Due to the way R^2 works mathematically, each variable added can only ever increase this value which gives a huge sense of false confidence in the model results.

In layman's terms imagine you have 22 people and you are trying to predict their height based on a number of features. A typical model would perhaps take into account their weight and whether they were male or female. This is a reasonable statistical model, it has 2 predictor variables, weight and sex, and 1 response variable which is their height. However, you could keep adding new variables to this model. Imagine you now include the race of the individual, whether they are married or not, what their favorite color is. If you had more observations much of this data would be meaningless, but because you have such a small set of people in the dataset you can easily use this information to make "better" predictions. Imagine there is only one person who is female, white, married and whose favorite color is blue. Given this you can now perfectly predict their height, but not because your model is telling you anything about their height, simply because there is only one observation that falls in that group. In fact, you can probably get pretty close to the exact height for each person in your data using these variables, however if you add a new person to the data, your model is going to be horribly inaccurate because it hasn't actually understood any real relationships.

This is essentially what is happening in the tax incentive model. Because the data is annual, and the model only has a few years to test, it is very easy to build a model with a bunch of variables that purports to understand the dynamics. But it hasn't actually learned anything, it's just that adding a lot of variables makes it appear as if the model is doing something. Even more worryingly, adding variables that are correlated together can make variables that are significant appear insignificant, because the model can effectively split the effect across both of them. So, although this paper reports a lack of statistical significance for the program impact, it's not clear why we should believe that is the case. There could absolutely be no significant impact from these tax incentive policies, but this model alone provides little evidence one way or the other.

In addition, the choice to use the percentage employment change seems odd given that it is unlikely that the relationship between money spent and employment changes is likely to be simple and linear. An increase in tax incentives for a place with zero employment is going to result in a massive percentage increase in employment, but for a state like California, with an already sizeable employment base in the industry, an increase in spend is likely to have a very small percentage increase in employment. This could be true even when the changes in tax incentives are expressed in percentage changes as well.

In short, while the general methodology chosen here is reasonable enough, the paucity of data with which to fit the model coupled with the excessive number of explanatory variables used means that there is not much significance to the findings. Coupled with the choice to express the changes in percentage terms it is unlikely that these results should be used to determine any policy choices.

If you have additional questions, please feel free to contact the LAEDC Institute for Applied Economics.