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Employment impact of local economic development incentives: the case of Texas economic development corporations

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Abstract

Texas allows cities to create economic development corporations that are funded using local sales tax revenues. Over time, many cities have used these corporations to fund a broad range of economic development projects. This study examines whether these corporations can be linked to any change in employment and/or unemployment in the adopting cities. Using a panel of data for Texas cities, there is limited evidence for an association between corporation adoption and labor market conditions.

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1. Introduction

Many local governments in the United States offer incentives to firms in the hopes of spurring economic growth in their communities (Zheng and Warner 2010). One of the primary goals of these policies is job creation, and traditionally policymakers measure the success of these programs in terms of employment growth (Wasylenko 1999). This paper examines the impact of the adoption of sales tax funded economic development corporations (EDC) in Texas cities on local employment and unemployment in these cities. These city-level EDCs use a portion of the local sales tax to fund incentives to businesses in the hopes of developing new economic activity in their local areas. This is the first study to use longitudinal data to study the dynamic link between Texas EDC formation and local area employment and unemployment. Using a fixed effects panel framework, no evidence exists for increased employment or decreased unemployment levels after cities adopt these corporations. However, cities that adopted EDCs are estimated to have higher unemployment and lower employment rates before EDC adoption, but not after adoption. This finding could be interpreted as evidence of the effectiveness of EDCs, although this result is not robust to the definition of labor market condition, nor is it found for all types of EDCs.

2. Literature Review

Although local targeted business incentives have been studied extensively, there is currently no consensus as to whether these types of firm-level tax breaks and subsidies generate new jobs (Bartik 1991; Patrick 2014; Peters and Fisher 2004). Goss and Phillips (1999) argued that the discrepancies in findings might be the result of the variety of empirical methodologies and the differences in quality of data and methods used to examine the impact of these programs. However, several recent studies of state and local tax incentives find no relationship between job growth and these types of programs (Hansen and Kalambokidis 2010; Whitacre et al. 2016).

Rather than examining all state and local incentive programs, this paper focusses on the activities of two particular types of EDCs in Texas cities. In 1979, the Development Corporations Act allowed for Texas cities to create EDCs, but it was not until a 1987 law change that taxpayer dollars could be used for private development projects (Blanco 2009). An amendment in 1989 allowed for the formation of what became known as type A EDCs, in which voters in cities with county populations of less than 500,000 could approve a portion of the local sales tax to be designated towards economic development incentives.[1] Once created, these non-profit EDCs could fund projects and provide direct business incentives, with city council approval. Several additional statutory changes in the 1990s eventually allowed voters in all Texas cities to potentially approve the creation of type B EDCs, and further relaxed the types of projects that could be funded using sales tax revenues. Broadly, type A/4A corporations must generally use sales tax revenue to fund manufacturing, industrial facilities, research and development projects and other projects that create new, primary jobs. Type B/4B EDCs can also allocate funds to projects intended to improve the quality of life for residents, such as parks, sports facilities, and even affordable housing projects (Hegar 2016). Either type of EDC can offer a variety of incentives including payments for land, buildings, equipment, infrastructure, debt service, and property tax

[1] The Texas state sales and use tax rate is set at 6.25%, but local areas may also impose an additional tax rate of up to 2% (Hegar 2016). Although some voters have designated a portion of the local revenue towards economic development, other portions of the local revenue may be designated to city and county operations, hospital, library, and other governmental services.

abatement. Not all cities in Texas have a 4A or 4B EDC, and not all cities adopted in the first year for which they were statutorily permitted.

Very little prior work has directly examined the impact of Texas EDCs on employment. Blanco (2009) provided an overview of the number and activities of EDCs in Texas, and examined whether EDCs complied with existing laws. For example, 4A EDCs may only fund projects that support the creation of primary jobs, which are defined as jobs in companies that export a majority of its goods or services to regional, state-wide, national, or international markets, or job training activities (Blanco 2009).

Jarmon et al. (2012) examined the impact of EDCs formation on Texas cities with populations of more than 5000 residents. They found that the formation of 4A EDCs was related to lower unemployment rates in the future. However, they found no impact of 4B corporations on employment. The authors argued that this result fit with the different missions of the two types of EDCs, with 4A focused on job creation activities and 4B funds available for quality of life projects. The main limitation of Jarmon et al.'s study is the cross-sectional nature of the data used. The authors estimated the impact of EDC formation on the change in unemployment between 1999 and 2005, with a dummy variable for formation of an EDC in the period. The authors did include population, race, and ethnicity, proximity to large metropolitan areas, per-capita income of residents, and city structure as control variables. However, one major concern to interpreting the results of this study is the endogenous nature of EDC formation and economic development policies. A city with a more effective economic development environment may also find it easier to set up an EDC in its community. The improved labor market conditions may be mistakenly attributed to the EDC formation and subsequent activities, rather than some other city-specific development environment. If cities that form EDCs are systematically different in some unobservable way, the difference in unemployment rates over this time period may be mistakenly attributed to the formation of the EDC. This paper attempts to re-examine the impact of EDC formation in Texas using panel data.

3. Data and Methodology

Rather than examining a one-time, cross-sectional change in employment, I constructed a panel of employment/unemployment rates for Texas cities from 1990-2015 using the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics. These data were collected for the 115 Texas cities with populations greater than 25,000 during this period. This restriction necessarily includes fewer cities than Jarmon et al., as the BLS does not estimate annual employment for smaller cities. Employment data were then combined with information about EDC adoption from the Texas Comptroller's Office (Texas Ahead).

Table 1 contains unemployment rates for the sample of cities, reported separately by whether the city-year observation falls after the formation of an EDC. Selection into an EDC does not appear to be random; the first cities to adopt EDCs have higher unemployment rates, on average. Over time more cities adopt EDCs, and the number of cities grows over time as more cities reach the 25,000 population threshold that the BLS uses to report annual city employment data. At the end of the period, 75 of the 115 cities had either a 4A or 4B EDC.

Table 1. Unemployment Rates for Texas Cities by EDC/No EDC

	No EDC			After EDC		
Year	Mean	S.D.	N	Mean	S.D.	N
1990	6.9	4.9	93	--	--	--
1991	6.6	3.5	84	13.8	8.8	9
1992	7.2	3.6	82	12.8	8.6	11
1993	6.6	3.4	78	10.8	7.3	15
1994	6.1	3.4	70	8.7	6.2	23
1995	5.8	3.6	66	7.9	6.1	27
1996	5.6	3.8	59	6.7	5.7	34
1997	4.9	3.2	52	6.5	5.3	41
1998	4.3	2.8	51	6.2	5.3	44
1999	4.2	2.6	47	5.5	4.3	48
2000	4.2	2.0	51	4.3	2.1	61
2001	5.0	2.1	49	5.0	2.1	63
2002	6.3	2.3	47	6.3	2.1	65
2003	6.6	2.3	44	6.5	2.2	68
2004	5.9	2.0	43	5.8	2.0	69
2005	5.3	1.7	41	5.1	1.1	71
2006	5.0	1.7	41	4.7	0.9	71
2007	4.4	1.5	41	4.2	0.9	71
2008	4.9	1.3	40	4.8	1.1	72
2009	7.3	1.7	39	7.4	1.5	73
2010	8.0	1.9	40	8.0	1.8	75
2011	7.8	1.9	40	7.6	1.9	75
2012	6.9	1.7	40	6.7	2.0	75
2013	6.3	1.6	40	6.2	1.9	75
2014	5.2	1.4	40	5.1	1.4	75
2015	4.4	1.5	40	4.3	1.3	75
Total	**5.9**	**3.0**	**1358**	**6.1**	**3.3**	**1386**

Although relying on annual employment figures eliminates smaller cities from analysis, there are several advantages to this approach. First, a fixed effects regression framework can be implemented, which will eliminate any unobserved, time-invariant heterogeneity between cities. Second, the dynamics of EDC adoption can be investigated. It is possible that is might take several years for an EDC to impact employment in a particular city, and a panel approach can explore these dynamics. The following empirical specification is used:

$$E_{it} = \alpha_i + D_{it}\beta + \gamma_t + \varepsilon_{it} \tag{1}$$

The dependent variable is a measure of employment or unemployment for cities, while D_{it} contains dummy variables indicating EDC adoption in a current, past, or future year. The specification also includes year dummy variables, and individual fixed effects α_i. A common interpretation of the fixed effects methodology is a within-transformation, where each observation is demeaned by its average within the group, in this case by each city. Because α_i is time-invariant, this transformation necessarily eliminates any time-invariant differences between cities. The only error remaining in this model is the time-varying differences within cities. One potential downside to a fixed effects approach is the inability to use the variation between cities to explain differences in unemployment rates. A random effects model could be used as an alternative, where both variation between and within cities is used to estimate the model. Additionally, random effects models allow for the estimation of the impact of time-invariant independent variables, where fixed effects models do not. Unfortunately, a Hausman test rejected the random effects model as inconsistent. Therefore, the fixed effects approach is used. It should be noted that the 40 cities which never adopted an EDC also remain in the sample. Although they do not contribute to the estimation of the impact of EDCs in a fixed effect model, they will contribute to estimations of other control variables later in this paper.

4. Empirical Results

Table 2 contains the results of the fixed effects regressions, with logged employment and unemployment in both levels and rates as the dependent variable. Columns 1-4 use dummy variables to indicate both 4A and 4B EDC adoption in current, past, or future years. Because of the long time series, these dummy variables are grouped into categories for tractability; for example, observations occurring between six and ten years after EDC formation are grouped together. Columns 5-8 only include dummies for 4A EDCs, as there is some prior expectation that these organizations may support projects directly targeted towards job growth. In other words, given that these types of EDCs are only meant to support projects linked to job growth, any impact on employment should be strongest for this subset of cities. One additional dummy variable is included to control for whether the EDC changed type over the period, as some cities moved to the more flexible 4B structure after it because available.

In general, the results do not provide strong evidence of either lower unemployment or higher employment after EDC adoption for either type of EDC. The fixed effects approach relies on only the variation within a city to estimate the impact of EDCs on employment, and there is no evidence that cities have statistically different employment environments after EDC adoption. For the full sample of both types of EDCs, the rates of unemployment and employment are statistically significantly different from zero before EDC adoption. Specifically, cities have higher unemployment rates and lower employment rates before they adopt EDCs. This result suggests that cities may be more likely to adopt these programs when they have comparably poor labor market conditions. One interpretation of this result is that cities that adopt EDCs had higher unemployment rates before the EDC adoption and no longer have higher unemployment rates after the implementation. This result could be interpreted as evidence of the effectiveness of EDCs, as these cities no longer have higher unemployment rates after adoption. However, this result is not robust to all specification of the model. Jarmon et al. focused on the impact of unemployment and employment in levels, and in these specifications of the model there is no evidence of differences between EDC and non-EDC cities before adoption. Additionally, the effect is not present for 4A EDCs, which theoretically should have the strongest impact on a cities' unemployment rates. Cities that introduced 4A EDCs are not estimated to have either lower unemployment rates after adoption, or higher unemployment rates before adoption.

Table 2. Estimation Results for Fixed Effects Regressions

	TYPE 4A and 4B				TYPE 4A only			
	ln (urate)	ln (ulevel)	ln (erate)	ln (elevel)	ln (urate)	ln (ulevel)	ln (erate)	ln (elevel)
3 years prior to year EDC formed (Yes=1)	0.096*	0.077	-0.008**	-0.026	0.011	-0.075	-0.005	-0.092
	(2.30)	(1.01)	(2.63)	(0.56)	(0.18)	(0.66)	(1.39)	(1.38)
1-5 years after EDC formed (Yes=1)	0.120	0.100	-0.013*	-0.032	-0.001	-0.055	-0.010	-0.064
	(1.77)	(0.95)	(2.04)	(0.57)	(0.02)	(0.39)	(1.64)	(0.81)
6-10 years after EDC formed (Yes=1)	0.137	0.145	-0.012	-0.004	0.045	0.043	-0.009	-0.010
	(1.58)	(1.19)	(1.70)	(0.07)	(0.45)	(0.27)	(1.35)	(0.12)
11-15 years after EDC formed (Yes=1)	0.095	0.159	-0.006	0.057	-0.079	0.008	0.002	0.090
	(1.00)	(1.22)	(0.82)	(0.83)	(0.76)	(0.05)	(0.33)	(0.87)
16 or more years after EDC formed (Yes=1)	0.030	0.186	0.001	0.157	-0.172	-0.001	0.009	0.179
	(0.27)	(1.25)	(0.08)	(1.81)	(1.42)	(0.01)	(0.90)	(1.33)
Switch to Type B (Yes=1)	--	--	--	--	-0.331	-0.079	0.041	0.293**
					(1.56)	(0.36)	(1.42)	(2.95)
Observations	2744	2744	2744	2744	2744	2744	2744	2744
Number of groups	115	115	115	115	115	115	115	115
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Absolute value of robust t-statistics in parentheses, where * significant at 5%; ** significant at 1%
urate=(unemployed/labor force)
erate=(employed/labor force)

Because of the cross-sectional nature of their study, Jarmon et al. include control variables for city population demographics, as well as proximity to large metropolitan areas. Geographic location is obviously fixed, and would be netted out in any fixed effects approach, as in the one taken in this paper. However, time-varying demographic changes can occur, and could impact the labor markets of cities. Unfortunately, annual data on population and demographic changes are not available for all 115 cities in the sample. As an attempt to control for regional changes in population and demographics, I use intercensal county population estimates (Roth 2016) to proxy for local population changes.[2] Table 3 contains results for estimates including annual controls for county population, as well as the percent of the population that is Hispanic or Black. The estimates show an impact of changing demographics on city unemployment rates; specifically, cities that are becoming more Black and Hispanic are estimated to have higher unemployment rates. However, these control variables do not change the estimates of the impact (or lack thereof) of EDC adoption on

[2] Some cities lie in multiple counties; in these cases the city is linked to the county with the largest number of city residents.

local labor market conditions. Although not shown in Table 3, results are similarly unchanged from Table 2 when estimating the rate of employment and the levels of employment and unemployment.

Table 3. Estimation results with additional county population controls and state/national subsidy dummies

	TYPE 4A AND 4B			TYPE 4A ONLY		
	ln(unrate)	ln(unrate)	ln(unrate)	ln(unrate)	ln(unrate)	ln(unrate)
3 years prior to year EDC formed (Yes=1)	0.09*	0.09*	0.08*	0.04	0.02	0.01
	(2.33)	(2.33)	(2.12)	(0.64)	(0.25)	(0.19)
1-5 years after EDC formed (Yes=1)	0.12	0.11	0.10	0.04	0.01	0.01
	(1.83)	(1.78)	(1.59)	(0.46)	(0.14)	(0.08)
6-10 years after EDC formed (Yes=1)	0.14	0.13	0.12	0.10	0.07	0.06
	(1.70)	(1.69)	(1.47)	(1.07)	(0.78)	(0.73)
11-15 years after EDC formed (Yes=1)	0.10	0.09	0.07	-0.01	-0.05	-0.05
	(1.07)	(1.00)	(0.79)	(0.12)	(0.47)	(0.53)
16 or more years after EDC formed (Yes=1)	0.04	0.04	0.02	-0.09	-0.10	-0.11
	(0.35)	(0.37)	(0.20)	(0.78)	(0.90)	(0.94)
County population	0.00**	0.00	0.00	-0.26	-0.12	-0.15
	(3.78)	(0.57)	(0.62)	(3.37)	(0.43)	(0.48)
Percent Hispanic	--	3.19**	3.25**	--	3.12**	3.17**
		(2.76)	(2.82)		(2.74)	(2.80)
Percent Black	--	6.32**	6.27**	--	6.27**	6.19**
		(3.81)	(3.79)		(3.80)	(3.80)
Non-local subsidy (Yes=1)	--	--	-0.09*	--	--	-0.09*
			(2.03)			(2.26)
Switch to Type B (Yes=1)	--	--	--	-0.26	-0.12	-0.15
				(1.14)	(0.56)	(0.66)
Observations	2,744	2,744	2,744	2,744	2,744	2,744
Number of groups	115	115	115	115	115	115
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Absolute value of robust t-statistics in parentheses, where * significant at 5%; ** significant at 1%
urate=(unemployed/labor force)

An obvious concern in estimating the impact of EDCs on local labor markets is that there are potentially additional factors changing over time in cities that would need to be controlled for. As an example, the state of Texas also provides companies with state-level incentives, which could potentially affect local area unemployment rates. Because of the empirical approach used, the time dummies should account for any changing state or national conditions that affect all cities in the same way. However, there could be state or federal incentive programs that impact one or more cities in the sample differently. Unfortunately, there is limited information available on the allocation of state/federal incentives at the local level (Wang 2016). Recently, Good Jobs First has built a subsidy tracker to attempt to build a comprehensive database of all business incentives given to companies (Good Jobs First 2019). Unfortunately, the database is somewhat incomplete with respect to the geographic location of recipients of subsidies; only about 10 percent of the subsidy entries contain information on the city where the business is located.

In order to attempt to control from the impact of these state and national programs, the subsidy tracker data was merged with the previously described sample of Texas cities. Overall, 46 of the 115 Texas cities in the sample had a business that received a national or state subsidy during this time period. If a business located in the city received a subsidy at the national or state level in any previous year, a dummy variable was set equal to one and otherwise set equal to zero if no previous subsidy was observed in the city. The inclusion of these dummies does not substantially change the estimated impact of EDCs on employment conditions, as reported in Table 3. Interestingly, the estimated coefficient from non-local subsidies is estimated to be statistically different than zero, as displayed in columns 3 and 6 of Table 3. A city with a business that previously received this type of subsidy is estimated to have lower unemployment rates. However, because of the very incomplete nature of this database, one should be cautious in interpreting this coefficient. Most of the subsididies in the sample are not able to be assigned to a specific city. Additionally, the vast majority of these subsidies lack information about the dollar value of the development benefit, and so there is no way to know the magnitude of the subsidy. It is possible that many of the subsidies listed in the dataset are very small.

5. Concluding Remarks

This paper provides limited evidence that Texas cities experience any change in labor market conditions after adopting a sales tax funded EDC, although is some model specifications cities no longer have higher unemployment rates after adding an EDC. Additionally, there is no evidence that 4A EDC adoption is related to lower unemployment rates; of the two types of EDCs, this type is more theoretically linked to local area labor markets. Several reasons could explain this finding, even if EDCs do impact employment in their areas. For example, it is possible that cities may substitute sales tax funded EDCs with other development mechanisms. Therefore, EDC adoption may not have an impact on employment if other development strategies were eliminated. Also, Blanco (2009) notes that some EDCs are not in compliance with program guidelines and provide funding for projects not primarily aimed at job creation. Finally, it could be that these programs are simply not large enough to have substantial impact on a city's employment conditions. Other development experts argue that local subsidies are essentially attempts at central planning and that it should not be surprising that they are ineffective (Buss 1999). These detractors argue that governments have had little success in trying to 'pick winners' and that tax dollars could be better used for other programs to improve local communities.

Economic development efforts have evolved substantially over time. Some development experts categorize economic development into waves (Bradshaw and Blakely 1999; Olberding 2002; Osgood et al. 2012). In the first wave, local governments pursed large manufacturing companies by offering business incentives. This approach is sometimes referred to as smokestack chasing. In the second wave, which started in the 1970s, localities focused on retaining and helping existing firms to expand, with a focus on small business development. Starting in the 1990s, third, fourth, and even fifth wave strategies have been identified (Osgood et al. 2012; Hammer and Pivo 2017). These waves involve a more holistic approach to community development, where policymakers develop programs to increase human capital, improve environmental conditions, and/or improve social institutions at a local level. Although beyond the scope of this paper, it would be interesting to examine which EDCs have taken these different approaches to development and whether these different approaches have had varying levels of success on the development of local communities.

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