

**DOES FDI DIMINISH LOCAL EDUCATION SPENDING
INEQUALITY? AN ANALYSIS OF US PANEL DATA****1992-2002**Hong ZHUANG*¹

Abstract: A significant education and economic literature worries about the within-state inequality in public school spending, while the studies focus on the impacts of state constitution and political structure. Motivated by the literature and recent research on the effect of FDI on public education provision, this paper is the first to examine the impact of FDI on public school resource inequality within a state empirically. Using the US state-level panel data from 1992 to 2002 and a GMM estimation approach to control for unobservable state fixed-effects, time series issues, and endogeneity, the findings of the paper suggest that a 1-percent increase in the ratio of foreign employment relative to state non-farm employment is associated with the decrease in the within-state public school spending inequality by 5.2 percent on average. Thus, FDI contributes not only to increase jobs at state level but also to diminish inequality in public school spending within the state.

JEL Classifications: F0, I22

Key Words : Foreign Direct Investment, FDI, Education Finance

1. Introduction

Elementary and secondary (K-12) education in the United States has traditionally been financed by local property taxes with the consequence that rich school districts have been able to spend more expenditure per pupil than poor districts. Therefore, the substantial variation in distribution of public education spending across communities resulting from a heavy reliance on local property wealth has drawn fierce criticism by the general public and stimulated constitutional challenges to the educational finance system (Card and Payne, 2002).

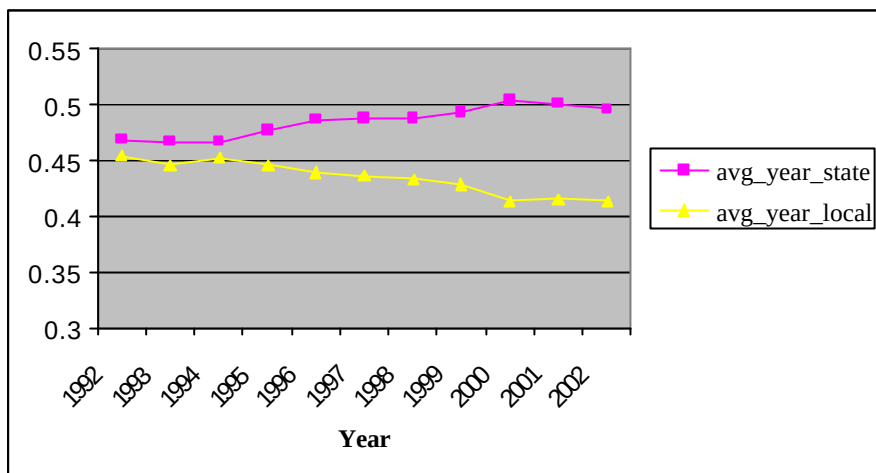
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In consequence, the education-finance reform has shifted the costs of education finance to the state level in order to break the link between wealth and learning (Schmidt and Scott, 2004). Figure 1 illustrates the average shares of state and local revenues in total school finance in the US during the period of 1992- 2002 and implies that more and more public education finance burden has shifted to the state level over time. Motivated by intermittent and distinct school finance reforms over the last thirty years, a growing empirical literature investigates the impacts of litigation and legislative changes on education spending inequality within the state.

Murray et al. (1998) use US decennial census data on school finance at the state-level from 1972 to 1992 and find that court-mandated education-finance reforms lead to a significant decrease in within-state inequality. Card and Payne (2002) find evidence that states tend to increase the relative funding available to lower-income districts under the court-induced education finance reform, which results in a more equal distribution of education spending across school districts by using district-level data from 1977 and 1992. Figlio et al. (2004) employ state-level data between 1972 and 1992 and find that the court decisions on restructuring of the state's education finance system have a substantially negative impact on the inequality in state school resources. Furthermore, they also identify a wide range of determinants that affect the degree of school spending equality within the state.

However, besides the legislative pressure, public education expenditures in local communities may be affected by firms' activities as well, especially by multinational corporations (MNCs). Recent studies have examined the effects of foreign direct investment (FDI) on public goods provision on education and yield mixed results. Blonigen and Figlio (2000) examine county-level data in South Carolina from 1980 to 1995 and find that greenfield manufacturing FDI leads to less public school spending per pupil. Greenstone and Moretti (2003) use county-level data of large industrial plant including both FDI and domestic investment in the US between 1970 and 1999 and present evidence of an increased trend break in both aggregate property values and government finance on public education in counties winning the investment.

Figure 1



The findings of the above empirical studies thus begin the question of whether FDI can affect the distribution of education resources within jurisdictions provided that the level of education expenditure is influenced by foreign affiliates. This topic has yet to be studied in the FDI or education finance literature. Therefore, this paper is the first of its kind to examine the impact of FDI on public school spending inequality empirically.

In particular, this paper supplements the literature on the spillover effects of FDI on host countries, which provides better insights into the potential effects of MNCs on local communities. In the wake of intensive competition for foreign investment, there is a general concern whether higher wages and more job opportunities associated with the inflows of foreign affiliates are achieved at the cost of public goods provision. As though there is empirical evidence suggesting that FDI affects per capita public education expenditures, it is unclear whether FDI has an impact on the distribution of education spending across school districts. Moreover, an exploration of the role of FDI in education spending inequality may also improve the understanding of the determinants of spending inequality.

The empirical analysis uses data on FDI into US states from 1992-2002 to examine the impact of FDI on public school spending inequality. The estimation results show that a 1-percent increase in the employment share of foreign affiliates is associated with 5.2 percent reduction in the Gini coefficient of education expenditures per pupil across school districts, *ceteris paribus*. Furthermore, the results are robust to different specification and measures of inequality.

The remainder of the paper is organized as follows. Section 2 summarizes state education funding formulas in 1991. Section 3 discusses how FDI affects the inequality of local education spending. Section 4 presents the econometric model to identify the effect of FDI. Section 5 describes the data used in this paper. Section 6 presents the analysis of the empirical results. Section 7 is the conclusion and future extension.

2. Background of School Financing Systems

Since 1971, many US states have experienced dramatic changes to the system of financing K-12 education with the explicit objective of providing more equalized resources. In the wake of education finance reforms, US states have adopted certain equalization schemes to reduce the disparity of school spending across school districts either under state supreme court orders or voluntarily. According to Card and Payne (2002), school funding formulas in the US are classified into three broad categories (shown in table 1): a flat grant formula, minimum foundation aid plans and variable grants.² A flat grant (FG) formula allocates a fixed amount of education spending per pupil to each school district and has little effect on the improvement in the distribution of education resources (Card and Payne, 2002).

² The table is borrowed from "School Finance Reform, the Distribution of School Spending, and the Distribution of Student Test Scores", Card and Payne (2002).

Table 1 State Funding Formulas³

State	Funding Formulas in Use (1990-1991)	State	Funding Formulas in Use (1990-1991)
Alabama	MFP	Nebraska	MFP
Arizona	MFP	Nevada	MFP
Arkansas	MFP	New Hampshire	MFP
California	MFP+FG	New Jersey	MFP
Colorado	MFP	New Mexico	MFP
Connecticut	VG	New York	VG+FG
Delaware	VG+FG	North Carolina	FG
Florida	MFP	North Dakota	MFP
Georgia	MFP+VG	Ohio	MFP
Idaho	MFP	Oklahoma	MFP+VG
Illinois	MFP+VG+FG	Oregon	MFP
Indiana	MFP+FG	Pennsylvania	VG
Iowa	MFP+FG	Rhode Island	VG
Kansas	VG	South Carolina	MFP
Kentucky	MFP+FG	South Dakota	MFP
Louisiana	MFP	Tennessee	MFP
Maine	MFP	Texas	MFP+VG
Maryland	MFP+VG	Utah	MFP
Massachusetts	VG	Vermont	MFP+FG
Michigan	VG+FG	Virginia	MFP
Minnesota	MFP	Washington	VG
Mississippi	MFP	West Virginia	MFP
Missouri	MFP+VG+FG	Wisconsin	VG
Montana	MFP+VG	Wyoming	MFP

A minimum foundation aid plan (MFP) provides the difference between a minimum target of school expenditures per

³ FG, MFP and VG denote a flat grant formula, minimum foundation aid plans and variable grants respectively.

pupil for all school districts and a local revenue level generated by a certain district. Variable grants (VG) offer the difference between an expected revenue level set by the state government and the actual revenue level collected by a given district. Therefore, both the MFP and VG schemes distribute more state aid to poorer districts and are more likely to lessen the school spending disparity across districts.

The summary of US state funding formulas for 1991 in table 1 shows that after twenty years of education finance reforms, almost every state (except North Carolina) implements certain equalization programs to attain more equal distributions of education expenditures.

3. How Does FDI Affect the Inequality of Public School Spending

Public schools in the US are financed jointly by federal, state and local governments, but state and local revenue together accounts for the majority of public school finance. Most state funding for the public schools is from sales and income taxes, while most local funds are from local property taxes. Prior research on the spillover effects of MNCs suggests that FDI may affect local education spending inequality across school districts by taking into account the spillover effects of FDI on employment creation, wage increase, productivity promotion and land prices.

First, state funding for public schools may increase with the inflows of FDI, because MNCs pay higher wages and are more productive than domestic firms, which leads to a rise in sales and income tax revenue. For instance, Feliciano and Lipsey (1999) examine industry-level data and find that foreign-owned establishment in the US pay higher wages, on average, than domestically-owned establishment and lead to the increase in average wages whether inside or outside manufacturing industries. Doms and Jensen (1998) use manufacturing plant-level data in the US and find evidence that higher wage and productivity exist not only in foreign firms, but also in any plants associated with a multinational firm, foreign- or US- owned. With the increased state budget, state government is more likely to invest more in public schools and reduce the disparity of education expenditure allocation across school districts because poor districts receive more state aid

for public schools than rich districts under the education-finance equalization scheme.⁴

Second, local revenue for public schools may be affected by FDI as well due to the increase in local land values through the opening of new foreign affiliates. Greenstone and Moretti (2003) provide two reasons for the rise in land values. One reason is the higher demand for local land from the direct purchase by greenfield FDI.

Furthermore, higher wages paid to employees by MNCs also increase the demand for housing; the other reason is that MNCs may bid up land prices to gain access to agglomeration economies. Therefore, local government is able to provide more funding for its public schools with property value appreciation. However, the location decisions of foreign firms will have different impacts on the inequality of education spending. If, attracted by cheap land prices and labor cost, MNCs decide to locate in poor districts, the disparity of education spending allocation is likely to be reduced, because more funding are devoted to public schools in poor districts. However, if MNCs choose to build plants in rich districts due to the abundant resources of educated workers, the inequality is deteriorated by the entry of MNCs.

According to the above discussion, the empirical analysis is necessary to investigate the relationship between the flows of FDI and the equality of education spending distribution within the state.

4. Empirical Specification

To empirically assess the effect of FDI on local education inequality, I utilize the following model:

$$(1) \quad Inequality_{it} = b_1 + b_2 \underset{(?)}{pfdi_{it}} + b_3 X_{it} + g_t + d_i + e_{it}$$

where *Inequality* is the measure of within-state inequality in education expenses; *pfdi* represents the percentage of foreign

⁴ As shown in table 1, since 1991, most of US states have carried out some education finance equalization schemes that distribute relatively more money to poor districts than rich districts. Hence, state funding can mitigate the inequality of public school spending across poor and rich school districts.

employees in total non-farm employment; X is a vector of control variables; and η_t and d_i are dummy variables for the unobservable fixed effects for time t and state i respectively.

The measures of within-state inequality in education expenses include the Gini coefficient, Theil index, coefficient of variation and the ratio of the 95th to 5th percentile. The Gini coefficient is used in most of regressions because of its frequent use in empirical analysis of inequality. It typically ranges from zero to one, but I rescale the Gini coefficient by multiplying it by one hundred. Other measures of inequality are used for robustness checks. The inequality measures are based on the education expenditure per pupil across a state's school districts.⁵

pfd_{it} is the key variable in the empirical analysis. Rather than measuring the absolute level of foreign affiliate activity, the construction using the percentage value of foreign employment in the US scales how important affiliates are relative to the state's employees.⁶

Murray et al. (1998) and Figlio et al. (2004) are used as sources for defining the control variables. First, $metro_pinc_{it}$ is metropolitan income per capita in state i in year t and is expected to have a positive impact because a wealthier metropolitan areas implies that more local property tax revenue will be devoted to local public schools within the district and lead to more unequal distribution of resources. This variable is in thousands of 1992 dollars. Furthermore, I will use state income inequality as a sensitivity check in empirical analysis. Second, $black_1_{it}$ is the percentage of black population in state i in year t . Since it is typically assumed that blacks attend inferior schools, the rise in the black population percentage in a state is associated with an increase in variance of education expenditures distribution across school districts (Figlio et al. 2004). Third, as the percentage of school age

⁵ The methodology of calculating education expenses inequality follows that in Murray et al (AER, 1998).

⁶ I also use the absolute level of employment in foreign affiliates as the measure of FDI and estimate equation (1) and obtain qualitatively identical results to the regressions using the percentage of employment in MNCs. I do not report the results due to the restriction of the length of the paper.

students in state i in year t ($age5_17_{it}$) rises, households may have greater incentives to choose school districts based on their preferences and income conditions, which causes larger inequality in education expenditure distribution. On the other hand, as the percentage of working age population in state i in year t ($age25_66_{it}$) increases, the concern of house determination will be less dependent on school quality preference, which may lead to less education expenses disparity within the state. Fourth, the education attainment within a state is also an important factor that affects education inequality. Hence, the econometric model includes the variable col_{it} , which measures the percentage of population aged 25 and over with at least 4-year college education in state i in year t . The higher percentage of state population with better education implies higher permanent income, which may lead to more equal demand for school spending across school districts. Fifth, $disstu_{it}$ measures the number of school districts per student in state i in year t . Fewer districts per student is expected to be associated with less resource inequality across school districts in states, because fewer school districts give households less opportunity to choose school districts to match the most preferred school quality and leads to less variation in income across districts in states. Finally, $metro_bea_{it}$ is the percentage of metropolitan population in state i in year t . There are usually more school districts and income variation in metropolitan areas, which provides more opportunity and incentives for families to find school districts to satisfy their demand for school quality. Hence, as the percentage of state population living in metropolitan areas rises, there may be more disparity in school expenditure distribution.

The proper estimation of equation (1) requires addressing a few empirical concerns. First, the direction of causality may go from local education expenditure inequality to FDI such that FDI is endogenous. Specifically, manufacturing FDI may be more likely to locate in regions with cheap land and low labor cost; hence, states with higher inequality of education spending may attract more manufacturing FDI. However, skill-labor intensive FDI may have a greater tendency to locate in regions with more equal education spending distribution, as more well-educated workers are available in these regions. Second, more than one endogenous variable may exist in the estimated equation. For example, the education attainment

variable is also endogenous, because more equal distribution of public school spending may lead to higher stock of human capital, on average, in a state's population. Finally, contemporaneous education spending inequality may be affected by previous inequality and the presence of the lagged dependent variable will make least squares estimators inconsistent.⁷ Hence, to control for these issues, I estimate equation (1) including the one-year-lagged inequality of education expenditure by a Generalized Method of Moments (GMM) estimator developed by Arellano and Bond (1991).⁸ In the estimation procedure, I specify the variables, FDI and education attainment as endogenous variables and the other control variables as strictly exogenous variables. Next, the GMM estimator first-differences the estimated model to remove the state specific effects and then estimates the transformed model by using lagged levels of the dependent variable and the endogenous variables and differences of the strictly exogenous variables as instruments. Furthermore, I also present the ordinary least squares (OLS) and random-effects (RE) estimates in the section of empirical analysis as well for the completeness and robustness check.

Arellano and Bond (1991) propose two tests for the accuracy of the GMM estimator. First, a Sargan test of over-identifying restriction, which tests the null hypothesis of no correlation between the instruments and the residuals (Forbes, 2003). Second, a test of second-order serial correlation in the residuals. If this test fails to reject the null hypothesis of no second-order autocorrelation in the regression, then the lagged endogenous variables are valid instruments. Furthermore, to investigate whether the lagged variables are weak instruments, following the method suggested by Staiger and Stock (1997), I regress each endogenous variable on its instruments

⁷ The presence of lagged dependent variable on the right hand side of the model leads to the violation of the assumptions of least squares estimators. For example, the covariance of independent variables and error terms is not equal to 0, $\text{cov}(X_t, e_s) \neq 0$ if $s < t$, and thus, $E[e_t \mid \text{future } X_s] \neq 0$

⁸ When estimating a Tobin's q equation, Forbes (2003) also uses the GMM estimator to control for the multiple endogenous variables and the presence of lagged dependent variable in the estimated equation.

and examine the F-statistics. If the F-statistics of the regressions is greater than 5, the instruments are valid. Finally, a Breusch and Pagan LM test for the null hypothesis of no state specific effects is necessary as the justification for random-effects and the GMM estimators. If the test accepts the null hypothesis, then the OLS estimator is more efficient than the panel-data estimators.

5. Data and Descriptive Statistics

To estimate equation (1), I use the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), the US Census (Census) and National Center for Education Statistics (NCES) matched data from 1992 to 2002 to construct a panel of data. To compute the measures of inequality in education expenditures within a state, I obtain data on school district expenditures on K-12 education from the Elementary-Secondary School System Finance (F-33) Files in different years on the website of the US Census. Furthermore, the data on the number of K-12 students in school districts are available in the State Non-Fiscal Public Elementary/Secondary Survey Data File on the website of NCES.

To avoid the difference in spending due to grade coverage of school districts, the sample is restricted to unified school districts which cover all grades. Thus, Montana and Vermont are excluded from the sample for all years because they have virtually no unified school districts.⁹ Furthermore, Hawaii and Washington D.C are dropped because they have one state-wide or region wide school district. Alaska is also deleted from the sample. Therefore, the final sample covers 11 years of data from 46 states in the US yielding 506 observations.¹⁰

⁹ The selection of districts in the sample data follows Murray et al. (1998). Because secondary schools generally cost more than elementary schools, districts without unified elementary and secondary schools are excluded to ensure the accurate comparison of education resources across districts.

¹⁰ There are only 505 observations of the inequality measures because the data on public education expenditures in school districts in New Jersey are missing in 1997.

Data on employment in foreign plants, metropolitan income per capita and metropolitan population are available on the website of BEA. Metropolitan income per capita and metropolitan population are retrieved from the interactive table under regional account, while employment in foreign plants in each state is from the table G7 of “Financial and Operating Data of Foreign Direct Investment in the US” and is measured in thousands of employees. Furthermore, I use data on total non-farm employment from the website of BLS to create a ratio of foreign firms in state employment in each state.

Data on other control variables, such as race and age characteristics, as well as education attainment variables, are obtained from the Current Population Survey (CPS) of the US Census. Moreover, data on the number of school districts in a state is also from the State Non-Fiscal Public Elementary/Secondary Survey Data File on the website of NCES.

Table 2, in the Annex, reports the basic descriptive statistics of the variables and Table 3 shows the correlation among the four measures of inequality. The Gini Coefficient, Coefficient of Variation, the Theil Index are strongly correlated with each other, while the ratio of 95th to 5th percentile of per-pupil expenditures has lower correlation with the other inequality measures.

Table 3 Correlation of the Inequality Measures

	gini	theil	ratio	cov
gini	1			
theil	0.7585	1		
ratio	0.6017	0.5310	1	
cov	0.9097	0.6575	0.3765	1

6. Empirical Analysis

(1) Basic Results

Table 4 summarizes the results from estimating equation (1) with the ordinary least square (OLS), random-effects (RE), random-effects with instrument and generalized method of moments (GMM) estimation procedures that control for the issues of unobservable

effects, endogeneity and autocorrelation step by step. The estimated results show that FDI have a negative effect on local education spending inequality and the finding is pretty consistent across different specifications and regressions.

Table 4 Basic Results¹¹. Dependent Variable: Gini Coefficient

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	RE	RE/I V	GM M	GMM	GM M
Gini _{t-1}					0.309 (0.00 0)** *	0.458 (0.000) ***	0.084 (0.00 0)** *
	- 0.793	- 0.61 9	- 0.72 2	- 1.05 5	- 0.612	-0.572	-0.63 (0.00
Percentage of FDI Employment	(0.09 2)*	(0.3 09)	(0.1 96)	(0.1 56)	(0.01 4)**	(0.007) ***	0)** *
	1.188 (0.00 0)** *	0.97 3 (0.1 20)	2 (0.0 14)* *	2 (0.0 19)* *	0.376 (0.02 7)**	0.437 (0.094) *	
Metropolitan Income Per Capita							3.396 (0.48 2)
State Income Gini	2.07 (0.00 0)** *	0.22 9	0.11 2	0.06 2	0.255		0.793 (0.14 4)
Percentage of State Population Aged 5-17		- 0.07 6	- 0.07 7	- 0.13 1	0.002	-0.097	- 0.002
Percentage of State Population Aged 25- 66	0.844 (0.00 3)** *	(0.7 21)	(0.7 15)	(0.6 39)	(0.95 3)	(0.024) **	(0.97 4)
Percentage of Black Population	-0.27	0.02 1	0.31 7	0.29 7	0.079	-0.051	0

¹¹ p values are presented in parentheses.* significant at 10%; ** significant at 5%; *** significant at 1%

	(0.00 0)** *	(0.9 22)	(0.0 12)* *	(0.0 22)* *	(0.03 2)**	(0.283)	(0.99 3)
	-	-	-	-	-		-
	0.651	0.27 3	0.36 5	0.22 8	0.262	-0.159	0.041
	(0.00 1)** *	(0.1 52)	(0.0 43)* *	(0.5 97)	(0.00 0)** *	(0.124)	(0.27 8)
Education Attainment							
	0.727	0.93 1	0.05 5	0.08 7	- 0.146	-0.02	0.332
	(0.00 0)** *	(0.0 29)* *	(0.8 45)	(0.7 64)	(0.41 1)	(0.897)	(0.00 7)** *
	0.304	1.63 2	0.16 4	0.14 7	0.865	0.814	1.429
Percentage of Metropolitan Population	(0.00 0)** *	(0.0 23)* *	(0.1 21)	(0.2 13)	(0.20 2)	(0.183)	(0.01 4)**
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
	-	-	-	-			
Constant	101.3 08	42.9 26	4.77 8	1.53 5	0.003	0.135	- 0.222
	(0.00 0)** *	(0.2 21)	(0.8 15)	(0.9 50)	(0.97 7)	(0.121)	(0.03 7)**
Observations	505	505	505	505	411	411	183
		0.80					
R-squared	0.262	9					

In regression (1), which reports the OLS estimation results and controls for year fixed effects only, FDI presents a negative impact on the within-state inequality of education expenditure distribution and the coefficient is statistically significant at the 10 percent level. Specifically, a one-percentage increase in FDI is associated with 5.2 percentage reduction in local education expenditure disparity measured by the Gini coefficient on average, all else equal. Furthermore, most of the control variables have the expected signs and are consistent with the results in Figlio et al. (2004). In regression (2), the OLS estimation controls for both year and state fixed effects, which increase the value of R^2 from 0.262 to

0.809. FDI still presents a negative effect on the within-state inequality, though the coefficient on FDI is not significant at the conventional level.

Next, I proceed to the RE estimation and report the results in regression (3).¹² The key variable, *pfdi*, retains the negative sign and similar magnitude to the OLS estimates, though it is statistical insignificant at the 10-percent level. As discussed in section IV, a potential problem with the econometric model is that the variables of FDI and education attainment may be endogenous. Therefore, I instrument the endogenous variables by their lagged values and present the RE estimation results in regression (4). FDI still has a negative effect on the education expenditure inequality with an improved magnitude and statistical significance.

To control for fixed effects over time and across states, endogeneity and the inclusion of lagged dependent variable, equation (1) is estimated by the GMM two-step estimator and the results are reported in regression (5).¹³ A maximum of five lags of the endogenous variable is included in the regression since the additional lags do not improve the explanatory power, but undermine the power of instruments. Consistent with the previous regressions, the FDI variable, *pfdi*, is revealed to have a negative coefficient, which is significant at the 5-percent level. Furthermore, according to the test statistics associated with the regression, Sargen test fails to reject the null hypothesis, which excludes the concern of over-identifying restriction; and the second-order autocorrelation test does not reject the null hypothesis, which indicates that there is no second-order autocorrelation in the data. Moreover, there are two concerns of the

¹² The Hausman test fails to reject the null hypothesis that fixed-effects estimates are not statistically different from random-effects estimates, which indicates that random-effects estimates are preferred to fixed-effects estimates.

¹³ The GMM estimator first-differences the estimated model to remove the state-specific effects and then estimates the transformed model by using lagged levels of the dependent variable and endogenous variables and differences of the strictly exogenous variables as instruments. Furthermore, the GMM two-step estimates are asymptotically more efficient than one-step estimates. The GMM one-step estimation obtain the similar results.

validity of GMM estimates. First, to address the issue of weak instruments, I regress the first difference of the endogenous variables on their instruments; and the F-statistics is greater than 10 in both regressions, which implies that the instruments are reliable (Staiger and Stock, 1997).¹⁴ Second, the GMM estimator will be inefficient if there is no state specific effect. A Breusch and Pagan Lagrange multiplier test for random effects rejects the null hypothesis of no state-fixed effects at 1 percent significant level. Hence the GMM two-step estimates are consistent and efficient.

Since the GMM estimator is preferred to the OLS and panel data estimator, I will employ this estimation approach in the following regressions. As for the instruments in regression (5), the structure of lagged endogenous variables starts from period $t-2$ and leads to the concern that lagged FDI may affect current inequality, which makes the GMM estimates biased.¹⁵ Hence, in regression (6), I employ the lagged endogenous variables starting from period $t-4$ as the instruments.¹⁶ But, the change of lag structure of the instruments has little effect on the coefficients of FDI and other variables. Furthermore, the GMM estimation yields qualitatively identical results by using more recent or further periods of lagged endogenous variables as the instruments. In regression (7), I substitute the Gini coefficient of per capita state income, which measures the degree of

¹⁴ The F-statistics is 10.86 and 15.26 in the regressions of FDI and education attainment respectively.

¹⁵ The valid instrument should be correlated with the endogenous variable, but uncorrelated with the error term. In this case, lagged FDI is strongly correlated with contemporaneous FDI, with a correlation coefficient of 0.9132 between FDI_t and FDI_{t-2} . However, if FDI_{t-2} may affect the inequality, the asymptotic estimate of b_{FDI} can be shown as:

$$\text{plim } \hat{b}_{FDI} = b_{FDI} + \frac{\text{cov}(z, e)}{\text{cov}(z, X_{endog})}, \text{ where } z \text{ is the instrument and}$$

e is the error term. The second term of this equation is the bias. If $\text{cov}(z, e) \neq 0$, the estimated coefficient is biased.

¹⁶ To determine which lag to start, I substitute lagged FDI into equation (1) and run the GMM two-step estimation. The results show that FDI_{t-4} has no impacts on the within-state inequality.

the inequality of state income distribution, for metropolitan income per capita, because more equal income distribution is likely to be associated with more equal distribution of public school spending across school districts. The data on income inequality are computed by Wu, Golan and Perloff (2002) and available for the periods from 1982 to 1997. Because the data on the other variables are from 1992 to 2002, regression (7) suffers a great loss of degrees of freedom, but the coefficient on FDI maintains the similar magnitude and the negative sign and is statistically significant at the 1-percent level.

Table 5 presents the GMM two-step estimation results for the empirical model using other measures of inequality. The impact of FDI on education expenditure inequality is quite insensitive to different measures of inequality. The coefficient of the FDI variable stays negative and significant at 1-percent level in all specifications. Therefore, in the following analysis, I only examine the Gini Coefficient as my inequality measure and report the results.

Table 5 Other Measures of Inequality

Dependent Variable	(1) Theil GMM	(2) Ratio GMM	(3) COV GMM
Theil $t-1$	0.605 (0.000)** *		
Ratio $t-1$		0.068 (0.000)** *	
COV $t-1$			-0.064 (0.000)** *
Percentage of FDI Employment	-0.145 (0.000)** *	-6.08 (0.015)** *	-20.708 (0.000)** *
Education Attainment	-0.025 (0.018)** 0.147 (0.000)** *	9.035 (0.000)** * -16.275 (0.000)** *	-10.104 (0.000)** * 12.31 (0.000)** *
Metropolitan Income Per Capita	*	*	*
Percentage of Black Population	0.001	-1.445	0.803

			(0.003)**
	(0.749)	(0.140)	*
	-0.048	-10.872	3.365
Percentage of State Population Aged 5-17		(0.001)**	
	(0.268)	*	(0.075)*
	-0.022	-6.754	4.844
Percentage of State Population Aged 25-66	(0.001)**	(0.000)**	(0.000)**
	*	*	*
District/student	0.064	-9.579	-1.994
	(0.000)**		
	*	(0.010)**	(0.097)*
	0.05	-5.525	14.948
Percentage of Metropolitan Population			(0.000)**
	(0.720)	(0.057)*	*
Year Fixed-Effects	Yes	Yes	Yes
State Fixed-Effects	Yes	Yes	Yes
Constant	-0.049	5.006	0.876
	(0.000)**	(0.000)**	
	*	*	(0.291)
Observations	411	411	411

(2) The Impacts of Lagged FDI

The basic regression analysis uses contemporaneous level of FDI, which may not be an ideal measure of foreign employment for the purpose of explaining the changes of school expenditure inequality. First, in the practice to entice foreign investment, state and local governments tend to offer MNCs a temporary tax break for several years. Therefore, the tax waiver for foreign firms may undermine state governments' budget and squeeze the available funding away from local schools. Second, it may take time for FDI to affect the industry production and local property value, which potentially influences government expenditures on local schools. To explore this, I include lagged *pfdi* variables up to 7 years of lag in the regression and report the results in table 6. Furthermore, since I obtain data on employment in foreign firms and state non-farm industries before 1992 from the BEA and BLS websites, the GMM two-step regression analysis does not lose any degrees of freedom.

The estimation results show that contemporaneous FDI still has a considerable amount of negative effects on the school spending

inequality, but the magnitude declines dramatically and becomes statistically insignificant since the inclusion of lagged FDI in six periods. Furthermore, the regression results also indicate that the lagged FDI has a negative impact on the school spending inequality as well. To obtain a general idea how long the impact of FDI on the distribution of public school expenditures will last, I test the joint effects of contemporaneous and lagged FDI in table 6. The test statistics shows that the combined effects become statistically insignificant after the inclusion of 2-year lagged FDI, which implies that the impact of FDI may last for two years.

Table 6 Lagged FDI. Dependent Variable: Gini Coefficient

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Gini _{t-1}	0.271 (0.000) ***	0.288 (0.000) ***	0.259 (0.000) ***	0.244 (0.000) ***	0.223 (0.000) ***	0.285 (0.000) ***	0.325 (0.000) ***
Percentage of FDI Employment	-0.38 (0.055) *	-0.366 (0.068) *	-0.847 (0.037) **	-0.717 (0.022) **	-0.736 (0.021) **	-0.236 (0.636)	0.292 (0.312)
Percentage of FDI Employment _{t-1}	-0.083 (0.765)	-0.284 (0.468)	0.315 (0.468)	0.275 (0.532)	0.341 (0.492)	-0.419 (0.429)	-0.095 (0.863)
Percentage of FDI Employment _{t-2}		0.402 (0.209)	0.325 (0.451)	0.223 (0.659)	0.678 (0.288)	0.091 (0.849)	-1.019 (0.206)
Percentage of FDI Employment _{t-3}			-0.133 (0.755)	-0.268 (0.529)	-0.473 (0.285)	-0.279 (0.529)	-0.02 (0.964)
Percentage of FDI Employment _{t-4}				-0.612 (0.322)	-1.018 (0.100) *	-0.071 (0.893)	-0.285 (0.621)
Percentage of FDI Employment _{t-5}					-0.183 (0.647)	0.286 (0.559)	0.458 (0.273)
Percentage of FDI						0.495 (0.462)	-0.17 (0.809)

Employment nt _{t-6}							
Percentage of FDI							1.608
Employment nt _{t-7}							(0.086) *
Metropolitan Income	-0.164	0.204	0.215	0.058	0.104	-0.586	-0.245
Per Capita	(0.480)	(0.352)	(0.341)	(0.826)	(0.719)	(0.144)	(0.698)
Percentage of Black	0.135	0.072	0.127	0.092	0.069	0.066	0.034
Population	(0.000)	(0.016)	(0.001)	(0.052)			
Percentage	***	**	***	*	(0.204)	(0.331)	(0.616)
of State Population	0.444	0.622	-0.61	-0.919	-1.843	-0.908	2.907
Aged 5-17	(0.382)	(0.257)	(0.649)	(0.390)	(0.182)	(0.565)	(0.196)
Percentage of State Population	-0.008	0.059	-0.082	-0.012	-0.025	0.055	-0.039
Aged 25- 66	(0.817)	(0.182)	(0.162)	(0.835)	(0.670)	(0.366)	(0.653)
Education Attainment	-0.22	-0.28	-0.105	-0.155	-0.151	-0.265	-0.045
t	(0.004)	(0.000)			(0.092)	(0.003)	
	***	***	(0.411)	(0.104)	*	***	(0.797)
District/ student	-0.18	0.041	0.36 (0.098)	0.284	0.265	0.157	0.259
	(0.193)	(0.821)	*	(0.211)	(0.235)	(0.466)	(0.237)
Percentage of Metropolitan	1.179	2.133	2.429	2.535	2.017	1.376	3.309
Population Year	(0.072)	(0.004)	(0.111)	(0.004)	(0.019)	(0.346)	(0.010)
	*	***		***	**		**
Fixed- Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed- Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.201	-0.017	-0.15	-0.078	-0.147	0.265	0.048
	(0.044)						
	**	(0.881)	(0.267)	(0.589)	(0.462)	(0.141)	(0.876)
Observations	411	411	411	411	411	411	411

7. Conclusion

After many years of fast growth of FDI within the US, policy makers and economists are starting to examine foreign firms with more scrutiny. A common concern is whether the incoming FDI may affect the adequate and equal supply of public education. This paper examines the impact of FDI on local education spending inequality empirically. Using US state-level data from 1992 to 2002 and a GMM estimation approach to control for fixed effects, time series issues and endogeneity, the empirical analysis finds that holding other variables constant, a 1-percent increase in foreign employment relative to state non-farm employment is associated with 5.2 percent decrease in the inequality of school spending measured by Gini Coefficient significantly. This result is robust by using different specifications and other inequality measures such as Theil Index, Coefficient of Variation, and the ratio of 95th to 5th percentile of school spending per pupil.

FDI contributes not only to the diminution of local education spending disparity, but also to the rise of local school expenditures. Prior studies find that FDI adds to local employment, increases average wage level, improves productivity (Feliciano et al, 1999 and Doms et al, 1998), and stimulates land price rise (Greenstone and Moretti, 2003). These spillover effects suggest that FDI inflows may expand local government tax revenue and therefore increase local school spending.

In future work, I will get information on how states have changed educational redistribution policies since 1991 to examine the impacts of policy change on the inequality of local education spending in empirical analysis. Furthermore, it might be interesting to explore how gross and different types of FDI interact with the policy change to affect education spending inequality respectively.

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Annex

Table 2 Basic Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini (100)	505	15.190	12.345	3.5	75.2
Percentage of FDI Employment (100)	506	4.101	1.391	1.061	10.489
Metropolitan Income Per Capita (Thousands of 1992 Dollar)	506	21.956	3.095	15.597	33.602
Percentage of State Population Aged 5-17	506	18.887	1.424	15.886	26.021
Percentage of State Population Aged 25-66	506	53.312	2.536	43.658	61.756
Percentage of Black Population (100)	506	11.074	10.106	0	41.225
Education Attainment District/student	506	20.474	4.753	9.457	35.705
Percentage of Metropolitan Population	505	4.702	4.917	0.268	28.527
	506	73.748	17.244	29.794	100