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Do Economic Development Efforts Benefit All? Business Attraction and Income Inequality*

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Abstract: This paper extends the current literature on county-level income distribution in the United States by explicitly exploring the effect of business-attraction efforts by state governments. Using county-level job attraction and retention data from 2000 to 2005 in Virginia to explain the income distribution from 2006 to 2010, while controlling for demographic and socioeconomic conditions of local communities, this study shows that bringing in manufacturing jobs can reduce income inequality at the local level while attracting jobs in professional and business services tends to increase local income inequality. The results indicate that state and local governments' efforts to attract and retain manufacturing jobs help improve local income distribution.

Keywords: economic development, income distribution, inequality, business attraction

JEL Codes: R58, O25, J31

1. INTRODUCTION

The recent Great Recession (2007–2009) and prolonged slow economic recovery revealed many deeply rooted issues in American society that were masked by the rapid economic expansion in the 1990s and 2000s. The financial crisis, massive job losses, and uneven income growth during and after the recession gave rise to the Occupy Wall Street movement. The ensuing debates about "one percenters" and minimum wages showed a good share of Americans was concerned about income inequality.

Poverty and income inequality at the local level has almost always been an issue of interest among academics (Bartik, 1994; Ngarambe, Goetz, and Debertin, 1998; Levenier, Partridge, and Rickman, 2000; Marcouiller, Kim, and Deller, 2004; Rupasingha and Goetz, 2007). From the 1980s through to 2000, income distribution in the United States had become increasingly unequal (Autor, Katz, and Kearney, 2008). It would be interesting to see what has happened in the United States since the Great Recession—in particular, whether or not a new set of the income dynamics is underway at the local level.

The above national economic trends seemed to be at play in Virginia as well. But we know that during the past two decades Virginia benefitted substantially from the information technology revolution of the 1990s as well as its proximity to the main nexus of federal government offices. The latter enabled Northern Virginia to develop into a hub of high-tech and defense industries, with many corporate headquarters located in the area as well. Indeed, during the most recent recession and recovery, the state's unemployment rate remained well below the

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nation's. For example, in May 2013, the state unemployment rate was 5.8 percent, compared with 7.2 percent for the nation (Bureau of Labor Statistics, 2013). But, development was uneven across the state. While places like suburban counties in northern Virginia—such as Arlington, Fairfax, and Loudoun—were among the richest in the nation, places like Radford, Harrisonburg, and Emporia in western and southern Virginia had poverty rates over 30 percent between 2008 and 2012 (U.S. Census, 2013).

During the Great Recession and the ensuing slow economic recovery, Virginia's state government intensified its economic development efforts to attract businesses and engaged in multiple trade and marketing missions, both domestically and internationally. While those efforts focused on boosting the overall state economy, with the heightened awareness of income inequality in the current climate, state policy makers were sensitive to the distributional effect of economic policies. But did those business attraction efforts affect income distribution in Virginia communities? More specifically, did the benefits of those efforts improve the welfare of wealthy residents or of those at the bottom of the income ladder? Unfortunately, previous studies addressing this critical question show results have been mixed at best.

This study examines the determinants of county-level income distributions within the state of Virginia. An emphasis is placed on the effect of the state's business-attraction effort. The insights from this research can help state economic development officials to better target industries for their development efforts and to help focus their efforts toward policies that benefit more people in the state.

I chose the Commonwealth of Virginia as the geographic scope of the study primarily for the sake of data consistency and availability. A cross-state study is complicated by different legal/political environments and policies (like tax credits) that may cause dissimilar effects on income distribution. Moreover, states embrace different sets of policies that make classifying a consistent policy-identification measure difficult. In research on the relationship between economic growth and income inequality, de Dominicis, Florax, and de Groot (2008) advise using data either for a single country data or for regions with similar characteristics. In terms of data availability, the Virginia Economic Development Partnership, a state agency, has kept excellent records of development announcement projects over the past 20 years. Similar systematic databases for tracking economic development efforts are not always available for many states. Using only the few states for which data are available is clearly capricious. Thus, only one state was chosen for this study.

The rest of this article is organized as follows. The following section is a review of the literature on the determinants of local income inequality, with special emphasis on the role of business-attraction efforts. Section 3 is a summary of the current pattern of local income distribution in Virginia and the state's business-attraction efforts. The data and model specifications are discussed in Section 4. Results appear in Section 5, followed by a conclusion.

2. ECONOMIC DEVELOPMENT AND LOCAL INCOME DISTRIBUTION

2.1 **Determinants of Local Income Distribution**

From the theoretical perspective, the most famous explanation of the determination of national income distribution is offered by Kuznets (1955), who proposed that income inequality followed an inverted U-shaped curve in the process of economic growth. Income distribution becomes more unequal at the early stages of economic development, before moving to a more equal distribution during later stages (Kuznets, 1955). A key implication from the Kuznets theory is that a change in income distribution, at least at the national level, is caused by economic structural changes. As an economy transitions from an agrarian to an industrial one and, later, to a service economy, income inequality exhibits an inverted U-shaped curve. However, recent research on income distributions in developed countries (such as the United States, France, Great Britain, Australia, and Canada) has shown that inverted U-shaped income distribution might be an historic anomaly rather than the rule (Atkinson, Piketty, and Saez, 2011). The U-shaped income distribution theory was developed in the 1950s. The Great Depression severely damaged the top-income earners, especially those with income from capital. World War II generated large fiscal shocks, especially in the corporate sector (Piketty and Saez, 2003). Those historic events caused income distribution in developed economies to move toward being more-equal distribution during ensuing decades; since the 1970s the income distributions in those economies have at best stagnated and often become more disparate.

In advanced economies, where more-equal income distributions are expected based on Kuznets's theory, income inequality has only grown over the past three decades (Autor, Katz, and Kearney, 2008). Most research on the rising inequality in the United States points to factors not included in Kuznets's theory. Autor, Katz, and Kearney (2008) find that increased imbalance of demand and supply for skilled labor widens the income gap. Lee (1999) finds that the stagnation of real minimum wages contributes to a large portion of increasing inequality, especially for those at the low end of the income spectrum. Globalization, especially out-sourcing of manufacturing jobs to developing countries, contributes to income inequality in the United States (Feenstra and Hanson, 1999). Political factors and increased polarization in the U.S. political process play roles in enlarging income inequality (Bonica et al., 2013).

The dynamics that drive national income distribution may be quite different from those affecting income distributions at state or local levels. Research on state and local income distributions is largely empirical in nature. These studies generally examine sub-national level inequality in terms of different demographic characteristics, socioeconomic conditions, industrial compositions, and other labor market factors (Peters, 2012). Unfortunately, little consensus has emerged, warranting further investigations.

Demographic variables, such as age and racial composition, can affect local income distribution. When investigating Midwestern United States, Peters (2012) found that higher percentages of resident young people under age 24 tend to raise local inequality, while high concentrations of people over age 64 tend to reduce inequality. Higgins and Williamson (1999) studied panel data for the 1960s to 1990s and found that greater shares of the population aged 40–59 decrease inequality, supporting the hypothesis that high concentrations of both younger and older populations enhance income dispersion. Shelnutt and Yao (2005) contradict these results and showing that a high concentration of working-age people is associated with a high level of income dispersion in Arkansas.

The effect of the racial composition of a community on income distribution is also unclear. In a study on county-level income distribution in the United States from 1970 to 2000, Moller, Alderson, and Nielsen (2009) show that larger populations of non-African Americans minorities tend to raise local inequality. More specifically, Moller, Alderson, and Nielson (2009) show that a high percentage of African Americans in a population is associated with lower inequality. McLaughlin (2002) shows, however, that same population characteristic is associated with higher inequality in nonmetropolitan areas in 1980 and 1990. Because income dynamics of different racial groups are evidently very complex, analysts should avoid forming variables that would necessarily test for a uniform response across all minority groups.

Education is often credited as a way of lifting people out of poverty; thus, higher average levels of it should reduce income inequality at the local level. This relationship tends to hold true for variables representing the percentage of the local population with high school and associated degrees, but results are mixed for education at the college level (Peters, 2012). For example, Marcouiller, Kim, and Deller (2004) find that the share of the population with a high-school education is an income-equalizer in the Midwestern states of Wisconsin, Minnesota, and Michigan, but a concentration of college graduates has no effect on local income distribution. Shelnutt and Yao (2005) find that a higher share of college students yields greater income inequality in Arkansas.

A key mechanism that can influence local income distribution is commuting. As a result of increased commuting of the U.S. workforce (Shuai, 2010), incomes of local residents are less attached to the economies of their home counties. People can obtain employment outside their home counties; thus, commuting flattens the income distribution. A study of Arkansas confirms that more commuting reduces income inequality (Shelnutt and Yao, 2005). Furthermore, poverty can affect income distribution. Peters (2012) found that high initial states of poverty are associated with relatively lower levels of income inequality in the Midwestern states of Minnesota, Iowa, Missouri, North Dakota, South Dakota, and Nebraska.

Regarding the role of industry structure on the income distribution of a county, empirical studies have not reached a consensus. Peters (2012) finds that employment concentration in the construction sector is associated with higher inequality over the past 30 years for Midwestern states, but not in manufacturing or other sectors. Marcouiller, Kim, and Deller (2004) find that tourism employment can reduce income inequality, but that employment in manufacturing or retail industries does not. More recently, Shelnutt and Yao (2005) find that a high concentration in professional service employment can increase income inequality.

Finally, additional research has emphasized the role of social capital in determining county-level poverty and income distribution. It is theorized that high social capital proxies for activities like volunteerism and charitable contributions by local residents. Both benefit low-income populations of a community. Using the Gini coefficient as an explicit measure of income distribution in U.S. states, Kawachi et al. (1997) discover that a high level of social capital, measured as the participation in volunteering groups and social trust, is associated with more equal income distribution in the states. At a local level, using a composite index that included per-capita number of non-profit organizations and voter turnout, Rupasingha and Goetz (2007) show that high social capital is associated with a low level of poverty in the United States.

2.2 **Economic Development and Income Distribution**

Studies that examine the effect of state economic development policies on income distribution tend to focus on broad policy instruments, such as taxes and the business climate. Few focus specifically on policy tools at the disposal of economic development professionals, such as recruiting and retention efforts or incentives to attract businesses. One broad strand of literature focuses on how local distribution of income affects local economic growth. A meta-analysis performed by de Dominicis, Florax, and de Groot (2008) reviews the varying and sometimes conflicting literature in this area. They find that estimation methods, data quality, and sample coverage systematically affect research findings.

The present analysis focuses on causation in the opposite direction—how economic development affects income distribution. A key question often asked in the literature is whether rising tides lift all boats (a Pareto improvement) or whether economic growth affects income levels of households in all income groups. Bartik's (1994) study of metropolitan-area income distribution in the United States during the 1980s, finds a positive relationship between growth and improved income distribution. In a county-level study in the U.S. South, Ngarambe, Goetz, and Debertin (1998) conclude contrarily—that rapid growth is associated with a more extreme income distribution. These studies focus on the 1980s and 1990s; relationships may have changed since then. A recent study on state-level growth and income distribution finds that economic growth affected poor, middle income, and rich households in a similar fashion. This suggests that the sort of growth that has occurred since the 1990s may not affect the distribution of incomes (Hasanov and Izraeli, 2011).

Using state-level data, Goetz et al. (2011) examined the effect of five statewide economic policy variables on income distribution measured by the Gini coefficient: (a) tax climate, (b) regulatory and firm assistance programs, (c) human and social capital, (d) entrepreneurship and innovation, and (e) government expenditures and investment. Interestingly, none of these variables had a direct effect on the state-level income distribution. Only health coverage had a significant effect on the Gini coefficient (Goetz et al., 2011). In particular, they find that no programs under the control of the economic development agencies affect state income distribution in a manner that could be detected with statistical significance. A detailed search uncovered no such research for county-level income distribution.

Goss and Phillips (1997) found that state economic development spending had a positive but moderate effect on employment as well as income growth at the state level. But they did not study the effect on the income distribution of such spending.

In summary, the study of local income distribution is still evolving, and no consensus appears to have been reached concerning the role of demographics, socioeconomics, and policy factors. Further study is, therefore, needed to understand the current role of these variables. Thus, this study contributes to the literature by specifically modeling the effect of economic development activities on income distribution at the local level. It also poses the important question of whether business attraction efforts benefit all citizens in a community.

3. INCOME DISTRIBUTION AND ECONOMIC DEVELOPMENT IN VIRGINIA

3.1 **Measurement of Income Distribution**

Income distribution measures the allocation of income in a society. Common measures of income distribution are percentile ratios, expressed as the relative income ratio between residents in the high-income brackets and those in low-income brackets, such as a 90/10 income ratio (Shelnutt and Yao, 2005). Some studies have used such measures as 90/50 and 50/20 income ratios to understand the income distribution within the top half and lower half of the income segments. Those ratio measurements do not satisfy an important principle of inequality called *the transfer principle*, which states that inequality should decrease when income is transferred from a rich person to a relatively poor person. A 90/10 ratio ignores income movement in the middle, which can significantly affect a society's income distribution. Rupasingha and Goetz (2007) used the ratio of mean income to median income as a measure of inequality, a measurement subject to similar limitations. The standard deviation of incomes has also been used in several studies

(Kopczuk, Saez, and Song, 2010), but it is scale-dependent and, hence, difficult to compare across different countries or regions.

The measure of income distribution with perhaps the most widespread use is the Gini coefficient (Shelnutt and Yao, 2005; Kopczuk, Saez, and Song, 2010). It is scale independent, population independent, obeys the transfer principle, and is bounded (Farris, 2010). The Gini coefficient is built using the Lorenz curve, which is the cumulative income share of a society after rank ordering all incomes from the lowest to the highest. Following Farris (2010), in equation (1), $L(x)$ represents the Lorenz curve, and the Gini coefficient is expressed as

$$Gini = 1 - 2\int_0^1 L(x)dx. \tag{1}$$

Bounded between 0 and 1, a higher Gini coefficient indicates that income is more unevenly distributed and vice versa. In practice, when the exact functional form of the Lorenz curve is unknown but the individual income of population (n) is known, an alternative Gini calculation can be expressed (Farris, 2010):

$$Gini = \frac{1}{n-1}\left(n + 1 - 2\frac{\sum_{i-1}^{n}(n+1-i)y_i}{\sum_{i=1}^{n} y_i}\right) \tag{2}$$

where y_i indicates the income of i^{th} person and is indexed in nondecreasing order ($y_i <= y_{i+1}$). This study uses the Gini coefficient as the measurement of income distribution in Virginia's localities.

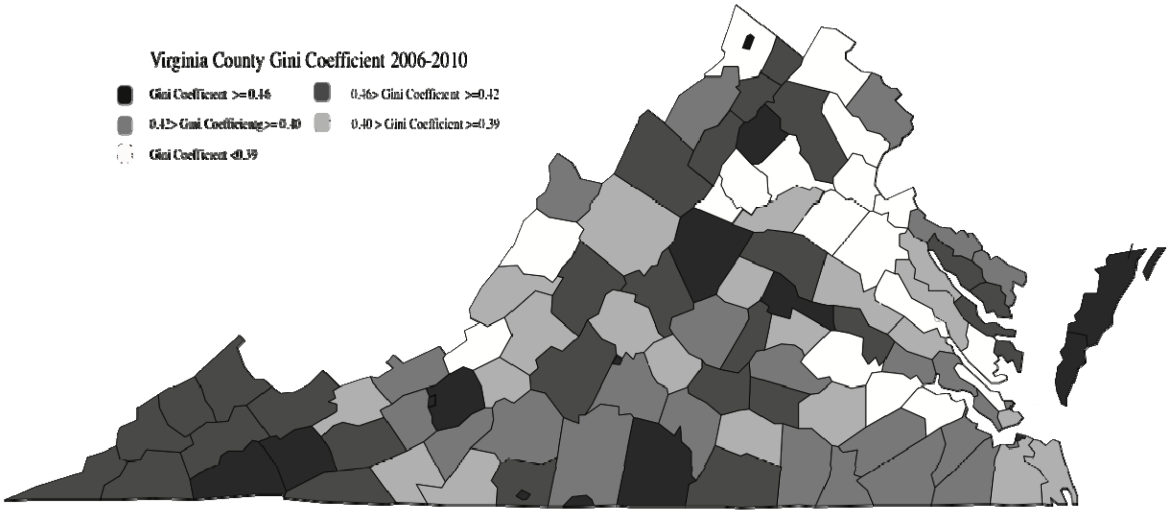
3.2 **Income Distribution in Virginia**

Since 1967, the distribution of income in the United States has become increasingly unequal. It has grown 18 percent during the period with nearly half of that growth occurring during the 1980s (Bee, 2012). More recently, however, the growth of income inequality has tapered off (Kopczuk, Saez, and Song, 2010). The U.S. Bureau of the Census (2013) has estimated local Gini coefficients in Virginia for the 2006–2010 period. The average Gini coefficient for Virginia is 0.444 during that period, ranging from 0.326 for Bath County to 0.539 for Norton City. As a comparison, the five-year 2006–2010 Gini coefficient for the United States as a whole was 0.467 (Bee, 2012).[1]

Figure 1 shows the income distribution for Virginia's localities, based on the Census estimates for 2006–2010. There is no clear geographic pattern of income inequality in Virginia. While the localities in southwestern Virginia seem to have high Gini coefficients, there are also pockets of high inequality elsewhere in southern and central Virginia. It does appear that there are clusters of localities in northern and eastern Virginia with Gini coefficients lower than the state average. Furthermore, no clear association between income inequality and income level is evident. While some rural areas in southern and southwestern Virginia experienced higher income inequality, affluent counties such as Albemarle and Goochland also had high Gini coefficients.

[1] The five-year average Gini coefficient is used in this analysis because data on the county-level Gini coefficient are only published every five years. While the annual American Community Survey (ACS) can be used to estimate the annual Gini coefficient based on income distributions, for smaller counties, those data are only available on a five-year basis.

Figure 1: Gini Coefficient for Virginia (2006-2010)



3.3 **Business Attraction Activities**

The Virginia Economic Development Partnership (VEDP) is the state agency that coordinates the economic-development effort across the state. It maintains a database on all business attraction activities in which it is involved, including the number of businesses attracted or retained, jobs created, private capital invested, and the types of industries these projects impacted. The database used here includes all projects from 1990 to 2013 (VEDP, 2013). This is the most complete data source tracking economic development activities in the state. All projects with state assistance (financial or technical) from the state government are included.[2]

The data on business attraction activities reflect the state's efforts in expanding manufacturing and professional services. On the state economic-development website, the following ten industries are listed as key industries for development: food processing, aerospace, plastic and advanced materials, data centers, information technology, life sciences, automotive, energy, distribution, and corporate headquarters (VEDP, 2014a). Six of them are manufacturing sectors, and the rest are high-tech or professional services and the distribution industry (VEDP, 2014a).

To attract those industries, state incentives are tailored toward manufacturing and professional services. Firms in manufacturing industries are the primary targets for state incentives. According to the latest publication of all business-related incentives in Virginia, 50 state programs give preferential treatment to businesses, including tax incentives, infrastructure assistance, enterprise zones, financial assistance, and technical support (VEDP, 2014b). Some of those incentives are open to businesses in all industries, such as small business financial assistance or training. Some of them target specific industries, such as the Virginia Coalfield Tax Credits to support coal-mining. Of the 50 state incentives, 40 indicate that manufacturing businesses are eligible for the program. Manufacturing businesses are not eligible only for the programs offered by the Center for Innovative Technology, which is focused on developing the high-tech industry in Virginia. In comparison, only 29 incentive programs are available for

[2] This study does not include relocations and investment behavior that does not involve state government.

Table 1: Virginia Economic Development Incentives

	Total	Manufacturing	Professional Business Service	Retail
Tax incentives	12	12	5	6
Enterprise/technology zones	4	4	2	0
Training	6	6	6	6
Infrastructure	4	3	1	0
Discretional incentives	6	4	3	1
Regional assistance	1	1	1	1
Financial assistance	10	9	6	8
Management and technical support	7	1	5	0
Total incentives programs	50	40	29	22

Note. Adapted from Virginia Economic Development Partnership.

professional and business services, which the state also wishes to cultivate. The retail industry is eligible for 22 business incentives, most of which are open to all industries. Some very specific manufacturing programs are the Virginia Leader in Export Trade (VALET), the Virginia Investment Partnership Fund, and the Major Eligible Employer Fund.

Incentive policies indicate that, in terms of jobs and investments attracted to Virginia, manufacturing and professional services are profoundly important.[3] Almost half (49 percent) of jobs attracted from 2000 to 2005 in Virginia were in the Professional and business service sector, and 24 percent were in the Manufacturing sector (See Table 2). The Information, Finance, insurance, and real estate (FIRE) and Trade sectors also attracted a sizable number of jobs while Construction, Leisure, Education, and Health services attracted the fewest jobs, according to VEDP data.

Table 2: VEDP Business Attractions (2000-2005)

	Jobs	% of Total	Investment ($ million)	% of Total
Construction	989	0.5%	$38.9	0.2%
Education and health	175	0.1%	$3.8	0.0%
Finance, insurance, real estate	14,843	7.4%	$866.7	4.3%
Government	0	0.0%	$32.6	0.2%
Information	19,610	9.8%	$2,584.3	12.7%
Leisure	75	0.0%	$0.4	0.0%
Manufacturing	48,054	24.0%	$9,564.3	47.1%
Natural resources	28	0.0%	$10.6	0.1%
Other services	387	0.2%	$6.6	0.0%
Professional & business service	98,160	49.1%	$3,874.9	19.1%
Trade	13,813	6.9%	$1,156.3	5.7%
Transportation, warehouse, utility	3,690	1.8%	$2,171.5	10.7%
Total	199,824	100.0%	$20,310.7	100.0%

Note. Adapted from Virginia Economic Development Partnership.

[3] While it would be ideal to link jobs and investment attracted to Virginia to specific incentives, the publicly accessible database does not include such information because businesses are reluctant to disclose incentives received from the state. Thus, jobs and investment attracted are the only quantifiable results of the incentive policies.

In terms of the amount of investment, the Manufacturing sector brought in the most: $9.6 billion from 2000 to 2005, accounting for 47.1 percent of total investment (both private and public). This high figure is likely due to the extraordinary capital requirements of the sector. Transportation and utilities also received relatively high levels of investment. The professional and business service sector accounted for only 19 percent of all investment, even though the sector accounted for almost half of all new jobs over the study period. The disconnect between jobs and investment suggests that both variables should be investigated with regard to their effects on local income distribution.

Figure 2 shows the number of jobs attracted to Virginia's localities from 2000 to 2005, according to VEDP data. During the six-year span, VEDP coordinated the creation of 199,824 jobs in the state, by luring investment totaling $20.3 billion in both the private and public sectors. Most of the jobs and investments were located in the three largest metropolitan regions of the state (northern Virginia, Hampton Roads, and greater Richmond). Still, some economically depressed areas, such as Martinsville, Danville, and Mecklenburg in southern Virginia, also attracted and retained a large number of jobs, which may indicate success for state efforts to draw jobs there.

As Table 3 shows, all of the top ten localities in terms of jobs attracted are in those three metropolitan areas. The county or independent city receiving the most jobs and investment was Fairfax County in northern Virginia, attracting 60,910 jobs and $1.99 billion in investments during those six years, accounting for one third of all jobs created in the state during that time. Other localities receiving a large number of jobs and investments were Arlington County, Henrico County, and Chesapeake City.

Figure 2: New Jobs Announced in Virginia (2000-2005)

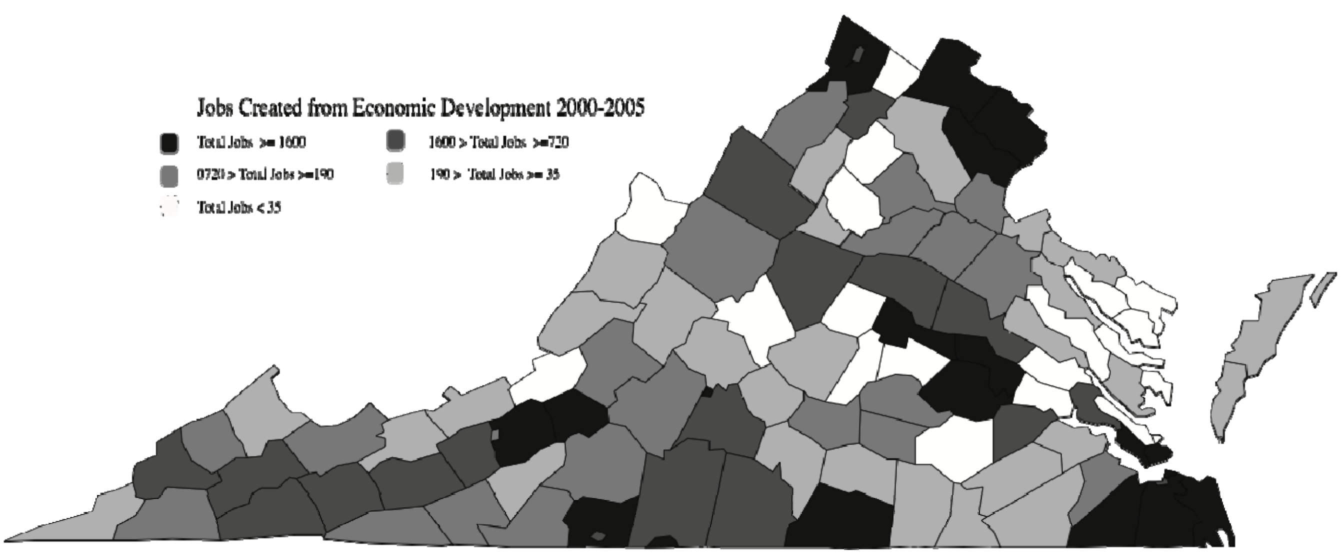


Table 3: Top Ten Localities in Job Attraction (2000-2005)

	Number of jobs	Investment ($ million)
Fairfax County	60,910	$1,990
Arlington County	11,915	$544
Henrico County	10,430	$1,538
Chesapeake city	8,418	$353
Loudoun County	7,228	$1,438
Virginia Beach City	6,224	$476
Chesterfield County	5,703	$791
Norfolk City	4,807	$983
Hampton City	4,680	$61
Prince William County	4,625	$1,519

Note. Adapted from Virginia Economic Development Partnership.

4. MODEL SPECIFICATION AND DATA

The dependent variable of the model is the average county-level Gini coefficient in Virginia from 2006 to 2010. The key independent variables—economic development efforts (*ED*)—are measured as jobs and investments resulting from business attraction activities from 2000 to 2005.[4] The economic development efforts are normalized by population size, so that the value per capita is used.[5] Following the literature on factors influencing local income distribution, this study includes the following major types of independent variables as control—demographic variables (*D*), such as population density and age structure; social economic variables (*E*), such as education attainment, per capita income, poverty, social capital, and commuting pattern;[6] major industry mix of localities (*I*); and policy variables (*P*), such as property tax rates. The detailed explanations of dependent and independent variables are provided in Table 4.

In Equation (3), *i* denotes a given county in Virginia. To evaluate the factors affecting income inequality, the following model will be estimated:

$$Gini_i = \alpha + \sum_i \beta_j D_{ij} + \sum_k \delta_k E_{ik} + \sum_l \theta_l P_{il} + \sum_m \gamma_m I_{im} + \sum_n \varphi_n ED_{in} + \varepsilon_i . \tag{3}$$

Several specification tests were run before estimation to ensure the model specification and estimation strategy were appropriate. The model applies a cross-sectional approach, which makes it susceptible to endogeneity concerns. Such concerns could make it difficult to evaluate the direction of potential causality. To minimize that concern, this study incorporated Granger causality, a technique common in regional economic analysis (Rupasingha and Goetz, 2007; Goetz et al., 2011). It involves lagging the independent and dependent variables by a selected years. The independent variables in this model, such as the demographic, social, and economic variables, are all in 2000 values. The business attraction variables are from 2000 to 2005. None of these variables were determined using data after 2005; the dependent variable—the Gini

[4] The five-year investment horizon was chosen for data reasons. Please see Section 5 for further explanations.

[5] The author thanks an anonymous referee for this suggestion. Normalization of business-attraction activities using land area did not result in meaningful results.

[6] Following a referee's suggestion, social capital was tested, yet its effect is less significant because of high correlation with per-capita income. Thus, this variable was not included in the core model.

Table 4: Descriptions of Variables in Equation (3)

Variable	Explanation	Data source
Gini coefficient (2006-2010)	Gini coefficient for location *i*, average 2006–2010	Census
Demographic variables		
Population (2000)	Population for location *i* in 2000 (log terms)	Census
Population density per square mile (2000)	Number of resident per square mile in 2000 (log terms)	Census
Age 30 and younger (%, 2000)	Percent of population less than 30 years old	Census
Age 65 and older (%, 2000)	Percent of population over 65 years old	Census
Race, African American (%, 2000)	Percent of population who are African American	Census
Social economic variables		
Bachelor's or higher degree (%, 2000)	Percentage of the adult population with a bachelor's or higher degree for location *i* in 2000	Census
Less than high school diploma (%, 2000)	Percentage of the adult population with less than high school education for location *i* in 2000	Census
Per capita income ($, 2000)	Per capita income for location *i* in 2000 (log terms)	
Poverty rate (%, 2000)	Percent of the population in poverty in 2000	Census
Out commute (%, 2000)	Percent of employment who commute out of a county in 2000	Census
Social capital (Index, 2005)	An index of social capital including non-profit association, voter turn-out and other indicators	NERCRD PSU
Policy variable		
Real estate tax (%)	Property tax rate of the county i in 2000	Univ. of Virginia
Economic development variables		
Jobs attracted in manufacturing (2000-2005)	Per capita total number of manufacturing jobs attracted to a county from 2000 to 2005	VEDP
Jobs attracted in professional and business service (2000-2005)	Per capita total number of professional and business service jobs attracted to a county from 2000 to 2005	VEDP
Jobs attracted in other sectors (2000-2005)	Per capita total number of jobs on other sectors attracted to a county from 2000 to 2005	VEDP
Total jobs attracted (2000-2005)	Per capita total number of jobs attracted to a county from 2000 to 2005	VEDP
Investment attracted in manufacturing ($ Million, 2000-2005)	Per capita total investment in the manufacturing sector attracted to a county from 2000 to 2005	VEDP
Investment attracted in professional and business services ($ Million, 2000-2005)	Per capita total investment in professional and business service sector attracted to a county from 2000 to 2005	VEDP
Investment attracted in other sectors ($ Million, 2000-2005)	Per capita total investment in other sectors attracted to a county from 2000 to 2005	VEDP
Total investment attracted ($ Million, 2000-2005)	Per capita total Investment attracted to a county from 2000 to 2005	VEDP
Industry mix variables		
Agricultural employment (%, 2000)	Percent of employment in agriculture, natural resource, and mining industry in 2000	BLS
Manufacturing employment (%, 2000)	Percent of employment in manufacturing industry in 2000	BLS
Service employment (%, 2000)	Percent of employment in service-related industry in 2000	BLS

made under the assumption that other future investments *will* be made. Hence, Hausman tests for endogeneity did not reject the null hypothesis of key independent variables of interest being exogenous. Thus, further treatment of endogeneity, such as using instrumental variables, was not applied.[7]

Since contiguous counties are used in the econometric analysis, spatial autocorrelation was also tested. Moran's I for various model specifications ranged between -0.008 and -0.010, with *p* values between 0.61 and 0.82 (Table 6) and, hence, failed to reject the null hypothesis of no spatial autocorrelation in errors terms. Thus, it was not necessary to use spatial modeling techniques.

The variable inflation factors (VIF) for all independent variables in each model specification were computed to test for possible multicollinearity.[8] A general rule of thumb is that a VIF value greater than 5.0 for an independent variable suggests its high correlation with other independent variables. The only model with a multicollinearity concern was Model 6, in which the focus is the effect of demographic variables—age, race, income, and education attainment. It is not surprising that some of these variables are correlated with one another. But the main conclusions of the study are not derived from this model. All key variables of interest—the state business attraction activities—were not heavily correlated with other independent variables: none had VIFs exceeding 3.0.

Last, in a cross-sectional model, heteroskedasticity is a concern. As the Gini coefficients are bounded between 0 and 1, such concerns are mitigated. χ^2 statistics for heteroskedasticity ranged from 40.32 to 97.12 with a p-value between 0.25 and 0.95 (Table 6). This confirmed the homogeneity of the error terms at the 95 percent significance level. There are also concerns of a structural break among large and small counties. The Chow tests for structural break were conducted breaking countries into two groups based on population. The F-statistics failed to reject the null hypothesis of no structural breaks. Those specification tests indicate that ordinary least squares (OLS) method is appropriate to estimate the model. The summary statistics are shown in Table 5.

5. ANALYSIS OF RESULTS

5.1 General Results

All 134 independent cities and counties in Virginia are included in this study. The OLS regression results are shown in Table 6. Because many different variables must be tested for their effects on income distribution, the potential lack of degrees of freedom through use of just 134 observations is a concern. To mitigate this concern, the most parsimonious model (Model 1) was estimated, including only variables with coefficient estimates that have *p* values less than 0.15 (or significant at the 85 percent level). This set of important variables, plus the key independent variables of interest (job attractions), form the core model (Model 2). Other variations of the model with a combination of the core model and different groups of control variables were also tested to show the robustness of the key independent variables. These models were constructed as the core model plus the following groups of control variables: overall job attraction and

[7] The Hausman tests were conducted on three key variables of interest: per capita jobs attracted in manufacturing, per capita jobs attracted in professional and business service, and per capita jobs attracted for other services. With the null hypothesis being no endogeneity, test results failed to reject the null hypothesis at a 95 percent significance level.

[8] The author thanks an anonymous referee for this suggestion.

Table 5: Descriptive Statistics

Variable	*M*	*SD*	Min	Max
Gini coefficient (Average 2006-10)				
Demographic variables				
Population (00)	52,793	102,273	2,536	969,749
Population density per square mile (2000)	780	1,402	6	8,452
Age 30 and younger (%, 2000)	39%	6%	27%	63%
Age 65 and older (%, 2000)	14%	4%	4%	28%
Race, African American (%, 2000)	20%	17%	0%	80%
Social economic variables				
Education with bachelor's or higher degree (%, 2000)	18%	10%	6%	61%
Education with less than high school diploma (%, 2000)	25%	9%	5%	45%
Per capita income ($, 2000)	$25,543	$7,099	$16,582	$51,640
Poverty rate (%, 2000)	13%	7%	3%	33%
Out commute (%, 2000)	51%	17%	11%	90%
Social capital index (2005)	-0.0437	1.1784	-2.7496	5.0838
Policy variable				
Real estate tax (%)	0.70%	0.30%	0.10%	1.70%
Economic development variables				
Per capita jobs attracted in manufacturing (2000-05)	0.0089	0.0104	0.0000	0.0540
Per capita jobs attracted in professional and business service (2000-05)	0.0073	0.0244	0.0000	0.2574
Per capita jobs attracted in other sectors (2000-05)	0.0025	0.0057	0.0000	0.0402
Per capita total jobs attracted (2000-05)	0.0187	0.027	0.0000	0.2597
Per capita investment attracted in manufacturing ($,2000-05)	$1,393.20	$3,385.60	$0.00	$34,276.10
Per capita investment attracted in professional and business services ($, 2000-05)	$496.60	$2,617.80	$0.00	$28,936.10
Per capita investment attracted in other sectors ($, 2000-05)	$649.50	$2,970.90	$0.00	$25,603.30
Per capita total investment attracted ($, 2000-05)	$2,539.30	$5,058.20	$0.00	$34,539.60
Industry mix variables				
Agricultural employment (% in Total, 2000)	2%	4%	0%	27%
Manufacturing employment (% in Total, 2000)	17%	9%	1%	41%
Service employment (% in Total, 2000)	73%	10%	46%	97%

investment (Model 3), job attraction and investment volume by sector (Model 4), industry mix (Model 5), and demographic variables (Model 6). Those variables groups were tested only in combination with the core model and not with each other. This strategy was used by Goetz et al. (2011) to manage a small number of observations with the degrees of freedom concern. Overall, the different models can explain over 60 percent of the variation in county-level Gini coefficients in Virginia.

First, among various demographic variables by region, such as race and age, only one of them exerted a strong influence on the county-level income distribution: the percentage of residents older than 65 years.[9] In Virginia's localities, having many people over 65 years old is associated with a high Gini coefficient. This result is significant and robust across all model specifications, regardless of whether other control variables are included. A similar result was

[9] Because per capita investment and jobs were used, the model excluded the population size.

Table 6: Coefficient Estimates

	Model 1 Parsimonious model	*Model 2* Core model	*Model 3* Core & general attractions	*Model 4* Core plus detailed effort	*Model 5* Core+ industry mix	*Model 6* Core+ Demographic
Intercept	-0.1293	0.0063	-0.02467	0.02877	0.02945	0.1646
	(-0.62)	*(0.03)*	*(-0.12)*	*(0.13)*	*(0.14)*	*(0.67)*
Demographic variables						
Age 65 and older (%, 2000)	0.1876	0.2136	0.1995	0.2137	0.1981	0.2273
	(2.89)*	*(3.40*)*	*(3.06*)*	*(3.33*)*	*(3.09*)*	*(2.17*)*
Population density (2000)						0.0025
						(0.89)
Age 30 and younger (%, 2000)						0.0211
						(0.24)
Race, African American (%, 2000)						-0.0052
						(-0.36)
Social economic variables						
Education with bachelor's or higher degree (%, 2000)	0.0988	0.1083	0.1233	0.1131	0.1245	0.1077
	(2.18)*	*(2.48*)*	*(2.76*)*	*(2.48*)*	*(2.67*)*	*(2.16*)*
Per capita income (log terms, 2000)	0.0466	0.0322	0.0346	0.0299	0.0248	0.0163
	(2.18)*	*(1.530*	*(1.59)*	*(1.36)*	*(1.15)*	*(0.70)*
Poverty rate (%, 2000)	0.5226	0.5123	0.5000	0.5128	0.5058	0.4287
	(10.90)*	*(11.02*)*	*(10.46*)*	*(10.87*)*	*(10.69*)*	*(5.29*)*
Out commute (% of employed, 2000)	-0.0339	-0.0309	-0.0201	-0.0304	-0.0303	-0.0405
	(-2.09)*	*(-1.99*)*	*(-1.25)*	*(-1.90**)*	*(-1.92**)*	*(-2.38*)*
Education with less than high school diploma (%, 2000)						0.0567
						(0.90)
Social capital (2005)						0.0046
						(1.58)
Policy variable						
Real estate tax (%)	-1.6907	-1.5054	-1.8121	-1.481	-1.5198	-2.1317
	(-1.59)	*(-1.47)*	*(-1.72**)*	*(-1.41)*	*(-1.45)*	*(-1.56)*
Economic development variables						
Jobs attracted in manufacturing (Per Capita, 2000-05)	-0.4284	-0.4822		-0.4784	-0.5251	-0.5093
	(-1.81)*	*(-2.11*)*		*(-1.87**)*	*(-2.17*)*	*(-2.15*)*
Jobs attracted in professional and business service (per capita, 2000-05)		0.2892		0.2237	0.2954	0.3
		(3.12)*		*(0.90)*	*(3.18*)*	*(3.13*)*
Jobs attracted in other sectors (log terms, 2000-05)		0.6		0.6667	0.5829	0.6249
		(1.56)		*(1.62)*	*(1.49)*	*(1.60)*
Total jobs attracted (per capita, 2000-05)			0.2086			
			(2.11)*			
Investment attracted in manufacturing (per capita, $, 2000-05)				-0.0698		
				(-0.10)		
Investment attracted in professional and business services (per capita, $, 2000-05)				0.6506		
				(0.28)		
Investment attracted in other sectors (per capita, $, 2000-05)				-0.3418		
				(0.44)		
Total investment attracted (per capita, $, 2000-05)			-0.1164			
			(0.22)			

	Model 1 Parsimonious model	*Model 2* Core model	*Model 3* Core & general attractions	*Model 4* Core plus detailed effort	*Model 5* Core+ industry mix	*Model 6* Core+ Demographic
Industry mix variables						
Agricultural employment (% total, 2000)					0.0731	
					(1.02)	
Manufacturing employment (% total, 2000)					0.0653	
					(1.56)	
Service employment (% total, 2000)					0.0539	
					(1.40)	
Number observations	134	134	134	134	134	134
Adjusted R^2	0.627	0.6557	0.6304	0.6479	0.6546	0.6521
χ^2 for heteroskedasiticity	40.32	54.81	40.9	86.3	69.53	97.12
(p value for χ^2)	0.2465	0.4463	0.6054	0.5909	0.9462	0.9295
Moran's I	-0.00845	-0.0095	-0.00654	-0.00931	-0.0096	-0.0087
(p value for Moran's I)	0.8199	0.6218	0.8115	0.6602	0.6112	0.766

Note. Numbers below the coefficient estimate are the *t* values.
*Significant at the 95 percent level. **Significant at the 90 percent level.

also observed by Deaton and Paxson (1997), who concluded that a higher concentration of older residents tended to increase income inequality. Having an older population could cause a high income disparity in Virginia because state residents are generally relatively wealthy, compared to the national average. This may explain why Shelnutt and Yao (2005) the opposite ,i.e., that a high concentration of a working-age population is associated with a high level of income dispersion in Arkansas counties, a result that appears to contradict these present results. In a relatively poor state like Arkansas, which has high rates of unemployment and yet also is a retirement destination, a high return on skills to working adults would enhance the income gap.

Other demographic variables did not have a strong effect on the county-level Gini coefficient in Virginia (Model 6). Population density was not related to local income distribution, a result similar to Peters (2012), who found a significant effect for population size but not population density in Midwestern states. The percentage of the population that was African American does not appear to be associated with the income distribution in Virginia's localities either. In addition, regression results indicate that the share of area population that is younger residents did not affect Virginia income inequality. This result implies that younger adults in Virginia, because of similar experiences and educations among them, did not manage to exhibit income differences among themselves that were large enough to affect local income distributions. As mentioned, there is a high level of correlation among certain demographic variables, such as age and race, with variables such as income and education attainment, so that their coefficients were not statistically significant.

All four socio-economic variables showed strong relationships with local income distribution, although with differing levels of robustness. Consistent with Shelnutt and Yao (2005), the positive and significant coefficient estimates for the share of the population with a bachelor's or higher degree indicates that having more people with at least a college degree tends to increase income inequality. This result is robust in different model specifications because college education tends to increase income at the high end of the distribution while having little effect on improving the earnings of those at the low end of income groups, thus the high income disparity. This result could change if most residents have college degrees. Interestingly, Moretti

(2004) found that the share of college students had a spillover effect on the incomes of residents with low-educational attainment.

At first glance, the findings of Moretti (2004) appear to contradict the robust finding in this present study. However, the association between high education attainment and larger Gini coefficients is driven by the manner by which the Gini coefficient is computed. As long as the college graduates in a community do not constitute a majority, raising the share of college graduates should increase the Gini coefficient. The spillover effects found by Moretti (2004) do have a certain effect but will not change the fundamental trajectory of relationships between the Gini coefficient and the share of college graduates, provided the share is low.[10] On the other hand, the share of people with a high school education does not have an effect on the income distribution. Marcouiller, Kim, and Deller (2004) find that this share is an income equalizer in the Midwestern states of Wisconsin, Minnesota, and Michigan, but not the share of college graduates.

Income per capita in 2000 appears to exert a strong influence on the county-level Gini coefficient. High average income is associated with high income inequality. This suggests that high average income in Virginia localities is the result of wealth concentration in top-income earners rather than from high-level incomes in all segments of the society. For example, such correlation can occur when low-level workers, such as cashiers or restaurant workers, earn similar wages (i.e., the minimum wage) across all counties. However, some localities had high concentrations of top executives while, in others, people in the top-income brackets were professionals, such as accountants or teachers. Thus, high income per capita is associated with high income dispersion. This variable is significant in the parsimonious model, but it becomes less statistically significant as more variables are included, largely because of its high degree of correlation with other socio-economic variables.

The poverty indicator has a positive and statistically significant effect on the county-level income distribution. That is, having a higher percentage of people under the poverty threshold indicates a higher level of income inequality in Virginia's localities.[11] These results are strong and robust in all six model specifications. Peters (2012) found the opposite—that high poverty rates were associated with lower income inequality. Both results are plausible. The direction depends on the general income compositions of communities. In low-income communities, high poverty rates are associated with a low level of income for a large number of residents, thus indicating lower income inequality. However, in high-income areas, high poverty rates would imply greater income dispersion—a society with a bipolar type of income distribution. It seems that Virginia belongs to the second category of relatively wealthy places with areas of high poverty, indicating high income disparity.

Furthermore, the commuting pattern had a strong effect on income distribution, indicating labor market mobility is an equalizer of income distribution, but its robustness was

[10] To illustrate this point, in a community with only high school and college graduates, without spillover effects, the Gini coefficient would increase from 0 to 0.1 as the percentage of college graduates increases from 0 to 0.5 and would decline afterward. With Moretti's spillover effects, the Gini coefficient would increase from 0 to 0.1 as the share of college graduates increased from 0 to 0.4 and would decline afterward as the share of college graduates continued to rise. Thus, even with the Moretti spillover effect, as long as the share of college graduates is relatively low, the high percentage of college graduates is associated with a high Gini coefficient.

[11] Virginia is one of the most affluent states in the country, with a poverty rate of about 10 percent, much lower than the national average. If poverty rates are high, this relationship may reverse.

weaker than that of college education and poverty but stronger than that of income per capita. Coefficients only of two of the six models were statistically significant at the 95 percent level although three were statistically significant at the 90 percent level. All these models indicate that having a high share of residents commuting to work outside of the county could reduce income inequality. This result supports that of Shelnutt and Yao (2005). People commute from their counties of residence because the wages they can earn from jobs in other counties are clearly higher than those they can earn in their home counties. If this was not true, people would not commute as it adds a burden to a household's budgets, both monetarily through direct transportation expenses and through its leisure and work-time preferences via the opportunity costs of the commuting time itself. For example, County A and County B are similar in their socio-economic conditions. If a large number of low-income residents in County A commute out of the county to work, earning a higher income from outside jobs can reduce income gaps in County A, reducing income inequality. On the other hand, if a large number of high-income residents commute and receive higher incomes elsewhere, they could increase the income gaps in their home counties. Thus, the manner by which commuting can affect income distribution depends on the income composition of the commuters. In Virginia, it appears from the findings here that the number of commuters earning high incomes may be smaller than the number of low-income commuters. The net effect is that high commuting activity tends to reduce income gaps among residents.

For policy variables, the local property tax has a negative effect on the county-level Gini coefficient, with a high property tax rate indicating a more equal income distribution. This result was not generally robust across all six models, however. A high property tax attracts fewer low-income households because they may be priced out of the housing market, making the locality more homogenous with high-income households. On the other hand, a lower property tax rate in rural areas in Virginia can attract low-income households, as well as very wealthy households with large estate homes who want to minimize their property taxes, resulting in high income inequality.

Several studies (Marcouiller, Kim, and Deller, 2004; Shelnutt and Yao, 2005; Peters, 2012) have found that industry mix plays an important role in affecting county-level income distribution,. Model 5 aggregates all industries into four sectors – agricultural, manufacturing, services, and government, but only three are included to avoid over-identification issues through multicollinearity. The concentration of the manufacturing industry seems to be correlated with increased income inequality, although the coefficient estimate is statistically significant at the 90 percent level. High concentrations of service or agricultural industries appear to have no statistically detectable effect on income inequality. As mentioned, no consensus exists about the set of industries that might be introduced reduce or decrease income inequality. Peters (2012) found that construction and Marcouiller, Kim, and Deller (2004) found that tourist employment can reduce income inequality. Other studies, such as Shelnutt and Yao (2005), found that professional and service industries can increase income inequality.

5.2 **Effect of Business Attraction Efforts**

Different combinations of business attraction variables were tested. First, Model 3 included the total number of jobs attracted and total amount of investment in a locality. The resulting coefficient estimates for investment per capita were not statistically significant. However, jobs per capita had a positive and statistically significant effect on the Gini coefficient. This suggests that the overall business attraction efforts, in terms of attracted investment amount, had no effect on improving or decreasing the income distribution. But, more jobs per capita do tend to enhance regional income inequality. This suggests that attracting new jobs tends to benefit high-income workers, which in turn increases area income inequality.

This result has negative implications for economic development efforts, at least vis-à-vis county-level income distribution. But maybe it is a matter of the types of jobs created. So let us explore the matter in greater detail.

Typically, economic development efforts can help reduce income inequality if the jobs created are taken by individuals in the lower income bracket or unemployed workers, increasing their incomes. Those efforts improve upward income mobility and income equalization for low-income residents. Recall that in Virginia many of the jobs created between 2000 and 2005 were professional and management jobs. Such jobs require workers with high levels of education, basically those already earning higher incomes, so their arrival in Virginia either increased incomes of existing high-income workers in the area or brought even more high-income workers to the area. Thus, it may be that those jobs that were attracted were not ones likely to equalize the income distribution at the local level in Virginia. Nevertheless, business attraction efforts in different industries may affect local income distribution differentially. Thus, treating business attraction efforts in aggregate across all industries likely masks those varying effects.

To test the hypothesis that jobs attracted in various industries have different effects on income inequality, Model 2 includes the manufacturing and the professional and business services jobs separately. The results confirmed that manufacturing jobs appear to reduce local income inequality. For example, each additional new job per capita in the manufacturing industry appears to reduce the Gini coefficient by 0.42 (Model 2). These results are robust across different model specifications, possibly because jobs created in the manufacturing sector tend to be taken by people in lower income groups, perhaps many of them previously unemployed because of widespread outsourcing over the past decades. When low-income local residents take those jobs (it is unlikely that people will migrate or commute far for low-income jobs) , which increases the income of lower-income residents, it should reduce the income gap. This result is robust and statistically significant at a 95 percent confidence level for all six models.

On the other hand, many of the professional jobs attracted to Virginia are in corporate headquarters and high-tech companies. For example, in recent years, Virginia was able to lure several Fortune 500 headquarters, including Northrop-Grumman, Mead Westvaco, and SAIC. Such corporate relocations brought high-paying executive jobs to certain Virginia localities. Business-attraction efforts of this sort expand the earning power of those already in relatively high-income groups; thus such jobs do not reduce income inequality. Indeed, to the contrary, they apparently increase income inequality. These results are robust across different model specifications. One additional job per capita in the professional and business services industry can increase the Gini coefficient by 0.28 (Model 2).

The model results also show that it is job attraction rather than investment that is more strongly associated with income distribution. Neither total investment (Model 3) nor investment by industry (Model 4) proved to be statistically associated with the county-level income distribution. This appears to be due to the highly varying relationship between investment and job created across industries (Table 1). The great difference in capital intensity across industries seems to be the key. Some business attraction efforts require high investment but create very few jobs (such as power generation). The low job count makes it hard for the investment affect the income distribution, which is largely affected by shifts in population across income levels. Hence, job creation necessarily has a more immediate effect on income distribution at the local level since more households are likely to alter their relative income levels.

The five-year cumulative business attraction data were chosen for data availability reasons. Many initial demographic and social economic variables were available for 2000, and the Gini coefficient data indicate the average of 2006 to 2010. The results indicate five-year cumulative business attraction efforts affect county-level income distribution. Using a similar technique used by Rodriguez-Pose and Fratesi (2004), I used single-year business attraction data from 2000 to 2005 as independent variables, but this yielded insignificant results. However, using 3- or 4-year cumulative business attraction data yielded significant results, indicating that size matters in this context and the accumulation of several years' effort makes a difference.[12]

Considering the job attraction efforts reported by VEDP in Section 3, it is apparent that Virginia focused on job attraction in two sectors: (a) professional and business services and (b) manufacturing. The state should continue its efforts to attract manufacturing jobs, which can benefit people at the low end of the income spectrum and reduce income inequality in a community. Despite the fact that attracting jobs in the professional and business service sector tends to increase income inequality, the state may want to pursue such a strategy for other reasons, such as improving overall economic growth and job creation or increasing state or local tax revenues.

6. CONCLUSION

This paper extends the current literature on local income distribution by explicitly exploring the effect on local income distribution of business attraction efforts by a state government. It finds that not all jobs are equal in effecting change in income distributions, at least not in Virginia. In particular new manufacturing jobs reduced income inequality while new jobs in the professional and business service sectors make it more disparate. I postulate that manufacturing jobs tend to be taken by local residents in the lower-income range, so they effectively increase income of low-income residents, thereby improving income distribution.

This model has two possible extensions that should be examined in the future. First jobs in this study are direct jobs only. But, in general equilibrium, indirect and induced jobs support by the direct jobs, and such "subsequent" jobs may affect local income distribution in a very different manner. Thus, the nature of these indirect and induced jobs—including their spatial connection to the direct jobs and their impact on local economic development—needs more investigation. The second avenue for research is investigating how state business attraction efforts may crowd-out the effects of other, perhaps more valuable, economic development efforts the state could undertake. That is, state investment used for business attraction could be used to invest in transportation and communications infrastructure, social assistance, or education and training, among many other possibilities. These other investment alternatives undoubtedly have varied impacts on local income distribution. In this vein, the relative dynamic effect of business attraction efforts need to be evaluated as well.

Different methodological approaches should be used as well. It would be helpful if future research in this area is able to use panel data. Currently, small sample sizes force concerns with

[12] Those regression results were not reported to keep this paper to a reasonable length.

the degrees of freedom, so that an estimation strategy limited the number of independent variables that could be tested in the course of the present study. A deep panel would likely enable more interaction among variables, Moreover, panel data can enable better control for omitted variable bias via locality-specific fixed effects.

The present study showed that some demographic and socio-economic variables (here, specifically education and poverty) may have thresholds that affect income inequality. No consensus has developed for the role of the variables on income distribution. A deeper investigation into them could help reconcile some mixed results that persist in the literature concerning demographic and social economic factors.

Because of very specific state-policy programs, as well as the existing social economic conditions of Virginia, the results of the present study likely cannot be readily extended as recommendations to other states. For example, in those regions where the manufacturing industry enjoys higher-than-average wages, manufacturing jobs may actually increase income inequality. Nonetheless, the framework and approach used in this study could be generalized toward further research on business attraction efforts on income distribution in other regions.

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