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Big-Box Retailers and Personal Income Growth in the U.S.

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Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, MA, July 31-August 2

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Abstract

This paper addresses a research gap in the literature by investigating the impact of big-box retailers' presence on personal income growth in U.S. counties between 2000 and 2005, based on neoclassical growth models of cross-country income convergence. Whether big-box retailers have a negative effect on local economic growth has been a permeating question amongst regional developers, policy makers and economists. Walmart's and Target's economic impacts are estimated in regards to the degree in which their individual presence affects personal income growth. Different model specifications are applied in the analysis, including spatial models that control for spatial autocorrelation. Results suggest that counties with the presence of both Walmart and Target stores have experienced slower growth in personal income - even after controlling for spatial autocorrelation. Walmart's individual effect on personal income growth is negative and highly significant. Target's individual effect is also negative, but statistically insignificant after controlling for spatial dependence.

Key Words: Personal Income, Growth, Income Convergence, Spatial Econometrics, Walmart, Target.

JEL Codes: O47, O51, R11

1. Introduction

During the last two decades, big-box retail stores such as Walmart and Target have become the focus of a series of studies researching their impacts on local economic outcomes (i.e. employment, wages, poverty level, food prices, etc.) within specific regions, states, counties and localities in the U.S. The sizable growth and expansion of these big-box retailers, especially Walmart, have drawn significant attention from the media, other retailers, local policymakers and academics (Bonanno and Goetz, 2012). According to Walmart annual reports, Walmart has sustained a positive growth in net sales in spite of recent tumbles in the global economy. In the U.S. alone, Walmart employs over a million associates with a total of 4,516 stores along with more than 600 Sam's Clubs (Walmart, 2015). Additionally, similar retail stores such as Target, which is a more upscale big-box retailer, and yet has to some extent mirrored Walmart's growth across the U.S. (Basker, 2007). To date Target has a total of 1,795 stores in the U.S. and 347,000 team members worldwide (Target, 2015).

A large amount of previous research has focused on examining Walmart's effect on local economic outcomes (i.e. employment, wages, poverty level, food prices, etc.) within specific regions, states, counties and localities in the U.S. This is perhaps a byproduct of Walmart's aggressive and large expansion throughout the U.S., its industry leader status, and success over its common competitors such as Kmart and Target (Basker, 2007). In fact, the degree to which Walmart's impact on local economies is quantitatively or qualitatively different from the effect of other "big-box" retailers such as Costco, Target, or Kmart, remains an important open question (Basker, 2007). One exception is Jia (2008), who estimates the effect on small general merchandise stores from both Kmart and Walmart, and concludes that they have similar impacts on the small stores' exit decisions. In this paper Walmart's and Target's impact is estimated along with the degree to which their individual or aggregate presence affects personal income growth in U.S. counties. Different model specifications are applied in the analysis including a spatial error model to control for spatial autocorrelation.

Some relevant studies in the literature include Keil and Spector (2005), which examines the effect of Walmart on income differentials and unemployment between the black and white populations in Alabama - using county census data from 1980 and 1990. They find that Walmart's presence significantly correlates to lower unemployment for blacks, while the impact on income is trivial after controlling for other socio-economic variables. Basker (2007) explores Walmart's competitive advantage and how its presence affects consumer prices, local labor markets, global and local competitors including Target, suppliers and product selection. Although the study is more of a qualitative analysis and survey of the literature on Walmart, the author emphasizes how Walmart's location decision depends on the local economic conditions. Basker (2011) uses quarterly data for 1997-2006 to estimate the aggregate income elasticity of revenue for Walmart and Target. She finds that during an economic downturn, Walmart's revenues increase whereas Target's revenues decline.

In a related vein, Jantzen, Pescatrice, and Braunstein (2009) use cointegration techniques and causality tests to examine the relationship between Walmart sales and a set of macro measures of income, employment, production, and prices. They conclude that Walmart's sales soar during periods of slow economic growth and decline during periods of economic boom. However, their study uses aggregate data (national level) and does not account for other competing retailer's economic impact. It is important to note that for the average consumer, Walmart is perceived as a discount haven. As such, Walmart's entry is considered to have an overlapping effect, since its lower prices indirectly influence competing stores to lower their own prices. This indirect effect is accounted to vary from 3% in overall to 13% for specific items (Basker, 2005a, Hausman and Leibtag, 2007).

In general, the impact of Walmart's entry on local retailers' sales is considered to be negative for direct competitors although some complementary establishments may reap positive benefits from Walmart's presence (Ailawadi, et al., 2010, Artz and Stone, 2006, Irwin and Clark, 2006, Jia, 2008, Stone, 1995). Similarly, other studies link Walmart and large discount chains' presence to the closure of small shops in downtown and local main streets, declines in employment and wages, community disruption and higher poverty (Goetz and Swaminathan, 2006, McGee and Gresham, 1996, Quinn, 2005). However, Barnes, et al. (1996) do not find a negative effect on the number of establishment nor their sales due to Walmart presence in Northeast markets. On the other hand, some researchers have focused specifically on the effect from Walmart's presence on local retail employment and wages (Basker, 2005b, Bernstein and Bivens, 2006, Hicks, 2007, Ketchum and Hughes, 1997, Neumark, Zhang and Ciccarella, 2008). While some authors find modest gains in employment as a result of Walmart's entry (Basker, 2007, Basker, 2005b, Hicks and Wilburn, 2001, Ketchum and Hughes, 1997), others argue on decreasing employment (Hicks, 2008, Hicks, 2007, Neumark, Zhang and Ciccarella, 2008). Most studies find little to modest increases in retail wages for areas with a Walmart (Goetz and Shrestha, 2009, Hicks, 2008, Hicks and Wilburn, 2001, Ketchum and Hughes, 1997). However, Neumark, Zhang and Ciccarella (2008) find slight decreases on retail payroll (wages) due to Walmart's presence.

This research intends to address a research gap in the literature by investigating the local economic impact of Walmart's and Target's presence on county level personal income growth in the U.S. counties, within the 48 contiguous states. To the best of the authors' knowledge, there is no study that investigates the effect from Walmart and Target stores in regards to the degree in which their individual or aggregate presence affects personal income growth in U.S. counties - while controlling for spatial autocorrelation. The empirical model is built upon the theoretical framework of neoclassical growth models of cross-county income convergence (Barro and Sala-i-Martin, 1992, Mankiw, Romer and Weil, 1992). The research objective is to determine if there is a relationship between personal income growth and the presence of Walmart and Target stores.

2. Methodology and Data

2.1. Income Growth Model

The model in equation (1) is based on neoclassical growth models of cross-country income convergence, i.e., poor countries tend to grow faster and catch up with rich countries, as in Barro and Sala-i-Martin

(1992), and Mankiw, Romer and Weil (1992), to evaluate the impact of Walmart's and Target's presence on personal income growth:

$$\delta_i = \beta_0 + \beta_1 wlmt_{2000,i} + \beta_2 trgt_{2000,i} + \beta_3 \ln Y_{2000,i} + \boldsymbol{\theta}'\mathbf{E}_{2000,i} + \boldsymbol{\phi}'\mathbf{X}_{2000,i} + \sigma_s + \varepsilon_i, \tag{1}$$

where $\delta_i = \ln Y_{2005,i} - \ln Y_{2000,i}$ is the personal income growth rate between 2000 and 2005 in county i. The base year is 2000. The period of analysis is selected according to the data availability at the county level for Walmart and Target, as well as to the socio-demographic data from the US Census. The term $wlmt_{2000,i}$ denotes the number of Walmart stores in county i in year 2000; $trgt_{2000,i}$ is the number of Target stores in county i in year 2000, and $\ln Y_{2000,i}$ is the natural log of per capita personal income in year 2000; $\mathbf{E}_{2000,i}$ is a vector of shares of earnings for the county industry sectors considered in the analysis; $\mathbf{X}_{2000,i}$ is a vector of socio-economic and demographic variables measured in year 2000; σ_s is the state-specific dummies for the fixed effect, and ε_i is the error term. The coefficients β_1 and β_2 in equation (1) test the statistical significance of the effect of Walmart's and Target's presence on personal income growth.

2.2. Controlling for Spatial Dependence

Analysis of regression relationships with sample data that is spatial in nature can produce spurious estimation results. This is because spatial data typically violates the assumption made by ordinary regression models in which each observation is assumed to be independent of other observations (LeSage, 2014). For the income growth model proposed in equation (1) spatial econometrics is used to account for the presence of potential spatial effects in the regression analysis. An extensive overview of the relevant methodology is beyond the scope of this paper, but technical aspects of spatial regression diagnostics are reviewed in Anselin (1988), Anselin and Bera (1998), Anselin (2001), LeSage and Pace (2009), LeSage (2014), among others.

To test the presence of spatial dependence in the sample data, the Moran's I test as in Cliff and Ord (1972) is calculated. As discussed in Anselin and Bera (1998), the test was originally developed as a two dimensional analog of the test of significance of the serial correlation coefficient in univariate time series. In Cliff and Ord (1972), Moran's I statistics is formally expressed as:

(2) $$I = \frac{N}{S_0}\left(\frac{\mathbf{e}'\mathbf{W}\mathbf{e}}{\mathbf{e}'\mathbf{e}}\right),$$

where $\mathbf{e} = \mathbf{y} - \mathbf{X}\widehat{\boldsymbol{\beta}}$ is a vector of least squares residuals, $\widehat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$, $\mathbf{W}$ is the spatial weights matrix based on contiguity or distance, N is the number of observations, S_0 is a standardized factor that is equal to the sum of spatial weights, or $\sum_i \sum_j w_{ij}$. Here S_0 simplifies to N for a row-standardized weights matrix $\mathbf{W}$, because each row sum equals 1. The Moran's I statistic then becomes

(3) $$I = \frac{\mathbf{e}'\mathbf{W}\mathbf{e}}{\mathbf{e}'\mathbf{e}}.$$

A statistically significant Moran's I statistic suggests a problem with spatial autocorrelation. Different model specifications may be used once spatial autocorrelation is detected in order to address this matter. These include the spatial lag and spatial error regressions. First the spatial lag model is shown in equation (4):

(4) $$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where $\mathbf{y}$ is a N by 1 vector of the dependent variable, $\mathbf{W}\mathbf{y}$ is the spatially lagged dependent variable with weights matrix $\mathbf{W}$, ρ is the spatial autoregressive parameter, an N by K matrix of explanatory variables is given by $\mathbf{X}$, $\boldsymbol{\beta}$ is a K by 1 vector of coefficients, and $\boldsymbol{\varepsilon}$ is a N by 1 vector of errors. The reduced form of the spatial lag model is expressed as:

(5) $$(\mathbf{I} - \rho\mathbf{W})\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where $(\mathbf{I} - \rho\mathbf{W})\mathbf{y}$ is a spatially filtered dependent variable (i.e., with the effect of spatial autocorrelation removed). This is somewhat analogous to first differencing the dependent variable in time series. However, the $\rho = 1$ scenario is not allowed in the parameter space of equation (5). Correspondingly, the spatial autoregressive parameter ρ must be explicitly estimated. The independent variables explain the variation in the dependent variable that is not explained by the neighbors' value or autoregressive parameter.

As described in Anselin and Bera (1998), a second way to incorporate spatial autocorrelation in a regression model is to specify a spatial process for the disturbance terms. Anselin and Bera (1998) present the most common specification as a spatial autoregressive process in the error terms:

(6) $$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \lambda\mathbf{W}\boldsymbol{\varepsilon} + \mathbf{v},$$

where λ denotes the spatial autoregressive coefficient for the lag of the error $\mathbf{W}\boldsymbol{\varepsilon}$, $\mathbf{v}$ is an uncorrelated and homoscedastic error term, $\mathrm{E}(\mathbf{v}) = 0$, $\mathrm{E}(\mathbf{v}\mathbf{v}') = \sigma^2\mathbf{I}$. Alternatively, (6) may be rewritten as

(7) $$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{v}.$$

Despite the power in Moran's I statistic to detect model misspecifications (and not simply spatial autocorrelation), it is not suitable in suggesting the alternative model specification that should be used. As such, the spatial regression model selection is done using Lagrange Multiplier test statistics. Although initially the range of available test statistics for spatial autocorrelation may be puzzling, one can follow a fairly intuitive process or decision rule for a spatial regression model selection as shown in results section.

3. Data

The selection of variables for the model in equation (1) follows the economic growth literature including Acemoglu, Johnson and Robinson (2003), Bloom, Canning and Malaney (2000), Dixit (1973), Higgins, Levy and Young (2006), Lucas (1988), Malmberg (1994), Mankiw, Romer and Weil (1992), Quigley (1998), Zak and Knack (2001), and James and Aadland (2011). The period 2000-2005 is selected based on data availability at the county level for Walmart and Target stores, along with the socio-demographic data from the US Census. A control variable with the share of earnings in the high-tech industry sector is introduced for 2000, in order to control for the dot-com bubble. The sample data covers 3,050 counties in the 48 contiguous States of the U.S., after dropping 94 counties due to missing data.

Personal income and population data are obtained from the Bureau of Economic Analysis (BEA). The BEA defines personal income as the income received by persons from all available sources. It is the sum of net earnings by place of residence, property income, and personal current transfer receipts. For the sample, personal income (per capita) in current dollars is deflated using the 2009 GDP deflator. Industry earnings (percentage of total industry earnings) are obtained from the US Census Bureau's County Business Patterns database for the natural resource sectors (the sum of agriculture, forestry, fishing, and mining) and high-tech sectors.[1] Other socio-economic variables such as percentage of population with only high school diploma, percentage of population with a college degree or higher, poverty rate, and population density (metro dummy)[2] are compiled from the U.S. Census Bureau database. Similarly, longitude and latitude data for the spatial analysis are compiled from the U.S. Census Bureau.

The Walmart variable measures the number of stores in year 2000 at the county level. The number of Walmart stores during this period is compiled from Holmes' (2011) database which is available at http://www.econ.umn.edu/~holmes/data/WalMart/, and normalized by population (per 100,000 inhabitants). Walmart made a public file which lists a Walmart store, address, store number, store type (supercenter or regular one), and opening data in November 2005. Holmes (2011) combines these data with additional information posted at Walmart website and lists the opening date for each store. For the analysis in this chapter, the store count by county in year 2000 is generated using Holmes' data set. Target store count was generated in a similar fashion using the Target Store Openings data available at FLOWINGDATA https://flowingdata.com/2009/10/22/target-store-openings-since-the-first-in-1962-data-now-available.

Definition of the variables in the model and descriptive statistics are presented in Table 1. The average income growth rate is 7% (median 6%) between 2000 and 2005 across the counties in the sample. The average number of Walmart per 100,000 inhabitants is 1.51 in 2000, while for Target this figure is only 0.16. The average share of earnings in resource sector is about 2.2%, while the high-tech sector share of earnings accounts for 3% across counties. In 2000, an average of 16% of the population held at least a college degree, while the average poverty rate sat at 14%.

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[1] The NAICS code considered in formulating the share of earnings for the "high-tech" most relevant industries to the dot-com bubble include 334 (Computer and Electronic Product Manufacturing), 51 (Information), 5415 (Computer Systems Design and Related Services), 5417 (Scientific Research and Development Services), 5232 (Securities and Commodity Exchanges), 8112 (Electronic and Precision Equipment Repair and Maintenance).

[2] Metro dummy= 1 if population per square mile in 2000 exceeds 300, else zero following James and Aadland (2011).

Table 1. Definition of Variables and Summary Statistics

Variable	Definition	Mean	Std. Dev.	Min	Med.	Max
δ	Growth in personal income between 2000 and 2005	0.07	0.08	-0.31	0.06	0.71
$ln(Y_{2000})$	Personal income per capita in 2000	10.25	0.22	9.42	10.24	11.52
Walmart	No. of Walmart stores (per 100,000 people) in 2000	1.51	2.07	0	0.64	16.50
Target	Number of Target stores (per 100,000 people) in 2000	0.16	0.83	0	0.00	24.70
Resources	% of earnings in natural resources in 2000	0.02	0.07	0	0.00	0.96
High-tech	Percent of earnings in high-tech industries in 2000	0.03	0.04	0	0.01	0.40
High School	% of population with only high school education in 2000	0.35	0.07	0.11	0.35	0.53
College	% of population with at least a college degree in 2000	0.16	0.08	0.05	0.14	0.61
Young	Percent of population that is less than 18 years old in 2000	0.26	0.03	0.15	0.25	0.45
Old	Percent of population that is at least 65 years old in 2000	0.15	0.04	0.02	0.14	0.35
Poverty	Percent of population at or below poverty line in 2000	0.14	0.07	0	0.13	0.57
Ethnicity	Percent of Caucasian population in 2000	0.82	0.19	0.02	0.90	1.00
Metro	1 if population/square mile in 2000 exceeds 300, else zero	0.10	0.30	0	0.00	1

Notes: $N = 3050$ observations for all variables in the sample. Figures have been rounded to the nearest decimal.

4. Empirical Results

4.1. Least Squares Estimation

The robust standard error OLS results from equation (1) are shown in Table 2. As shown in Table 2, five different regression models are estimated to control for initial income, shares of industry earnings (resource, high-tech), human capital, age structure, ethnicity, poverty, and population density (metro dummy). In all five regressions, state-specific fixed effects were included, but estimated coefficients are not reported to save space. Instead, F statistics for joint significance are reported in. The coefficient for the Walmart variable is negative and significant in all models, and it suggests that counties with a Walmart presence have grown slower in terms of personal income. This negative relationship between Walmart and personal income growth can also imply that more Walmart stores might slow down the local economic growth due to the possible closure of small downtown and main street stores, leading to declines in employment and wages, as noted in McGee and Gresham (1996), Quinn (2005) and Goetz and Swaminathan (2006).

Table 2. Robust Estimates for Income Growth

Variable	Model 1 Coeff. (std. err.)	Model 2 Coeff. (std. err.)	Model 3 Coeff. (std. err.)	Model 4 Coeff. (std. err.)	Model 5 Coeff. (std. err.)
Constant	0.0965***	1.3798***	1.3506***	1.8983***	1.8704***
	(0.0060)	(0.0862)	(0.0878)	(0.1914)	(0.1900)
Wal-Mart	-0.0018***	-0.0024***	-0.0023***	-0.0019***	-0.0018***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Target	-0 .0054***	-0.0025*	-0.0026*	-0.0032*	-0.0031*
	(0.0019)	(0.0014)	(0.0014)	(0.0016)	(0.0016)
$\ln(Y_{2000})$		-0.1264***	-0.1237***	-0.1930***	-0.1902***
		(0.0084)	(0.0086)	(0.0195)	(0.0194)
Resources			0.0659**	0.0856***	0.0843***
			(0.0263)	(0.0272)	(0.0273)
High School				-0.0502	-0.0511
				(0.0452)	(0.0452)
College				0.3353***	0.3595***
				(0.0489)	(0.0495)
Young				0.3150***	0.3151***
				(0.0733)	(0.0729)
Old				0.3552***	0.3475***
				(0.0548)	(0.0546)
Poverty				0.0023	0.00451
				(0.0454)	(0.0454)
Ethnicity				-0.0069	-0.0075
				(0.0130)	(0.0130)
Metro				-0.0074	-0.0036
				(0.0045)	(0.0045)
High-tech					-0.1306***
					(0.0385)
F stat. state FEs	25.79***	24.16***	23.45***	13.51***	13.90***
R^2	0.230	0.317	0.319	0.355	0.357

Notes: Superscripts ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Robust standard errors are in parentheses. The state fixed-effects estimates are not shown. However, the F statistic are reported for the joint significance of the state fixed-effects. The R^2 values are reported for each OLS estimation.

The coefficient for the Target store variable also shows a negative relationship with respect to personal income growth. One can interpret these results as Target also having a negative impact on local personal income growth. However, the target coefficient is only significant at the 10% significance level for most of the models shown in Table 2. Meanwhile, other estimates for equation (1) show that the logged initial income has a negative and statistically significant coefficient. This is consistent with the theory of the conditional income convergence (Higgins, Levy and Young, 2006), i.e., poor regions grow faster. The share resource earning coefficient is positive. This is contrary to the "curse of natural resources" argued in James and Aadland (2011). This curse refers to the link found in the resource literature between lower economic growth and natural resource dependence. The coefficient on high-tech earnings, as expected, is negative and statistically significant. This indicates that counties with a larger share of earnings in high-tech industries have experienced slower income growth. This is likely as a result of the dot-com bubble burst during early 2000s. Human capital variables such as college (percent of population with at least a college degree in 2000) have a positive and significant influence on personal income growth as suggested in Higgins, Levy and Young (2006), Lucas (1988), and Mankiw, Romer and Weil (1992). The poverty rate and the ethnicity variables have the expected sign. The density (metro dummy) coefficient is negative although not significant.

4.2. Spatial Models

Following the spatial regression decision process outlined in Anselin (2004), the OLS regression model is estimated along with the diagnostics for spatial dependence. The OLS model specification follows equation (1). The spatial weight matrix used in the spatial analysis is a distanced-based spatial weight matrix, with a distance band of 90.84 miles. This is the minimum distance threshold ensuring that each county will have at least one neighbor. The county centroids are approximated using GeoDa (https://geodacenter.asu.edu/), since the longitude and latitude data is unprojected. The regression diagnostics reveal considerable non-normality and heteroscedasticity. This indicates the presence of heteroskedastic errors, possibly as a result of spatial autocorrelation. The diagnostics for spatial dependence are given in Table 3. A total of five test statistics are reported.

Table 3. Diagnostics for Spatial Dependence

County Distance Weight Matrix (row-standardized)		
Tests	Statistic Value	P-value
Moran's I (Error)	19.50	0.000
Lagrange Multiplier (LM) (Lag)	279.26	0.000
Robust LM (Lag)	55.96	0.000
Lagrange Multiplier (LM) (Error)	231.94	0.000
Robust LM (Error)	8.63	0.003

Notes: The distanced band used in the weight matrix is 90.84. This is the minimum threshold distance ensuring that each county will have at least one neighbor.

The spatial lag model is estimated by maximum likelihood methods. The model follows a similar structure as in (5). The estimates and measures of fit are also given in Table 4. The pseudo-R^2 is not directly comparable with the measure given in the OLS estimation results in Table 4. Nonetheless, more appropriate measures of fit are reported (e.g., Log-Likelihood, AIC, and SC). For comparison purposes, the spatial error model is also estimated and reported in Table 4.

Comparing these values to those for OLS, one can notice an increase in the value of log-likelihood. Additionally, considering the fit with respect to the added spatially lagged dependent variable, both the AIC and SC decrease relative to OLS estimates. This again suggests an improvement of fit for the spatial lag specification over least squares. The spatial autoregressive coefficient (rho) is 0.4941, and highly significant. Similar to the OLS results in Table 4, for the spatial lag model the coefficient for Target is negative but not significant (at the 5% level). This means that Target's presence alone may not have an impact on personal income growth after controlling for spatial dependence. The coefficient on Walmart for the spatial lag model although slightly smaller relative to the OLS results, it is also negative and highly significant. This implies that Walmart presence in year 2000 had a negative impact on personal income growth between 2000 and 2005. All the other coefficients are similar (albeit smaller in absolute value) to the OLS; except for poverty rate, ethnicity and metro dummy that changed signs, and high school variable that becomes statistically insignificant. Overall, the explanatory power of the model in (1) that had been attributed to their own in-county value has been improved due to the consideration of neighboring counties. The coefficient of the spatially lagged dependent variable picks up this effect.

Table 4. Spatial Analysis for Income Growth

Variable	OLS (Model 5) Coeff. (std. err.)	Spatial-lag Coeff. (std. err.)	Spatial-error Coeff. (std. err.)
Constant	1.8718***	1.6870***	1.7899***
	(0.1241)	(0.1193)	(0.1230)
Wal-Mart	-0.0018***	-0 .0017***	-0.0017***
	(0.0006)	(0.0006)	(0.0006)
Target	-0 .0027*	-0.0022	-0.0018
	(0.0016)	(0.0015)	(0.0015)
$\ln(Y_{2000})$	-0.1904***	-0.1745***	-0.1828***
	(0.0119)	(0.0115)	(0.0118)
Resources	0.0843***	0.0503***	0.0325*
	(0.0195)	(0.0187)	(0.0195)
High School	-0.0495	-0.0141	0.0019
	(0.0426)	(0.0407)	(0.0443)
College	0.3591***	0.3289***	0.3480***
	(0.0387)	(0.0370)	(0.0390)
Young	0.3155***	0.2562***	0.2689***
	(0.0594)	(0.0568)	(0.0584)
Old	0.3497***	0.2549***	0.2599***
	(0.0468)	(0.0450)	(0.0476)
Poverty	0.0049	-0.0098	0.0152
	(0.0384)	(0.0367)	(0.0390)
Ethnicity	-0.0075	0.0007	0.0075
	(0.0125)	(0.0119)	(0.0136)
Metro	-0.0039	0.0005	-0.0009
	(0.0052)	(0.0050)	(0.0050)
High-tech	-0.1321***	-0.1097***	-0.0911**
	(0.0389)	(0.0371)	(0.0372)
Rho		0.4941***	
		(0.0348)	
Lambda			0.5894***
			(0.0361)
N =	3050	3050	3050
R-squared	0.357	0.402	0.403
Jarque-Bera	8727.9333		
P-value	0.0000		
Bresch-Pagan Test	1111.819	1024.301	1012.833
P-value	0.000	0.000	0.000
Log-likelihood	4058.65	4149.60	4140.8699
Akaike info criterion	-7997.31	-8177.20	-8161.74
Schwarz criterion	-7635.93	-7809.80	-7800.37
Likelihood Ratio test		181.893	164.432
P-value		0.000	0.000

Note: Superscripts ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are in parentheses. The state fixed-effects estimates are not shown. A row-standardized distance-based weight matrix is used to fit the spatial lag and spatial error model. The distanced band used in the weight matrix is 90.84. This is the minimum threshold distance ensuring that each county will have at least one neighbor.

A limited number of diagnostics are provided with the maximum likelihood spatial lag estimation. As shown in Table 4, the Breusch-Pagan test for heteroscedasticity is significant suggesting that heteroscedasticity may still be a problem. The likelihood ratio test (Anselin, 2004), as one of the three classic specification tests, contrasts the null model (the least square specification) to the alternative model (spatial lag specification). The resulting LR value of 181.89 indicates that the spatial autoregressive coefficient is significant. Although the three classic tests are asymptotically equivalent, in finite samples they should follow the ordering: $W > LR > LM$ (Anselin, 2004). For the lag model, the Wald test is $W = 14.22^2 = 202.21$ (the square of the z-value of the asymptotic t-test (not shown), $LR = 181.89$ (Table 4) but LM-lag =279.26 (Table 3). This does not align with the expected order and implies a less than satisfactory model specification so far.

The spatial error model is also estimated to compare the results between the spatial errors and lag model specification (Table 4). In terms of coefficient magnitude, sign and significance, the results are analogous to those of the spatial lag model. As emphasized in Anselin (2004), this highlights the difficulties in discriminating between the two spatial models. The value of the log likelihood in the spatial lag model (4149.6) is marginally better than the spatial error model (4140.87). By the same token, the AIC is lower for the spatial lag model (-8177.2) compared to the error model (-8161.74). Nevertheless, the close similarity between the two models' results and the indication of remaining specification problems advocates further refinement of the model specification.

5. Summary and Concluding Remarks

Whether the big-box retailers' presence, particularly Walmart and Target, have a negative impact on local economic growth has been a permeating question amongst regional developers, policy makers and researchers. This paper examines the relationship between the presence of these big-box stores and personal income growth at the county level between 2000 and 2005. Walmart and Target stores' impacts are estimated along with the degree to which their individual presence affects personal income growth at the level of U.S. counties. Different model specifications are applied in the analyses, including a spatial model to control for spatial autocorrelation.

Empirical results suggest that counties with Walmart and Target stores have experienced slower growth in personal income. After controlling for spatial autocorrelation, Walmart seems to drive the negative impact. The impact of Target is also negative, but insignificant. Even though the spatial model improves the fit of the model, further diagnostics on the spatial model specification (Table 4) indicate some possible remaining misspecifications issues. Presumably, possible endogeneity between the big-box retailers' location decision and personal income growth may be a source of misspecification.

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