Transportation and Infrastructure, Retail Clustering, and Local Public Finance: Evidence from Wal-Mart’s Expansion

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Transportation Infrastructure, Retail Clustering, and Local Public Finance: Evidence from Wal-Mart’s Expansion

Michael J. Hicks

The author examines the role highway infrastructure and local property tax rate variability play in retail agglomeration in Indiana from 1988 through 2003. To account for data errors and the potential endogeneity of taxes and infrastructure on retail agglomeration, he introduces a unique identification strategy that exploits the entrance timing and location of Wal-Mart stores in Indiana. Using a time-series cross-sectional model of Indiana’s 92 counties from 1988 through 2003, he estimates the impact highway infrastructure, property taxes, and big-box competition have in creating regional agglomerations. Among two separate specifications and a full and rural-only set of the data, the author finds considerable agreement in the results. In the full sample, he finds no relationship between property tax rates or highway infrastructure and retail agglomeration. Within the non-metropolitan statistical area (MSA) counties, this relationship is very modest, though it possesses considerable statistical certainty. Highway impacts within the non-MSA counties are significant and positively related to retail agglomeration, with the presence of highways explaining about 10 percent of total agglomeration variability. (JEL R11, R53)

dominant challenge to this type of research (Wasylenko, 1997).1

This paper addresses the role transportation infrastructure and property tax rates play in retail agglomeration in Indiana. I also provide a description of the general changes to the retail sector in Indiana. To correct for the endogeneity concern with regard to retail agglomeration with public infrastructure and taxation, I employ a unique identification strategy that captures active firm entrance decisions by the nation’s leading retail firm, Wal-Mart.

To examine this issue, I review recent studies of the role transportation and public finance play in local agglomeration. I then provide a theoretical description and an empirical model of agglomeration economies and outline my instrument selection. This is followed by a discussion of the data, econometric considerations, and estimation results. I conclude by providing an explanation of the results and routes for further analysis. Before proceeding, it is important to clearly frame the problem I try to solve and outline my strategy and assumptions.

THE RESEARCH STRATEGY

The retail sector is enjoying a resurgence of interest from policymakers. Because retail, like the service sector, is subject to less capital mobility, it factors into an increasing number of economic development investment efforts. Also, a well-developed retail sector is often viewed as an important local amenity that helps attract workers and commerce (Gibson, Albrecht, and Evans, 2003). Regional economists are showing increased interest in the retail sector both because of newfound policy interest and the dramatic changes that have occurred in the sector over the past two decades. These changes are heavily associated with Wal-Mart’s expansion.2

The strategy I pursue in this paper is to evaluate how local tax rates and public infrastructure may influence agglomeration. To do this I focus analysis narrowly on a single infrastructure measurement and limited tax instruments. This process of narrowly examining tax and infrastructure impacts can bias estimates (by omitting important contributing variation), which I seek to avoid by limiting my analysis to a single state—Indiana. The choice of Indiana is motivated by the statewide homogeneity of relevant public finance structure, with the exception of property tax rates, on which I focus my analysis. Unfortunately, this approach suffers the problem of simultaneous determination of agglomeration and tax rates. To address this I exploit the variability in entrance location and timing of the region’s leading retailer, Wal-Mart.

The second concern I address is in my infrastructure measurement. Because I acknowledge the possibility that public infrastructure, broadly defined, plays a role in retail agglomeration, I would prefer to employ measures of infrastructure that fully capture these impacts. Unfortunately, the flow of benefits from public infrastructure is poorly measured.3 To circumvent this, I also use the timing and location of Wal-Mart to correct for this problem. Relegating the econometric discussion to later sections, I follow with a discussion of the problems of endogeneity in public infrastructure and taxation.

The third method I employ is to both structure my model to account for location fixed effects and to estimate separately the full sample of 92 Indiana counties; in a separate regression, I limit my estimation to non-MSA counties. The former consideration was made in response to several leading critics of this type of model, who point out the need for cross-sectional fixed effects (Holtz-Eakin, 1994; and Evans and Karras, 1996). The latter approach is mimicked by Chandra and Thompson (2000), who also examine highway impacts on economic growth at the county level.

ENDOGENEITY IN PUBLIC INFRASTRUCTURE, TAXATION, AND DATA QUALITY

Estimates of the role public infrastructure and taxation play on local economic conditions such
as retail agglomeration are plagued by the potential for endogeneity and data quality concerns. For example, are highways constructed to exploit existing retail patterns, or do they spawn agglomeration? Are property taxes intentionally kept low to foster capital investment, or are they low due to the influence of a politically active business sector? Also, are public infrastructure data, such as the presence or extent of highways, sensitive to local quality differences?

These and similar questions persistently darken much regional economic analysis, and studies of public infrastructure and taxation often treat the problem. Early criticism of studies that did not account for endogeneity include Holtz-Eakin (1994), Evans and Karras (1996), and later Chandra and Thompson (2000). Each of these researchers attempted to avoid endogeneity through specification techniques in panel models (regional fixed effects) or through exclusion of the most problematic data points (for example, MSA counties). I will incorporate both techniques and extend the method to an instrumental variable method that enjoys growing popularity.

The instrumental variable panel method employs multiple equations that evaluate cross sections (such as counties or states) over time. These models may directly outline a structural relationship, use lagged dependent variables, or combine these techniques to account for the endogeneity of the variable under consideration. This is accomplished by first estimating the dependent variable (the first stage) and then estimating the impact of the explanatory variables on the adjusted dependent variable (the second stage). The process is sometimes repeated (a third stage). Unfortunately, though this process is very widely employed, there are several limitations. First, there are no clear mathematical methods that generate an unambiguous choice of the structure of the first equation. The reason is that an appropriate instrument is correlated with the dependent variable, but not the error term (which is not known). This means that the structure of the equation must be supported

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4. The two-state method is known as two-stage least squares (2SLS); with the additional step, it is three-stage least squares (3SLS). Both are also estimated using techniques other than least squares (most usually the maximum likelihood method).

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Despite these limitations (and indeed in the face of counter evidence of endogeneity) many researchers prefer the incorporation of direct corrections of endogeneity in the estimation. This may perhaps be recommended because, in a panel setting, two more palatable improvements on the estimation process are available. The first is a simple first-stage estimate, which includes the lagged independent variables. This process is viewed almost as a default approach in panel models because the direct causal link is indeed broken (it may be argued that no variable in time \(t\) determines another variable in time \(t - 1\)).

6. Second, the use of panel models in general, and instrumental variable methods in particular, are widely viewed as more robust to errors in data than other econometric techniques. Despite these drawbacks of these techniques, their use in this setting is especially appropriate. It is this method I employ to estimate agglomeration of retail trade.

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**AGGLOMERATION, GROWTH, AND PUBLIC INFRASTRUCTURE**

A number of research efforts to identify public infrastructure’s role in agglomeration and growth have appeared in recent years. Transportation infrastructure is often part of broader studies for both policy and technical reasons. Wasylenko (1997) provides a key review of findings, as does Fox and Porca (2001), with the latter focusing on rural growth and the former reviewing the broad literature. Empirical studies include Eberts (1991) and Fox and Murray (1990).

Studies specifically examining the agglomeration/growth nexus include Chandra and Thompson (2000) and Hicks (2002 and 2005b). The former

5. A recent front page *Wall Street Journal* article concerns Caroline Hoxby’s research on school choice (using streams to adjust for the endogeneity of school districts) and an emerging debate on Wal-Mart’s impact. See Dube, Edilin, and Lester (2005), Hicks (2006), and the economics section of *The Economist* for this debate.

6. This relationship is described as a predetermined, not strictly exogenous relationship.
authors evaluate county-level impacts of interstate highways in a quasi-experimental panel setting. They find that the construction of highways leads to aggregate economic growth in counties with the interstate and that selected sectoral earnings increase. (Notably, for our purposes, these include retail trade.) They also find that counties adjacent to interstate highways experience a decline in many of the same sectors, suggesting an inter-regional reallocation. This study is consistent with findings by Holtz-Eakin (1994), whose state-level study found no net increase in economic activity associated with highway construction.\textsuperscript{7} Hicks (2002 and 2005b) examines firm-level productivity along an Appalachian development corridor. Employing three different models, he finds three distinct but related effects. In the first model (a panel vector autoregression), he finds that there is considerable evidence of leakage associated with the construction of a highway. In the second model, in which he tests convergence in a fixed-effects panel model, he finds that even with the leakages, regions tend to experience sectoral-share convergence, suggesting that the net impact of the infrastructure is greater than zero. In the final model (a CES [constant elasticity of substitution] production function), he finds a modest aggregate productivity increase associated with proximity to the highway, amounting to roughly 1 percent per mile. Notably, he finds considerable cross-industry variation. The proximity of the findings in Chandra and Thompson (2000) and Hicks (2002 and 2005b) speak to a familiar story of some potential growth associated with highway construction, but matched by considerable inter-regional reallocation of trade.

More generally, the results of growth on agglomeration are mixed. An example of the difference in similarly focused studies is Harmatuck (1996), who found output elasticities of public investment to average 0.03. These findings were largely supported by Holtz-Eakin and Schwartz (1994), who found little evidence of meaningful linkages between marginal increases in public investment and output changes in private sector economic activity.

\textsuperscript{7} Munnell (1990) and Rephann and Isserman (1994) identified leakages along public infrastructure, which is consistent with both Chandra and Thompson (2000) and Holtz-Eakin (1994).

Other research does find sector-specific linkages, most often in manufacturing. Morrison and Schwartz (1991) find modest increases in manufacturing output associated with aggregate public infrastructure. The retail literature focuses on the transactions costs associated with shopping. The resulting cost savings to consumers are often explained as demand externalities (see Eppli and Benjamin, 1994). More recent studies are turning to supply linkages (Cho, Sohn, and Hewings, 2000), a seemingly important area of inquiry given the dominant role supply chains play in big-box retail locations.\textsuperscript{8}

Variations in the type of agglomeration may also be a factor in the type of public infrastructure impacts. Localization economies (the regional concentration of an industrial sector) may lead to regional scope economies, which share inputs or exploit spillovers to reduce costs that result in one type of agglomeration (see Fujita and Thisse, 1996, for a description of agglomerations). Malmberg and Maskell (2001) note this phenomenon, which the retail literature refers to as demand externalities.

Agglomeration of population due to concentration in urban areas potentially reduces cost through scale economies, which are obviously a growing characteristic of the retail sector in recent years. For example, Boyd (1997) reports the average retail firm size (in terms of sales) grew 40 percent from 1997 to 1992, while the number of firms declined from over 1.8 million to almost 1.4 million. This trend has continued.

Both types of agglomeration should yield similar results in aggregate industry estimates, so I loosely refer to them together for the remainder of this paper. Whichever definition of agglomeration is employed, a far less theoretical concern is the quality of data used in a model. What constitutes a road and, more importantly, what generates a flow of services are difficult to capture in the types of data sets that are publicly available. One clear example is that two census tracks (or indeed two counties) may enjoy the presence of an interstate highway, but only the track with an exit will experience any local benefit in retail trade. Thus, even

\textsuperscript{8} See also Gulyani (2001).
fairly precise data on infrastructure may poorly measure benefits. Despite these limitations, some researchers have examined public infrastructure with some success. Carlino and Mills (1987), using a two-stage least-squares model, found that gross measures of highway infrastructure positively affected aggregate growth rates. Rainey and Murova (2004) found roads provide a direct link to growth in a regional Cobb-Douglass production function. One result of this is the development of local agglomeration. It is not clear, however, that these studies do no not suffer from simultaneity or endogeneity bias. These authors all specified their empirical model in different ways, asserting either production relationships or supply relationships leading to regional variation in a number of measures of interest. The tendency of the literature to focus on manufacturing likely motivates these choices. For the retail sector, agglomeration resulting from travel costs is a clearer presentation. To illustrate the point, it is useful to deal with a description of travel costs. Adapting from Madden and Savage (2000), I posit two inverse demand functions:

$$P_s = \alpha_1^s + \alpha_2^s Q_s$$

$$P_d = \alpha_1^d + \alpha_2^d Q_d$$

with travel costs represented as the difference between the competitive prices for each equation such that $$T = P_d - P_s$$. The equilibrium conditions are, hence,

$$Q^* = (\alpha_1^d - \alpha_1^s - T) / (\alpha_2^d + \alpha_2^s);$$

the first derivative of equilibrium output with respect to travel costs is then

$$\frac{\partial Q^*}{\partial T} = -\frac{1}{(\alpha_2^d + \alpha_2^s)},$$

which is obviously non-positive. Extending this analysis regionally, one can see informally that if $$T > \alpha_1^d - \alpha_1^s$$ in equilibrium, there will be no local retail. Hence, agglomeration will occur in locations with lower transactions costs. (Notably this model could trivially extend this example to taxes.)

In summary, though there are mixed findings about infrastructure across the literature (much of which I have not reviewed), there is at least tentative (and theoretical) evidence of a role of infrastructure in local agglomeration, even if the aggregate general equilibrium effects are not clear. A familiar story might be that infrastructure improves productivity (hence growth), but also reallocates economic activity, which potentially net out. The research also relies on the rather crude estimates of infrastructure to populate the model. However, the role of this paper is not to provide yet another estimate of this relationship broadly, but instead to exploit a unique method of estimating regional variations in public infrastructure not represented clearly by the data. To do this it is also useful to understand the relationship between agglomeration and taxation.

### Agglomeration and Taxation

As with public infrastructure’s role in generating agglomeration, the effects of tax structure on economic development is widely researched. Most studies of local taxation and commercial economic activity focus on footloose industries, such as manufacturing and research and development, that should be more sensitive to local tax issues. Bartik’s (1991) review of existing studies finds that tax elasticity of output ranges from –0.1 to –0.6, with the mean at about –0.3. Other studies include Carlton (1979), Bartik (1985), and Helms (1985), all of whom found property taxes to significantly influence firm location decisions. Few studies have examined property tax rates and retail. Thus, for a population-linked industry such as retail, an ideal choice of tax instrument is local varying property taxes of the type found in Indiana. Tax rates (or calculated effective tax rates) are the dominant measure of taxation in these studies.

As with the issue of public infrastructure, this paper seeks to extend the literature through the application of an instrumentation choice, which serves two purposes: control data errors and eliminate endogeneity.

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10 See Ondrich and Waslenko (1993) and Hines (1996) for examples of studies of corporate tax and industry location.
The Retail Sector in Indiana

Indiana’s retail sector and the upstream wholesale sector have garnered an increasing share of the state’s employment over the past three decades. This is consistent with national trends (see Figure 1), and the mix of retail activity is not dissimilar from the national mix (see Table 1).

Regionally, retail has become very modestly less agglomerated in the recent two decades, with the maximum of the Gini coefficient declining, but with almost no change in the median of the Gini. Another inequality measure, Theil’s T, provides similar results, with very little change in the mean inequality, but with some reduction in extremes. (See Figure 2.)

As with much of the nation, a significant change

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**Table 1**

Percent Difference in Retail Trade Subsector Share, 2000 (Indiana – U.S.)

<table>
<thead>
<tr>
<th>Subsector</th>
<th>Establishments</th>
<th>Sales ($1,000s)</th>
<th>Payroll ($1,000s)</th>
<th>Employees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor vehicles and parts</td>
<td>1.9</td>
<td>0.5</td>
<td>–0.1</td>
<td>–0.4</td>
</tr>
<tr>
<td>Furniture and home furnishings</td>
<td>–0.1</td>
<td>–0.6</td>
<td>–0.4</td>
<td>–0.4</td>
</tr>
<tr>
<td>Electronics and appliance stores</td>
<td>0.0</td>
<td>–0.6</td>
<td>–0.5</td>
<td>–0.3</td>
</tr>
<tr>
<td>Building and garden equipment</td>
<td>1.7</td>
<td>1.2</td>
<td>1.8</td>
<td>1.2</td>
</tr>
<tr>
<td>Food and beverage</td>
<td>–2.0</td>
<td>–2.7</td>
<td>–2.8</td>
<td>–2.9</td>
</tr>
<tr>
<td>Health and personal care stores</td>
<td>–0.6</td>
<td>0.0</td>
<td>0.0</td>
<td>–0.1</td>
</tr>
<tr>
<td>Gasoline stations</td>
<td>0.6</td>
<td>1.2</td>
<td>1.0</td>
<td>1.2</td>
</tr>
<tr>
<td>Clothing and clothing accessories</td>
<td>–2.3</td>
<td>–1.7</td>
<td>–2.0</td>
<td>–2.1</td>
</tr>
<tr>
<td>Sporting goods</td>
<td>–0.1</td>
<td>–0.7</td>
<td>–0.6</td>
<td>–0.8</td>
</tr>
<tr>
<td>General merchandise</td>
<td>0.5</td>
<td>1.9</td>
<td>2.8</td>
<td>3.9</td>
</tr>
<tr>
<td>Miscellaneous retailers</td>
<td>0.4</td>
<td>–0.3</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Non-store retailers</td>
<td>0.1</td>
<td>1.7</td>
<td>0.9</td>
<td>0.7</td>
</tr>
</tbody>
</table>

SOURCE: Bureau of the Census, County Business Patterns, and author’s calculations.
to the retail industry has been the growth of Wal-Mart stores across Indiana. Wal-Mart’s expansion since 1962 has been a much heralded wave emanating from Bentonville, Arkansas, toward the coasts. Although the structure of the entrance decisions have been hotly debated, it is clear that the retailer enters a state proximally to regional distribution centers and fills the void between stores quickly, in perhaps 3 to 5 years. Wal-Mart’s entrance at the state level is marked by a surge of stores, as can be seen in Figure 3. Note the difference in magnitude between entrance in counties with and without interstates (just under half of Indiana counties have interstate highways). Notably, following the initial burst of entrance, only four Wal-Mart stores are located in counties without interstate highway access.

Figure 4 provides a geographic snapshot of the entrance of Wal-Mart stores since 2000. The cumulative impact of Wal-Mart’s presence since 1983 then illustrates the result of this burst of entrance, followed by the lower persistence of Wal-Mart stores entering in predominantly interstate-accessible counties, a pattern that differed from the early focus predominance of entrance into non-interstate counties. (See Figure 5.)

The patterns evidenced by higher retail trade shares and entrance by Wal-Mart accompany a
decrease in spatial distribution differences in retail trade. This is probably best exemplified through an examination of the Moran’s I for retail employment in the state. Moran’s I is a measure of local spatial autocorrelation and is represented as

\[
M_j(\theta) = \frac{n \sum_{i=1}^{n} \theta_i \sum_{j=1}^{n} W_{ij} \theta_j}{W \sum_{j=1}^{n} \theta_j^2},
\]

where \( \theta \) is the Gini index of retail employment. Moran’s I is a straightforward estimate of the degree of local spatial autocorrelation in retail employment inequality in Indiana’s counties. This Moran’s I was calculated annually for each year in the 1988-2004 period. As is clear from Figure 6, Indiana has experienced a large reduction in spatial autocorrelation in retail unemployment.

One conclusion to be drawn from the evidence of spatial agglomerations, Wal-Mart entrance, and the spatial autocorrelation of retail employment inequality is that the increase in retail’s share of employment results in more spatially even distribution in retail accessibility. This is consistent with, among other things, a general reduction in transportation-related transactions costs in retail shopping (at the intercounty level). Of course, a significant proportion of any retail shopping travel occurs within counties and is not addressed in this analysis.

Another facet of this phenomenon is that the growth in the employment share of retail trade accompanies a decline in spatial inequality in employment in general. This should be an especially welcomed finding for rural areas. For the question at hand, these data provide an insight into the average change in retail markets. Of perhaps greater policy import is the marginal effect of fiscal structure and public infrastructure on agglomeration. For answers to this question, I turn to an empirical model of retail agglomeration.

**MODELING RETAIL AGGLOMERATION**

The lesson of the existing literature is that the potential public infrastructure and public finance impacts—in this case property tax rates—on agglomeration warrant empirical analysis. Following a consideration of the theoretical model above (where travel costs of tax rate differentials generate agglomeration), I propose the following empirical model of agglomeration:

\[
A_{i,t} = \beta_1 + \beta_2 \Pi_{i,t} + \beta_3 \Gamma_{i,t} + \delta W A_{i,t} + \phi A_{i-1,n} + \epsilon_{i,t},
\]

where local agglomeration in county \( i \) in year \( t \) is a function of a common intercept and county fixed effects; county property tax rates, \( \Pi \); the number of interstate highways, \( \Gamma \); and the spatial autocorrelation component, \( W A_{i,t} \), which includes the first-order contiguity matrix \( W \) of \( A \), in surrounding

**Figure 4**

**Indiana Wal-Mart Stores, 2000 to Present**
contiguous counties $j$ in time $t$. This first-order contiguity matrix is composed of a value 1 for each county $j$ contiguous to county $i$ and 0 otherwise. The matrix is row standardized to, among other things, account for the differing number of contiguous counties to the 92 counties in the state. This specification includes the time autoregressive components $\phi$, for $A$ in $t-n$ lags. The $\epsilon$ denotes the error term, assumed to be white noise.\textsuperscript{11} To identify this equation, I developed an identification strategy around interpretation of Wal-Mart’s entrance decision.

Wal-Mart’s entrance decision is hotly debated in the literature examining big-box impacts on employment and earnings and fiscal impact. This work has yielded insight into the retailer’s choice. Several econometric studies of Wal-Mart were unable to reject exogeneity of local growth in Wal-Mart’s entrance decision (e.g., Hicks and Wilburn, 2001; Franklin, 2001; and Global Insight, 2005). Basker (2005) offered an entrance-timing dummy to identify the wage and industry structure equations. Neumark, Zhang, and Ciccarella (2005) offer an appealing observation that Wal-Mart built its

\textsuperscript{11} Another common representation of the fixed effects is as a representation of an error component where $e = m + v$, with $m$ being the fixed effect and $v$ the observation varying component of the error term.
retail store network roughly concentrically from Bentonville, Arkansas, extending new firms within a day’s drive of existing regional headquarters. Hicks (2006) provided a market-size instrument based on a radio interview with a Wal-Mart official who claimed market size was a leading factor in site location.\(^{12}\) Hicks (2006) compares exogeneity tests and identification strategies and finds no significant variation across instruments and only modest evidence of endogeneity across a wide variation in choice variables.

The evidence in the Wal-Mart research is useful in identifying a model of agglomeration for two reasons. Concern regarding endogeneity of local tax structures is an important fixture in the public finance literature. Brueckner (2003) offers a thorough review of strategic tax models. Thus, identifying agglomeration based on the dominant firm’s entrance decision should precede the endogeneity concern because its entrance should be correlated with the agglomeration measure, but not the error term in the ordinary least squares specification. Second, Wal-Mart’s well-known supply-chain channels are closely linked to public infrastructure (primarily interstates and their intersections), thus evidence of supply-chain network decisions by the leading retailer should aid in identifying the equation.

One weakness is that the data (and indeed Wal-Mart’s birth) are all subsequent to the interstate highway system, so earlier path dependencies on retail agglomeration are not visible in this modeling effort. Nonetheless, the short-run agglomeration effects are of interest.

Thus, the identifying equation for the estimation takes the form

\[
\tilde{A}_{i,t} = \beta_1 + \beta_2 X_{i,t} + \beta_3 \left[ \theta_{i,t} \right] t + \beta_4 N_{i,t} + \epsilon_{i,t},
\]

where agglomeration, \(\tilde{A}_{i,t}\), is estimated as a function of an intercept; a Wal-Mart entrance dummy, \(X_{i,t}\); a weighted Wal-Mart exposure variable, \([\theta_{i,t}] t\), which is a presence dummy multiplied by a time trend, county population \(N\) in county \(i\), and time \(t\); and the standard white noise error term, \(\epsilon_{i,t}\). Lagged explanatory variables from equation (4) are also included in this specification. This is the identifying equation, to which will be added lagged predetermined variables, as is the common approach for panel models in order to account for the bias caused by ordinary least-squares estimates of spatial lag models. This approach has been referred to as a spatial 2SLS and is shown to be an unbiased, near equivalent of the more computationally demanding maximum likelihood method (Franzese and Hays, 2004).

DATA AND ECONOMETRIC CONSIDERATIONS

The data are from several common sources. The Wal-Mart data are from two data releases by Wal-Mart and are described in some detail in Hicks (2005a). These releases have been employed by a number of studies.\(^{13}\) The data clearly describe the entrance data of Wal-Mart, the county, and whether or not the store is still operating. The big-box data are the sum of all retail establishments with more than 100 employees and are from the U.S. Census Bureau’s County Business Patterns, 1988 to the present, as are retail employment data.\(^ {14}\) The infrastructure data are from the U.S. Department of Transportation, Office of Freight Management, Freight Analysis Framework, and were compared with date information confirmed by the Indiana Department of Transportation. Chandra and Thompson (2000) employed the PR-511 master file, which identifies the opening and closing of each of the highways in the interstate highway system. My data collection problem was considerably less difficult, because most links were completed prior to the beginning of the data period. I code the data as count variables for the presence of each open interstate highway in the county.\(^ {15}\) The tax data are from the Indiana Department of Transportation.

\(^{12}\) Neumark, Zhang, and Ciccarella derived this instrument from a reading of Sam Walton’s autobiography, whereas Hicks relied on a radio broadcast describing market size as an entrance.

\(^{13}\) See Hicks (2005a,b and 2006), Neumark, Zhang, and Ciccarella (2005), and Sobel and Dean (2006).

\(^{14}\) Clearly, the definition of big-box is more than employment and includes store style, but this is used to reflect the presence of other large retailers.

\(^{15}\) I chose to employ this count measure of highways as an improvement of the more commonly employed presence dummy. Other alternative
Revenue and are county-specific property tax rates for commercial property. One caution is that Indiana communities do have some flexibility in assessment of local property taxes. For example, Wal-Mart received tax incentives of mixed types in the location of four facilities in the state (three distribution centers and one store). A detailed treatment of these is offered by Mattera and Purinton (2004). The tax data were available only from 1988 to the present, which is the limit of the analysis. The dependent variable is a modified Theil’s inequality index of retail employment, which was modified to center on 1 for ease of interpretation.  

Each of the variables appears stationary (both visually and through an augmented Dickey-Fuller test), though the relatively brief time series available obviously weakens these tests. Autocorrelation was addressed through the addition of the first-order autocorrelation component. Further, a Hausman test confirms that fixed, rather than random, effects are appropriate in this model. Without testing, I transform each model’s standard errors, using White’s (1980) method to generate homoskedastically distributed errors. Summary statistics of some relevant variables appear in Table 2.

**Table 2**

**Selected Summary Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail employment</td>
<td>2,920</td>
<td>2,227</td>
<td>20,026</td>
<td>165</td>
<td>2,919</td>
</tr>
<tr>
<td>Property tax rate (mils)</td>
<td>7.310</td>
<td>7.683</td>
<td>21.444</td>
<td>1.335</td>
<td>2.849</td>
</tr>
<tr>
<td>Interstate</td>
<td>0.489</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>0.500</td>
</tr>
<tr>
<td>Retail pull factor</td>
<td>1.000</td>
<td>0.994</td>
<td>1.182</td>
<td>0.989</td>
<td>0.022</td>
</tr>
<tr>
<td>Per capita big-box retail</td>
<td>0.00006</td>
<td>0.00005</td>
<td>0.00024</td>
<td>0.00000</td>
<td>0.00005</td>
</tr>
</tbody>
</table>

Specifications were possible (e.g., number of miles of interstate), but I elected not to test that model because I was convinced that the number of miles failed to capture the importance of multiple interstate in measuring the flow of benefits of the highways.

The scaling process also reduces concerns over the normality of the error term. One concern here is in the interpretation of a coefficient, which is essentially a logarithmic transformation of an index value. One interpretive technique championed by Kennedy is in the transformation of the estimated coefficient such that the marginal effect is described as \( \exp \left( \frac{1}{2} \log(\beta) \right) - 1 \). The Theil’s T is the logarithm of the ratio of county retail per capita to state retail per capita.

**ESTIMATION RESULTS AND ANALYSIS**

Table 3 illustrates the estimates of equation (5) above, including two modifications: model 1, without time or space autocorrelation components, and model 3, the additional specification of per capita big-box retail stores. The models are tested on the full sample and rural (non-MSA) counties. The sample period was from the 1990-2003 period, which included 34 suppressed observations in the full sample. The suppressed observations were due to Census protection of firm identities. All of the suppression occurred in the 1990s.

Model 1 in both instances is biased through autocorrelation, which appears both spatially and temporally. The results from models 2 and 3 across all Indiana counties and the non-MSA counties provide insight regarding the urban/rural differences on tax and infrastructure’s impact on agglomeration.

In the state as a whole, property tax rates do not play a role in retail agglomeration; whereas, in the non-MSA counties alone, the effect is statistically important, but near the minimally significant threshold for economic effects. A 1-percentage-point decrease in property tax rates (which is about one-quarter of the standard deviation) leads to an increase in the Theil’s T of roughly 1 percent of the state’s standard deviation. At the margin, this is a small effect, which should be noted only because the spread of the property tax rates is more than 10 mils, or four times the standard deviation.

As with property tax rates, highway infrastructure possesses a statistically certain effect on retail inequality only in the non-MSA regions of Indiana.
And, the effect of highway infrastructure is economically meaningful, with the presence of a highway leading to about a 10 percent increase in the relative share of retail employment in a county.

The per capita big-box variable had no effect on retail agglomeration. The spatial and time autocorrelation variables behave as expected, while the model diagnostics are satisfying.

**SUMMARY AND CONCLUSIONS**

This paper presents an extension to the analysis of tax and infrastructure’s role in generating industry agglomeration. The first major contribution is in evaluating the retail sector—an often ignored component of regional economic activity. Secondly, my strategy for identifying firm entrance offers a novel approach to solving a ubiquitous concern with agglomeration studies.

Using this approach, I find first that neither property taxes nor highway infrastructure contribute to retail agglomeration in a sample that includes both MSA and non-MSA counties in Indiana. This finding mimics those of Holtz-Eakin (1994) and Evans and Karras (1996). However, in non-MSA counties, I find that a modest increase in local retail agglomeration is associated with lower property tax rates. This is the only relevant regionally varying tax instrument in Indiana. Second, I find that highway infrastructure explains about 10 percent of the variation in retail agglomerations at the county level in Indiana.

These questions in general are not new; however, the results suggest that the leakage impact of highways on rural retail is far lower than that found by Chandra and Thompson (2000) and Hicks (2002 and 2005b). What is especially novel in this analysis is the use of firm-level entrance decisions by the leading firm in this industry to identify the model. Further, analysis of retail agglomeration by transportation researchers is notably lacking. For these reasons, this study provides insight into matters of retail agglomeration, public infrastructure, and taxation.

Additional analysis is warranted. Extension of this modeling approach regionally would be insightful. One caveat is that the selection of Indiana was made to isolate variations in tax structure, so any extension of this modeling effort must take into account other location-determining tax instruments. Second, evaluation of the competitive environment for retail subsequent to the reduction in spatial inequality is also important. Although spatial inequality may be a welcomed

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17 The statistical significance of this variable in the full model approached common levels of significance, but the magnitude of the coefficient was far below any meaningful threshold of economic importance.

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**Table 3**

**Estimation Results, Dependent Variable Is Retail Inequality**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full sample (N = 1,258, with 92 counties)</th>
<th>Rural (N = 742, with 55 counties)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Common intercept</td>
<td>–0.21 (–7.17)</td>
<td>–0.06 (3.64)</td>
</tr>
<tr>
<td>Property tax rate</td>
<td>–0.006 (–3.16)</td>
<td>–0.0009 (–1.13)</td>
</tr>
<tr>
<td>Interstate count</td>
<td>0.03 (0.85)</td>
<td>–0.13 (–0.73)</td>
</tr>
<tr>
<td>Per capita big-box</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Spatial lag</td>
<td>—</td>
<td>0.39 (8.35)</td>
</tr>
<tr>
<td>AR(1)</td>
<td>—</td>
<td>0.61 (13.83)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.93</td>
<td>0.96</td>
</tr>
<tr>
<td>D-W</td>
<td>0.47</td>
<td>1.45</td>
</tr>
</tbody>
</table>

NOTE: The t-statistics are in parentheses.
economic outcome, if it occurs at the expense of competition, its welfare effects may be uncertain. Also, upstream linkages, especially in wholesale, are also important to evaluate within the context of agglomeration and transportation. This would be a natural extension of this study.

Finally, these results imply policy considerations. First, local policymakers should carefully assess the role of local tax rates with respect to public infrastructure. And, while this is hardly a novel prescription, the findings that regional retail agglomeration are sensitive to local property tax rates should provide a cautionary note to public policymakers. Perhaps most important is the finding that public infrastructure plays a role in agglomeration, even in a period of robust declines in spatial autocorrelation and spatial inequality. Although this falls short of a prescription for highway construction (I have neither assessed benefits nor costs), it should herald the worth of specific local analysis.

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