Commuting's Effect on Local Retail Market Performance

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Abstract: The ever-increasing spatial dimension of commuting sheds suggests that the nature of the economic impact of new job creation on the local community is changing. From a community perspective, an increasing number of any new jobs created are taken by in-commuters as opposed to in-migrants. To gain insight into the nature of this change, we simulate the impact of different levels of in-commuting versus in-migration on local retail markets.

I. INTRODUCTION

The ability of a community's retail sector to attract and retain customers is vital to the economic health of the community. In particular, a community's success in capturing and circulating retail sales dollars is a key indicator of the overall economic fitness of the community, with higher circulation levels indicative of healthier communities (Ginder, Stone and Otto 1985; Stone 1987; Deller, McConnon, Holden and Stone 1991; Ayres, Leistritz and Stone 1992). Notions of circulation become especially important when evaluating the potential economic impacts of some event. For example, when evaluating economic impacts of a proposed manufacturing plant, local merchants and policy makers are often especially sensitive to potential impacts on the local retail sector.

It is generally understood that the regional economic impacts of an event are often determined by the extent of local leakages, with local benefits being greater in regions that are more self-reliant. When dealing with small, open economies, one obvious source of economic leakage is the loss of locally generated earnings via commuting. Specifically, when new jobs are taken by in-commuters, there is potentially a great and immediate leakage of many of the direct, and subsequently indirect and induced effects of the new development. With respect to retail sales, the magnitude of this particular leakage depends on whether commuters are prone to spend their money near their place of work or near their place of residence.

While several recent studies have investigated the determinants of rural retail trade (Walzer and Schmidt 1977; Deller and Chicoine 1989; Gruidl and Andrianaco 1994; Gale 1996; McGurr and DeVaney 1996; Ebai and Harris 1997), it is somewhat surprising that little work has been conducted explicitly examining the relationship between retail sales and commuting.[1] Instead, much of the

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[1]One notable exception is the recent article by Pinkerton et al. (1995) that uses micro survey data to investigate the importance of workplace on in-shopping in two Missouri communities. The authors find that workplace affects in-shopping for some but not all categories of retail sales.

previous work acknowledges the importance of spatial labor market issues only indirectly. For example, while Walzer and Schmidt (1977) suggest that people may make purchases near their place of work, they do not examine commuting *per se*. Instead, the authors use proximity to a large employment center as a reason for lower local retail sales. The implied hypothesis is that people will often shop near their place of work, and if a neighboring region is an employment center, people will do some shopping near work rather than home. The difficulty with this approach is that large employment centers also tend to be higher on the central place hierarchy. Thus, it is impossible to tell if proximity is capturing commuting effects or agglomeration effects. The end effect is that commuting's influence on retail sales has not been quantified.

Our purpose in this study is twofold. First, we address the historic neglect of commuting in aggregate retail studies by developing a model of retail sales for Wisconsin counties that explicitly incorporates in- and out-commuting. We draw upon previous studies of spatial retail markets in specifying a theoretical and econometric model of the determinants of per capita retail sales variation. Overall, our results support the hypothesis that per capita retail sales are higher in regions with higher levels of in-commuting, and lower in regions with higher levels of out-commuting, *ceteris paribus*. Our second purpose is to examine the differential effects that migration and commuting have on local retail sales. Using the econometric results to specify a simulation model, we investigate the differential impacts of commuting and migration on local retail sales. While our results support the hypothesis that per capita retail sales are higher in those counties with high levels of in-commuting, we find that migrants have a greater total impact on local retail sales than do commuters.

II. THEORETICAL AND EMPIRICAL MODEL OF LOCAL RETAIL SALES

The topic of retail sales in rural areas has been of periodic interest in the regional science literature. W.J. Reilly (1931) conducted an early investigation into the topic of retail sales, culminating in the classic *The Law of Retail Gravitation*. In this work, Reilly showed that variation in the level of retail sales across communities was a function of the population of the communities and the distance that separated them. While remaining influential to this day, Reilly's work is atheoretical in the sense that it has no foundation in economic concepts (Holden and Deller 1993).

Early theoretical treatments of retail sales in spatially extensive markets begin with Beckmann (1968), who derived a theoretical specification of consumer purchase decisions in markets with a single retailer. Ingene and Yu (1981) expanded Beckmann's results to include the competitive market case and introduced household characteristics into the theoretical model.

On the demand side, a utility-maximizing household is assumed to possess a linear demand curve for the retail output of a typical store of the form

(1) $q = a(\Theta) - bp$

where q is quantity, $a(\Theta)$ is the maximal demand quantity (as a function of household characteristics Θ), and p is the delivered price. The simplest way to introduce the notion of space into the analysis is to consider transportation costs—households will not buy from a firm too far away because transportation costs are too high. To explicitly introduce space, consider household i facing price

(2) $p_i^k = \hat{p} + tD_i^k$

where $\hat{p}$ is the store price of the retail good, D_i^k is the distance from household i to the store selling good k, and t is the cost (including time) per unit distance of a round trip. This spatial price can now be substituted into the representative household's demand curve (suppressing subscripts and superscripts) to specify retail demand as a function of distance, among other things:

(3) $q = a(\Theta) - b(\hat{p} - tD).$

Now, turn to the profit maximization problem of the retail store proper. Losch (1954) forwards a "demand cone" to describe the extent of spatial markets. Essentially, this cone adds a spatial component to the typical demand curve facing a firm. Incorporating the spatial demand function into the "Loschian" demand cone, a typical store located in the center of a market with radius D has (potential) total sales (Q) of

(4) $Q = 2\pi\phi\int_0^D D(\, a(\Theta) - b(\, \hat{p} - tD)\,)dD$

where ϕ is the (population) density of demand. As usual, profits (G) are the product of the store price and quantity, less total costs, or

(5) $G = 2\pi\phi(\hat{p} - c)D^2\int_0^D D(\, a(\Theta\,) - b(\, \hat{p} - tD)\,)dD - f$

where f is a fixed cost of operation and $(\hat{p} - c)$ is the gross margin. Integrating the profit function, differentiating with respect to $\hat{p}$, and setting the first order condition equal to zero gives the profit maximizing price:

(6) $\hat{p} = \frac{1}{2}\left(\frac{a(\Theta)}{b} + c\right) - \frac{tr}{3}.$

Substituting this price into the integrated value of the total sales function gives a quantity of sales per store as

(7) $Q = \pi\phi bD^2\left(\frac{a(\Theta)}{2b} - \frac{c}{2} - \frac{tD}{3}\right).$

Summing this quantity over N stores and multiplying by store price gives total retail sales dollars (S) for the community:

(8) $S = N \cdot \hat{p} \cdot Q.$

Thus, per capita retail sales are

(9) $s = \frac{S}{P}$

where P is the local population. A general form of the per capita retail sales model can be written

$$(10) \quad s = s(\phi, a(\Theta), D, t, c, \hat{p})$$

with important variables becoming those that affect $(a(\Theta)/b)$, b, and t.

Given this basic theoretical framework, we are interested in the factors relating retail sales to population market size, population density (ϕ), distance (D), income, and other local demographic characteristics (Θ).

Papadopoulous (1980, p. 57) commented that "...once a consumer reaches a trade center for whatever reason, shopping appears to be a significant secondary opportunity." One possible reason people reach a trade center is that it is their place of work (i.e., they commute). While there is little existing empirical evidence on the effect of commuting on retail sales, it has been documented that rural residents are now commuting more than ever before (Stabler, Olfert and Greuel 1996). At the same time, studies have found that local retail leakages from rural areas are increasing. For example, Stone (1987) finds that leakages in Kansas, Nebraska, and Missouri increased from an average of 5 percent in the 1950s to 15 percent in the 1970s. Stone's subsequent analysis for rural Iowa indicates that leakages averaged over 20 percent in the 1980s.

Our focus here is on exploring the relationship between these two trends. In the context of the framework developed above, we hypothesize that commuting is important in how it affects the local market size. In regions with more in-commuters, one would expect higher local retail sales. Analogously, in regions where a large proportion of the local labor force out-commutes, it might be expected that per capita retail sales are comparatively low. Of course, commuting is not the only factor that can determine local sales. A turn to the empirical literature suggests other factors potentially influencing local retail activity.

Income. Early studies examining the effects of income on both total and per capita retail sales focus primarily on urban areas. For example, in a cross section study of retail sales in SMSAs, Ferber (1958) and Tarpey and Bahl (1968) find a positive relationship between *total* income and *total* sales. Later research conducted by Liu (1970) and Ingene and Yu (1981)—also at the SMSA level—not only supports the earlier findings, but also reports a similar positive relationship at the *per capita* level.

While the literature on rural retail trade is relatively scarce, several researchers have recently addressed the topic. Notable studies include Walzer and Stablein (1981) and Henderson (1990), each of which test the hypothesis that local retail sales are correlated with income. Their findings are consistent with the earlier work in that income seems to have an important role in determining rural retail sales.

Population and agglomeration economies. In the theoretical framework above, population is important in the way it contributes to agglomeration economies, which reduces uncertainty for consumers (McLafferty and Ghosh

1986; Brown 1989). First, regions with larger populations tend to be higher in the hierarchy of central places, hence they tend to offer a larger variety of goods and services. Such variety is attractive to consumers (Holden and Pritchard 1996; Linder 1995). An additional benefit of variety is that it encourages multi-purpose shopping trips (Vandenbroucke 1995). A third benefit of agglomeration economies arises from the concentration of local retailers (Harris and Shonkwiler 1997). In many larger regions, similar types of retailers tend to cluster (e.g., automobile dealers, antique dealers), thus allowing consumers to comparison shop. In the context of the theoretical model developed above, the overall effect of agglomeration is to reduce the costs and uncertainty of shopping.

Distance. The most obvious spatial characteristic of regional retail markets is distance. Like agglomeration effects, proximity to larger markets reduces transportation costs faced by consumers. In examining the importance of distance on rural retail trade patterns, Walzer and Stablein (1981) investigate the relationship between rural retail sales and distance to a major retail center in Illinois. Controlling for socioeconomic factors analogous to those considered above, the authors find a negative and statistically significant relationship between proximity to a larger retail center and per capita sales in small neighboring towns. In their analysis of retail trade in Nebraska, Yanagida et al. (1991) find a positive and statistically significant relationship between distance and pull factors as a measure of retail capture.

Demographics. The impacts of population age and unemployment on retail sales have also been extensively studied. Walzer and Schmidt (1977) suggest that older people, as a group, are less mobile, hence they tend to shop locally. Additional support for this hypothesis is provided by Pinkerton et al. (1995) who, using survey data for two Missouri communities, find that age is the socioeconomic variable most strongly related to in-shopping. Also, it is quite reasonable to expect that the types of items within consumption bundles tend to vary across age groups.

It is expected that high local unemployment rates are inversely related to local retail sales. Two interpretations are reasonable. First, higher unemployment (temporarily) reduces the disposable income available in the community. Second, high unemployment may cause households to have low expectations of future income as wages are unlikely to increase (Ingene and Yu 1981). Walzer and Schmidt (1977) and Ingene and Yu (1981) provide empirical evidence of a negative relationship between unemployment and sales. Based on this theoretical and empirical discussion, a general form for local per capita retail sales can be written

$$pcretail = s(income, population, demographics, commuting, distance).$$

III. AN ECONOMETRIC SPECIFICATION OF LOCAL RETAIL SALES

In this section we present an estimable equation for county-level per capita retail sales in sector m, which differs from its theoretical counterpart by assuming a linear functional form and the addition of the unobserved term $\epsilon_{m,t}$, an index for the year and a region-specific dummy variable. The dependent variable uses pooled sales data for ten categories from the 1982, 1987, and 1992 *Census of Retail Sales*. The complete empirical model we estimate is written:

$$(11) \quad pcretail_{m,t} = \beta_0 + \beta_1 pci_t + \beta_2 unemp_t + \beta_3 elderly_t + \beta_4 popdens_t + \beta_5 outcom_t + \beta_6 incomut_t + \beta_7 dist + \beta_8 estab_t + \sum_{j=9}^{11} \beta_j region_j + \sum_{k=12}^{13} \beta_k year_k + \epsilon_{m,t}$$

where *pci* is per capita income in the county in census year *t, outcom* is the number of local residents who work in another county (out-commute), *incomut* is the number of non-residents who work in the county (in-commute), *dist* is the linear distance to the nearest city with at least 25,000 people, and *estab* is the number of retail establishments in category *m* per 1,000 local residents. The variables *region* and *year* will be discussed further below. Variable definitions and data sources are fully described in Table 1.

TABLE 1

Variable definitions and sources for local retail sales module

Variable	Description	Source
pcretail(m)	Per capita retail sales: auto, furniture, building materials, miscellaneous, food stores, eating establishments, drug stores, general merchandise, apparel, gas service stations	Census of Retail, 1982, 1987, 1992
pci	Real per capita income	
elderly	Percent of population 65+ years old	BEA-REIS/Woods & Poole
popdens	Population density (people/sq mile)	BEA-REIS/US Census Bureau
outcom	Number of out-commuters	1980, 1990 Census
incomut	Number of in-commuters	1980, 1990 Census
dist	Distance to nearest city with > 25,000 people	WI Dept of Transportation
		Census of Retail, 1982, 1987, 1992
estab(m)	Number of establishment per 1,000 residents	

Based on the above theoretical model, we expect that regions with higher per capita incomes and larger population densities will have higher per capita retail sales (β_1, β_4>0). We expect that regions with higher unemployment rates will, in general, have lower per capita sales due to lower expectations of future earnings (β_2<0). We further anticipate that regions with a higher number of out-commuters will have lower per capita sales (β_5<0), while we expect higher per capita sales in those counties with a large number of in-commuters (β_6>0). Regarding other spatial considerations, we expect that per capita sales will be higher as the distance to a local retail center increases, reflecting the high transportation costs of traveling long distances (β_7>0). We also expect the coefficient on the agglomeration variable to be positive, capturing the expectation of higher sales at stations higher up the hierarchy of central places (β_8>0). Finally, we do not predict a sign for the percentage of local population that is elderly because the effects of reduced mobility could be offset by differences in the composition of local consumption bundles.

Estimation procedure for the local retail sales module

When estimating model parameters econometrically using pooled (or panel) data, the performance of any estimation procedure for the model depends on the statistical characteristics of the unobserved components of the model. Consider a panel data model involving observations over time and across cross sections:

$$(12) \qquad Y_{it} = \sum_{k=1}^{K} x_{it}\beta_k + \mu_{it} \quad i = 1,\ldots N; \quad t = 1,\ldots T$$

where *N* is the number of cross sections, *T* is the length of the time series for each cross section, and *K* is the number of independent variables.

One approach to specifying the behavior of the disturbance term when combining cross section and time series data has been adopted by the proponents of the fixed effects model. The idea behind the fixed effects model is that each cross-sectional unit and each time period is characterized by its own unique intercept (Kmenta 1986).[2] According to this approach, the unobserved term can be written:

$$(13) \qquad \mu_{it} = v_i + \omega_t + \epsilon_{it}$$

where ϵ_{it} is a classical disturbance term with zero mean and a homoscedastic covariance matrix. If the effects are fixed, it is possible to estimate the model by introducing dummy variables for each time series and cross section, and then treat the model within the framework of the classical regression model, including the standard assumptions about the disturbance term. For fixed effects models, OLS estimation is best linear unbiased.

We adopt a variant of the fixed effects approach in our model. To simplify the (results of the) model, instead of using a separate dummy variable for each cross section (i.e., each county), we develop taxonomy of economic regions in Wisconsin. This taxonomy was developed using cluster analysis on a number of county attributes and allows us to partition counties in a way such that homogeneous counties are grouped together. In the analysis here we identify four unique economic regions (i.e., diverse, resource-based, tourism and agricultural) for Wisconsin. See the Appendix for more details.

IV. EMPIRICAL RESULTS OF THE PER CAPITA RETAIL SALES EQUATIONS

In Table 2 we provide basic descriptive statistics for select county-level retail variables. In Table 3 we provide the OLS parameter estimates for the model of local retail sales, while the elasticities for these equations are provided in Table 4. Overall, the performance of the individual equations varies substantially, with

[2]The random effects model is a second common technique for analyzing pooled data. In the random effects model, the disturbance term is assumed to consist of three components, a time-series component, a cross-section component, and a time series cross section component. Baltagi (1995) suggests that fixed effects models are appropriate when the sample is exhaustive (e.g., all Wisconsin counties) and a random effects model should be chosen when the observations are a random sample of a larger population.

equation R^2 statistics ranging from 0.79 for the furniture sales equation to 0.12 for gasoline sales. Individual equation F-statistics are provided along with the R^2 statistics at the bottom of Table 3.[3]

TABLE 2

County-level summary statistics for select retail variables

Variable	Mean	Std Dev	Minimum	Maximum
PER CAPITA RETAIL SALES (1)				
Furniture, home furnishings	$218	$203	$0	$1,283
Automobile dealers	$1,417	$723	$27	$3,193
Building materials, hardware	$476	$242	$12	$1,039
Apparel and accessories	$172	$156	$0	$610
Drug stores	$198	$238	$0	$1,998
Food stores	$1,317	$388	$45	$2,724
General merchandise	$717	$528	$0	$1,884
Eating and drinking places	$671	$534	$45	$1,5578
Miscellaneous retail stores	$783	$770	$149	$5,647
Gasoline service stations	$740	$318	$38	$1,826
Average Total Retail Sales	$7,120	$4,730	$2,397	$41,557
Real per capita income (2)	$17,058	$2,964	$12,893	$28,317
Local unemployment rate (2)	5.6%	1.5%	2.2%	10.9%
Percent 65+ years (2)	16.0%	3.2%	9.6%	24.6%
Distance to city with 25,000 people	40	22	0	94
Number of out-commuters (3)	6,335	9,077	648	66,708
Number of in-commuters (3)	4,598	8,401	218	63,886
Population density (4)	93	119	8	574
NUMBER OF ESTABLISHMENTS PER 1,000 RESIDENTS (1)				
Furniture, home furnishings	0.37	0.16	0.00	0.94
Automobile dealers	1.14	0.34	0.37	2.78
Building materials, hardware	0.50	0.21	0.20	1.61
Apparel and accessories	0.44	0.25	0.00	1.70
Food stores	0.76	0.26	0.23	2.41
General merchandise	0.22	0.11	0.00	0.66
Eating and drinking places	2.44	0.81	0.98	6.83
Miscellaneous retail stores	1.30	0.54	0.37	4.04
Other retail	7.17	1.95	3.28	16.95

Data Sources: 1) 1992 Census of Retailers; 2) BEA-REIS; 3) US Census; 4) City and County Data Book.

In general, we find broad support for the theoretical arguments and previous empirical evidence that as the number of out-commuters increases, per capita retail sales are lowered, and as the number of in-commuters increases, per capita sales increase. The elasticity estimates vary substantially across the sales categories. For example, a 1 percent increase in the number of out-commuters results in a 0.42 percent decrease in per capita furniture sales and a 0.14 percent increase in per capita apparel sales. Note that apparel is the only positive elasticity with respect to out-commuting that is statistically significant, a finding that we cannot adequately explain. Regarding in-commuting, parameter estimates are statistically significant for all categories except drug stores and gas stations. In terms of elas-

[3]In preliminary analysis, we used OLS to estimate the time series cross section retail sales equations by including binary variables for each census year on the right-hand side. We then examined the importance of the "year" variables by means of a simple F-test—we simply estimated the model with and without the time series dummies and compared the resulting total error sum of squares. This test ($F_{stat} = 0.12 < F_{crit/95\%} = 1.00$) failed to reject the hypothesis that the "year" was unimportant, so we dropped it from the analysis.

TABLE 3

Parameter estimates for per capital retail sales equations

Variable	Furniture	Autos	Building	Apparel	Drug Store	Food	General	Easting est	Misc	Gas
Intercept	221.400	-1058.100	306.030	285.700	52.100	188.450	1102.160	415.600	-1714.000	238.800
	(2.62)	(2.07)	(1.71)	(3.27)	(0.64)	(0.52)	(2.83)	(2.53)	(2.16)	(0.69)
Real PCI	0.004	0.127	0.006	-0.010	0.004	0.053	0.022	0.020	0.100	0.001
	(1.09)	(5.91)	(0.38)	(2.90)	(1.22)	(3.55)	(1.35)	(2.96)	(2.88)	(0.04)
Unemp rate	-2.303	-20.560	-5.100	-3.180	-2.580	28.650	-32.960	2.810	19.540	11.560
	(1.05)	(2.47)	(1.08)	(1.48)	(1.31)	(3.11)	(3.32)	(0.69)	(1.02)	(1.35)
Percent elderly	-13.140	-20.560	-7.940	-4.430	-0.450	12.780	-24.740	-224.790	-4.790	0.362
	(5.19)	(1.26)	(1.44)	(1.70)	(0.17)	(1.12)	(2.03)	(4.82)	(0.20)	().03)
Pop density	0.380	0.082	-0.01	0.337	0.027	-0.219	0.427	0.014	0.583	-0.559
	(4.10)	(0.14)	(0.11)	(2.50)	(0.30)	(0.53)	(0.97)	(0.08)	(0.66)	(1.44)
Out-commuters	-0.013	-0.026	-0.010	0.004	0.002	-0.005	-0.035	-0.012	-0.035	0.002
	(9.39)	(3.03)	(3.21)	(3.14)	(1.45)	(0.81)	(5.24)	(4.34)	(2.62)	(0.44)
In-commuters	0.013	0.028	0.009	0.004	-0.002	0.010	0.029	0.009	0.024	0.002
	(9.28)	(3.31)	(3.11)	(3.14)	(1.10)	(1.67)	(4.53)	(3.21)	(1.83)	(0.35)
Distance to city w/25K	-0.582	-7.360	-1.550	-0.430	-0.430	-3.760	-7.360	-1.580	3.730	-1.380
	(1.54)	(3.49)	(2.04)	(1.14)	(1.29)	(2.49)	(4.57)	(2.35)	(1.15)	(0.96)
Estab/1000	320.390	766.540	574.900	354.400	12.600	501.890	589.800	157.800	367.940	67.920
	(8.96)	(6.66)	(8.29)	(13.31)	(3.41)	(4.79)	(2.29)	(9.13)	(2.87)	(4.27)
Housing starts	5.00		8.810							
	(2.38)	(1.88)								
Resource region	-7.440	397.060	-83.420	4.930	-15.670	101.650	15.110	-96.120	274.680	-134.300
	(0.31)	(2.76)	(1.65)	(0.20)	(0.68)	().99)	().13)	(2.08)	(1.23)	(1.36)
Agriculture region	-8.660	250.620	-108.750	-30.520	-27.430	-134.800	-209.600	-97.000	317.140	-63.100
	(0.43)	(2.05)	(2.49)	(1.45)	(1.42)	(1.53)	(2.25)	(1.71)	(1.68)	(0.76)
Tourism region	-14.170	-5.330	-7.250	4.450	-50.980	430.090	2.620	160.500	-54.800	-272.800
	(0.48)	(0.03)	().01)	(0.15)	(1.70)	(3.45)	(0.02)	(2.76)	(0.19)	(2.11)
R^2	0.79	0.57	0.46	0.27	0.28	0.47	0.54	0.65	0.18	0.12
F-stat	58.30	23.60	13.40	48.70	6.64	15.41	20.97	32.10	3.84	2.59
Condition Index	58.59	56.97	59.25	55.61	56.6	56.24	56.02	56.06	57.15	56.6
Chi-square	67.43	65.98	85.64	75.89	70.97	51.2	86.62	57.32	37.17	55.76
Pr	0.90	0.64	0.42	0.32	0.47	0.96	0.10	0.87	0.99	0.90

Figures in parenthesis are t-statistics.

TABLE 4

Elasticity estimates for per capita retail sales equations

Variable	Furniture	Autos	Building	Apparel	Drug store	Food	General	Eating est	Misc	Gas
Real PCI	0.31	1.65*	0.24	-0.89*	0.39	0.62*	0.60	0.49*	2.29*	0.01
Unemp rate	-0.09	-0.13*	-0.09	-0.14	-0.12	0.17*	-0.45*	0.03	0.22	0.13
Pct elderly	-1.02*	-0.25	-0.27	-0.37	-0.04	0.14	-0.65*	-5.24*	-0.10	0.01
Pop density	0.18*	0.01	0.00	0.17*	0.01	-0.01	0.07	0.00	0.08	-0.08
Out-commuters	-0.42*	-0.13*	-0.14*	0.14*	0.07	-0.02	-0.38*	-0.12*	-0.32*	0.02
In-commuters	0.31*	0.10*	0.10*	0.10*	-0.04	0.03	0.23*	0.06*	0.16	0.01
Distance to city w/25K	-0.09	-0.18*	-0.11*	-0.07	-0.08	-0.08*	-0.38*	-0.07*	0.16	-0.06
Estab/1000	0.6*	0.71*	0.65*	0.87*	0.53*	0.28*	0.22*	0.59*	0.59*	0.71*
Housing starts	0.11*		0.08							

*Denotes significance at the 5% level.

ticities that are statistically significant, the percentage increase in per capita sales due to a 10 percent increase in the number of in-commuters varies between 0.3 percent (food) and 3.1 percent (furniture).

Because leakages due to out-shopping are a major concern in many rural areas, these commuting effects have important local development ramifications. Proponents of initiatives designed to enhance local shopping opportunities need be aware of local commuting patterns and how they are affected by economic change. If a large contingent of the work force is employed outside the county, then a local retail development may not perform according to expectations. Conversely, if the county is (or becomes) an employment center, then there may exist opportunities to capture additional retail dollars by enabling in-commuters to spend more money near their place of work.

Though it varies across sectors, the income elasticity is positive in all cases but one, suggesting that higher per capita sales can typically be expected as income increases. For example, a 1 percent increase in per capita income leads to a 1.7 percent increase in automobile sales per capita and a 2.3 percent increase in miscellaneous sales per capita. The estimated income elasticities are not significantly different from zero, however, in five of the equations: furniture, building materials, drug stores, general merchandise and gasoline sales.[4] The lack of statistical significance is surprising in the per capita furniture equation. Apparel sales is the one category where the parameter estimate on per capita income is negative and statistically significant—here a 1 percent increase in real per capita income leads to a nearly 1 percent reduction in local per capita retail sales. At this time, we have no reasonable explanation for this particular result.

The empirical results offer limited support for the hypothesis that per capita retail sales will be higher in counties with higher population densities (i.e., agglomeration economies). While the estimated coefficients are positive for all categories except building materials and food sales, they are only statistically significant for furniture and apparel.[5]

The number of retail establishments per 1,000 residents is a second measure of agglomeration economies analyzed. In all sales categories, the "concentration" of retailers is positively and statistically significantly related to per capita retail sales, supporting the notion that retail clustering can increase per capita sales. These results may indicate that shoppers appreciate variety and the ability to comparison shop. From a policy perspective, the concept of agglomeration economies needs to be recognized because it suggests that retail development strategies should explicitly consider the number of stores as well as other spatial and demographic attributes.

While commodity demand is surely affected by price, the only component of a good's expense we consider here is transportation costs. We do this because

[4]Ingene and Yu (1981) find statistically significant coefficients for income in SMSAs for these categories, but their elasticity estimates are still close to zero.
[5]These ambiguous results are actually quite similar to those reported by Ingene and Yu (1981) in their study of per capita retail sales in SMSA's.

we do not have good measures of industry prices. Using distance to the nearest city with 25,000 people or more as a proxy for transportation costs, we find that local per capita retail sales actually *decrease* as distances to cities increase, countering the working hypothesis. What this suggests is that distance may cut both ways—not only is it a cost to local residents, but it also may discourage outsiders from shopping in the community. Putting it somewhat differently, increased remoteness implies lower overall retail activity.

While the empirical findings are not unanimous, there is some support for the idea that higher expectations of future employment can influence retail sales. Here, a 1 percentage point increase in the unemployment rate leads to a $21 reduction in per capita auto sales, a $33 reduction in per capita general merchandise sales, and a $29 increase in per capita food sales.

The empirical results suggest that counties with a higher proportion of elderly have lower per capita retail sales in all categories except per capita food and gasoline sales. The estimated coefficients are significantly different from zero, however, for only the furniture, apparel, general merchandise, and eating establishment categories. *Prima facie*, the results do not lend support to the notion that the elderly shop close to home (i.e., a positive coefficient), countering the findings of Walzer and Schmidt (1978) and Pinkerton et al. (1995). When examining all results simultaneously, we see that per capita sales are lower in general for counties with a large elderly population. The implication is that the elderly may have a different expenditure pattern than younger people, *ceteris paribus*. It very well may be that the elderly shop close to home, but tend to consume less on average.

V. A SIMPLE SIMULATION TO EXAMINE RETAIL SALES IMPACTS OF COMMUTING AND MIGRATION

One way to examine the meaning of the results is to conduct a relatively straightforward simulation. In accomplishing this, we compare how migration and commuting can affect local retail sales. Here, we forward a scenario where 100 new jobs are created in the local economy and consider three cases where the jobs are allocated between commuters and in-migrants. In the first case, all jobs go to in-commuters; in the second case, all new jobs go to in-migrants; and in the final case, 50 jobs go to in-commuters and 50 jobs go to in-migrants. The simulations involve simply adjusting the independent variables (from the state mean) to reflect the local economic change.

Before continuing, we need to specify several important assumptions underlying the analysis. First, we assume that per capita income in the region does not change, allowing us to focus specifically on the commuting versus migration aspect of the analysis. Second, we assume that each migrating household has 2.6 members, which is the average household size in Wisconsin. This assumption is important because it allows us to determine the change in total population, which will drive total retail sales. Finally, we assume that the unemployment rate is endogenous and all labor force participants in the migrant households become fully employed. Thus, the migration scenarios see slight decreases in the local unemployment rate, while there is no change in the local unemployment rate in the 100 commuters' scenario.

Turning to the simulation results (Table 5), we see that total per capita retail sales increase by about $13, or 0.2 percent, when all the new jobs are taken by commuters; about $8 when half the new jobs are taken by commuters; and less than $5 when all the jobs are taken by migrants. It is important to note that in each case the increase in total per capita sales over the baseline is less than 0.2 percent.

Still, for several categories, the increased in-commuting has notable effects on per capita sales. For example, under the all in-commuting scenario, per capita automobile sales increased by $2.84, about 0.2 percent, while under the all in-migrant scenario, automobile sales increased by only $1.77, a 0.1 percent increase over the baseline. Also, under the all in-commuting scenario, general merchandise per capita sales increase by $2.45, a 0.3 percent increase over the baseline. But under the all in-migration scenario, general merchandise per capita sales decrease $0.77, or 0.1 percent from the baseline. The fact that per capita sales increase substantially more in the commuting scenario than they do in the migration scenario is consistent with our expectations that people do sometimes shop near their place of work. The relative change in population also is a factor in understanding the changes in per capita levels. Specifically, the denominator is changing at the same time as simulated retail sales.

Of course, retailers are probably more interested in the effects on total sales (per capita sales times population) than they are in per capita sales, and here is where the differences are most obvious (Table 6). In the all in-commuter scenario, total retail sales increase more than $760,000, a 0.2 percent increase over the baseline, while total retail sales in the all in-migrant scenario increase more than $2 million, a 0.5 percent increase. These differences offer a strong indication of the important local implications of the substitution between migration and commuting.

Our results suggest that an additional in-commuter will increase local retail sales by about $7,600. In comparison, when a household (2.6 people) migrates into the region, total sales increase by about $20,200. The effect of filling a new job with an in-migrating household rather than a single in-commuter is to increase total local retail sales by nearly $13,000.

VI. CONCLUSIONS

In this paper we develop a model of per capita retail sales in rural Wisconsin. Our goal is to investigate the importance of commuting (and migration) when investigating retail impacts of local employment change in rural areas. Overall, our results support the hypothesis that per capita retail sales are higher in regions with higher levels of in-commuting, and lower in regions with higher levels of out-commuting, *ceteris paribus*.

From an economic development perspective, the importance of commuting can not be overstated. If workers tend to spend their money near their place of

TABLE 5

Per capita retail Sales Impacts of Three Scenarios (by category)

		100 commuters			50 commuters and 50 migrants			100 migrants		
Per Capita Retail Sales	baseline	simulation	impact	pct	simulation	impact	pct	simulation	impact	pct
furniture	$218	$129	$1.31	0.6%	$219	$0.72	0.3%	$218	$0.25	0.1%
autos	$1,417	$1,420	$2.84	0.2%	$1,418	$1.44	0.1%	$1,419	$1.77	0.1%
building	$476	$477	$0.93	0.2%	$476	$0.47	0.1%	$476	$0.26	0.1%
apparel	$172	$172	$0.47	0.3%	$172	$0.30	0.2%	$172	$0.28	0.2%
drug stores	$198	$198	-$0.15	-0.1%	$198	-$0.07	0.0%	$198	$0.14	0.1%
food stores	$1,317	$1,318	$1.02	0.1%	$1,319	$1.57	0.1%	$1,319	$1.80	0.1%
general	$717	$720	$2.98	0.4%	$719	$1.57	0.2%	$719	$1.80	0.3%
eats	$671	$672	$0.88	0.1%	$671	$0.44	0.1%	$671	-$0.14	0.0%
misc	$783	$785	$2.45	0.3%	$784	$1.33	0.2%	$782	-$0.77	-0.1%
gas	$748	$740	$0.20	0.0%	$740	$0.00	0.0%	$739	-$0.78	-0.1%
Total Per Capita	$6,709	$6,722	$12.93	0.2%	$6,717	$7.76	0.1%	$6,714	$4.62	0.1%

TABLE 6

Total Retail Sales Impacts of Three Scenarios (by category in $000)

		100 commuters			50 commuters and 50 migrants			100 migrants		
Per Capita Retail Sales	baseline	simulation	impact	pct	simulation	impact	pct	simulation	impact	pct
furniture	$12,813	$12,890	$77	0.6%	$12,883	$71	0.6%	$12,884	$72	0.6%
autos	$83,281	$83,448	$167	0.2%	$83,550	$269	0.3%	$83,754	$473	0.6%
building	$27,976	$28,031	$55	0.2%	$28,065	$89	0.3%	$28,115	$139	0.5%
apparel	$10,109	$10,137	$28	0.3%	$10,149	$40	0.4%	$10,170	$61	0.6%
drug stores	$11,637	$11,628	-$9	-0.1%	$11,659	$22	0.2%	$11,697	$60	0.5%
food stores	$77,404	$77,464	$60	0.1%	$77,667	$263	0.3%	$77,853	$449	0.6%
general	$42,140	$42,315	$175	0.4%	$42,326	$185	0.4%	$42,433	$293	0.7%
eats	$39,437	$39,488	$52	0.1%	$39,550	$113	0.3%	$39,603	$166	0.4%
misc	$46,019	$46,163	$144	0.3%	$46,199	$180	0.4%	$46,177	$158	0.3%
gas	$43,492	$43,504	$12	0.0%	$43,588	$96	0.2%	$43,639	$147	0.3%
Total Retail	$394,308	$395,068	$760	0.2%	$395,637	$1,329	0.3%	$396,325	$2,017	0.5%

residence, the impacts of employment growth on local retailing will depend largely on whether migrants, locals, or commuters fill the new jobs. This finding has a number of important local implications. We find that when commuting substitutes for migration, the impacts on total local retail sales are significantly mitigated, as commuters are a significant source of local income leakages.

APPENDIX 1: A NOTE ON ECONOMIC REGIONS[6]

Wisconsin is a state of economic contrasts. Much of the northern third of the state is heavily forested and many communities are economically dependent on natural resources. In comparison, much of the southwestern part of the state is agriculture-based, while the southeastern part is primarily urban. Due to this diversity, it is reasonable to attempt to accommodate differences in important regional characteristics when building economic models using county-level data.

In this paper we account for regional differences by identifying four groupings of similar counties through cluster analysis. The clusters are remarkable because members of any particular cluster are homogeneous, while the clusters themselves are heterogeneous. Given that this method identifies county similarities, one could readily interpret the clusters as differentiated economic regions. These clusters are used as the basis for introducing dummy variables into the econometric equations that capture important structural differences between Wisconsin counties. These dummy variables allow the intercepts of the econometric equations to be adjusted to partially capture the unique attributes of the economy of interest in applied simulation analysis.

Variables Used in Defining Economic Regions

In defining regions, we consider five indicators of county economic structure. These indicators represent major sectors of economic activity for the state as a whole.

1. *Agriculture*. Although agriculture contributes only about 3 percent to total GSP, the residents of many regions in the state rely heavily on farming for employment and income. This study uses the location quotient approach for employment to capture the relative importance of agriculture to the county economy. The general formula for a location quotient is:

$$(14) \qquad LQ(EMP)_{i,j} = \frac{\dfrac{EMP_{i,j}}{TOTEMP_i}}{\dfrac{EMP_{i,WI}}{TOTEMP_{WI}}}$$

where *EMP* is employment in industry *j*, *TOTEMP* is total employment, and *i* indexes the county. Here, all employment and income data is drawn from BEA-REIS.

[6] Details of the clustering procedure used in this analysis can be found in Shields (1998).

2. *Forestry.* In the SIC listings, earnings from timber, lumber, and other forest related products are considered part of durable goods manufacturing. However, since much of Northern Wisconsin is dependent on the forest industry, we have taken a subset of income generated by the forest sector and used it in developing a separate location quotient for forestry.
3. *Manufacturing.* In Wisconsin, manufacturing contributes more than 30 percent to total GSP. For this analysis, we include a location quotient for manufacturing employment.
4. *Services.* The importance of the service economy in Wisconsin is well documented (Shields 1995). Here we present a broader definition of the service sector than that presented at the one-digit level of the SIC. Whereas there exists a one-digit SIC title "Services," we have chosen to include Finance, Insurance and Real Estate (FIRE) in the location quotient for the service industry. This was done to limit the number of service sector variables clustered.
5. *Tourism.* Many counties in Wisconsin generate substantial revenues and employment from tourism.[7] Natural amenities, such as parks and lakes, attract thousands of visitors each year. Northern Wisconsin, in particular, annually entertains many vacationers from both Milwaukee and Minneapolis/St. Paul. Other counties may generate tourist revenues due to the presence of a casino. Tourism is a significant economic variable in that earnings generated from tourism-related industries, such as restaurants and motels, are essentially export income: the good is consumed locally, but the revenues are injected into the region from the outside. By like reasoning, seasonal home ownership often precursors an infusion of income from outside the region. Marcouiller and Deller (1993) show that much of the housing stock in northern counties consists of seasonal homes. Due to the absence of tourism-specific employment and income measures, we use the number of lodging rooms per 1,000 residents as a proxy. This data is from the 1990 Census.

Using Cluster Analysis to "Find" Economic Regions

Cluster analysis is a statistical technique designed to minimize variation between variables within a group while maximizing differences between groups.[8] For this analysis, we can think of it as grouping counties that are most alike economically, while excluding counties that differ significantly from the members in the group. Counties excluded from one group are clustered with other excluded counties most like themselves.

The algorithm used in defining clusters is an iterative four-step process that minimizes the squared Euclidean distance between observations and the cluster mean (see Anderberg 1973). First, an initial observation is selected as the seed. The researcher specifies the number of seeds. Next, temporary clusters are

[7]Tourism is an economic variable that can help differentiate regions geographically. Leatherman and Marcouiller (1994) conduct a cluster analysis for Wisconsin based strictly on indicators of tourism.
[8]For a more detailed discussion of cluster analysis, see Aldenderfer and Blashfield (1984).

formed by assigning each observation to the cluster of the nearest seed. The mean calculated for this temporary cluster is based upon the addition of the new observation. The third step is to form new clusters by assigning each observation to the nearest (new) seed. After all observations are assigned, cluster seeds are replaced by cluster means. The last step entails forming final clusters by assigning observations to the nearest seed (here the cluster mean). Because it is important that variables are of similar scale in cluster analysis, all variables were standardized with the mean equaling zero and the standard deviation equaling one.

It is the researcher's discretion to specify the number of clusters (seeds) in the analysis. Reluctant to arbitrarily choose the number of clusters, we carried-out eleven iterations of the analysis. The first specified one cluster (the state) the last specified eleven clusters. Each iteration of the analysis provides a pseudo-F statistic $(R^2/(c-1))/(1-R^2/(n-c))$, where R^2 is the observed overall R^2, c is the number of clusters, and n is the number of observations. Typically, the number of clusters is then chosen based upon the highest value of the pseudo-F. For this analysis, the pseudo-F had neighborhood maximums at one and four clusters. For this project, one is an uninteresting case.

For the most part, the cluster analysis corroborates typical perceptions of local economic base in the state. The regions we identify are:

Diverse: This cluster is comprised of seventeen counties, containing nearly all of the state's most populous counties (excluding Milwaukee). These economies are highly diversified, with extensive economic activity in manufacturing, services and FIRE.

Resources: This cluster contains thirteen counties, all but one located in the northern third of the state. These counties are sparsely populated and forestry is the major economic activity in this region.

Agriculture: Thirty-two counties, primarily dependent on agriculture, make up this cluster.

Tourism: This cluster consists of seven counties, with tourism being an important contributing factor to the local economies. Two major vacation destinations—Door County and Sauk County (Wisconsin Dells)—are in this cluster, as well as the northern vacation and retirement destinations. The forestry and service sectors are also important economic sectors for this cluster.

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