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Contextualizing Location Affordability: Urban Sprawl and Foreclosure

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Urban Sprawl and Foreclosure

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Abstract

Location affordability is a policy concept that links housing costs with transport costs, recognizing that assessing affordability should consider the combined costs incurred by a given location choice. As a more holistic perspective on affordability than traditional thresholds of housing costs alone, location affordability opens new possibilities for applied analyses that suggest a need for stronger coordination between housing and transport sectors in policy, planning, and project development.

A range of housing and transport system configurations can result in affordable locations. For example, it may be that high housing cost burdens in densely developed urban markets can be softened by the use of low-cost transportation services, such as public transit, cycling, or walking. Intensely urban areas are usually more compatible with low-cost transport modes because distances are shorter and density concentrates people so as to make public transit feasible. Conversely, in areas where there is little pressure on land markets and development is at low densities, housing prices are usually lower. Yet such areas are inefficient and expensive to serve by public transit; at the same time, long distances between work and residential locations make walking or cycling infeasible. As a result, households rely on private automobiles for transport, which require substantial investment to purchase, maintain, and operate one or more vehicles. Between these two extremes are a variety of patterns where households' housing and transport costs reflect the joint configuration of the land development and transport systems in a city. This joint configuration, or urban form, creates an influential backdrop for household location decisions and affects household cost structures.

In recent decades, scholars have focused on the phenomenon of urban sprawl, broadly understood to be ex-urban, low-density development, with segregated land uses and an orientation toward automobile use. Although there is general agreement on what sprawl is, there is weak consensus on a consistent definition appropriate for use in empirical studies. This is not merely an academic problem: If research is to provide evidence on location affordability to policy- and decision-makers, a coherent and clear conceptualization of the relevant dimensions of urban form is needed to identify specific strategies that support affordability.

This paper makes two contributions to the affordability literature. First, it operationalizes location unaffordability using Census tract-level mortgage foreclosure rates during the recent housing crisis as an outcome measure. From this perspective, foreclosures are an observable effect of some combination of factors that resulted in a dwelling unit becoming unaffordable such that the homeowner defaults on a home mortgage. This is in contrast to typical methods that accept normative thresholds for affordability (i.e. 30% of household income). Second, it uses multi-dimensional measures of urban form--recently developed by Andrea Sarzynski, George Galster, and Lisa Stack (2014)--to estimate the effect of particular patterns of development on affordability. These data are combined with demographic and household cost data in a series of spatial regression models for 35 US cities that exhibited the greatest changes in their development patterns over the preceding decade (1990s).

Introduction

Location affordability is a policy concept that links housing costs with transport costs. It expands on traditional approaches to assessing housing affordability by adding the transportation costs incurred for a given location choice. As a more holistic perspective on affordability than traditional thresholds of housing costs alone, location affordability opens new possibilities for addressing important social and economic questions, yet it will require closer coordination across the housing and transportation sectors. More specifically, transportation agencies will need to engage with the issue of location affordability in policy, planning, projects, and programs. This engagement begins when transportation agencies are motivated by evidence for the importance of their role, coupled with empirical insights into where and how they can support location affordability.

This paper seeks to contribute to the knowledge base on location affordability. It presents a quantitative analysis that supports the location affordability concept, finding that high transportation costs have important implications for households. The analysis makes two contributions to the affordability literature. First, it operationalizes location unaffordability using Census tract-level mortgage foreclosure rates during the recent housing crisis as an outcome measure. From this perspective, foreclosures are an observable effect of some combination of factors that resulted in a dwelling unit becoming unaffordable such that the homeowner defaults on a home mortgage. This is in contrast to typical methods that accept normative thresholds for affordability (i.e. 30% of household income). Second, it uses multi-dimensional measures of urban form recently developed by Andrea Sarzynski and colleagues (2014) to estimate the effect of particular patterns of urban development on affordability. These data are combined with demographic and household cost data in a series of spatial regression models for the 35 US cities that exhibited the greatest changes in their development patterns over the preceding decade. The models investigate what spatial patterns in demographics, household cost burdens, and urban form are associated with foreclosure.

Literature Review and Background

The concept of location affordability is rooted in classic theories of the interrelationship between land development patterns and transportation systems. These theories reach back to von Thünen's bid-rent theory of land markets (1966) and Alonso's urban location theory of housing choice (1964) in which proximity to desired destinations adds a premium to housing prices, while distance imposes a discount. That is, housing prices account for the anticipated and assumed costs of transportation that will be incurred by a location choice. A vast literature has elaborated on these concepts, with contributions from researchers in many disciplines including regional science, real estate economics, urban studies, and city planning. The location affordability concept, however, represents something of a departure. It asserts that any consideration of housing affordability must explicitly evaluate the transport costs incurred as a consequence of a location choice rather than assume those costs are capitalized into the cost of housing. The benefit of decomposing location costs is the potential for a more nuanced understanding of household choices and constraints, and of the factors that influence them.

A range of housing and transport system configurations can result in affordable locations. For example, it may be that high housing cost burdens in densely developed urban markets can be softened by the use of low-cost transportation services, such as public transit, cycling, or walking. Intensely urban areas are usually more compatible with low-cost transport modes because distances are shorter, enabling walking or cycling, and density concentrates people, so as to make public transit feasible. Conversely, in areas where there is little pressure on land markets and development is at low densities, housing prices are usually lower. Yet such areas are inefficient and expensive to serve by public transit and long distances between work and residential locations make walking or cycling infeasible. As a result, households rely on private automobiles for transport, which require substantial investment to purchase, maintain, and operate. This is the sketch of the arguments against urban sprawl and in favor of compact patterns of urban form (i.e. "Smart Growth"), where households' housing and transport costs reflect the joint configuration of the land development and transport systems in a city (see e.g. Ewing and Cervero, 2010; Khan et al., 2014). Yet the evidence of the effect of sprawl on travel behavior, congestion and physical health are mixed (see e.g. Khattak and Rodriguez, 2005; Sarzynski et al., 2006; Eid et al., 2008). The impacts for housing costs are also unclear. In a recent policy evaluation by Litman (2015), the effect of anti-sprawl policies such as constraining urban expansion, promoting high density infill development, requiring higher design standards, and remediating brownfields can be expected to increase housing costs, especially for single family dwelling units.

One of the reasons for these mixed results may be related to the wide variation in the way urban sprawl has been defined and measured. While sprawl is broadly understood to be ex-urban, low-density development, with segregated land uses and an orientation toward automobile use; there is no consensus on a consistent definition that is appropriate for use in empirical studies. In a particularly pointed critique, Galster et al (2001) called the sprawl literature a 'semantic wilderness' where advocates, apologists, and critics confuse patterns of urban form with processes of urban development, causes with effects. Conceptual problems are compounded by technical issues that can affect results including the selection of threshold levels, unit of analysis, metro areas sampled, and the modifiable areal unit problem (MAUP).

Suggestions for improving measurement include using a multi-dimensional approach. Cutsinger et al (2005) proposed measuring urban form with the dimensions defined by factor analysis to bring greater quantitative rigor to definitions of urban sprawl. The effect of definitional differences is clearly demonstrated in a paper by Kelly-Schwartz and colleagues (2004) where the effects of sprawl on physical health in 29 Metropolitan Statistical Areas (MSAs) are evaluated. No significant relationship between sprawl and health metrics is found when a composite measure of urban form was used. However, measures of particular dimensions of urban form did have differential effects: high street network connectivity was associated with improved health, although increased density had a negative effect on health. Different dimensions of urban form may similarly have differential effects on location affordability.

Banai and DePriest (2014) describe the relationship between definitions of sprawl, data, measurement methods, and impacts as constituting a 'disjointed epistemic system'. It is a system because each of the components affects the other, and the understanding of impacts is shaped by how sprawl is defined and measured and the data available. It is disjointed because definitions vary across and within disciplines; methods also vary, ranging from simple indices using a single metric to urban models with high computational and data input requirements. These authors argue for a more connected system, where measurement methods are more strongly linked to impacts, so as to inform practice and develop applied research programs.

With the increase in the coverage, detail, and content of spatial data, scholars are producing new datasets and new methods for measuring urban form, contributing to the pool of knowledge about sprawl and its effects. These new data and methods can support more rigorous evaluation of impacts. A high profile example is the 2010 Sprawl Index, developed by the advocacy organization Smart Growth American (2014). Drawing from the literature to extend a previous iteration using 2000 data, the 2010 Sprawl Index is a composite index, constructed from sub-indices of density, land use mixing, centrality, and road network characteristics. Taking a more data-driven approach, Sarzynski and colleagues (2014) used ecological factor analysis to develop four dimensions of urban form to rank 257 metropolitan regions on each dimension in 1990 and 2000.

Similarly, definitional questions arise when considering how to define affordability. For housing, costs of less than 30% of household income is usually defined as affordable. In the U.S. this ratio is used to establish rent prices for subsidized units, to determine whether households qualify for subsidized mortgages, and to identify metropolitan areas where program resources will be directed. Interestingly, this threshold is an axiom, which can be traced to the 19th century saying, 'one week's pay for one month's rent' (Hulchanski, 1995). It is important to note that this is a normative definition of what households 'should' spend on housing, irrespective of housing quality or quantity, local housing market conditions, or household preferences and budgets (see Hulchanski, 1995, for a full discussion). Alternative methods for defining high housing costs have been proposed, including the residual income approach (Stone 2008), which is a considerable methodological improvement, but is difficult to apply because of data requirements.

Compared with housing affordability, a definition of transportation affordability is far less clear. Transportation costs are paid unevenly over time and to many entities for a wide range of fixed and variable costs (purchase, insurance, fuel, maintenance, road taxes, parking, etc.). Thus it can be difficult for policy makers, researchers, and even households to ascertain the costs of their transportation consumption. The recent interest in location affordability has spurred some efforts to define an affordability threshold, with some consensus around 15 to 20% of household income (see e.g. Litman, 2015; Lucas et al., 2007). Wang and colleagues (2015) take a slightly different approach to develop their Transportation Cost Index (TCI), conceptually similar to the Consumer Price Index. The TCI calculates the time and monetary costs of a 'basket of trips' to calculate the cost of accessibility by location. Costs are based on regional travel models and can be used to compare costs across a region and among various land development scenarios in long-range planning efforts.

Prominent examples of a location affordability indices based on the ratio definitions for affordability and developed for application in practice include the influential Housing+Transportation (H+T) Index, which was first released by the Center for Neighborhood Technology in 2006. The H+T Index maps affordability using predefined thresholds for household costs. The Location Affordability Portal, a joint project of the United States Department of Transportation and the United States Department of Housing and Urban Development (HUD; 2015), presents detailed housing and transportation cost projections for a variety of household types and travel behavior profiles.

The recent proliferation of spatial data, along with improvement in methods and capacity for data processing and presentation are opening new possibilities for research and practice. Yet for location affordability to be adopted as a part of routine work in the transportation and housing sectors, a more coherent and complete knowledge base is needed. Research can contribute by revisiting accepted definitions and testing new datasets and measurement methods for use in practice. Of particular importance in building interest in the transportation sector is research that moves beyond the descriptive to analyze outcomes. This is because transportation agencies increasingly operate in an environment of accountability where resource allocation decisions in planning, project prioritization, and routine system operations are made using performance measures and data-driven processes. Research efforts can support integrating location affordability into these processes with a stronger focus on emerging data and measurement methods in analyses of observable outcomes rather than descriptive studies.

Data

In this analysis, the dependent variable is the estimated foreclosure rate for 2007 to June 2008 from the US Housing and Urban Development (HUD) data for the Neighborhood Stabilization Program (NSP). The data were released when the foreclosure crisis was well underway and HUD was seeking to provide information to state and local agencies for use in targeting programs and resources toward areas of greatest need. Because these data were developed to evaluate risk, they are comprised of several measures known to contribute to foreclosure in addition to actual foreclosure filings. These measures include the number of vacant addresses, the share of mortgage loans that are high-cost loans, housing price decline from the area price peak between 2000 and 2008, and the county unemployment rate in June 2008 (see U.S. Department of Housing and Urban Development, 2008, for full documentation). However, the foreclosure estimates may be conservative estimates of troubled households: they do not include information on households that were able to avoid default through a short sale, renegotiating the terms of a mortgage, or even changing living arrangements (taking in family members or others, i.e. "doubling up"). Of course, the 2008 foreclosure crisis may prove to be a unique event, however it does provide an opportunity to explore factors that contribute to or erode positive outcomes in times of economic stress.

The predictor variables include demographic data from the U.S. Census (2000, Summary File 3), again at the Census tract level. In the analysis, variables are selected to describe basic neighborhood characteristics: median income for homeowners, share of Black homeowners, and share of Hispanic/Latino homeowners. Two control variables are included: the number of housing units as a control for tract size, and the number of housing units occupied by homeowners as a control for the number of mortgages. Cost variables are shares of residents reporting high housing costs (according to the 30%-of-income threshold), and shares of households with high levels of automobility (3 or more vehicles available to a household). An interaction term, multiplying income by the automobility variable is also included.

The emphasis on automobility (the use of and reliance on private autos) as an indicator of high transport costs follows from the positive relationship between household transportation expenditures and auto ownership and, conversely, the reduction in transportation expenditures for households who use transit or non-motorized modes (cycling, walking; Litman, 2015). The three-car threshold draws from information from the Bureau of Labor Statistics Consumer Expenditure Survey (CES; http://www.bls.gov/cex/csxreport.htm#annual), where the national average expenditure per vehicle was $3,679 in 2000 and $4,045 in 2008, with some small variability by Census region. Multiplying these values by three gives a national average cost for high automobility of $11,037 in 2000 and $12,137 in 2008, equivalent to nearly 25% of average income in 2000 and just over 19% in 2008, figures in line with thresholds for transportation affordability suggested in the literature. It is noteworthy that the CES reports average national income increased dramatically from 2000 to 2008, by just over 40%; yet the share of income expended on vehicles dropped by about 5%, in large part because expenditures on gas and oil doubled. This highlights the vulnerability of households with high levels of automobility for whom dramatic rises in the variable costs of driving can offset any increases in income.

The characteristics of urban form are represented in the model by a set of variables measuring land use characteristics developed by Sarzynski et al. (2014). These scholars compiled a set of 14 land use metrics for 257 U.S. metropolitan regions (MSAs plus any territories that are functionally dependent on an urban center, dependency defined as areas where 30% or more of residents commute to the urban area) for the year 1990 and for 2000. Using these data and following their method in Stata, a factor analysis reduces the 14 metrics to a solution retaining four factors:

- Intensity: housing density, job density, and the continuity of development within the metropolitan area
- Compactness: the degree to which housing and jobs are concentrated toward the central core of the city and the density of development at the center compared to the periphery
- Mixed use: the degree to which housing and jobs are integrated at a fine scale
- Core-dominance: the ratio of jobs located in the central business district compared to jobs located in all other job concentrations

These factors capture characteristics often included in definitions of urban sprawl, with the possible exception of core-dominance, which is a measure of monocentricity (vs polycentric form). The four factors explain 81% of the variation of all 14 measures in 1990 and 84% of the variation in 2000. Notably, the interrelationships among the factors changed little over time (with intensity and compactness switching places as first and second component from 1990 to 2000), suggesting stability in the measurement of important characteristics of urban form. Further, there is little correlation among the factors, suggesting they differentiate dimensions of land use.

The scoring coefficients for the factors are then used to calculate a score for each city on each factor. These scores identify those places that had exhibited the greatest amount of change over the 1990-2000 time period, where a decrease on a factor represents an increase in sprawl and vice-versa. For each of the four factors, the five cities that displayed the greatest increase and the five with the greatest decrease are included in the models (see Table 1). Note that some cities are among the places with the greatest change along multiple factors.

The unit of analysis is the 2000 Census tract, with tracts selected by Census boundaries for MSAs in 2000. This varies somewhat from the geography used in defining the urban form factors, where functionally dependent areas were included along with the Census-defined MSA. Here, data limitations require the assumption that the amount and degree of land use change across the factor geography (MSA + functionally dependent areas) provides valid information about urban form characteristics and change that affect the territory of the Census-defined MSA. In other words, while functionally dependent areas outside the MSA boundary are included in the calculation of the urban form factors, these areas are not included in the analysis presented in this paper.

The time lag between the predictor variables (2000) and the outcome variable (2008) allows for evaluating the effects of precursor conditions, as well as addressing potential reverse causality. Prior to estimating the model, tracts that had fewer than 10 mortgages in 2008 were removed from the dataset; these tracts were usually located in dense urban centers where commercial or institutional uses (e.g. university campuses) predominate. Table 2 lists the variables used and descriptive statistics.

Method

This study uses a series of regressions to investigate the relationship between demographic, household cost, and urban form variables and estimated foreclosure rates. Models are estimated using RStudio (Version 0.98.1091), a platform for the open source statistical computing language R.

Initial exploration of the data reveals definite spatial structure, where nearby values for tract-level estimated foreclosure rates are similar. For this analysis, a spatial neighbors matrix assigns Census tracts with shared boundaries as neighbors (first-order, Queen contiguity). This draws from studies of the neighborhood effects of foreclosure, which find the spatial extent of the impact of a foreclosure on nearby properties tends to be limited (see, e.g., Yin et al., 2009; Immergluck and Smith, 2006; Kobie, 2010).

The matrix is then adjusted so that tracts are only defined as neighbors if they are in the same MSA, even if they are adjacent to tracts of a different MSA (as is the case for several MSA border tracts in regions where MSAs are adjacent). This defines any spatial interaction effects related to foreclosure and housing markets as occurring between tracts in the same MSA, not across MSA boundaries. In the few cases where tracts are islands (either physically or created by the removal of tracts with fewer than 10 mortgages), the nearest tract is defined as a neighbor. Finally, the spatial neighbors matrix is row-standardized to create a spatial weight matrix.

Results

Models with Urban form Variables

The first models include an OLS model, a spatial error model (SEM), and a spatial lag model SLM). Variables include the demographic and cost variables described previously, along with their spatially lagged versions. This allows for the estimation of the size and direction of the effect of neighboring tracts values on these variables, in addition to any effect of adjacency on the dependent variable (in the SLM) or on the value of the error (in the SEM). The land-use variables are not lagged as these values are metro-level variables and thus the same for all tracts in the same metro. The variables, outl1 and outl2 represent two outlier tracts in Jersey City which are associated with very large errors; these very high income tracts are retained but modeled using dummy variables to limit their effect on the error. Table 3 presents the results from these models.

Across all three models, income in the year 2000 has a significant and negative effect on the estimated foreclosure rates in 2008, while percent Black and percent Hispanic homeowners have positive effects. The high automobility variable is also positive, and gains significance in both spatial model specifications compared with the OLS model. The interaction term for income times automobility is also consistently positive, but loses some degree of significance in the SEM and SLM. Still, the relative size of the coefficients means the effect of this interaction term is always positive; increases in income are, at some point, offset by the increased cost burden of higher automobility. The variable for the percent of homeowners with high housing costs in 2000 has similar effects, although it declines in significance in the SLM, where some of its variation is captured in the spatially lagged dependent variable.

Turning to the lagged predictor variables, some interesting effects are revealed. For income, the coefficients for both the 'direct' (unlagged) and spatially lagged variables are negative. All else equal, increasing income in a tract decreases estimated foreclosure rates and increasing income in neighboring tracts is associated with a further reduction in foreclosure, a spatial spread effect. Contrast this with the pattern for percent Black homeowners in the OLS model. Here, the coefficients indicate that a tract with a high percentage of Black homeowners will have a high estimated foreclosure rate; however, if the adjacent tracts also have high shares of Black homeowners, the foreclosure rate is somewhat reduced, a so-called 'backwash' effect (Barkley et al., 1996). Conversely, if a tract with a high share of Black homeowners is surrounded by tracts with high shares of non-Black homeowners, the estimated foreclosure rate is further increased. Notably, the significance of the lagged variables is reduced or eliminated in the SEM, while these variables remain significant in the SLM, suggesting that capturing the spatial structure in the error term accounts for these interaction effects, except for the high housing cost variable.

The results for the effect of the urban form factors are somewhat mixed. The only consistent results are related to the intensity factor (intens00), where increased intensity is associated with increased estimated foreclosure rates, and being located in a metro with a trajectory of decreasing intensity (increasing sprawl) from 1990-2000 (intens_dum = 1) had a negative effect on estimated foreclosure rates. The other factors exhibit conflicting results between the factor value for 2000 and the trajectory of development (dummy variables) across the models.

The measure of compactness (comp00) is only significant in the OLS model, and the direction of change dummy proves unstable (see Table 3). The variable for the degree of land use mixing is significant and negative. However, the effect of change on this dimension, that is whether a city was becoming more mixed or less mixed from 1990 to 2000, varies both in direction of effect and level of significance. Finally, the degree of centrality of jobs (core00) is negative and significant across the models, while the dummy variable of direction of change is unstable in sign and level of significance.

As for overall model fit, the spatial diagnostics strongly suggest the need for using a spatial model, with a slightly stronger case for the SEM. However, in the SEM, the lambda coefficient is very large (0.708), indicating there is considerable information still contained in the error. (Note that collinearity diagnostics do not reveal substantial multicollinearity issues.) Relatedly, the standard errors of the coefficients are also large compared to the size of their respective coefficients. Thus the estimates, while unbiased, are inefficient.

Models with Metro Dummy Variables

To further explore the importance and relevance of the urban form factors in predicting location unaffordability, the models are re-specified, replacing the urban form factors with dummies for the metros, which effectively adds all the characteristics of each metro—observed and unobserved—to the model. The results are presented in Table 4. In this iteration, the overall fit of the models improves considerably: the adjusted R-square increases to 0.7471 (see Table 6).

The coefficients for the metro variables estimate the difference between each metro and the omitted reference case (Bellingham, WA, selected for its overall low foreclosure rate), so the interpretation of these estimates is of less interest that their contribution to overall fit. Still, the dummy variables for the MSAs are nearly all significant, most with a p-value below 0.0001.

Coefficients for income, percent Black, percent Hispanic, and high automobility rates continue to show the expected signs and remain highly significant. The percent of homeowners with high housing costs, however, becomes insignificant. The spatially lagged variables also lose significance, except for income, which retains its significant and negative effect. This suggests that the metro dummies explain much of the internal spatial interaction among tracts. The improvement in the model fit and the reduced significance of the lagged predictors indicate that, although the full set of characteristics and conditions of each metro are undefined, metros are better predictors of estimated foreclosure rates than are the urban form factors. This is an intuitive result, yet of interest for evaluating the value of urban form variables in analyses of location affordability.

Also of interest are the changes in the cost variables. The high housing cost variable becomes insignificant, 'washed out' by the metro dummies, which likely capture the overall housing market conditions in each metro. In contrast, the variation in high automobility rates within metros appears to matter; this variable retains its significant and positive effect on foreclosure, even with metro dummies accounting for characteristics of the transportation system (such as transit accessibility) that were not captured by the urban form factors. This result lends support for the location affordability concept that places transportation costs as an important household cost burden.

The spatial diagnostics strongly indicate a spatial error specification. The SEM results are similar to the OLS results, although the overall model fit improves, and the value for lambda coefficient is less than half that in the model with the urban form variables (0.235 vs 0.708; see Table 6). As expected, the amount of information yet remaining in the error term is much reduced by including the metro dummies, which account for a richer set of characteristics and conditions than the urban form factors alone.

As a final exploration of the data, metros are combined to investigate whether they fall into subgroups with similar characteristics. This was done through a stepwise process in which metro dummies with similar effects (differences in coefficients of ~0.025 or less and with the same sign) were combined into a single, dummy variable. After each combination, the model is rerun and model fit re-assessed. The process is repeated until the adjusted R-square begins to decline, indicating that additional combinations reduce the explanatory power of the model. The groupings of metros that produce the highest adjusted R-square are evaluated for internal similarities; in this way, a set of data-driven 'clusters' of metros is created, based on their similar effect on the dependent variable. For the 34 metros in the model, the process is repeated 17 times, reducing the number of dummy variables by half, to 16, with a corresponding increase in the R-square from 0.7471 to 0.7484. Due to space limitations, detailed results are not reported here, however, this procedure did not reveal any evident pattern of similarity in the urban form factors or geography in the subgroups of metros.

Summary and Conclusion

The recent foreclosure crisis presents an opportunity to investigate conditions that mitigate unaffordability by reducing economic vulnerability. The results presented in this paper suggest that in times of economic stress, neighborhoods with high shares of Black homeowners, high shares of Hispanic homeowners, and low income levels are particularly vulnerable to foreclosure. The spatial distribution of Black homeowners appears to have differential effects, with the largest increase in estimated foreclosure rates seen when Black homeowners are concentrated and isolated within an urban system.

The importance of the metro itself in explaining variation in foreclosure rates point to the presence of complex processes in addition to household cost burdens. These processes likely include economic, socio-demographic, and geographic factors at the regional and macroeconomic levels. The foreclosure crisis also unfolded differently in different cities, perhaps driven by differences in the structure of the employment sector and the labor market, demographics and demographic changes, and patterns in mortgage lending. Differences in time of the onset of the crisis may not be captured in this analysis. The importance of metro-specific variables in the models suggests the need to consider local and regional conditions in location affordability efforts.

The results for the effect of high housing costs on estimated foreclosure rates further suggests that metro-specific conditions are important. The share of homeowners with high housing costs generally had a significant and positive effect on estimated foreclosure rates in the models with the urban form variables. In the models with the metro dummies, this variable is insignificant. Thus the explanatory ability of high housing costs, defined by the conventional 30% ratio, for predicting foreclosure rates disappears when the specific metro area in which the Census tract is located in is controlled for. This suggests that the effect of housing cost burdens is a metro-level phenomenon, not a tract-level one. This is an interesting result that challenges the popular narrative that foreclosures were the inevitable result of people purchasing houses they cannot afford. It is also of interest in connection with the 30%-of-income threshold; it may be that this threshold is not predictive of unaffordable outcomes, a possibility that can be explored through a sensitivity analysis to test the effect of alternative thresholds.

The findings related to automobility are of interest for the transportation sector. The positive relationship between high rates of high automobility and estimated foreclosure rates suggests there is an important role for the transportation sector in location affordability. The variation in levels of high automobility within a metro is significantly and positively associated with estimated foreclosure rates. Thus, policy, planning, and projects that reduce high levels of automobility may improve location affordability outcomes, particularly for neighborhoods with additional characteristics related to increased foreclosure. While transit service is frequently suggested as the remedy to high automobility rates, emerging, flexible solutions such as car sharing or ride sharing could be even more promising. An important caveat, however, is that high levels of automobility may be an indicator for other patterns of household expenditures—high levels of consumer spending and perhaps debt—may increase foreclosure rates.

Notably, the urban form factors are found to be inconsistently related to variation in estimated foreclosure rates, with the exception of changes in development intensity. The models indicate that location affordability may be compromised by rising intensity; trajectories of change toward increased intensity need to be coupled with concerted efforts to support location affordability. The other urban form variables yield mixed results.

These results support the view that having the nebulous goal of 'reducing sprawl' is unlikely to provide adequate direction for applied practice. Instead, a multidimensional approach can tease apart the components of urban form with salient impacts and provide more specific information about likely effects of a change in urban form. However, limited explanatory power of the four dimensions used in this paper is a concern. It may be that the sample of metros introduces bias. It may be that this particular set of factors does not capture urban form appropriately for the question under consideration. Alternatively, since the relationship between urban form and location affordability is indirect, with urban form effects transmitted to households through land markets and transportation systems, the analysis could be improved by including data on these elements (e.g. public transit and roadway system characteristics). Or, it may be that sprawl does not have a measurable impact on affordability.

Strengthening the case for location affordability as a policy direction and objective for decision makers, will require continuing to develop an evidence base that can be tapped by both the housing and transportation sectors. This evidence base will need to include information on urban form, which shapes and is shaped by projects and policies in both of these sectors. The evidence base itself must constitute a connected system of knowledge, one in which the definition, data, measurement, and impacts of location affordability are linked, in order to move the concept to implementation (Banai and DePriest, 2014).

The analysis presented in this paper contributes to the evidence base with findings that confirm the importance of transportation costs to affordability outcomes. The analysis also explores the applicability of a recent index of urban form to location affordability and finds differential effects among factors of urban form. Yet expanding the models to include more information about metro level conditions is indicated. Continuing to build the evidence base for location affordability requires further work that harnesses new data resources, develops new measurement methods, refines definitions, and evaluates impacts of affordability. Coordinating these components to develop a functioning system of knowledge will support the development of a coherent knowledge system for location affordability that can be mobilized for improving the affordability conditions in cities.

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References

Alonso, W. 1964. *Location and Land Use. Toward a general theory of land rent*. Harvard University Press, Cambridge.

Banai, R. and T. DePriest. 2014. Urban Sprawl: Definitions, Data, Methods of Measurement and Environmental Consequences. *Journal of Sustainability Education*, Vol. 7.

Barkley, D.L., M.S. Henry, and S. Bao. 1996. Identifying "Spread" versus "Backwash" Effects in Regional Economic Areas: A Density Functions Approach. *Land Economics*, Vol 72, No. 3, pp. 336-357.

Center for Neighborhood Technology. H+T Index. Undated. http://htaindex.cnt.org.

Cutsinger, J., G. Galster, H. Wolman, R. Hanson, D. Towns. 2005. Verifying the Multi-Dimensional Nature of Metropolitan Land Use: Advancing the Understanding and Measurement of Sprawl. *Journal of Urban Affairs*, Vol. 27, No. 3, pp 235-259.

Eid, F., H.G. Overman, D. Puga, and M.A. Turner. 2008. Fat city: Questioning the relationship between urban sprawl and obesity. *Journal of Urban Economics*, Vol. 63, pp. 385-404.

Ewing, R., and R. Cervero. 2010. Travel and the built environment: a meta-analysis. *Journal of the American Planning Association*, Vol. 76, Issue 3, pp. 265-294.

Galster, G., R. Hanson, M. R. Ratcliffe, H. Wolman, S. Coleman , and J. Freihage. 2001. Wrestling Sprawl to the Ground: Defining and Measuring an Elusive Concept. *Housing Policy Debate*, Vol. 12, Issue 4, pp. 681-717.

Hulchanski, J. D. 1995. The concept of housing affordability: Six contemporary uses of the housing expenditure-to-income ratio, *Housing Studies*, 10:4, 471-491.

Immergluck, D. and G. Smith. 2006. The external costs of foreclosure: The impact of single-family mortgage foreclosures on property values. *Housing Policy Debate*, Vol. 17, pp 57-79.

Kelly-Schwartz, A.C., J. Stockard, S. Doyle, and M. Schlossberg. 2004. Is Sprawl Unhealthy? A Multi-level Analysis of the Relationship of Metropolitan Sprawl to the Health of Individuals. *Journal of Planning Education and Research*, Vol. 24, No. 2, pp. 184-196.

Khan, M., K.M. Kockelman, X. Xiong. 2014. Models for anticipating non-motorized travel choices, and the role of the built environment. *Transport Policy*, Vol. 35, pp. 117-126.

Khattak, A.J. and D. Rodriguez. 2005. Travel behavior in neo-traditional neighborhood developments: A case study in USA. *Transportation Research Part A*, Vol. 39, pp. 481-500.

Kobie, T.F. 2010. The Spatial-Temporal Impact of Residential Foreclosures on Single-Family Residential Property Values. *Urban Affairs Review*, Vol. 47, Issue 1, pp. 3-30.

Litman, T. 2015. Transportation Affordability. Evaluation and Improvement Strategies. Victoria Transport Policy Institute, Victoria B.C., Canada. http://www.vtpi.org/affordability.pdf

Lucas, K., G. Marsden,, M. Brooks, M. Kimble. 2007. An assessment and critique of capabilities for examining the long-term social sustainability of transport and land-use strategies. In *Proceedings of the 86th Annual Meeting of the Transportation Research Board*, CD-ROM. Transportation Research Board of the National Academies, Washington, D.C.

Litman, T. 2015. Analysis of Public Policies That Unintentionally Encourage and Subsidize Urban Sprawl. Victoria Transport Policy Institute, Supporting paper commissioned by LSE Cities at the London School of Economics and Political Science, on behalf of the Global Commission on the Economy and Climate (www.newclimateeconomy.net) for the New Climate Economy Cities Program. http://static.newclimateeconomy.report/wp-content/uploads/2015/03/public-policies-encourage-sprawl-nce-report.pdf.

Sarzynski, A., G. Galster, & L. Stack. 2014. Evolving United States metropolitan land use patterns. *Urban Geography, 35*, 25-47.

Sarzynski, A., H.L. Wolman, G. Galster, and R. Hanson. 2006. Testing the Conventional Wisdom about Land Use and Traffic Congestion: The More We Sprawl, the Less We Move? *Urban Studies*, Vol. 43, No. 3, pp. 601-626.

Smart Growth America. 2014. *Measuring Sprawl 2014*. Smart Growth America, Washington D.C. http://www.smartgrowthamerica.org/measuring-sprawl.

Stone, Michael E. 2006. "What is housing affordability? The case for the residual income approach." *Housing Policy Debate*, 17:1, pp 151-184.

U.S. Department of Housing and Urban Development. 2008. Neighborhood Stabilization Program - Methodology and Data Dictionary for HUD Provided Data. Washington, DC: HUD Retrieved from http://www.huduser.org/portal/datasets/nsp_foreclosure_data.html

U.S. Department of Housing and Urban Development. 2015. Location Affordability Portal, Version 2. http://www.locationaffordability.info/default.aspx.

von Thünen, J. H. 1966. Isolated state: an English edition of Der isolierte Staat. Chicago: Pergamon Press.

Wang, L., B. Reiff, B.J. Gregon, H. Yang, and J. Hsing-I Liu. 2015. Transportation Cost Index: A Comprehensive Multimodal Performance Measure of Transportation and Land Use Systems. Paper presented at the 94th Annual Meeting of the Transportation Research Board, January 2015, Washington, D.C.

Yin, Z., E. Rosenblatt, and V.W. Yao. 2009. Spillover Effects of Foreclosures on Neighborhood Property Values. *Journal of Real Estate Finance and Economics*, Vol. 38, pp. 387-407.

TABLE 1 Metros by Land Use Factor and Direction of Change

Factor	Metro and state	Direction of change	Code in regressions	No. Census tracts
Intensity	Florence, AL	-	aub	20
	Hattiesburg, MS	-	hatt	23
	Iowa City, IA[a]	-	iowa	13
	Las Cruces, NM[a]	-	lascru	30
	New Orleans, LA	-	nola	384
	Bakersfield, CA	+	bakr	136
	Greeley, CO	+	gree	36
	Merced, CA	+	merc	47
	Rochester, MN	+	roch	33
	Pittsfield, MA[a]	+	pitts	23
Compactness	Bellingham, WA	-	bell	26
	Casper, WY	-	casp	17
	Cheyenne, WY	-	chey	18
	Newburgh, NY-PA	-	newb	74
	Visalia, CA	-	visal	75
	Grand Forks, ND-MN	+	gfrk	26
	Las Cruces, NM[a]	+	lascru	30
	Pittsfield, MA[a]	+	pitts	23
	Tuscaloosa, AL	+	tusca	44
	Utica-Rome, NY	+	utica	88
Mixed use	Allentown-Bethlehem, PA	-	alln	141
	Auburn-Opelika, AL	-	aub	20
	New London-Norwich, CT-RI	-	nlond	66
	Pittsfield, MA[a]	-	pitts	23
	St. Cloud, MN[a]	-	stcld	34
	Chico-Paradise, CA	+	chic	42
	Dover, DE	+	dov	34
	Hagerstown, MD	+	hagr	31
	Iowa City, IA[a]	+	iowa	13
	San Luis Obispo-Atascadero-Paso Robles, CA	+	sanluis	42
Core-dominance	Cedar Rapids, IA	-	cedr	42
	Richland-Kennewick-Pasco, WA	-	richl	36
	Santa Barbara-Santa Maria-Lompoc, CA	-	santab	84
	Toledo, OH	-	toled	159
	Ventura, CA	-	vent	152
	Chico-Paradise, CA[a]	+	chic	42
	Jersey City, NJ	+	jers	149
	Redding, CA	+	redd	33
	Ocala, FL	+	ocal	46
	Orange County, CA	+	oran	572

[a] Metro changed on more than one land use factor.

TABLE 2 Variable definitions and descriptive statistics (N = 2807)

Variable Name and Description	Min	Max	Mean	Median	St. Dev.
PCTOWNOCC (% of occupied units that are owner occupied)	0.000	1.00	0.6254	0.6664	0.2256
TOTUNT_100 (number of occupied housing units divided by 100)	0.040	72.800	16.030	15.050	7.1380
trctinc_o (median income for homeowners divided by 10,000)	-0.00025	16.5800	5.4880	5.1360	2.1322
pct_hisp_o (% owner occupied housing units occupied by Hispanic or Latino owner occupant household)	0.000	1.000	0.11970	0.04654	0.1819
pct_blk_o (% owner occupied housing units occupied by Black owner occupant household)	0.000	1.000	0.08498	0.01062	0.2051
PCT_O_HHSG (% of specified owner occupied housing units, with mortgages and where 30% or more of income spent on housing in 2000)	0.000	0.8596	0.2271	0.2164	0.1014
PCTO_3PLS (% of owner-occupied housing units with 3 or more vehicles in 2000)	0.000	1.000	0.2198	0.2185	0.1022
INCAUTO (interaction variable: trctinc_o * PCTO_3PLS)	-1.47900	3.26800	0.07926	0.02378	0.2489
intens00 (value of intensity factor in 2000)	-1.8000	4.0770	0.7749	0.4842	1.6724
comp00 (value of compactness factor in 2000)	-1.8530	3.6180	-0.0572	-0.1717	1.3869
mix00 (value of land use mix factor in 2000)	-2.7680	2.5440	0.3510	0.1887	0.9876
core00 (value of core-dominance factor in 2000)	-2.2320	2.0330	-0.2097	0.08852	1.3158
intens_dum (dummy variable for direction of change on intensity factor from 1990-2000; 1 = decrease, 0 = increase)	0.000	1.000	0.5878	1.000	0.4923
comp_dum (dummy variable for direction of change on compactness factor from 1990-2000; 1 = decrease, 0 = increase)	0.000	1.000	0.5921	1.000	0.4915
mix_dum (dummy variable for direction of change on land use mix factor from 1990-2000; 1 = decrease, 0 = increase)	0.000	1.000	0.3595	0.000	0.4799
core_dum (dummy variable for direction of change on core-dominance factor from 1990-2000; 1 = decrease, 0 = increase)	0.000	1.000	0.5155	1.000	0.4998
LGSTTRFCL (estimated foreclosure rate, logistic transformed; dependent variable)	-7.338	-1.350	-3.049	-3.015	0.6911

TABLE 3 Model Results: Land use factors (dependent variable = LGSTRFCL, N = 2807)

OLS Model					SEM (Maximum Likelihood estimation): Lambda = 0.70837***			
	Estimate	**Std. Error**	**t-value**	**Pr(>|t|)**	**Estimate**	**Std. Error**	**z-value**	**Pr(>|z|)**
(Intercept)	-2.316968	0.109453	-21.169	***	-2.69815368	0.15778201	-17.1005	***
PCTOWNOCC	-0.012494	0.053559	-0.233		-0.07079425	0.04722149	-1.4992	-
TOTUNT_100	-0.00271	0.001409	-1.923	.	-0.00055334	0.00124722	-0.4437	-
trctinc_o	-0.139018	0.006658	-20.88	***	-0.11914218	0.00569647	-20.9151	***
pct_hisp_o	0.696661	0.073364	9.496	***	0.76295966	0.06169498	12.3666	***
pct_blk_o	0.949348	0.06367	14.91	***	1.01247663	0.05177912	19.5538	***
PCT_O_HHSG	0.448476	0.121455	3.693	***	0.38310299	0.10419187	3.6769	***
PCTO_3PLS	0.392858	0.128561	3.056	**	0.48062178	0.10994278	4.3716	***
INCAUTO	0.127146	0.040281	3.156	**	0.09123012	0.03594209	2.5383	*
intens00	0.117457	0.010764	10.912	***	0.10818101	0.0145421	7.4392	***
comp00	-0.074908	0.009917	-7.554	***	0.01118249	0.01305339	0.8567	-
mix00	-0.158248	0.014646	-10.805	***	-0.16478607	0.02253071	-7.3138	***
core00	-0.125195	0.014474	-8.65	***	-0.06037323	0.01898437	-3.1802	*
intens_dum	-0.075986	0.028449	-2.671	**	-0.53470169	0.048686	-10.9827	***
comp_dum	-0.162378	0.029349	-5.533	***	0.15157719	0.0437697	3.4631	**
mix_dum	0.146638	0.032939	4.452	***	-0.09709281	0.0484245	-2.005	*
core_dum	-0.126423	0.046538	-2.717	**	0.12628964	0.0607618	2.0784	*
lag.PCTOWNOCC	0.364129	0.103382	3.522	***	0.10804582	0.12152598	0.8891	-
lag.TOTUNT_100	-0.011408	0.002763	-4.128	***	-0.00029584	0.00324687	-0.0911	-
lag.trctinc_o	-0.078145	0.011712	-6.672	***	-0.02771682	0.01390241	-1.9937	*
lag.pct_hisp_o	0.21138	0.122393	1.727	.	0.01595653	0.14555572	0.1096	-
lag.pct_blk_o	-0.851209	0.109369	-7.783	***	-0.35895552	0.12422243	-2.8896	*
lag.PCT_O_HHSG	1.851665	0.216533	8.551	***	0.99442887	0.25399345	3.9152	***
lag.PCTO_3PLS	-0.916348	0.216456	-4.233	***	0.10155564	0.26953881	0.3768	-
lag.INCAUTO	0.261683	0.084496	3.097	**	0.10357642	0.09729835	1.0645	-
outl1	-3.195553	0.49697	-6.43	***	-3.50199069	0.37728992	-9.282	***
outl2	-3.201886	0.497478	-6.436	***	-3.49852611	0.37338477	-9.3698	***

Significance: < 0.0001 = *** 0.001= ** 0.01 = * 0.05 = . >0.05 = -

TABLE 3 (con't) Model Results: Land use factors (dependent variable = LGSTRFCL, N = 2807)

SLM Model (ML estimation) Rho: 0.62993					Model Diagnostics	
	Estimate	**Std. Error**	**z-value**	**Pr(>|z|)**		
(Intercept)	-0.8842662	0.0980115	-9.0221	***	**OLS**	**Value or test statistic**
PCTOWNOCC	-0.0620416	0.0424783	-1.4605	-	Adj. R-square	0.4935
TOTUNT_100	-0.001557	0.0011175	-1.3932	-	F-stat.	106.2 ***
trctinc_o	-0.1238567	0.0052832	-23.4436	***	AIC	4010.9
pct_hisp_o	0.7363551	0.0581882	12.6547	***	Log likelihood	-1977.461
pct_blk_o	1.0456777	0.0505372	20.6913	***	Resid. stand.error	0.4918 (2780 df)
PCT_O_HHSG	0.2422554	0.0965322	2.5096	.	Studentized Breush-Pagan test	269.4471 ***
PCTO_3PLS	0.446818	0.1019608	4.3823	***	Robust Jarque Bera test	1511.714 ***
INCAUTO	0.079332	0.0319566	2.4825	.	LM diagnostics for spatial dep.	
intens00	0.0665749	0.008719	7.6356	***	LM error	1363.647 ***
comp00	-0.0130806	0.007892	-1.6575	-	LM lag	1435.722 ***
mix00	-0.0764975	0.0119202	-6.4175	***	Robust LM error	7.3589 *
core00	-0.0610443	0.0115642	-5.2787	***	Robust LM lag	79.4334 ***
intens_dum	-0.1199508	0.0230037	-5.2144	***	**SEM**	
comp_dum	0.005406	0.0232866	0.2322	-	Log likelihood	-1427.006
mix_dum	0.0763116	0.0261322	2.9202	*	Likelihood ratio (vs OLS)	-1100.911 ***
core_dum	-0.008124	0.036909	-0.2201	-	AIC	2912
lag.PCTOWNOCC	0.1522147	0.0820661	1.8548	-	Asympt. stand.error	0.015689 ***
lag.TOTUNT_100	-0.0023406	0.0021934	-1.0671	-	Robust Jarque Bera test	6111.57 ***
lag.trctinc_o	0.0376912	0.0097144	3.8799	***	Lambda (coeff. spatial error term)	0.70837 ***
lag.pct_hisp_o	-0.5649613	0.0987515	-5.721	***	**SLM**	
lag.pct_blk_o	-1.0252542	0.0872358	-11.7527	***	Log likelihood	-1469.258
lag.PCT_O_HHSG	0.7722822	0.1734334	4.4529	***	Likelihood ratio (vs OLS)	-1016.407 ***
lag.PCTO_3PLS	-0.5254581	0.1716633	-3.061	*	AIC	2996.5
lag.INCAUTO	0.0193596	0.0672579	0.2878	-	Asympt. stand.error	0.017463 ***
outl1	-3.0340604	0.3946127	-7.6887	***	Robust Jarque Bera test	4928.71 ***
outl2	-2.9893883	0.3950788	-7.5666	***	Rho (coeff. spatial lag term)	0.62993 ***

Significance: < 0.0001 = *** 0.001= ** 0.01 = * 0.05 = . >0.05 = -

TABLE 4 Model Results: Metro dummies (dependent variable = LGSTRFCL, N = 2807)

OLS Model

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-3.2786888	0.1101146	-29.78	***
PCTOWNOCC	-0.0574438	0.0386281	-1.49	-
TOTUNT_100	-0.0003142	0.0010178	-0.31	-
trctinc_o	-0.1268937	0.0048343	-26.25	***
pct_hisp_o	0.6896252	0.055724	12.38	***
pct_blk_o	1.1112639	0.0459698	24.17	***
PCT_O_HHSG	0.0827225	0.0892926	0.93	-
PCTO_3PLS	0.5186691	0.0948902	5.47	***
INCAUTO	0.0715129	0.0288737	2.48	*
lag.PCTOWNOCC	0.141029	0.0777936	1.81	.
lag.TOTUNT_100	-0.0016788	0.0021163	-0.79	-
lag.trctinc_o	-0.0615989	0.0093384	-6.60	***
lag.pct_hisp_o	-0.2195257	0.0950721	-2.31	*
lag.pct_blk_o	-0.0990498	0.0839594	-1.18	-
lag.PCT_O_HHSG	-0.2712155	0.1856373	-1.46	-
lag.PCTO_3PLS	0.1652197	0.1741306	0.95	-
lag.INCAUTO	0.0421621	0.0639015	0.66	-
alln	0.9144893	0.0773308	11.83	***
aub	-0.2033302	0.1048645	-1.94	.
bakr	1.5982556	0.07902	20.23	***
casp	-0.2390047	0.1109808	-2.15	*
cedr	0.3807034	0.0899652	4.23	***
chey	-0.2218122	0.1086635	-2.04	*
chic	1.1504533	0.0874637	13.15	***
dov	0.5426	0.0942965	5.75	***
flor	0.4593408	0.0950044	4.84	***
gfrk	0.2582219	0.1000659	2.58	**
gree	1.3988777	0.0932479	15.00	***
hagr	0.689732	0.0953309	7.24	***
hatt	0.5392933	0.1018062	5.30	***
iowa	-0.752662	0.1197019	-6.29	***
jers	1.1806663	0.086519	13.65	***
lascru	0.1992232	0.1018674	1.96	.
merc	1.8117282	0.0905879	20.00	***
nlond	0.8114429	0.0833816	9.73	***
nola	0.3201231	0.0792752	4.04	***
newb	1.058797	0.0822256	12.88	***
ocal	1.3562331	0.0906164	14.97	***
oran	1.3978404	0.080353	17.40	***
pitts	0.4723637	0.1026883	4.60	***
redd	1.2301947	0.0918845	13.39	***
richl	0.3301102	0.0919584	3.59	***
roch	0.2878315	0.09756	2.95	**
sanluis	0.7037261	0.0897032	7.85	***
santab	1.2662755	0.0839356	15.09	***
stcld	0.9720328	0.0946084	10.27	***
toled	1.5567778	0.0785937	19.81	***
tusca	0.0308251	0.0903186	0.34	-
utica	0.7269972	0.0849549	8.56	***
vent	1.3925036	0.0837153	16.63	***
visal	1.4436878	0.0856036	16.87	***
outl1	-3.4279729	0.3515495	-9.75	***
outl2	-3.2578365	0.3520016	-9.26	***

Significance: < 0.0001 = *** 0.001= ** 0.01 = * 0.05 = . >0.05 = -
Reference metro = bell (Bellingham, WA)

TABLE 5 Model Results: Metro dummies dependent variable = LGSTRFCL, N = 2807)

SEM Model (Lambda = 0.23518)				
	Estimate	**Std. Error**	**z value**	**Pr(>|z|)**
(Intercept)	-3.37913563	0.12737281	-26.53	***
PCTOWNOCC	-0.06659914	0.03790407	-1.76	-
TOTUNT_100	-0.00030928	0.00099883	-0.31	-
trctinc_o	-0.12607421	0.00472317	-26.69	***
pct_hisp_o	0.66988312	0.05445382	12.30	***
pct_blk_o	1.11103144	0.04433738	25.06	***
PCT_O_HHSG	0.10647617	0.08798438	1.21	-
PCTO_3PLS	0.51805467	0.09268887	5.59	***
INCAUTO	0.0742294	0.02848504	2.61	*
lag.PCTOWNOCC	0.13302364	0.08323365	1.60	-
lag.TOTUNT_100	-0.00087796	0.00225121	-0.39	-
lag.trctinc_o	-0.05532891	0.009967	-5.55	***
lag.pct_hisp_o	-0.22911585	0.10111111	-2.27	.
lag.pct_blk_o	-0.05045979	0.08790471	-0.57	-
lag.PCT_O_HHSG	-0.14943848	0.19732922	-0.76	-
lag.PCTO_3PLS	0.20915971	0.18669441	1.12	-
lag.INCAUTO	0.04555338	0.06826841	0.67	-
alln	0.93330562	0.09233094	10.11	***
aub	-0.19298497	0.11934566	-1.62	-
bakr	1.61683178	0.09356026	17.28	***
casp	-0.15454605	0.12574405	-1.23	-
cedr	0.45120941	0.10576727	4.27	***
chey	-0.2193706	0.12155798	-1.80	-
chic	1.19630387	0.10470447	11.43	***
dov	0.5982575	0.11106303	5.39	***
flor	0.51544274	0.11461832	4.50	***
gfrk	0.28384537	0.11291424	2.51	*
gree	1.43945573	0.10771095	13.36	***
	Estimate	**Std. Error**	**z value**	**Pr(>|z|)**
hagr	0.6737592	0.10885892	6.19	***
hatt	0.53997449	0.11928322	4.53	***
iowa	-0.75151408	0.13138344	-5.72	***
jers	1.20572235	0.10252837	11.76	***
lascru	0.32766027	0.11650247	2.81	*
merc	1.83259828	0.10636927	17.23	***
nlond	0.83513167	0.09925785	8.41	***
nola	0.33724608	0.09306728	3.62	**
newb	1.06203876	0.09838932	10.79	***
ocal	1.38271859	0.10825846	12.77	***
oran	1.3872905	0.09476584	14.64	***
pitts	0.52054189	0.11653983	4.47	***
redd	1.25456541	0.10884371	11.53	***
richl	0.36820108	0.10855018	3.39	**
roch	0.29226786	0.11634137	2.51	.
sanluis	0.71167417	0.10295035	6.91	***
santab	1.266868	0.09982639	12.69	***
stcld	0.98978611	0.11166502	8.86	***
toled	1.58077475	0.09343516	16.92	***
tusca	0.04045656	0.10675108	0.38	.
utica	0.77259585	0.10058178	7.68	***
vent	1.39208254	0.09886958	14.08	***
visal	1.47289422	0.10201961	14.44	***
outl1	-3.43580488	0.34187561	-10.05	***
outl2	-3.31853377	0.34169138	-9.71	***

Significance: < 0.0001 = *** 0.001= ** 0.01 = * 0.05 = . >0.05 = -
Reference metro = bell (Bellingham, WA)

TABLE 6 Model Diagnostics: Models with Metro Dummies

OLS	**Value or test statistic**
Adj. R-square	0.7471
F-stat.	160.4 ***
AIC	2087.1
Log likelihood	-989.5652
Resid. stand.error	0.3475 (2754 df)
Studentized Breush-Pagan test	367.7234 ***
Robust Jarque Bera test	4724.011 ***
LM diagnostics for spatial dep.	
LM error	69.6857 ***
LM lag	57.5137 ***
Robust LM error	12.5584 **
Robust LM lag	0.3864 -
SEM	
Log likelihood	-956.4381
Likelihood ratio (vs OLS)	-66.2542 ***
AIC	2022.9
Asympt. stand.error	0.027287 ***
Robust Jarque Bera test	5360.28 ***
Lambda (coeff. spatial error term)	0.23518 ***

Significance: < 0.0001 = *** 0.001= ** 0.01 = * 0.05 = . >0.05 = -

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