Cityscape

A Journal of Policy Development and Research

Urban Problems and Spatial Methods
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Symposium

Urban Problems and Spatial Methods

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Guest Editors' Introduction

Advancing Thought on the Use of Spatial Techniques and Methods for Urban Analysis

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The views expressed in this introduction are those of the guest editors and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. government.

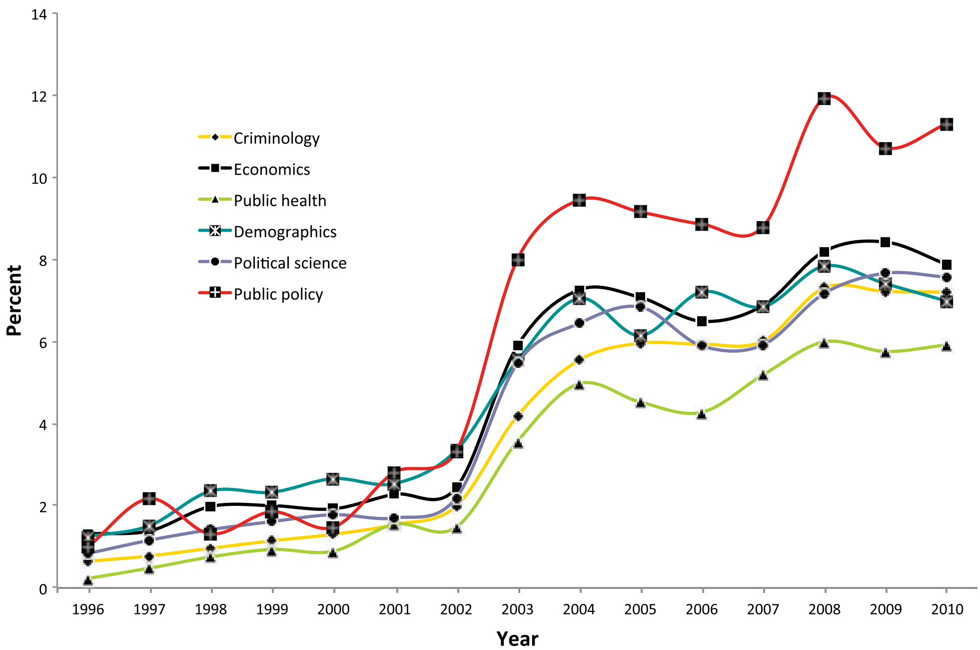
Over the past 20 years, spatial analysis has exploded across a range of uses. Primarily promoted by the rising capacity of Geographic Information Systems (GISs), spatial analysis is now its own scientific field of inquiry, with many journals, conferences, and academic degrees (see Goodchild, 2010, for a recent two-decade review of accomplishments). Analysts have developed spatial analysis tools across many scientific disciplines to measure local variations of social and environmental phenomena. More often than not, the interaction between these phenomena vary across space, suggesting that a spatial approach may be required to fully understand and respond to society's most pressing problems. Spatial tools provide us with a quantitative foundation for understanding these complex interactions and implementing place-based solutions. The symposium in this issue of *Cityscape* is designed to show how spatial techniques and methods can be creatively applied to a wide range of urban issues.

The Spatial Analysis and Methods (SpAM) department of *Cityscape* was created to demonstrate the use of spatial approaches for urban applications so that readers can replicate the methods in their own research. With SpAM, we also hope to combat the notion that spatial analysis is just mapmaking with GIS.

The remarkable growth in use of spatial methods may be expressed quantitatively. Exhibit 1 shows the percentage of journal articles published across several social science disciplines that use some form of spatial analysis. Other surveys demonstrate a similar multidisciplinary growth, such as

Exhibit 1

Trends in Use of Spatial Analysis Across the Social Sciences



Notes: Compiled from authors' tabulation from sociological abstracts, applied social sciences index and abstracts, and social service abstracts. Authors conducted a search using the following keywords: spatial, mapping, geographic information systems, GIS, hot spots, and crime mapping. The last two keywords are included to more accurately portray realistic levels in criminology and criminal justice, because those keywords represent spatial analysis that would not have been otherwise detected.

Fearon (2003), who presents a similar trend with spatial analysis growing from 1.3 percent in 1990 to 3.7 percent in 2001.[1] All charted disciplines show a marked upward trend in the use of spatial approaches in understanding the interaction between people and place.

This symposium covers a wide range of practical articles that are representative of the published papers represented in exhibit 1. The problems analyzed include crime, vacant land, residential mobility, urban population distribution, neighborhoods and housing, food deserts, segregation, and place meaning. The U.S. Department of Housing and Urban Development (HUD), like many local governments, is increasingly employing spatial analysis in its work, with the Office of Policy Development and Research (PD&R) playing the key role.

Many of HUD's programs are inherently place based. Program data are regularly geocoded and integrated with other spatially enabled sociodemographic and economic data for analytic purposes. PD&R manages the Enterprise GIS (eGIS) program, which supports and coordinates these activities across the entire agency. An important aspect of PD&R's role in eGIS is the adoption, practice, and promotion of geospatial analytical techniques like the ones presented in this symposium.

[1] The percentage of publications per year is higher in the Fearon paper than in exhibit 1 because Fearon's literature analysis includes a broader scope of disciplines than the authors' analysis in exhibit 1.

For example, the dasymetric approach that Jeremy Mennis addresses in his article has been implemented with block-level data to support the grant application process for a number of HUD's signature grant programs, including the Neighborhood Stabilization Program, Choice Neighborhoods, Rural Innovation Fund, and, most recently, Promise Zones. In another example, Masayoshi Oka and David W.S. Wong demonstrate in their article that "spatializing" common segregation measures improves the representation of social relationships between the races and ethnicities. PD&R staff use program data for monitoring and evaluating expected outcomes. Other examples of HUD spatial analysis appear in earlier SpAM articles, such as evaluating Housing Choice Voucher holder density changes for deconcentration (Wilson, 2012) and the spatial mismatch between the homeless and available resource locations (Mast, 2014). Many PD&R in-house and outside-funded research projects are increasingly using spatial techniques and methods as part of their evaluation strategies.

We hope this symposium spurs more readers to use spatial analysis beyond the typical visualization of data in maps. Many state and local governments are posting geocoded data on line, generating new opportunities for analytic experimentation. New technologies, from social media to sound sensors and smart-phone applications, are capturing geographic data, offering rich, new sources of nongovernmental data.

Spatial analysis is breaking new ground in finding fresh approaches to urban problems. We expect that many more groundbreaking examples will appear in future issues of *Cityscape*.

Guest Editors

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Robert Renner is a social science analyst in the Office of Policy Development and Research and the head of GIS activities at the U.S. Department of Housing and Urban Development.

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Goodchild, Michael F. 2010. "Twenty Years of Progress: GIScience in 2010," *Journal of Spatial Information Science* 1: 3–20.

Mast, Brent D. 2014. "Measuring Spatial Mismatch Between Homelessness and Homeless Resources With a Theil Index and Statistical Inference," *Cityscape* 16 (1): 339–350.

Wilson, Ron. 2012. "Using Dual Kernel Density Estimation To Examine Changes in Voucher Density Over Time," *Cityscape* 14 (3): 339–350.

Risk Terrain Modeling for Spatial Risk Assessment

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Abstract

Spatial factors can influence the seriousness and longevity of crime problems. Risk terrain modeling (RTM) identifies the spatial risks that come from features of a landscape and models how they colocate to create unique behavior settings for crime. The RTM process begins by testing a variety of factors thought to be geographically related to crime incidents. Valid factors are selected and then weighted to produce a final model that basically paints a picture of places where crime is statistically most likely to occur. This article addresses crime as the outcome event, but RTM can be applied to a variety of other topics, including injury prevention, public health, traffic accidents, and urban development. RTM is not difficult to use for those who have a basic skillset in statistics and Geographic Information Systems, or GISs. To make RTM more accessible to a broad audience of practitioners, however, Rutgers University developed the Risk Terrain Modeling Diagnostics (RTMDx) Utility, an app that automates RTM. This article explains the technical steps of RTM and the statistical procedures that the RTMDx Utility uses to diagnose underlying spatial factors of crime at existing high-crime places and to identify the most likely places where crime will emerge in the future, even if it has not occurred there already. A demonstrative case study focuses on the process, methods, and actionable results of RTM when applied to property crime in Chicago, Illinois, using readily accessible resources and open public data.

Introduction

Several methods can aim to clarify the forces that create risky places. Evaluating the spatial influences of features of the landscape on the occurrence of crime incidents and assessing the importance of each feature relative to one another combine to make a viable method for assessing such risk (Caplan, 2011). For an analogy that is much more benign than criminal offending, consider a place where children repeatedly play. When we step back from our focus on the cluster of children, we might realize that the place where they play has swings, slides, and open fields. The features of the place (that is, a place suggestive of a playground), instead of the features of other locations that lack such entertaining qualities, attract children. Just as playground equipment can influence and enable playful behaviors, in a *similar* way, features of a landscape could influence the seriousness and longevity of illegal behaviors and associated crime problems (for example, Caplan, Kennedy, and Piza, 2013a, 2012; Drawve, in press; Dugato, 2013; Kennedy, Caplan, and Piza, 2011). Risk terrain modeling (RTM) identifies the risks that come from features of a landscape and models how they colocate to create unique behavior settings for crime (Caplan and Kennedy, 2010).

Risk Terrain Modeling

RTM is an approach to risk assessment whereby separate map layers representing the spatial influence of features of a landscape are created in a Geographic Information System (GIS; Caplan and Kennedy, 2010). Risk map layers of statistically validated features are combined to produce a composite risk terrain map with values that account for the spatial influences of all features at every place throughout the landscape. RTM offers a statistically valid way to articulate crime-prone areas at the microlevel according to the spatial influence of many features of the landscape, such as bars, parks, schools, foreclosures, or fast-food restaurants. Risk values in an RTM do not suggest the inevitability of crime. Instead, they point to locations where, if the conditions are right, the risk of illegal behavior will be high.

RTM is not difficult to use with the freely available resources provided by the Rutgers Center on Public Security.[1] To make RTM more accessible for private and public safety practitioners, Rutgers University developed the Risk Terrain Modeling Diagnostics (RTMDx) Utility, a free[2] desktop software app that automates RTM (Caplan, Kennedy, and Piza, 2013b). Many police agencies regularly use it. Some current applications of RTM include ongoing projects in cities across the United States funded by the National Institute of Justice (NIJ).[3] Project sites (that is, police departments) include New York, New York; Newark, New Jersey; Chicago, Illinois; Kansas City, Missouri; Arlington, Texas; Colorado Springs, Colorado; and Glendale, Arizona. A key objective of these projects is to inform police-led interventions that address a designated priority crime type at target areas for each city.

[1] http://www.rutgerscps.org/.

[2] The educational version of the RTMDx Utility is free for noncommercial use. The professional version of the Utility is bundled with the RTM Training Webinar, offered biannually by the Rutgers Center on Public Security.

[3] NIJ Award Nos. 2012-IJ-CX-0038 and 2013-IJ-CX-0053.

RTM diagnoses the underlying spatial factors that create risk at high-crime places. Police interventions are then designed to suppress crime in the short term and mitigate spatial risk factors at these areas to make them less attractive to criminals in the long term (Caplan, Kennedy, and Piza, 2014).

RTM has 10 steps—

1. Select an outcome event.
2. Choose a study area.
3. Choose a time period.
4. Obtain base maps.
5. Identify all possible risk factors.
6. Select model factors.
7. Map spatial influence.
8. Weight risk map layers.
9. Combine risk map layers.
10. Communicate meaningful information.

In this article, we use a case study from Chicago to discuss the steps in the RTM process, including the statistical procedures that are automated by the RTMDx Utility (Caplan, Kennedy, and Piza, 2013b). This example is intended to diagnose the underlying spatial attractors (Brantingham and Brantingham, 1995) of burglaries (that is, step 1, select an outcome event) throughout the landscape of Chicago (that is, step 2, choose a study area) during calendar year 2013 (that is, step 3, choose a time period). Base maps and other datasets were downloaded from the Chicago Data Portal, provided by the Chicago Police Department (CPD), or purchased from Infogroup[4] (that is, step 4, obtain base maps). Reported incidents of burglary in Chicago during 2013 were obtained from official CPD administrative data. All data were acquired at the address or XY coordinate level. The following sections discuss steps 5 through 10.

Possible Risk Factors
(that is, step 5, identify all possible risk factors)

Environmental risk factors for this study were selected based on empirical research evidence and the knowledge of CPD personnel, who provided practical experience-based justification for the use of some factors. As a consequence, the pool of factors selected for inclusion in the RTM is not only empirically driven but also is theoretically and practically meaningful. Exhibit 1 shows the factors used in this study.

[4] Infogroup is a leading commercial provider of business and residential information for reference, research, and marketing purposes.

Exhibit 1

Risk Factors for Burglary in Chicago

Risk Factor	Count	Coefficient	Spatial Operationalization	Spatial Influence (feet)	RRV
In the risk terrain model					
311 service requests for street lights out	9,999	0.1595	Proximity	852	1.1730
311 service requests for alley lights out	9.995	0.4605	Proximity	852	1.5848
311 service requests for abandoned vehicles	7,137	0.6955	Proximity	1,704	2.0046
Apartment complexes	391	0.1434	Proximity	3,408	1.1542
Foreclosures	15,305	1.3849	Proximity	852	3.9944
Problem buildings	28,575	0.6645	Density	852	1.9434
Gas stations	140	0.1747	Proximity	3,408	1.1909
Grocery stores	933	0.2477	Proximity	1,704	1.2810
Laundromats	173	0.1202	Density	3,408	1.1278
Retail shops	235	0.1016	Density	3,408	1.1070
Schools	1,021	0.3264	Proximity	1,704	1.3860
Variety stores	124	0.1397	Density	3,408	1.1499
Bars	1,316	0.2013	Density	3,408	1.2230
Nightclubs	128	0.1946	Density	1,704	1.2148
Bus stops	10,711	0.2525	Proximity	1,704	1.2873
Intercept	—	– 4.1782	—	—	—
Tested, but not in the final model					
Banks	367				
Healthcare centers and gyms	176				
Homeless shelters	29				
Malls	29				
Parking stations and garages	218				
Post offices	53				
Recreation centers	33				
Rental halls	89				
Liquor stores	926				

RRV = relative risk value.

Sources: Chicago Data Portal; Chicago Police Department; Infogroup

This broad spectrum of factors, or features of a landscape, identified from a variety of sources, may pose general spatial risks of illegal behavior resulting in burglary. It is likely that only some of them will be significantly influential within Chicago, however. Therefore, it is hypothesized that (1) certain features of the physical environment will constitute significantly higher risk of burglary at microlevel places than at other places. And, furthermore, (2) the copresence of one or more risky features at microlevel places will have a higher risk of burglary incidents compared with places without those features.

Building a Risk Terrain Model

(that is, step 6, select model factors; step 7, map spatial influence; and step 8, weight risk map layers)

Chicago was modeled as a continuous surface grid of 426 by 426 foot cells (N = 36,480), with each cell representing a microlevel place throughout the city. The approximate average block length in Chicago is 426 feet, as measured within a GIS. This spatial dimension has practical meaning because the cell size corresponds to the block face of the Chicago street network, representing the most realistic unit for police deployment at the microlevel (Weisburd and Groff, 2009). Moreover, empirical research by Taylor and Harrell (1996) suggests that behavior settings are crime-prone places that typically comprise only a few street blocks (Taylor, 1997). As opposed to perpetrators of other types of crimes, such as street robbery, burglars operate within a slightly larger behavior setting because of their mobility (Hesseling, 1992).

To determine the optimal spatial influence of each risky feature within a few street blocks in Chicago, several variables were operationalized from 24 potential features, or risk factors. For each risk factor, we measured whether each raster cell in the grid was within 852, 1,704, 2,556, or 3,408 feet of the feature point or in an area of high density of the feature points based on a kernel density bandwidth of 852, 1,704, 2,556, or 3,408 feet. These distances represent approximately two blocks, four blocks, six blocks, and eight blocks in Chicago. These incremental units resulted in as many as 8 variables of spatial influence measured as a function of Euclidean distance or kernel density for each risk factor, respectively.

This process generated 192 variables (that is, 2 operationalizations x 4 blocks x 24 factors) that were tested for significance with incident locations of burglary in Chicago. Raster grid cells within the study extent that were inside each Euclidean distance threshold were represented as 1 (highest risk); cells outside this distance were represented as 0 (not highest risk). Density variables were reclassified into highest density (density ≥ mean + 2 standard deviations) and not highest density (density < mean + 2 standard deviations) regions. Raster cells within the highest density regions were represented with a value of 1; cells not within the highest density regions were represented with a value of 0. All these values were assembled into a table in which rows represented cells within the Chicago study area grid and columns represented binary values (that is, 1 or 0, as described in the previous section). Counts of burglary incidents located within each raster cell were also recorded.

We used the RTMDx Utility (Caplan and Kennedy, 2013) to identify a statistically valid RTM. The testing procedure within the Utility began by using 192 variables, operationalized from the 24 aforementioned factors (that is, independent variables) and 2013 burglary incidents (that is, dependent variables), to build an elastic net penalized regression model assuming a Poisson distribution of events. Generating 192 variables presents potential problems with multiple comparisons, in that we might uncover spurious correlations simply because of the number of variables tested. To address this issue, the Utility uses cross-validation to build a penalized Poisson regression model using the penalized R package. Penalized regression balances model fit with complexity by pushing variable coefficients toward zero. The optimal amount of coefficient penalization was selected via cross-validation (Arlot and Celisse, 2010). This process reduces the large set of variables to a smaller set of variables with nonzero coefficients. It is important to note that using the model resulting from this step (that is, the penalized model) would be perfectly valid, in and of itself (Heffner, 2013), because all resulting variables from this process play a useful (significant) part within the model. Because the goal is to build an easy to understand representation of crime risk, however, the Utility further simplifies the model in subsequent steps via a bidirectional stepwise regression process.

The Utility does this regression process starting with a null model with no model factors, and it measures the Bayesian Information Criteria (BIC) score for the null model. Then, it adds each model factor to the null model and remeasures the BIC score. Every time the BIC score is calculated, the model with the best (lowest) BIC score is selected as the new candidate model (the model to surpass). The Utility repeats the process, adding and removing variables one step at a time, until no factor addition/removal surpasses the previous BIC score. The Utility repeats this process with two stepwise regression models: one model assumes a Poisson and the other assumes a negative binomial distribution. At the end, the Utility chooses the best model with the lowest BIC score between Poisson and negative binomial distributions. The Utility also produces a relative risk value (RRV) for comparison of the risk factors. Rescaling factor coefficients produce RRVs between the minimum and maximum risk values (Heffner, 2013). RRVs can be interpreted as the weights of risk factors. In sum, RTM with the RTMDx Utility offers a statistically valid way to articulate risky areas at the microlevel according to the spatial influence of many features of a landscape.

Results: Spatial Risk Factors for Burglary in Chicago

In 2013, 17,682 burglaries were reported in Chicago. The factors that spatially correlate with these crime incidents are presented in exhibit 1, along with the most meaningful operationalization, spatial influential distance, and relative risk value. Exhibit 1 demonstrates that, of the pool of 24 possible risk factors, only 15 are spatially related to burglaries in this study setting. The most important predictor of burglary occurrence is proximity to foreclosed properties. The RRVs for the model factors in exhibit 1 can be easily compared. For instance, a place influenced by foreclosures has an expected rate of crime that is more than three times as high as a place influenced by retail shops (RRVs: 3.99 / 1.11 = 3.59). Places within one block of foreclosures pose as much as three times greater risk of burglary than what is presented by many other significant factors in the RTM. All places may accordingly pose risk of burglary but, because of the spatial influence of certain features of the landscape, some places are riskier than others.

Risk Terrain Map for Burglary in Chicago
(that is, step 9, combine risk map layers)

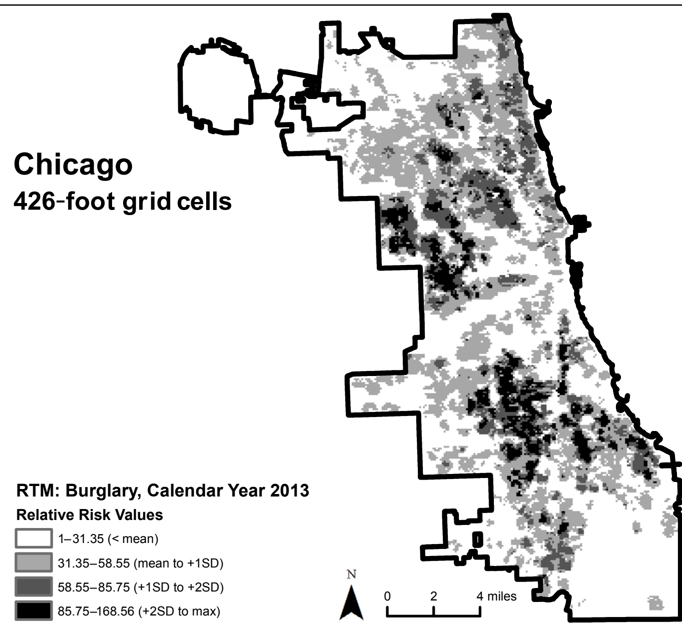
A place where the spatial influence of more than one model feature in exhibit 1 colocates poses higher risks. This proposition was tested by combining risk map layers of the 15 factors in the final model, using map algebra (Tomlin, 1994) and the ArcGIS for Desktop Raster Calculator, to produce a risk terrain map. The risk terrain map was produced using the following formula—

> Exp(-4.1782 + [1.3849 x Foreclosures] + [0.6955 x 311 Service Requests Abandoned Vehicles] + [0.6645 x Problem Buildings] + [0.4605 x 311 Service Requests Alley Lights Out] + [0.3264 x Schools] + [0.2525 x Bus Stops] + [0.2477 x Grocery Stores] + [0.2013 x Bars] + [0.1946 x Nightclubs] + [0.1747 x Gas Stations] + [0.1595 x 311 Service Requests Street Lights All Out] + [0.1434 x Apartment Complexes] + [0.1397 x Variety Stores] + [0.1202 x Laundromats] + [0.1016 x Retail Shops]) / Exp(-4.1782).

RRVs for each cell in the risk terrain map shown in exhibit 2 ranged from 1.00 for the lowest risk cell to 168.60 for the highest risk cell. The highest risk cells have an expected rate of burglary that is 168.60 times higher than a cell with a value of 1.00. The mean risk value is 31.35, with a standard deviation of 27.20. This microlevel map shows the highest risk cells symbolized in black (that is, greater than 2 standard deviations from the mean). These places have an 85.75 percent or greater likelihood of experiencing burglary compared with other locations.

Exhibit 2

Microlevel Risk Terrain Map for Burglary in Chicago



max = maximum. RTM = risk terrain map. SD = standard deviation.

Discussion
(that is, step 10, communicate meaningful information)

As the RTM demonstrates, one or more features of the physical environment can elevate the risk of crime. Comparing RRVs across model factors is useful for prioritizing risky features so that mitigation efforts can be implemented appropriately. For instance, foreclosed properties may be the direct targets of burglary; however, other properties within close proximity to foreclosures may also be at high risk because of the absence of invested caretakers who would otherwise serve as eyes and ears within the area. After risk factors are identified, stakeholders can explore the (likely) mechanisms through which risks are presented and then initiate mitigation efforts, such as improved community surveillance and new homeowner investment campaigns. In Chicago, for example, the CPD developed strategies to work with other city agencies, including the Chicago Housing Authority, to target problem buildings using city ordinances to improve conditions conducive to crime. The city agencies are also working with private lenders to address the broader scope of the foreclosure crisis.

Using environmental factors for crime forecasting has many benefits, such as enabling intervention activities to focus on places—not just people located at certain places—that could jeopardize public perceptions and community relations. Another benefit is that RTM is a sustainable technique because past crime data are not needed to continue to make valid forecasts. Police use RTM to be problem oriented and proactive in their effort to prevent new crimes without having to be concerned that a high success rate (and no new crime data) will hamper their ability to make new forecasts. In fact, the researcher-practitioner collaborations forged through the aforementioned NIJ projects have led to new approaches to police productivity that go beyond a heavy reliance on traditional law enforcement actions, such as stops, arrests, or citations. The police are now able to measure their effects on mitigating the spatial influences of risky features—with the goal of reducing one or more risk factor weights in postintervention RTMs or, better yet, suppressing their attractive qualities completely and removing them from the post model altogether.

All places may pose risk of burglary but, because of the spatial influence of certain features of the landscape (not simply past crime locations), some places are riskier than others. As demonstrated here, RTM helps to explain why spatial patterns of crime exist in a jurisdiction and what can be done to mitigate risks, not just chase the hotspots. With such spatial intelligence (Kennedy and Caplan, 2012), key stakeholders can identify the most vulnerable areas in a jurisdiction, enabling them to predict, with a certain level of confidence, the most likely places where crimes will emerge in the future—even if they have not occurred there already.

Conclusion

Giving high regard to place-based risk assessments makes theoretical and intuitive sense: offenders know they take risks and that these risks increase in certain locations, and police are often deployed to certain geographies to combat crime and manage other real or perceived public safety and security threats (Caplan, Kennedy, and Miller, 2011; Kennedy and Van Brunschot, 2009). In future work, additional research is needed to assess the temporal dynamics of burglary incidents, as well as the social and situational factors. In addition, RTM can be applied to a variety of other topics, including injury prevention, public health, traffic accidents, and urban development.

Acknowledgments

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Linking Public Health, Social Capital, and Environmental Stress to Crime Using a Spatially Dependent Model

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Abstract

This article reports the findings from a localized spatial modeling approach and visual assessment of crime determinants in Flint, Michigan. Factors pertaining to socioeconomic condition, public health, social capital, environmental stress, and neighborhood context were analyzed spatially and statistically using exploratory data analysis, exploratory spatial data analysis (ESDA), ordinary least squares regression (OLS), and geographically weighted regression (GWR). The ESDA indicated that elevated crime densities clustered in legacy residential areas, suggesting the need for a spatially explicit model. The OLS model was able to explain 46 percent of the variation in the model, although the GWR model proved superior, explaining approximately 56 percent. The GWR results largely supported the OLS results, while providing additional insights into the directionality, magnitude, and spatial variation of localized predictors of crime. The factors that contributed positively to crime rates may provide policymakers and law enforcement officials with nuanced information needed for targeted crime-reduction/prevention strategies.

Introduction

Environmental criminology examines how contextual conditions influence criminal behavior throughout space. This strategy allows law enforcement officials to observe the spatial copatterning of criminal events and possible correlates, providing an avenue for more efficient crime-reduction strategies (Phillips and Lee, 2011). The field has surged in popularity because of the availability of robust spatial datasets, advancements in Geographic Information Systems (GISs), and user-friendly spatial analysis tools, allowing for comprehensive spatial analysis of criminal activity (Anselin et al., 2000). Furthermore, environmental criminology and spatial analysis tools have taken root in large part because of the need to account for spatial autocorrelation. Evidence has shown that spatial correlation effects can undermine confidence intervals and significance tests in global regression models such as the ordinary least squares (OLS) model (Matthews et al., 2010). To counter these issues, spatial modeling has evolved to the extent that spatial effects can be minimized, providing a greater understanding of underlying criminal processes (Anselin et al., 2000).

As of the date of this writing, a minimal amount of research has used spatially explicit models to detail significant relationships among crime and its correlates. A few notable studies do exist, however. For instance, a study by Cahill and Mulligan (2007) used a geographically weighted regression (GWR) model to measure invariant local crime correlates throughout Portland, Oregon, and found that local variation of crime predictors was significant. Malczewski and Poetz (2005) used the same method to examine geographical variations of residential burglaries in London, Ontario, Canada. The authors found significant statistical and spatial variations in burglary risk factors such as dwelling value and multifamily housing density. Another important study found that with the use of GWR, crime correlates were spatially and significantly variant throughout an urban area (Graif and Sampson, 2009).

Displaying and interpreting GWR outputs cartographically has historically been complicated at best. Typical outputs from GWR is a choropleth map displaying the *t*-values for each parameter estimated (Mennis, 2006). For example, Graif and Sampson (2009) used classified surface maps of *t*-values to display the statistical significance of each explanatory variable. Using this approach, however, hides the magnitude, directionality, and statistical significance of each estimate on crime. Displaying the parameter estimates in conjunction with their statistical significance can provide more meaningful GWR results, while reducing the volume of maps to interpret (Mennis, 2006). With this concept in mind, one purpose for this research is to build on past studies that have efficiently produced robust GWR visualizations. The specific goals of this research are to (1) demonstrate the advantages of a using a local spatial modeling strategy for crime modeling; (2) institute a progressive cartographic technique that distinguishes among magnitude, directionality, and statistical significance of explanatory factors; and (3) provide a better understanding about the relationships among socioeconomic conditions, public health, social capital, environmental stressors, neighborhood context, and crime. The organization of the article is as follows: the next section, which provides an explanation of the data and preprocessing steps, is followed by a section that presents the modeling approach, and the article concludes with a research summary.

Data and Preprocessing

Reported crime incidence data (26,961 records) from the year 2010 were obtained from the City of Flint Police Department and served as the dependent variable. In this study the crimes selected were aggravated assault, homicide, robbery, and all forms of criminal sexual conduct. The crime incidence data were aggregated and normalized for each U.S. Census Bureau-defined census block group (CBG) because that was the unit level used for analysis.

The explanatory variables were grouped into five categories: socioeconomic condition, public health, social capital, environmental stress, and neighborhood context (exhibit 1). Several socioeconomic status (SES) factors were considered because of their long-standing links to crime (Sampson, 1995). The SES variables were obtained from the U.S. Census Bureau for 2010 at the CBG level.

Social capital factors were obtained from the Speak to Your Health! Survey (STYHS) disseminated to Flint residents in 2007. To ensure that the survey respondents represented all geographic regions of the city of Flint and Genesee County, random samples of households were drawn from Genesee County census tracts. At least 20 residents were obtained for each of the 39 residential census tracts in Flint. The frequency of positive responses per CBG was derived by dividing the number of "yes" responses by the total number of responses because of the ordinal scale of the data.

Public health variables in this study included body mass index (BMI) and nonmotorized mobility safety. BMI was obtained from the STYHS survey, and the average was joined to each CBG. Travel risk factors were obtained from the State of Michigan Department of Transportation for the year 2010.

Previous research has also posited that environmental stressors such as lead can have a long-lasting effect on criminal activity (Shaker, Rybarczyk, and Eno, 2009; Wright et al., 2008). Therefore, the average blood lead level (BLL) concentration from 9,000 adolescent people within each census tract was obtained from the State of Michigan Department of Community Health, Childhood Lead Poisoning Prevention Program, for the year 2010. An areal interpolation method was used to join

Exhibit 1

Initial Model Predictor Variables

Socioeconomic condition
- Median household income
- Residents driving to work
- Owner-occupied housing
- Renter-occupied housing
- English-speaking households
- Non-White residents
- Total households
- Households below poverty
- Total families
- Families below poverty
- Residents with diploma or GED

Public health
- Average body mass index, or BMI
- Bicycle crashes
- Pedestrian crashes

Social capital
- Quality of life
- Neighborly visitation
- Neighbors' willingness to help
- Trustworthiness of neighbors
- Neighborhood crime watch participation
- Fear of crime
- Safety during the day
- Safety after dark
- Comparative neighborhood crime
- General health perception
- Satisfaction with health care
- Stress

Environmental stress
- Blood lead levels
- Brownfields

Neighborhood context
- Bus routes
- Bus stops
- Bike trails
- Vacant lots
- Parks
- Railroads
- Schools
- Food outlet diversity
- Food outlets (fast food, liquor stores, convenience stores)
- Zoning variety
- Sidewalks

GED = general equivalency diploma.

these data to the CBGs. The interpolation method is used when the spatial units are not congruent (Flowerdew, Green, and Kehris, 1991). The open and closed leaking underground storage tank, or LUST, dataset served as a proxy for brownfields in this study. The data were obtained from the State of Michigan, Department of Environmental Quality, for the year 2007.

Several neighborhood contextual variables were obtained from the City of Flint, Planning and Engineering Departments. The most recent data were obtained and consisted of transportation routes (bus, bicycle, railroad, and sidewalks), schools, parks, land use, housing type (owner- or renter-occupied), and vacant parcels. Food outlet data were retrieved from the ReferenceUSA database for the year 2010 (http://www.referenceusa.com/). Food outlets were construed as an indicator of neighborhood quality, land use diversity, and opportunistic locations for criminal activity (Gruenewald et al., 2006).

Each explanatory factor in this research was aggregated and then normalized by the area (square feet) of each CBG. This process was used to bring all factors into the same resolution for further spatial analysis and minimize errors associated with the modifiable areal unit problem, or MAUP.

Modeling Approach

To examine relationships among crime, spatial, and aspatial factors within CBGs, we advanced a comprehensive statistical and spatial modeling approach. After cursory descriptive and spatial analysis procedures were conducted, two models were calibrated. The first model, OLS, was developed to detect global crime correlates. A second model, GWR, was then enlisted to highlight significant localized crime explanatory variables.

Exploratory Analysis

Exploratory data analysis (EDA) and exploratory spatial data analysis (ESDA) were conducted to detect for statistical or spatial relationships among crime and potential predictors. The EDA consisted of a Pearson's correlation analysis using SPSS software, version 19 (International Business Machines Corporation, or IBM). The analysis was used to test for linear relations among crime and potential predictors. To further refine potential variable selection, the variance inflation factor (VIF) index was also used to detect for multicolinearity; a threshold of 5 was established as a cutoff value based on previous statistical research (Kutner, Nachtsheim, and Neter, 2004). Exhibit 2 shows the final selection of independent model predictors and their descriptors.

ESDA was imparted in this research to examine spatial associations among all of the factors and to aid with model development. A classic spatial autocorrelation index, Moran's I, was implemented to explore spatial nonstationary effects on crime (Anselin et al., 2000). Exhibit 3 demonstrates that elevated high-high (HH) and low-low (LL) CBG crime densities are clustered throughout space, suggesting the need for a model that accounts for spatial relationships.

Exhibit 2

Selected Independent Variables

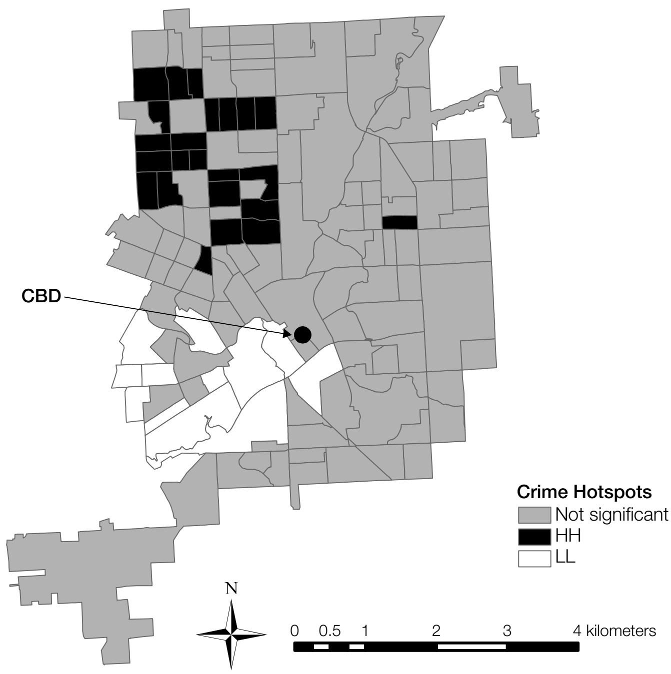
Predictor	Description (normalized by area)	Mean	Std. Dev.	VIF
Blood lead level, or BLL	Predicted BLL	0.0246	0.0173	3.539
Trails	Length of bike trails	0.0016	0.0026	1.313
Vacant lots	Number of vacant lots	0.6483	0.7275	1.396
Railroad	Length of railroads	0.0003	0.0009	1.287
Body mass index, or BMI	Average BMI per block group	0.2852	0.1678	3.193
Sidewalks	Length of sidewalks	113.329	79.9198	2.016
Renter-occupied housing	Number of renter-occupied houses	1.1362	0.6025	2.527
English speaking	Number of English-speaking households	2.6877	1.3175	4.154
Non-White	Number of non-White residents	4.4338	3.1630	3.008
Houses below poverty	Number of households below the poverty level	0.8879	0.6409	2.679
High school diploma or GED	Number of residents with a high school diploma or GED	1.7604	1.0540	2.119
Food outlets	Number of food outlets	0.0087	0.0131	1.098
General health	Attitude toward one's own general health*	0.3329	0.2463	1.138

GED = general equivalency diploma. Std. Dev. = standard deviation. VIF = variation inflation factor.

**Not normalized by area. Instead, measured in frequency of positive responses.*

Exhibit 3

Hotspot Analysis of Crime in the City of Flint, Michigan



CBD = central business district. HH = high-high. LL = low-low.

Model Development

A global regression model was developed using SPSS to determine the generalized causal associations among crime and the explanatory variables. The outputs from this model consist of global predictions of the dependent variable, using several independent variables. The OLS model's strength, coefficients, and residuals served as a comparison with the GWR model. To determine if the OLS model residuals were spatially autocorrelated, a global Moran's I was implemented. Spatially clustered residuals is an indicator of spatial nonstationarity.

A GWR model was developed to measure the magnitude, directionality, and geography of crime predictors for each CBG. The mathematical expression for GWR is similar to the OLS in that local parameters take the place of global parameters, while accounting for distance (Fotheringham, Charlton, and Brunsdon, 2002).

The GWR equation can be expressed as

$$y_i = \beta_0(\upsilon_i, \nu_i) + \sum_k \beta_k(\upsilon_i, \nu_i)\chi_{ik} + \varepsilon_i, \tag{1}$$

where y_i is the dependent variable at location i, $\beta_0(\upsilon_i, \nu_i)$ is the intercept at location i, $\beta_k(\upsilon_i, \nu_i)$ is the estimated kth parameter at location i, χ_{ik} is the independent variable of the kth parameter at location i, and ϵ_i is the error term at location i. The GWR model assumes that the error term is independent and identically distributed (Zhao and Park, 2004).

The GWR model was developed using GWR4 software, developed by Fotheringham, Charlton, and Brunsdon (2002). The GWR model produces parameter estimates for each CBG based on the kernel and the bandwidth selection, producing a continuous surface in return. In this research, a fixed Gaussian weighting scheme was used. The scheme is based on a distance-decay function following a Gaussian curve. The function is adjusted by the bandwidth setting, which dictates the distance that neighborhood parameters from the centroid *i* will count toward the estimate (Mennis, 2006). The bandwidth setting was set to automatically obtain optimal values to minimize the Akaike Information Criterion (AIC). The setting was chosen to account for the variation in size and quantity of the CBGs. Moreover, the AIC optimization technique assures a robust model, signified by an ideal goodness-of-fit and reduced degrees of freedom coefficients (Graif and Sampson, 2009). The outputs from the GWR model included parameter estimates, R^2 values, and *t*-values for each CBG.

The directionality, significance, and degree of spatial variability (nonstationarity) of the parameter estimates were assessed using ArcGIS software. The parameter estimates and diagnostics were assessed in accordance with the Mennis (2006) study. Significant relationships between each explanatory variable and dependent variable were obtained by querying *t*-values at the 90-percent significance level (z-scores ± 1.6565) for each unstandardized parameter estimate. Using a Jenks Natural Breaks sequential classification scheme, an area-class map was produced that grouped the significant estimates into five classes. Those parameter estimates that fell outside the significance threshold were displayed in white.

Results and Discussion

The OLS model coefficients are presented in exhibit 4. The output shows that the densities of English-speaking households and non-White residents are statistically significant ($p < .05$), with English-speaking households negatively affecting crime and non-Whites, by contrast, exhibiting a positive influence. The directionality and influence of these two factors are supported by previous research (Kennedy et al., 1998). The remaining explanatory variables were nonsignificant in this model, despite previous studies that demonstrate otherwise.

The strength of the OLS model is promising, exhibiting an adjusted R^2 of 0.45, which appears to be aligned with previous criminal justice research (Cahill and Mulligan, 2007; exhibit 5). Furthermore, the OLS residuals do not appear to exhibit spatial autocorrelation (exhibit 6). Because more than 50 percent of the model variance is unexplained, however, it is plausible that underlying processes may be affecting crime densities not captured in this assessment.

The GWR model exhibited an adjusted R^2 of 0.54, demonstrating a 19-percent increase in model robustness from the OLS model (exhibit 5). In addition, the AIC increased from -363.11 for the OLS model to -294.78, indicating a better fitting model. The GWR residuals display no significant spatial clustering (exhibit 6). The overall model results disprove that simple linear relationships exist among crime and the independent variables.

Exhibit 4

OLS Model Outputs

Predictor Name	Coefficient	Standard Error	*t*-value	Significance
Blood lead level, or BLL	– 0.133	0.544	– 0.244	0.807
Trails	– 2.508	2.223	– 1.128	0.261
Vacant lots	0.003	0.008	0.397	0.692
Railroad	– 6.222	6.006	– 1.036	0.302
Body mass index, or BMI	0.086	0.053	1.620	0.108
Sidewalks	0.000	0.000	1.876	0.063
Renter-occupied housing	0.017	0.013	1.261	0.210
English speaking	– 0.018	0.008	– 2.359	0.020
Non-White	0.011	0.003	3.934	0.000
Houses below poverty	0.023	0.013	1.798	0.075
High school diploma or GED	0.011	0.007	1.651	0.101
Food outlets	0.531	0.400	1.328	0.187
General health	0.003	0.002	0.153	0.879

GED = general equivalency diploma. OLS = ordinary least squares regression.

Exhibit 5

OLS and GWR Model Outputs

	OLS	GWR
Psuedo R^2	0.501	0.796
Adjusted R^2	0.446	0.536
Number of parameters	14.0	58.940
AIC	– 363.112	– 294.788
Sigma	0.057	0.052
Residual sum of squares	0.393	0.161

AIC = Akaike Information Criterion. GWR = geographically weighted regression. OLS = ordinary least squares regression.

Exhibit 6

Global Moran's I Index of OLS and GWR Model Residuals

	OLS	GWR
Moran's I index	0.045392	– 0.037639
Expected index	– 0.007576	– 0.007576
Variance	0.000334	0.000333
z-score	2.897516	– 1.647889
p-value	0.003761	0.099376

GWR = geographically weighted regression. OLS = ordinary least squares regression.

Exhibit 7 uniquely depicts the magnitude, directionality, and geography of crime correlates (unstandardized parameter estimates, β). Exhibits 7a through 7d indicate that SES estimates marginally affect crime. Renter-occupied housing (exhibit 7a) positively affects crime east of the central business district (CBD), while English-speaking residents in the same vicinity have a negative influence (exhibit 7b). Similarly, significant parameter estimates for non-White residents and households living below the poverty level appeared to affect crime in the same general area (exhibits 7c and 7d). The result suggests that these factors have a compounding effect on crime, requiring specific crime-reduction strategies. The SES estimate for educational attainment positively affects crime overwhelmingly in two CBGs south of the CBD (exhibit 7e). Interestingly, the relationship appears counter to previous research that has shown that reduced educational attainment increases crime (Kruger et al., 2007). We can infer from exhibit 7e, however, that criminal activity may be diffusing into this area from nearby locations because the neighborhood is of high SES status.

Exhibit 7f depicts a positive association between crime densities and BMI in several CBGs east of the CBD. The result supports previous research that has shown a link between obesity rates and the probability for criminal arrests (Kalist and Siahaan, 2013). Conversely, self-reported general health shows no significant statistical influence on crime densities (exhibit 7g). The factor is indirectly linked to the fear of crime, which has been purported to affect actual crime. The outcome in this research, however, contains no such linkages (Chiricos, Padgett, and Gertz, 2000). The concentration of BLL appears to negatively affect crime densities among several CBGs in Flint (exhibit 7h). It can be inferred from this result that areas with increased environmental stress do not statistically affect crime, despite prior research indicating otherwise (Needleman et al., 1979).

The neighborhood contextual factors that negatively altered crime densities included recreational trails (exhibit 7i) and railroads (exhibit 7k). The density of trails in the southern portion of Flint appeared to reduce crime. Strong spatial and statistical dependencies between railroads and crime were discovered along the western boundary of Flint (exhibit 7k). One possible inference from this result is that the population density is low in this area, thereby reducing opportunities for victimization. The neighborhood contextual factors that displayed a positive effect on crime included the density of food outlets (fast-food restaurants, liquor stores, and convenience stores) and sidewalks. As evidenced in exhibit 7l, the density of poor-quality food outlets moderately affects crime, with the strongest relationship evidenced in the southeast portion of the city. The positive relationship found in this study is supported by previous research. For example, Gruenewald et al. (2006) found that alcohol establishments had the propensity to accelerate criminal activity. Exhibit 7m exhibits the spatial patterning of significant sidewalk-density estimates on crime, albeit with marginal

Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (1 of 7)

Exhibit 7a. Renter-Occupied Housing

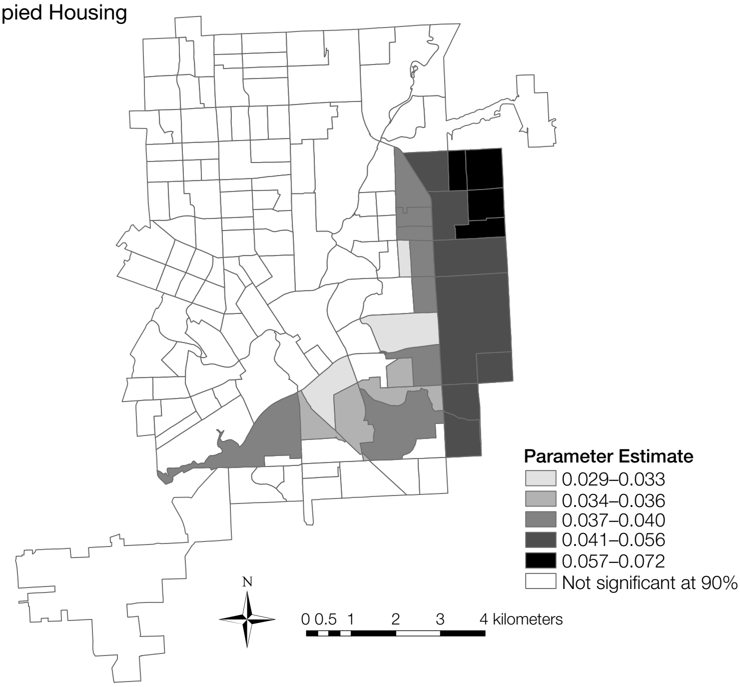


Exhibit 7b. English-Speaking Households

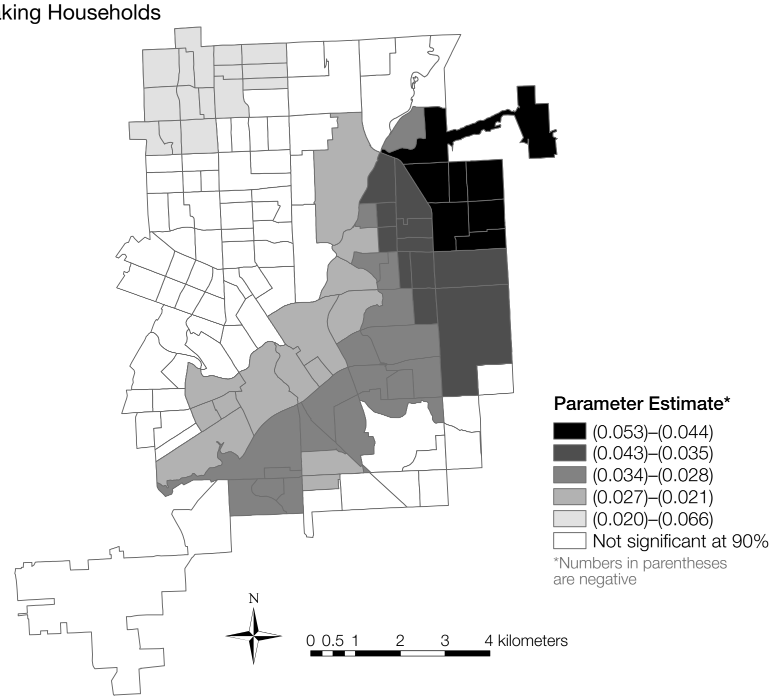


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (2 of 7)

Exhibit 7c. Non-White Residents

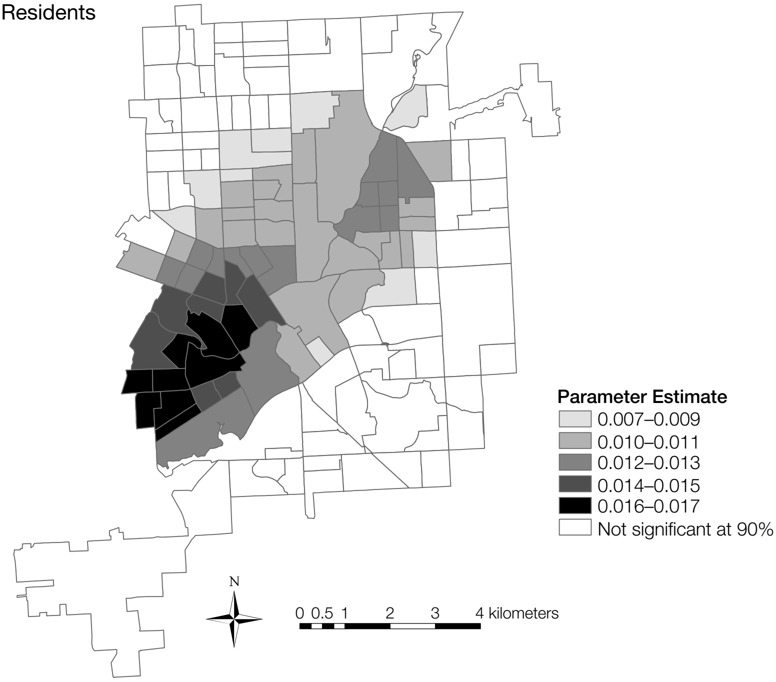


Exhibit 7d. Households Below Poverty

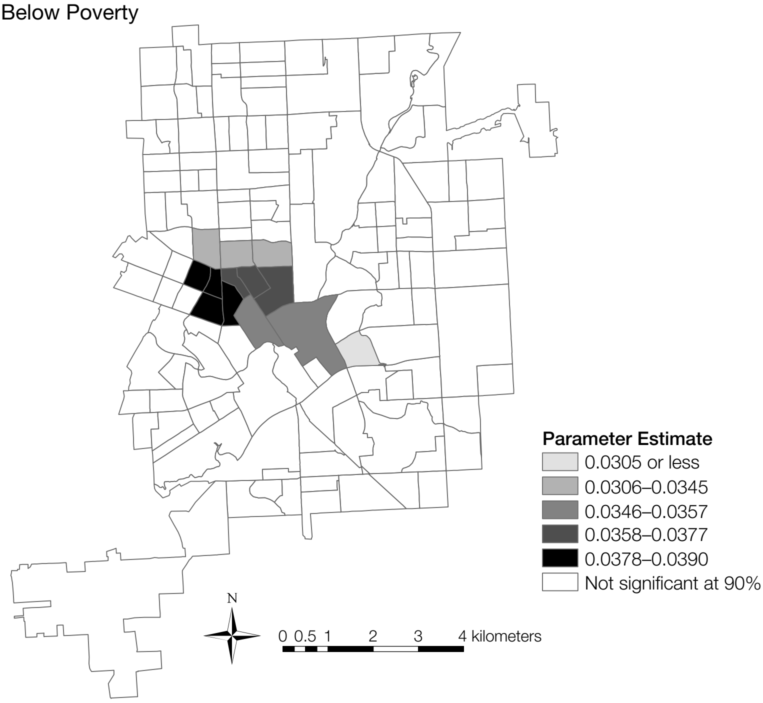


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (3 of 7)

Exhibit 7e. Education

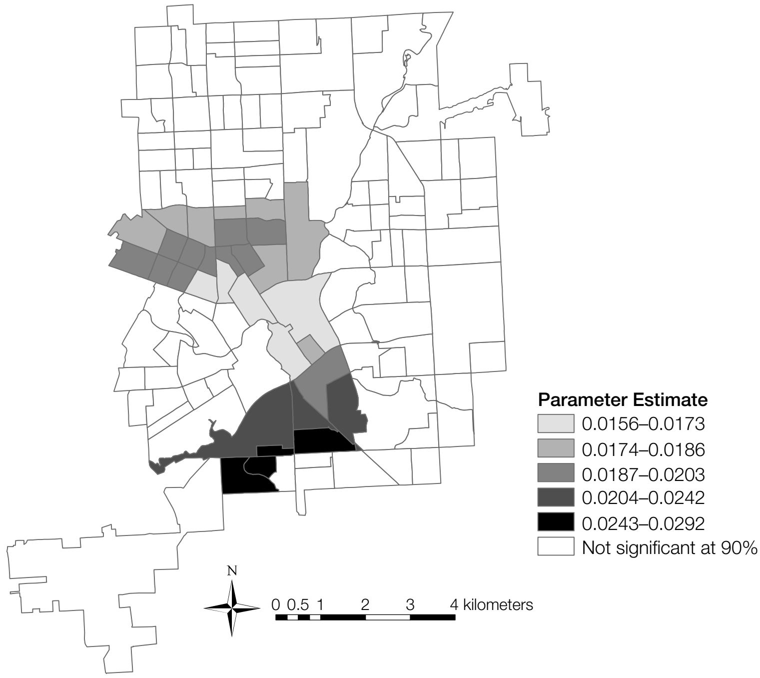


Exhibit 7f. Body Mass Index

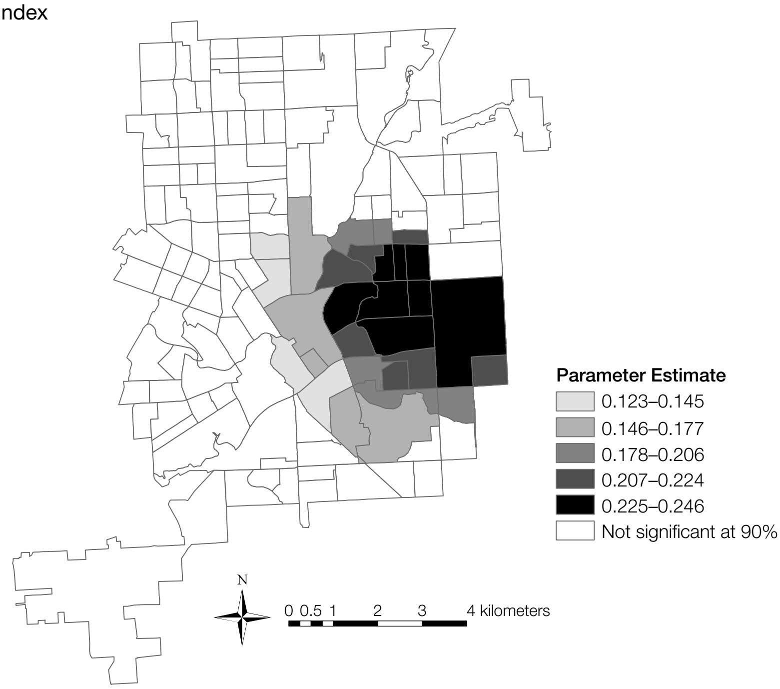


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (4 of 7)

Exhibit 7g. General Health

Exhibit 7h. Blood Lead Level

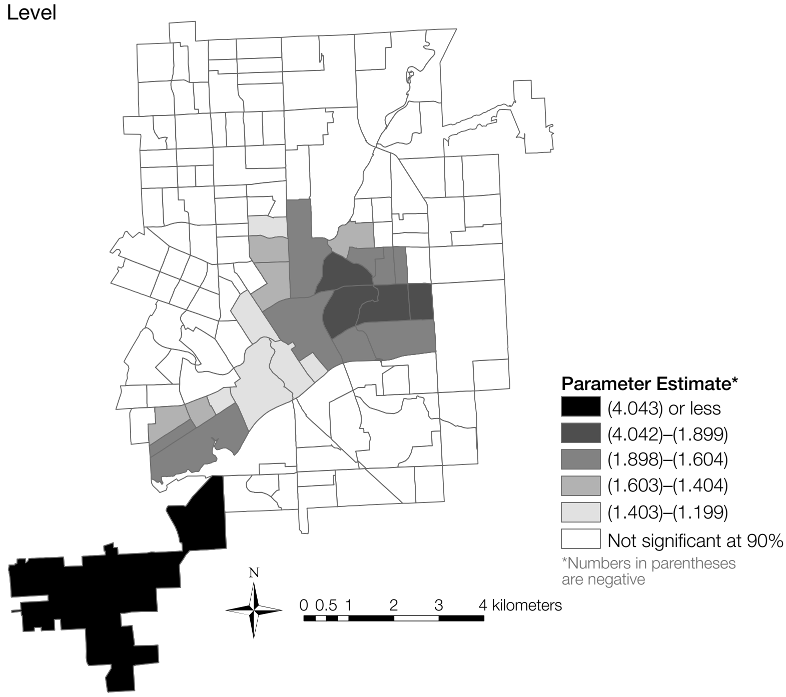


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (5 of 7)

Exhibit 7i. Trails

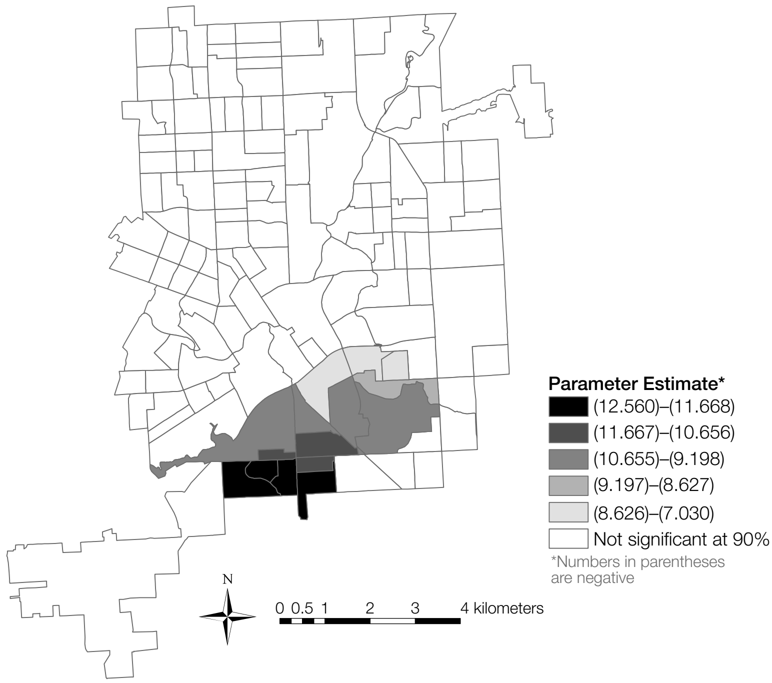


Exhibit 7j. Vacant Lots

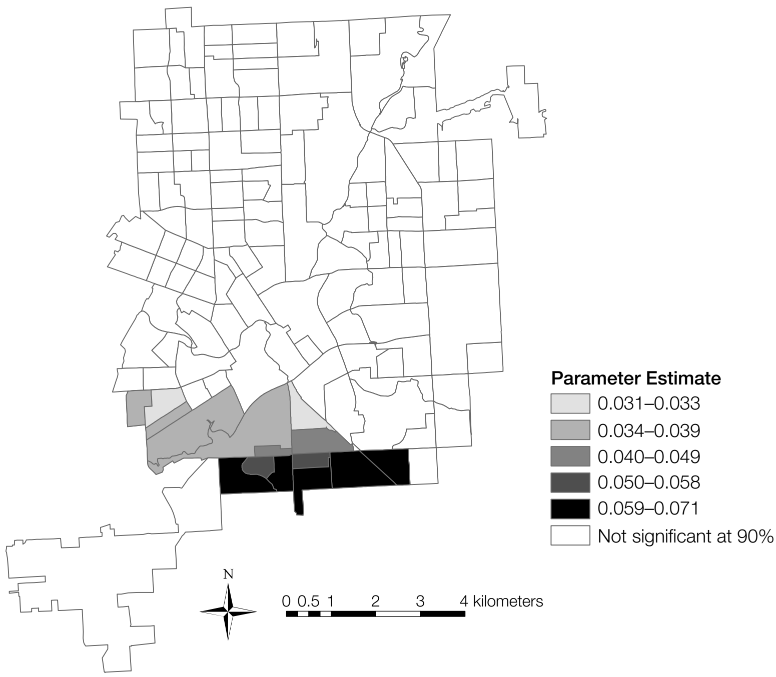


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (6 of 7)

Exhibit 7k. Railroads

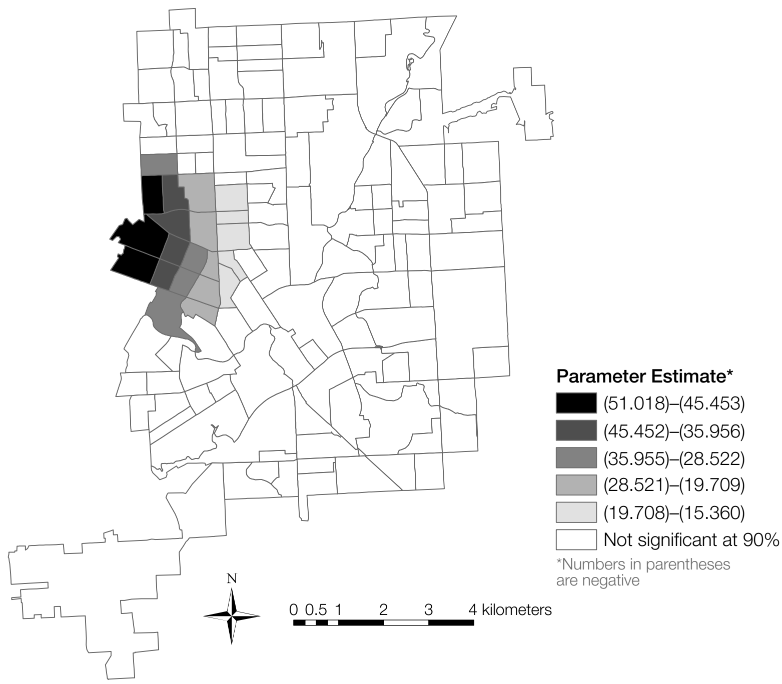


Exhibit 7l. Food Outlets

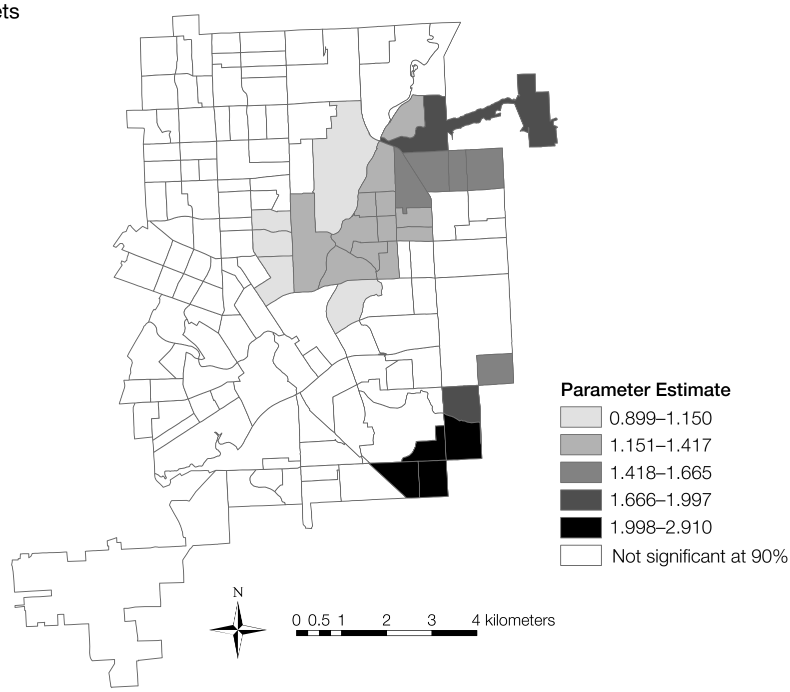
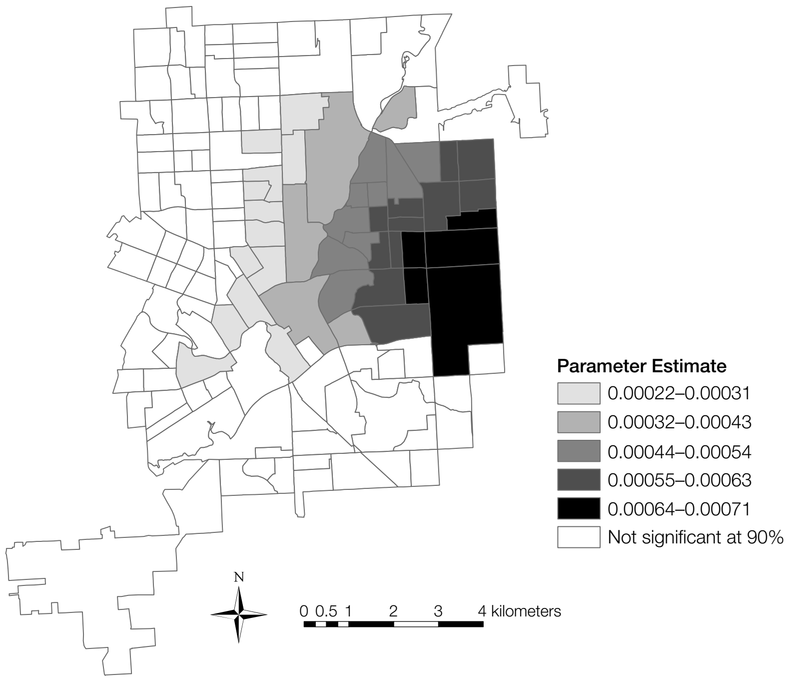


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (7 of 7)

Exhibit 7m. Sidewalks



influence. It is clear from the spatial pattern that sidewalk density may be facilitating criminal activity throughout a large portion of Flint. This result may partly be because sidewalks are vectors for criminal activity. In other words, the increase in pedestrian mobility and exposure may be increasing crime opportunities. The finding here is substantiated by earlier research conducted by Doyle et al. (2006), who found a positive correlation between neighborhood walkability and crime.

Conclusion

The key goal of this article was to critically examine the utility of a spatially explicit model and refined cartographic technique to uncover detailed relationships among crime and important socio-economic conditions, public health, social capital, environmental stress, and neighborhood contextual variables in Flint, Michigan. The objective was reached using a strategic modeling strategy that consisted of EDA, ESDA, global, and localized modeling approaches. The strength and performance of the GWR model were reasonably good in comparison with the OLS model, exhibiting an adjusted R^2 of 0.536. The GWR model provided local coefficients for each CBG, which were integrated into a robust visualization strategy using GIS. The results included several nuanced cartographic outputs that displayed statistically significant relationships between crime and the explanatory factors, which were not evidenced from the OLS model. More importantly, the visualization of the significant GWR coefficients suggest that targeted enforcement strategies should vary based on localized geography and contextual conditions. With a better understanding of how, and to what extent, various factors influence crime at a microscopic scale, law enforcement officials, community planners, and citizenry can develop more insightful crime-prevention/reduction strategies.

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Exploring the Spatial Diffusion of Homicides in Mexican Municipalities Through Exploratory Spatial Data Analysis

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Abstract

In this article, we explore the spatial dimension of violence in Mexico by investigating the existence of spatial diffusion patterns associated with the increase in homicides. We specifically use exploratory spatial data analysis, or ESDA, techniques during the 2005-through-2010 period to measure the extent to which Mexican municipalities have experienced an increase in violence levels that have diffused to contiguous municipalities. The findings indicate significant levels of spatial dependency leading to spatial clustering of high-incidence rates of homicides in specific regions of the country, with diffusion patterns of high levels of homicide rates to other nearby municipalities. Furthermore, it has been found that, during the period of analysis, municipalities that acted as contributors to the spread of high-incidence rates have not reduced their levels but are still experiencing high-incidence rates during the period of study.

Introduction

Mexico witnessed a dramatic increase in violence levels during the second half of the 2000s. The most violent scenarios arose in areas with a high level of drug-trafficking activities and a long-standing presence of drug-trafficking organizations (DTOs, or cartels). It has been argued that the dispute among the DTOs concerning taking control of specific territories has been a major contributing factor in terms of the steep increase in violence when compared with previous periods of relatively stable trends in violence.

The role of geography is a crucial aspect when analyzing recent violence levels in the country. This cruciality is because of well-defined patterns across the country of the distribution of past and contemporary violence levels and also the presence of DTOs. On the one hand, drug-trafficking activities routing from Mexico to the United States have very longstanding roots. Such activities date back to at least the mid-1980s, when Colombian cartels extended their influence to the United States via drug-trafficking networks, particularly after the successful enforcement efforts by Colombian authorities against the Colombian Cali and Medellin cartels that eventually gave rise to the emergence of Mexican DTOs. Colombians previously trafficked cocaine through Florida (Payan, 2006). Mexican smugglers made ties with Colombian traffickers and relocated the activity to the northern border.

On the other hand, DTOs have taken advantage of the rugged terrain of the mountains to plant marijuana and opium and, more recently, to produce synthetic drugs. The region referred to as the Golden Triangle, formed by the states of Chihuahua, Durango, and Sinaloa, historically has been a major producer of illicit drugs. Evidence suggests that, in fact, mountainous terrain has a positive relationship with proliferation of armed conflict, which eventually translates to rising homicide rates (Fearon and Laitin, 2003).

Although drug-trafficking and related violence have become serious problems and have hindered the government and national security, the concerns do not apply to the whole territory but only to particular areas. In such areas, the levels of violence, as measured by the number of homicides, have soared dramatically since the end of 2006. The unprecedented increasing levels of violence have been attributed to the confrontation among DTOs, especially after the deployment of federal armed forces to combat these organizations and to eliminate criminal control of public spaces.

These operations were coordinated by military and federal police forces and were backed by state and local security forces. The strategy included the dismantling of criminal organizations, the arrest of the largest possible number of criminals and the confiscation of drug shipments, the deployment of military operations in several regions of the country, and a permanent increase in resources devoted to the military forces. The states exposed to these joint operations were Michoacán (December 2006), Guerrero and Baja California (January 2007), Nuevo León and Tamaulipas (January 2008), Chihuahua (April 2008), and Sinaloa and Durango (May 2008). These states, with the exception of Nuevo León, not coincidentally have a long tradition of being involved in either drug trafficking or the production of illicit drugs. The map in exhibit A1 in the appendix depicts these regions.

These factors may certainly play an important role in explaining the rise in violence and, in particular, the location in which violence became noticeable. The areas with creation and expansion of illegal markets will produce extra murders when contextual factors conducive to lethal violence exist (Zimring and Hawkins, 1997).

In this article, we focus on the spatial dimension of this phenomenon by investigating the existence of spatial diffusion patterns associated with the increase in homicides in Mexican municipalities. We specifically use exploratory spatial data analysis (ESDA) techniques during the 2005-through-2010 period to measure the extent to which Mexican municipalities have experienced an increase in violence levels that have diffused to contiguous municipalities.

Our contribution in this study consists of characterizing the type of spatial diffusion process in municipalities with low or high incidence levels. Using official, publicly available data of homicide records at the municipal level, the analysis employs global and local ESDA techniques to provide a descriptive analysis of the spatial distribution of homicides as well as dynamic changes that enable us to look for patterns across space in spatial dependencies. The analysis aims to answer the following research questions: How does the spatial distribution of homicides depict significant hotspot areas of high violence levels across the country? To what extent is spatial diffusion of high violence focalized within and between those states with longstanding drug-trafficking activities and where the joint operations took place.

Identification of concentrations or clusters of greater criminal activity has appeared as a central mechanism to targeting law enforcement efforts and crime prevention response to crime problems. These clusters of crime are commonly referred to as hotspots—geographic locations "of high crime concentration, relative to the distribution of crime across the whole region of interest" (Chainey and Ratcliffe, 2005: 147). The main interest of the present study is to better understand the existence of hotspots of contemporary violence in the country; nonetheless, the identification of crime hotspots should be considered as the starting point of a more detailed analysis. The conclusion section of this article addresses further research venues on the topic.

The article is structured as follows. The next section, which introduces the methodology based on the ESDA techniques and describes the data used in the analysis, is followed by a section that outlines the results and the final section that draws some conclusions.

Methodology

The methods described in this section are based on the use of ESDA, which helps visualize and describe the spatial distribution of homicides and also helps identify global and local spatial dependencies in the distribution of homicides across municipalities.

When exploring the distribution of homicides through ESDA, a common global indicator of spatial autocorrelation is the Global Moran's I. It indicates the extent to which our variable of interest is clustered, dispersed, or randomly distributed across municipalities by formulating a null hypothesis of randomness in the entire data (Anselin, 1995). The Global Moran's I is denoted in the following equation—

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}) \sum_{j=1}^{n} (x_i - \bar{x})^2}, \tag{1}$$

where N is the number of cases, x is the mean of the variable, x_i is the variable value at a particular location, x_j is the variable value at another location, and w_{ij} is a weight spatial matrix specifying the spatial interdependency of i relative to j. Positive values of this statistic indicate spatial clustering (for example, high homicide rates are found in close neighbors), while negative values indicate dispersion in the variable of interest.

The significance of this statistic is influenced by the specification of the spatial relationship among the units of analysis or, in other words, by the choice of the spatial weight matrix. In the present analysis, four different standardized weight matrices are considered in the calculation of this indicator: (1) the first order contiguity matrix, (2) the second order contiguity matrix, (3) the k-4 nearest neighbors, and (4) the inverse distance.

Although global spatial measures help to assess the strength of spatial autocorrelation across all spatial units, generating one global statistic, local spatial variations may also exist in the degree of spatial dependency. The latter can be tackled through the computation of local measures of spatial autocorrelation. The use of local statistics can inform us about spatial nonstationarity or spatially varying relationships in our variable of interest, thus identifying statistically significant clusters (Fotheringham, 2009).

To analyze the nature of the local distribution of homicides, a local version of Moran's I or local indicator of spatial autocorrelation (LISA) is employed. This statistic assesses a null hypothesis of spatial randomness by comparing the values of local pairs (that is, the values of each specific location with the values in neighboring locations; Anselin, 1995). It is particularly useful because it allows for the decomposition of spatial association into four categories (HH, LL, HL, and LH): (1) HH, or high-high—when a location with an above-average value is surrounded by neighbors whose values are also above average; (2) LL, or low-low—when a location with a below-average value is surrounded by neighbors whose values are also below average; (3) HL, or high-low—when a location with an above-average value is surrounded by neighbors whose values are below average; and (4) LH, or low-high—when a location with a below-average value is surrounded by neighbors whose values are above average. See Anselin (1993) for a detailed description of the statistical properties of LISA statistics.

Detecting the Spatial Diffusion Process

To explore the possible mechanisms associated with the diffusion process of homicide rates in the municipalities, this section develops an exercise that is useful for studying spatial clusters in a dynamic framework. Cohen and Tita (1999) identified changes in the levels of local-neighbor pairs (LISA clusters), looking at the type of diffusion process of homicide rates within spatial units. Within this framework, it is possible to identify four different mechanisms that may lead to changes from low to high levels (or vice versa) in local spatial units. Expansion and relocation are forms of contagious diffusion in which the status among neighboring spatial units affects the future status of adjoining units, by increasing the level either locally or for the neighbors located in the same local-neighbor pair. A distinction between these two forms is that with relocation the object that is being diffused leaves the point of origin and spreads outward from that point, and with expansion diffusion also spreads from the center but continues to experience high incidence rates of the diffusing phenomenon.

Spatial units can also change from low to high levels through hierarchical diffusion in the forms of isolated or global increases, which reflect increases (or decreases) that do not depend on contact with nearby high-level (or low-level) spatial units. Here the spread does not occur with direct contact but happens more through cultural influences (innovation or imitation) that affect the population or a particular subgroup that may be widely dispersed geographically (Cohen and Tita, 1999).

The idea of this exercise is to compare municipalities with transitions among different significant LISA pairs in successive years. We are especially interested in exploring those yearly transitions (between time *t* and *t*+1) from low to high levels of homicide rates among statistically significant clusters.[1] The case of a transition from an LH at time *t* to an HL or an HH at time *t*+1 indicates a contagious diffusion of high homicide rates, while a transition from an LL to an HL or an LH denotes a hierarchical type of diffusion process. Exhibit 1 shows other possible transition combinations.

Exhibit 1

Dynamics of Change in the Spatial Distribution of Homicide Rates Over Successive Years

Direction of Change	Type of Diffusion	Mechanism of Change	Year-to-Year Change in Local Neighbor Pairs	
			Local Is Diffusion Outcome	Local Is Diffusion Source
From low to high levels	Contagious	Expansion among neighbors	LH to HH	HL to HH
		Relocation among neighbors	LH to HL	HL to LH
	Hierarchichal	Isolated increase	LL to HL	LL to LH
		Global increase	LL to HH	LL to HH
From high to low levels	Contagious	Expansion among neighbors	HL to LL	LH to LL
		Relocation among neighbors	HL to LH	LH to HL
	Hierarchichal	Isolated increase	HH to LH	HH to HL
		Global increase	HH to LL	HH to LL
No change	None	Stationary		

HH = high-high. HL = high-low. LH = low-high. LL = low-low.

Source: Cohen and Tita (1999)

Data Description

The data for homicides come from the vital statistics of the Instituto Nacional de Estadistica y Geografia (INEGI). These data consider all types of homicides (ICD-10: X85-Y09)[2] that occurred in Mexican municipalities from 2005 through 2010. We also explore a database for homicides related to drug rivalry or organized crime released by the Presidencia de la Republica. Starting in 2007, a database on homicides related to organized crime was produced for statistical purposes only; no ministerial or judicial information was included, only the numbers of deaths in municipalities and states. These deaths are classified as homicides related to organized crime if they occur with extreme violence or as an event involving more than two victims and include at least two of the following criteria: the body had an injury that resulted from the use of a firearm; the body had severe injuries and showed signs of torture; the body was found in the interior of a vehicle; the death of the body showed use of materials characteristic of the modus operandi of organized crime; and particular facts related to the death of the body, such as if the event occurred in an ambush, was a persecution, or included the finding of a message linked to organized crime.

[1] In this study, significance levels directly obtained from the LISA calculations differ from those of George and Tita (1990), which consider significant local pairs to be those that involve a change of at least two standard units in the value of LISA local pairs (see the reference for further details).

[2] International Classification of Diseases, World Health Organization.

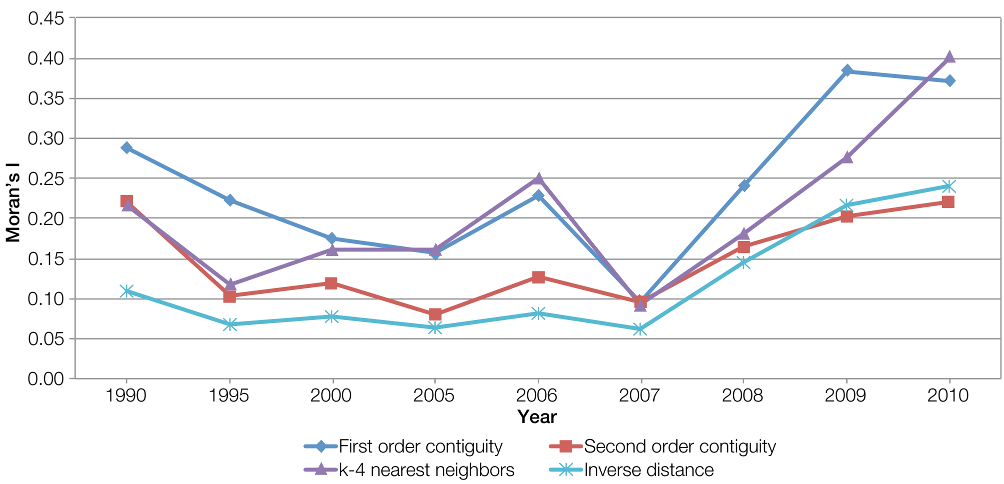
These data exhibit some issues related to data-gathering reliability, however, given that these criteria are used when classifying the homicides and because, for some of the cases, no official death certificate is attached. These factors in turn produce an overestimate of the total counts of homicides related to organized crime or drug rivalry compared with those officially reported by INEGI (Merino and Gomez, 2012). Although we analyze both databases currently available in Mexico, the final set of results is based on mortality data from an official vital statistics report by INEGI; in this sense, the data for narcotics-related homicides are used only for comparison, given the previously mentioned problems related to such a database.[3]

Results

Exhibit 2 shows the Moran's I value of total homicides obtained using different weighting matrices for 5-year intervals from 1990 through 2005 and yearly from 2006 up to 2010.[4] As noted, the spatial dependence of total homicide rates among municipalities does not follow a regular pattern until 2007, when thereafter a constant yearly growth is observed. This pattern indicates that high levels of homicide rates resulted in more clustering across spatial units,[5] and this pattern, obtained

Exhibit 2

Global Moran's I Statistic of Total Homicide Rates in Mexican Municipalities, 1990–2010



[3] Also, Rodriguez-Oreggia and Flores (2012) detected that between 8 and 12 percent of municipalities, at some point in time, have more homicides related to narcotics than the total official account of homicides.

[4] The respective Global Moran's I for narcotics-related homicide rates was also calculated, but the rates are not reported here. Data availability allows for the yearly calculation of homicide rates from 2007 onward, and the results show a higher degree of spatial autocorrelation among observations, confirming the descriptive analysis shown in the previous section. These results are available from the authors upon request.

[5] All values show statistical significance levels of at least $p < 0.05$.

from comparing different weight matrixes, is consistent. The calculations also suggest that the weight matrix assessing the higher degree of spatial dependence occurred with the first order contiguity matrix. The use of this matrix is appropriate for this study because we are interested in the diffusion of homicide rates occurring primarily in contiguous municipalities. Hence, the empirical evidence shown in the subsequent sections rests on this type of weight matrix.

Exhibit 3 reports the prevalence of municipalities within each local cluster type obtained from LISA on a yearly basis during the period of 2005 through 2010 for total homicides (Panel A) and for narcotics-related homicides since 2007 (Panel B). Three main results arise and are described as follows.

First, the number of municipalities exhibiting significance levels for any local-neighbor pairs (cluster type) of total homicide rates rose during the period from 418 to 548. For narcotics-related homicides, the number increased from 191 to 353 municipalities.

Second, at the beginning of the period, approximately 109 municipalities were showing an HH cluster type of total homicides, accounting for 4.4 percent of the municipalities. These municipalities have homicide rate values that are above average and are surrounded by neighbors whose values are also above average. Note that the HH cluster type reached its highest levels in 2008,

Exhibit 3

Percentage of Local-Neighbor Pairs of Homicide Rates in Mexico, 2005–2010

Cluster Type	Year					
	2005	**2006**	**2007**	**2008**	**2009**	**2010**
A. Total homicides						
HH (high-high)	4.44	4.97	3.42	7.09	6.32	5.58
	(109)	(122)	(84)	(174)	(155)	(137)
LL (low-low)	8.64	10.47	0.24	10.92	10.47	14.87
	(212)	(257)	(6)	(268)	(257)	(365)
LH (low-high)	2.57	2.04	2.53	2.24	1.96	1.43
	(63)	(50)	(62)	(55)	(48)	(35)
HL (high-low)	1.39	1.18	1.51	1.26	0.86	0.45
	(34)	(29)	(37)	(31)	(21)	(11)
No significant cluster	82.97	81.34	92.3	78.48	80.4	77.67
	(2,036)	(1,996)	(2,265)	(1,926)	(1,973)	(1,906)
B. "Narco" homicides						
HH (high-high)	NA	NA	3.38	4.48	5.54	5.38
			(83)	(110)	(136)	(132)
LL (low-low)	NA	NA	0.20	1.18	2.53	6.68
			(5)	(29)	(62)	(164)
LH (low-high)	NA	NA	2.69	2.36	1.87	1.47
			(66)	(58)	(46)	(36)
HL (high-low)	NA	NA	1.51	1.3	1.02	0.86
			(37)	(32)	(25)	(21)
No significant cluster	NA	NA	92.22	90.67	89.04	85.62
			(2,263)	(2,225)	(2,185)	(2,101)

NA = information not available.

Notes: Pairs of municipalities with significant local clusters (local indicator of spatial autocorrelation, or LISA) of the homicide rate for a respective year. The parentheses denote the total number of municipalities in each local cluster. N = 2,454.

with 7 percent of total municipalities, or approximately 174 municipalities, being included in this type. This HH cluster type shows a consistent decline after reaching its peak in 2009 and 2010, although its values are still higher than the initial values in 2005.

Third, higher levels of narcotics-related homicides surrounded by municipalities with HH levels were concentrated in approximately 83 of the municipalities, or about 3.4 percent of the total, in 2007. During the following 2 years, an upward trend was observed, suggesting an increasing number of municipalities with an HH cluster of narcotics-related homicides. By 2010, HH occurred in approximately 132, or 5.4 percent, of the municipalities.

A useful way to visualize clustering patterns of homicides in Mexico is through mapping. To this end, we combine ArcGIS and GeoDa software capabilities to create a series of maps, which summarizes much of the previous discussion. As discussed previously, we prefer to use total homicides instead of drug rivalry homicides. Consequently, the rest of the analysis relies on total homicide data from INEGI. In exhibit 4, it is possible to distinguish the states with army intervention and also the distribution of only the HH clusters of total homicide rates for each year from 2005 through 2010. The latter are displayed as centroid circles with a graduated color corresponding to each year.

As observed, much of the concentration of high homicide rates at the beginning of the period occurs in the states that will have army intervention later. This concentration in turn supports the argument that the federal government used to deploy armed forces to particular areas within the country that exhibit considerably high levels of violence.

Exhibit 4

Spatial Diffusion of High-High (LISA) Clusters of Total Homicides in Mexico, 2005–2010 (1 of 4)

a. 2005

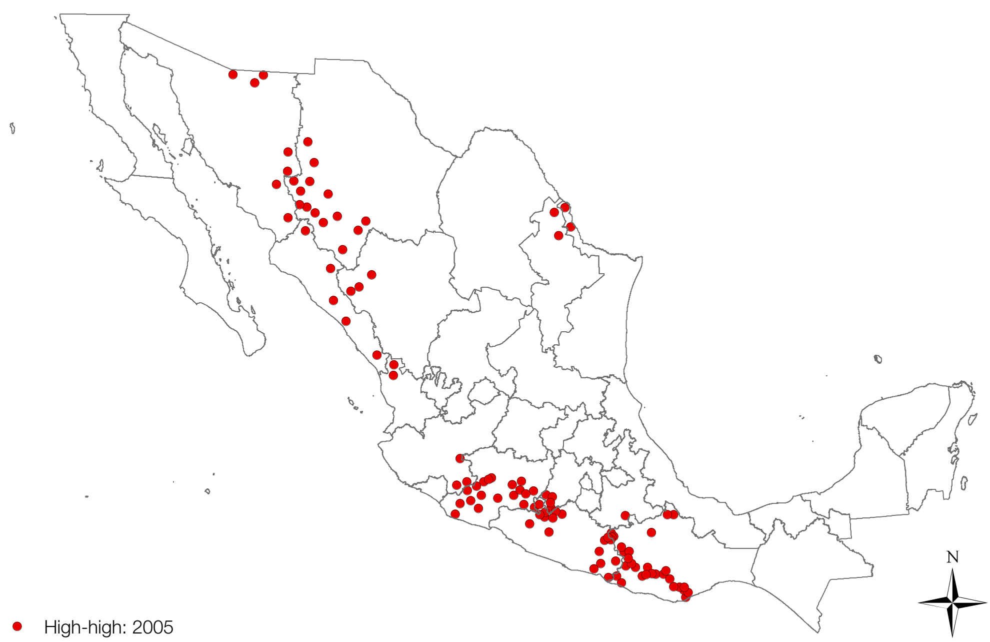
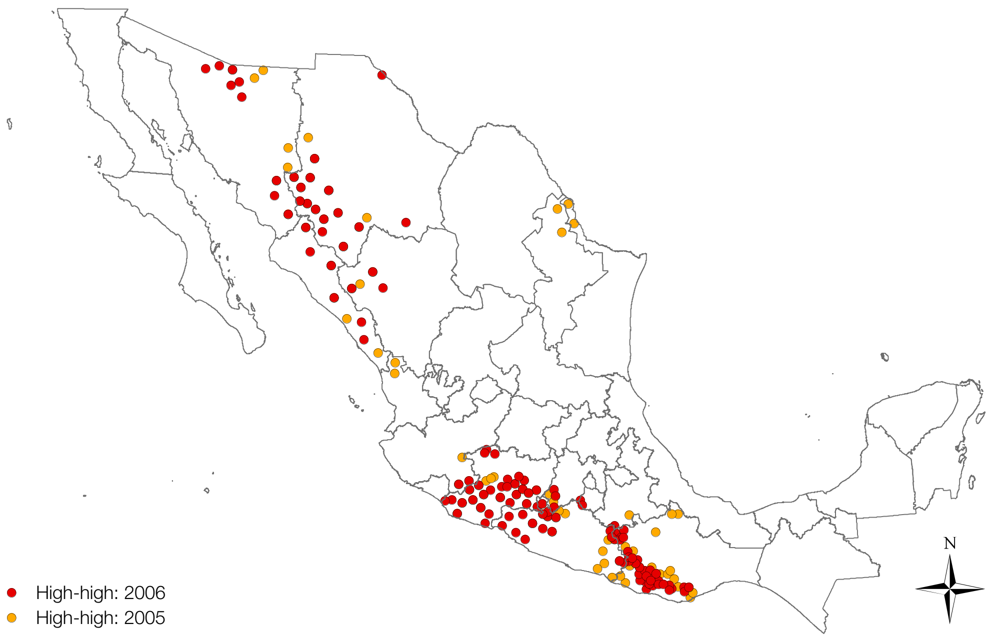


Exhibit 4

Spatial Diffusion of High-High (LISA) Clusters of Total Homicides in Mexico, 2005–2010 (2 of 4)

b. 2005–2006



c. 2005–2007

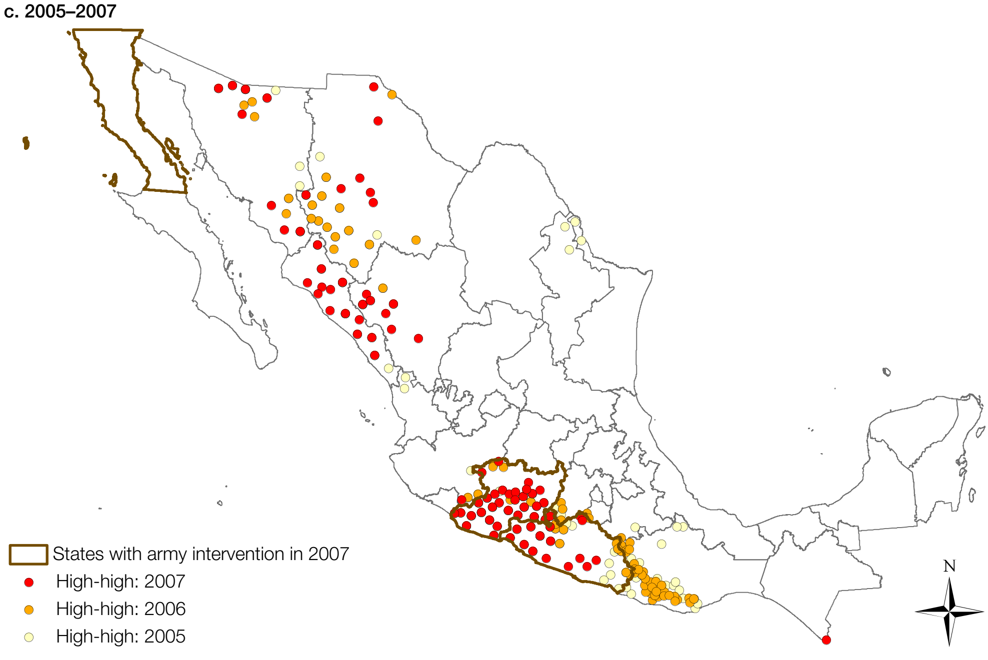
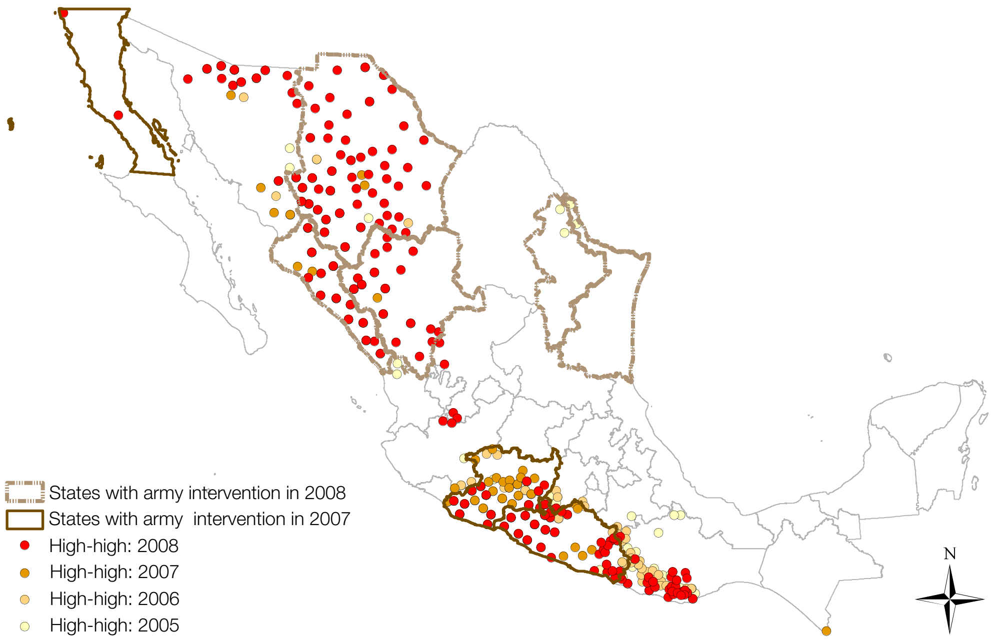


Exhibit 4

Spatial Diffusion of High-High (LISA) Clusters of Total Homicides in Mexico, 2005–2010 (3 of 4)

d. 2005–2008



e. 2005–2009

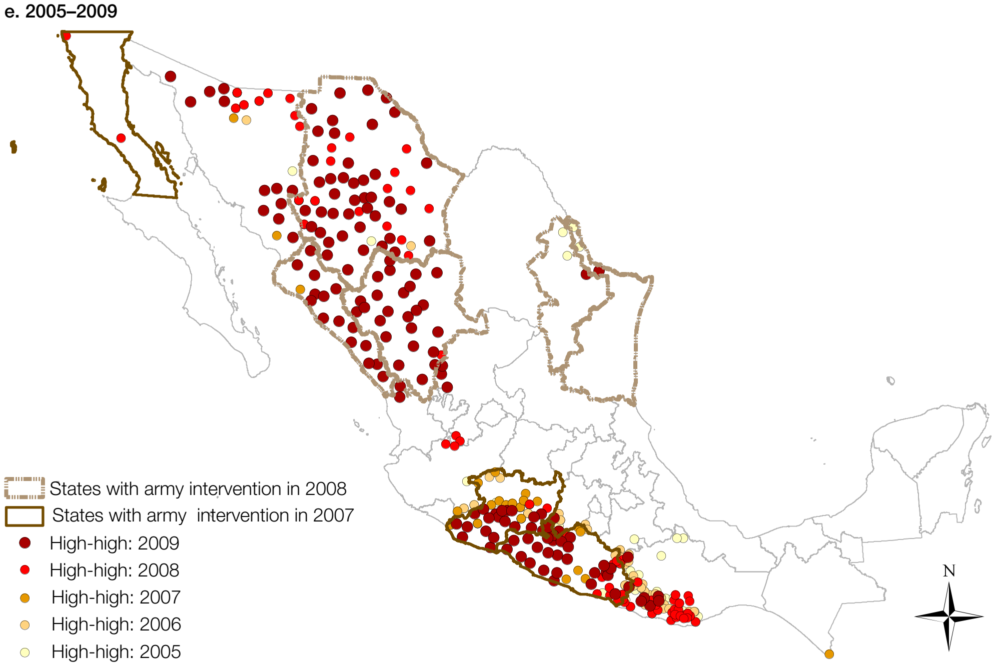
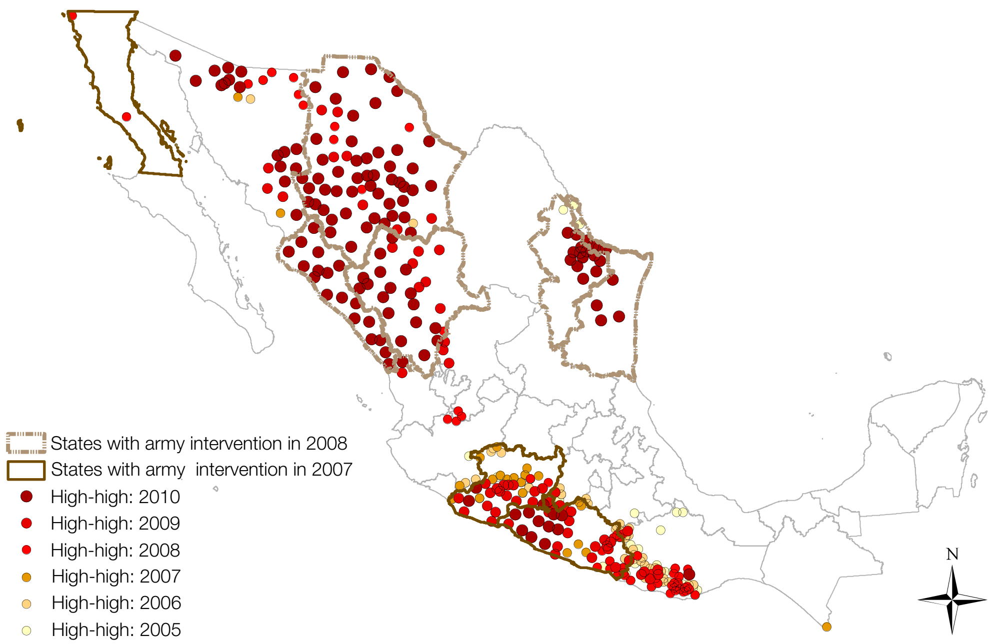


Exhibit 4

Spatial Diffusion of High-High (LISA) Clusters of Total Homicides in Mexico, 2005–2010 (4 of 4)

f. 2005–2010



LISA = local indicator of spatial autocorrelation.

The geographic dispersion patterns followed by these HH clusters are also noteworthy. On the one hand, a greater proportion of municipalities were experiencing clusters of the HH type within the states that, at the beginning of the period, were already experiencing high homicide levels. On the other hand, a considerable proportion of municipalities that experienced transitions from nonsignificant to significant spatial clusters, particularly to HH type, continued to experience high levels of homicide rates despite the deployment of federal forces.

Detecting the Spatial Diffusion Process: Results

The analysis then considers previous results (reported in exhibit 3) to calculate local pair changes. Exhibit 5 reports the results associated with the analysis of total homicide rates. To facilitate the explanation, we first provide the results for the proportion of municipalities that enter into each type of diffusion (contiguous or hierarchical) and have a direction change from low to high levels, and then we determine whether the local pair serves as an outcome or a source of these transitions.[6] As described previously, a high incidence of homicide rates for the period of study tend to be spatially clustered within states in which army interventions actively operate; hence, the analysis also performs a *t*-test for mean differences of each outcome to whether the municipality belongs these states as compared with the rest.

[6] The same analysis was performed for the transition from high to low levels of local significant clusters.

Exhibit 5

Patterns of Yearly Changes in Local-Neighbor Municipalities in Mexico, Homicide Rates, 2005–2010

Municipality As Outcome/Source of Diffusion of Increases in Homicide Rates	Proportion of Municipalities With Change in Homicide Rates in Successive Years
Effect of Neighbor Rate at Time *t* on Local Rate at *t* +1	**Diffusion[a] (all municipalities)**
I. Diffusion outcome	
a. Hierarchichal: isolated or global increases (LL to HL, LL to HH)	0.57
b. Contagious: expansion or relocation increases (LH to HH, LH to HL)	2.32***
II. Diffusion source	
c. Hierarchichal: isolated or global increases (LL to LH, LL to HH)	0.12
d. Contagious: expansion or relocation increases (HL to LH, HL to HH)	0.24
III. No change: stationary	
HH	0.33**
HL	0.00
LH	0.00
LL	0.00
No significant cluster	51.79***

HH = high-high. HL = high-low. LH = low-high. LL = low-low.

[a] Proportion of municipalities with change in homicide rate in succesive years.

*** $p < 0.05$. *** $p < 0.001$.*

Two main findings arise. First, the evidence suggests that transitions from low to high homicide rates follow a contiguous expansion or relocation diffusion type with significantly larger proportions in states with joint army intervention. The diffusion source of high levels of homicide rates is higher among local pairs of municipalities that are contiguous with municipalities that experience high homicide rates at the beginning of each period (year). Second, a significantly larger proportion of municipalities that stayed within the HH cluster type during each successive period occurred in states with army intervention. Approximately one-half of all the municipalities do not show statistically significant levels of any clustering type during successive periods.

As discussed previously, it is possible to identify whether a contiguous source of diffusion outcome has occurred through relocation or if an expansion type of diffusion has taken place. Exhibit 6 separates the proportion of municipalities whose local-pair transitions fit within each of these two types. The results indicate that the spread of homicides resulted from an expansion diffusion. These results provide evidence that the object being diffused (homicide rates) has spread from its original place (municipalities), while the original source of diffusion still has high incidence rates of homicides. Furthermore, a significantly large proportion of the diffusion seems to occur in those municipalities experiencing joint army interventions, as the respective *t*-test shows significant levels.

The findings in this section can be summarized as follows. On the one hand, the analysis reveals that the increase in levels of homicide rates in Mexico has occurred particularly within the states facing joint army interventions. Evidence also indicates significant levels of spatial dependency

Exhibit 6

Mechanism of Change of Homicide Rates in Local Neighbor Municipalities in Mexico, 2005–2010

Municipality As Source of Diffusion of Increases in Homicide Rates	Proportion of Municipalities With Change in Homicide Rates in Successive Years
Effect of Neighbor Rate at Time *t* on Local Rate at *t+1*	**Diffusion[a]**
Contiguous diffusion	
a. Expansion among neighbors (LH to HH)	2.24***
b. Relocation among neighbors (LH to HL)	0.08

HH = high-high. HL = high-low. LH = low-high.

[a] Proportion of municipalities with change in homicide rate in succesive years.

**** $p < 0.001$.*

among municipalities that have high incidence rates of homicides. On the other hand, it appears that high levels of homicide rates are being diffused to other nearby municipalities. The mechanism through which this diffusion takes place suggests that municipalities that act as contributors to the spread of high incidence rates have not reduced their levels, but, on the contrary, continue to experience high incidence rates and that this takes place in greater proportion in municipalities that experience army intervention.

Conclusions

In this article we aim to analyze the extent of the diffusion of violence, measured with the number of homicides, among Mexican municipalities from 2005 to 2010. During this period, Mexico was characterized by a rise in organized crime, and, while some army intervention was executed in some states, violence seems to have displaced to other localities. Here we look at this particular phenomenon using ESDA techniques aimed to examine the dynamics of local spatial clustering, measured by LISA transitions, and thus provide a better description of the extent to which spatial diffusion of violence occurred across the country. For a developing country immersed in an organized crime wave, the analysis and implications are relevant, not only for Mexico, but also for countries in the region facing a similar context.

The findings suggest an increase in significant spatial clusters of homicides for the period of consideration in 2 percentage points of the municipalities. Concentration tends to occur in the first years of analysis in states where army intervention took place later. Even after the army intervention, most of the municipalities in those states remained high-high clusters of violence. The significance test shows a clear contagious effect among neighbors, while HH clusters remain stationary after army interventions.

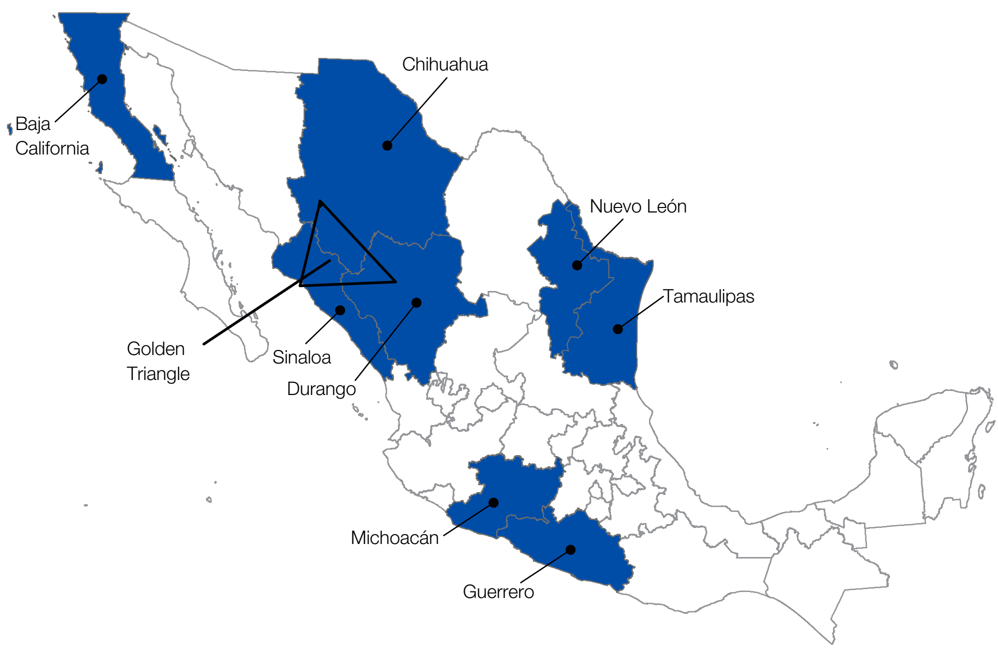
One implication of the analysis suggests that law enforcement policies applied in such hotspot areas were ineffective on spatially restraining levels of violence, at least during the period here considered, leading to the spread of violence levels to neighboring areas. Failure of law enforcement policies calls for the implementation of other actions, either to replace this action or be complementary to it, where homicides have increased and spread among areas.

A final comment addresses the theoretical framework and statistical techniques described here. As explained previously, these techniques explicitly consider the spatial distribution of homicides in which the goal was to show the existence of a geographic diffusion to areas immediately surrounding the direct focus of the policy efforts described. Nonetheless, the inference made from the empirical analysis does not imply a formal causality test between army intervention and rising homicides in absolute terms; other factors, such as clashes among drug cartels or groups within them, could be influential factors.

Appendix

Exhibit A-1

Mexican States Exposed to Army Joint Operations



Note: States with army intervention as part of the "Operativo Conjunto" are in blue.

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A Spatial Difference-in-Differences Approach To Studying the Effect of Greening Vacant Land on Property Values

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Abstract

This article details the use of a spatial difference-in-differences approach for measuring the effect of a vacant land greening program in Philadelphia, Pennsylvania, on nearby property values. Vacant land is a ubiquitous problem in U.S. cities, and many have recently begun to explore greening programs as an interim management strategy for vacant lots, in the hopes they will reduce the negative influence of vacancy and help to spur neighborhood development. The methods used here draw on previous approaches to modeling effects of greening on property values but expand on them to explore means of incorporating spatial relationships and allowing for spatial nonstationarity, in which the process being modeled changes across space. Spatial methods were used not only to derive data and choose appropriate observations but also to compare global and local versions of the analysis to assess spatial patterns and differences in outcomes across the study area, ultimately showing that, although greening vacant land increases surrounding property values, it does not do so uniformly across urban neighborhoods.

Introduction

The urban revitalization literature is chock full of ideas for how to improve distressed neighborhoods, but actually determining the effects of interventions has proven to be more challenging. One of the most commonly studied effects is the change in property values; these effects are generally studied because the housing market is seen as a good indicator of the desirability or perceived quality of a neighborhood (Galster, Tatian, and Accordino, 2006). Most methods for making these assessments rely at least in part on hedonic regression models, in which the value of an individual property is seen as reflecting a bundle of values of individual amenities, which would include both characteristics of the property itself and characteristics of the neighborhood, and a regression equation is used to estimate the value of each individual amenity or property characteristic (Rosen, 1974). Thus the effect of proximity to an intervention on property values might be assessed by comparing property values at varying distances to the intervention and checking the coefficient of the distance variable to see if lower distances correspond to higher values.

The difference-in-differences approach is an econometric case-control test that investigates whether an intervention influences an outcome over time by comparing observed differences in a case sample that receives the intervention to observed differences in a control sample that does not. This approach enables isolation of the treatment effect above and beyond any difference that would have been expected regardless of the treatment (Meyer, 1995). The difference-in-differences model specification has been used with hedonic modeling of property values to assess the effects of a range of neighborhood interventions, including new housing development (Ellen et al., 2001; Ellen and Voicu, 2005), establishment of community gardens (Voicu and Been, 2008), and tree planting programs (Wachter and Wong, 2008).

Incorporating Space

When it comes to measuring the effects of interventions such as new housing development or tree planting on neighborhoods, space cannot be ignored. A neighborhood is a fixed location in which residential and commercial buildings, amenities such as parks, and disamenities such as vacant lots all coexist with their distinct spatial relationships informing the influences they have on each other and the neighborhood as a whole. The value of any component of that neighborhood cannot be divorced from the values ascribed to the other components of the neighborhood, because it is reliant in part on those values. This reliance means that space and spatial relations must inform any attempt to measure those effects. That being said, the attempts to measure the effects of intervention cited previously take space into account in only one way—by incorporating the distance to an intervention into the equation to estimate its effect. These attempts often take the form of creating distance bands from the intervention within which a property is or is not located (Ellen et al., 2001; Wachter and Wong, 2008). For example, Ellen et al. (2001) studied the effects of new housing development on existing property values by specifying houses as affected if they were within three different distance bands of the new development—500 feet, 1,000 feet, or 2,000 feet—and designating control lots as outside the distance in question but within the same ZIP Code.

These models are helpful, but they often assume a single model that describes relationships and values that are constant across the entire study area. They are unable to account for potential differences in effects across locations, known as spatial nonstationarity, unless the drivers of those differences are known in advance and can be incorporated into the models as interaction terms. More explicitly, spatial methods are required to find differences that are not known from the beginning or are unable to be incorporated because of a lack of appropriate data.

This article details the methods used to measure the effects of a greening intervention to manage vacant land on surrounding property values in Philadelphia, with a focus on the means by which spatial patterns were assessed. The program, Philadelphia LandCare (PLC), uses a simple greening approach to treat vacant lots by removing any existing trash or debris, bringing in topsoil, planting new grass and a few trees, and erecting a split-rail fence to prevent dumping and give the lot a more managed look. During the first decade of the program, more than 5,000 individual parcels received treatment through the PLC program. For more details of the program, see Jost (2010) and Heckert and Mennis (2012).

For this research, which is described in more detail in Heckert and Mennis (2012), I adapted the difference-in-differences approach for spatiotemporal analysis of changes in property values surrounding treatment and control lots through use of a sampling strategy that ensured control lots mimicked the spatial distribution and economic characteristics of treated lots, while also remaining spatially distant enough to prevent diffusion of treatment, whereby any effect from the treatment might also be demonstrated by the control because of proximity. I modified the approach by creating a geographically weighted variant, using geographically weighted regression to explore geographic variation in the effects of the greening program.

Data and Methods

This analysis relied on four primary spatial datasets and on several supplemental datasets. The primary datasets were (1) data on lots that were treated as part of the PLC program represented as points at the center of each of 747 contiguous groups of lots that were greened together between 1999 and 2006; (2) data on vacant lots in Philadelphia in 2010 also represented as points at the center of each group of contiguous vacant lots; (3) a set of points representing all Philadelphia residential real estate sales valued at more than $1,000 between the years 1999 and 2007, with sales prices adjusted for inflation to 2007 dollars; and (4) boundaries for neighborhood planning districts, breaking the city into seven regions. Additional datasets included shapefiles with locations of commercial corridors and schools and a real estate market typology created by a local community development financial institution, which ranked the 2008 real estate markets in each census block group on a 9.0-point scale from distressed (1.0) to regional choice (9.0). The purpose of each dataset is described in more detail in the following section.

The difference-in-differences specification uses a case-control methodology where each case—in this instance, each lot that was ultimately treated through the PLC program—is matched with appropriate controls—in this instance, lots that could have been treated through the PLC program but were not. Although the data on the PLC program and the vacant land data for Philadelphia both started as data on individual parcels, adjacent parcels were merged together for analysis. This merging was necessary because the PLC program was implemented on groups of adjacent lots that look and feel like a single entity, even if they are technically separate properties, and the effects of two adjacent lots cannot be reasonably separated from each other. Following similar logic, the vacant lots used as controls were combined based on adjacency.

It is very important to note that site selection for the PLC program was by no means random and, thus, controls could not simply be assigned randomly from the universe of all vacant lots. The Pennsylvania Horticultural Society (PHS), which developed and manages the PLC program, describes several criteria that are used to determine lots for inclusion in the program. First and foremost, PHS targets communities with large concentrations of blighted vacant lots—PLC is not a program designed for neighborhoods with strong real estate markets and low populations of vacant lots to choose from. Within target neighborhoods, lots are chosen based on loose criteria intended to identify lots with most potential for effect, so that large collections of lots near schools or commercial corridors are prioritized (Jost, 2010). In an effort to select control lots that were closest in characteristics to the treated lots, I restricted the set of all vacant lots to those located within 500 feet of a school or commercial corridor before selection of control lots.

One challenge for selecting control lots was attempting to prevent diffusion of treatment effects, whereby the effect of a greened lot would also happen and be felt in the area of nearby nongreened lots. The concern here was that a large number of untreated vacant lots are also located in close proximity to treated lots, which is not surprising, given that the program targeted areas with large numbers of vacant lots. Although it was desirable to keep control lots as far as possible from the PLC lots to avoid the possibility that property values surrounding them also increased because of proximity to PLC lots, it was also necessary to ensure that controls were located in similar neighborhoods and thus represented appropriate counterfactuals. To mitigate diffusion of treatment effects, all vacant lots within 250 feet of a treated lot were excluded from the pool of potential control lots. To ensure that controls were in similar neighborhoods to treated lots, the final selection of controls matched each treated lot to three randomly selected controls from the pool, with the controls matching the treated lot in both the section of the city and the real estate typology score for the block group of the lot. Thus the matches did not guarantee that the control lots were in exactly the same neighborhood but required that the control lots face similar real estate market conditions and be in the same relative portion of the city.

For the specification of the difference-in-differences model, the unit of analysis was taken to be the lot, with values assigned to represent the value of residential properties at the location of the lot. Property values were assigned to each lot for each year between 1999 and 2007 based on inverse distance weighting of the price per square foot of the closest 15 properties sold in that year within 500 feet of the lot. This approach essentially calculates a weighted average of those sale prices, with the weightings assigned so that closer properties have higher weights. When fewer than 15 properties sold within 500 feet of a lot, the number of properties included in the calculation was reduced to 10. If fewer than 10 properties sold, the search radius was increased to ensure that at least 10 sales were included.

With sale price per lot as the dependent variable, the specification of the difference-in-differences model was

$$lnV_{it} = \beta_0 + \beta_1 P_i + \beta_2 G_{it} + \beta_3 P_i G_{it} + \beta_4 M_i + \beta_5 S_i + \beta_6 Y_t + \varepsilon_{it} \,, \tag{1}$$

where lnV_{it} is the natural log of the average price per square foot of residential real estate near vacant lot i at time t; P_i is a dummy variable set to 1 if lot i is part of PLC or 0 if it is not; G_{it} is a dummy variable set to 1 if time t is post-greening for lot i (for a control lot, this value is set to 1 when the associated treated lot is greened); $P_i G_{it}$ (that is, the interaction term defined as P times G) is a dummy variable set to 1 if lot i is in PLC and time t is post-greening; M_i is a variable encoding the real estate market index value of lot i; S_i is a fixed-effects variable for the Neighborhood Planning District of the city of lot i; Y_t is a fixed-effects variable for year to account for temporal effects; ε_{it} is an error term; and β terms are the coefficients to be estimated by the model.

This model provides an overall assessment of whether property values changed near greened lots in a manner that was different from changes near nongreened lots, but, as previously noted, it calculates a single equation that is assumed to represent the relationship between PLC and property values for the entire study area. I was, however, keenly interested in thinking about whether the PLC program behaved differently in different areas. One way of answering this question would be to split up the observations based on neighborhoods that might be expected to behave differently and to calculate model coefficients for each group separately. I attempted to assess neighborhood differences by running the model in two ways—first, by splitting the lots into planning neighborhoods and, second, by splitting lots into different real estate typology categories. That approach, however, requires some decision to be made in advance about the appropriate means for defining areas that might be expected to behave differently from each other. An alternative to the prescribed approach to splitting observations into neighborhoods is to use geographically weighted regression (GWR) instead of ordinary least squares regression in the specification of the difference-in-differences model.

The GWR model essentially calculates a separate regression equation for each observation in the dataset by calculating coefficients using only a subset of "nearby" observations, which are weighted based on proximity so that nearer observations have higher weights than those that are farther away (Fotheringham, Brunsdon, and Charlton, 2002).

The equation for the GWR model can be specified as

$$lnV_{it} = \beta_0(u_i,v_i) + \beta_k(u_i,v_i)\, x_k + \varepsilon_{it}\,, \qquad (2)$$

with (u_i, v_i) representing the coordinates of point i, and x_k representing the k^{th} independent variable in the model. All variables from the original global difference-in-differences model were included in the GWR variant. This model weights observations based on their distance to point i so that it creates a Gaussian weight surface in which closer locations are weighted closer to 1 and farther locations' weights decrease ultimately to 0. The GWR model was run with bandwidths specifying neighborhoods of ½ mile, 1 mile, and 2 miles in radius.

One final step taken after the models were run was the calculation for each lot of the percentage of surrounding lots that had been greened. For each greened lot in the study, the number of lots within 500 feet was counted and the percentage of lots that were greened through PLC was calculated. This measure was then averaged for each neighborhood to create a measure of "concentration of greening" within that area. These values were mapped against the model results as a purely visual assessment of a possible relationship between effects of the program and the structure of its implementation.

Results

The global difference-in-differences model coefficients (exhibit 1) showed that property values surrounding greened lots did increase more than property values surrounding control lots, but much more information was gleaned from the geographically focused models, which showed that this relationship varied considerably over space. In the neighborhood-specific models, only three of seven neighborhoods—Eastern North Philadelphia, West Philadelphia, and Southwest

Philadelphia—actually showed the pattern of increased property values surrounding greened lots, while the other four neighborhoods had coefficients that were not significantly different from 0. The real estate market-based model also showed variations across the city, with distressed markets showing increased property values as a result of the PLC program but transitional and steady neighborhoods showing no effect.

Both of these patterns were further illuminated by the GWR model, which similarly demonstrated wide variation in the effects of the PLC program. Exhibit 2 indicates the results of the GWR model with a 1-mile bandwidth, although the results were consistent at all bandwidths tested. Note that

Exhibit 1

Coefficients of the Global Difference-in-Differences Model

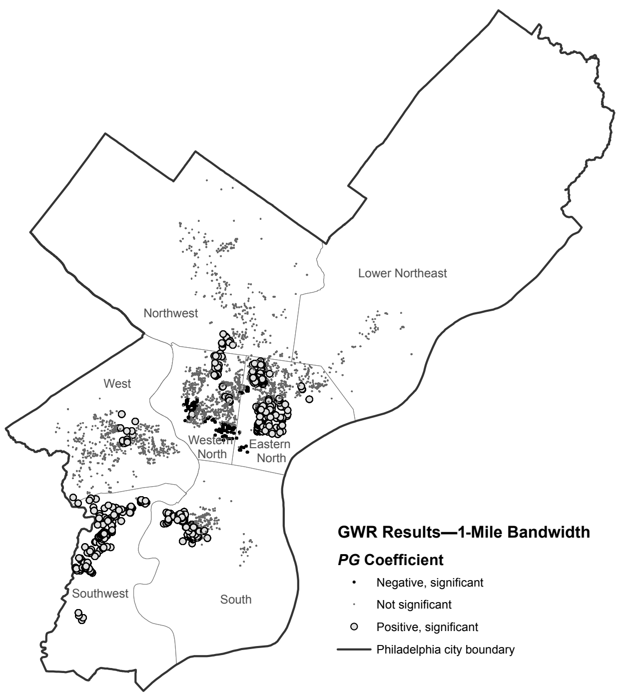
Independent Variable	Coefficient	R^2
P	– 0.084*** (– 8.729)	0.415
G	– 0.013 (– 0.987)	
PG	0.056** (3.100)	

* $p < 0.05$. ** $p < 0.01$. ***$p < 0.001$.

Notes: t-values are reported in parentheses. N = 26,608.

Exhibit 2

Results of the Difference-in-Differences Geographically Weighted Regression



GWR = geographically weighted regression. PG *= the* PG *term in the model equation.*

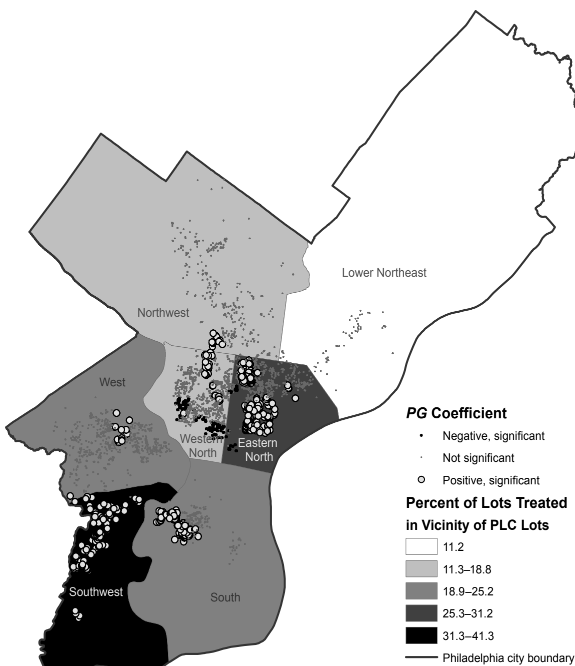
Note: Open circles indicate lots where the PG *coefficient is positive and significant (that is, locations where Philadelphia LandCare raised the nearby residential property values).*

this pattern matches the results of the neighborhood-specific models, with batches of positive coefficients in each of the neighborhoods that showed positive effects of PLC in its own model. The GWR results actually add additional nuance, however, highlighting the potential for variation of effects even within a neighborhood. In particular, additional small clusters of positive coefficients are found in South Philadelphia, Western North Philadelphia, and Northwest Philadelphia, indicating that PLC did lead to increased property values in parts of those neighborhoods, although not consistently throughout them. The GWR results also indicate areas of no effect within the three neighborhoods where the neighborhood models indicated PLC to have positive effects.

Comparison of the various model results with the concentration of greening measure showed that neighborhoods with the most positive effects of greening on property values in both the neighborhood-specific models and the GWR results tended to be those with the higher scores for concentration of greening (exhibit 3), suggesting that areas in which a higher proportion of lots were treated were more likely to see gains in property values. For additional tables, figures, and discussion of the results of this study, see Heckert and Mennis (2012).

Exhibit 3

Results of Geographically Weighted Regression Compared With Neighborhood Greening



GWR = geographically weighted regression. PG = *the* PG *term in the model equation. PLC = Philadelphia LandCare.*

Note: GWR results compared with the concentration of greening in each neighborhood, meaning the percentage of lots surrounding greened lots that also were greened.

Discussion

This analysis ultimately revealed that, although property values throughout the city increased during the study period, properties surrounding treated lots enjoyed a greater increase in value than properties surrounding controls, but it also showed that these effects were not felt evenly across the study area. The local models demonstrated that the effect was more pronounced in some parts of the city than others, a result that may have significant implications for continued implementation of the program.

This study further shows that the difference-in-differences method can be applied in understanding the spatial effects of an intervention—in this case, treatment of vacant lots by greening them—although special consideration must be given to spatial relationships in selecting appropriate controls. The additional use of a geographically weighted variant of the model was a key to generating meaningful results that can be used by program administrators and policymakers in future planning. The use of distinctly spatial methods was crucial throughout the study—first, for appropriate selection of control lots and specification of the initial aspatial model; second, for developing neighborhood and real estate market-specific variants of the model to begin to assess variations across the study area; and, third, in the development and specification of the GWR model, which ultimately provided the most nuanced results. Spatial methods were then able to be used to begin exploring how differences in program implementation in terms of the percentage of lots greened may have contributed to the differences in effects seen across neighborhoods.

The analysis provides direct, robust evidence for a positive change in nearby property values as a result of greening vacant lots while highlighting the importance of using spatial methods. The ability to compare local and global models to determine neighborhood factors that may influence program outcomes provides additional value in helping to target future initiatives to locations where they may be most likely to succeed.

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Does the House or Neighborhood Matter More? Predicting Abandoned Housing Using Multilevel Models

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Abstract

Multilevel models are important to use when data are nested. To demonstrate this point, an example is given where the probability of a house being abandoned is predicted using house- and neighborhood-level variables. The example illustrates the types of findings that are possible when different spatial scales are carefully considered. The final model indicates that for stable neighborhoods, house-level characteristics have a greater impact on the probability than do neighborhood-level characteristics; however, for more distressed neighborhoods, neighborhood characteristics matter more. Without the use of multilevel modeling techniques, this relationship might not have been found.

Introduction

Prediction is a powerful public policy tool. By being able to anticipate phenomena, policymakers are better able to make informed decisions. Given the importance of prediction, researchers often use multivariate regression to predict an outcome (for example, poverty, illness, and foreclosure) based on several potential predictors or causes. Although this method is popular, few researchers have considered the influence that spatial scale might have on their results and model interpretations. Thus, the primary objective of this article is to demonstrate why scale matters; the article does so using an example of abandoned housing prediction. The article will likewise add to the housing literature by providing new information about the spatial characteristics of abandonment. By considering two scales in the same model, one can identify the scale that has the greatest influence on the probability. Perhaps characteristics of a home matter more than the characteristics of the neighborhood where it is located. Some variables might be significant at one scale but not another.

There are many theories about the causes of abandonment. Because the focus of this article is methodological, a literature review on abandonment will not be provided. Nonetheless, the variables and data for this study were adopted from Morckel (2013) who predicted residential abandonment in Columbus, Ohio, using neighborhood-level factors.[1] The present study includes information on 120,109 properties in 382 Columbus neighborhoods, with neighborhoods defined as census block groups. The dependent variable is whether a house was identified by city code enforcement as being physically abandoned in 2011, and the independent variables are property values, property sales or transfers, arsons, demolitions, upkeep, property age, tax delinquency, and mortgage foreclosures in 2010. These variables are measured two different ways (at the house and neighborhood levels) to again demonstrate the importance of scale. Exhibit 1 provides additional information on the variables' data sources, measurements, and abbreviations in the forthcoming models.

Exhibit 1

Variables Included in the Models

Variable	Data Source	House-Level Measurement	Neighborhood-Level Measurement
		Whether a property…	***The percentage of properties in the neighborhood that…***
Property values	County Auditor's Office	Is less than the citywide median property value ($90,000) [H_Value]	Have a value less than the citywide median [N_Value]
Property sales	County Auditor's Office	Has been sold or transferred in the past year [H_Sale]	Have not sold or transferred in the past year [N_Sale]
Arsons	Columbus Fire and Bomb Investigations	Has been arsoned in the past year [H_Arson]	Have been arsoned in the past year [N_Arson]
Demolitions	Columbus Building and Zoning Services	NA[a]	Have been demolished in the past year [N_Demo]
Upkeep	County Auditor's Office	Is in poor condition [H_Upkeep]	Are in poor condition [N_Upkeep]
Property age	County Auditor's Office	Was built before 1945 [H_Age]	Were built before 1945 [N_Age]
Tax delinquency	County Treasurer's Office	Is tax delinquent [H_Tax]	Are tax delinquent [N_Tax]
Mortgage foreclosures	County Auditor's Office (sheriff's deed transfers)	Has been foreclosed on in the past year [H_Mfc]	Were foreclosed on in the past year [N_Mfc]
Abandonment	Columbus Code Enforcement	Is abandoned [H_Aband]	Are abandoned [N_Aband]

NA = not applicable.

[a] A property demolished in 2010 cannot predict abandonment in 2011.

Notes: "H" represents house-level variables. "N" represents neighborhood-level variables.

[1] Not all variables from Morckel (2013) were used; only those variables for which house- and neighborhood-level data were available were included.

Methods

Unlike traditional regression models, multilevel models enable researchers to predict the probability of a house being abandoned in a particular neighborhood, while taking into account house and neighborhood-level characteristics. Unfortunately, "…social scientists have tended to utilize traditional individual-level statistical tools for their data, even if their data and hypotheses are multilevel in nature" (Luke, 2004: 6). Using traditional methods is problematic with nested data (houses are *located within* neighborhoods), because not accounting for nesting can result in data dependency and correlated residuals, ultimately biasing regression estimates (Field, 2009). Likewise, it is better for regression analyses that use nested data to take on a multilevel form like the one that follows, for which the j subscripts indicate that a different level-one model is estimated for *each* of the j level-two units (that is, neighborhoods; Luke, 2004). The example is logistic because a house is either abandoned or not.

Level 1—

$$ln\ [P\ /\ (1 - P)]_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \ldots\ \beta_{nj}X_{nij}. \tag{1}$$

Level 2—

$$\begin{aligned}
&\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \gamma_{02}W_j + \gamma_{03}W_j \ldots + u_{0j} \\
&\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + \gamma_{12}W_j + \gamma_{13}W_j \ldots + u_{1j} \\
&\beta_{2j} = \gamma_{20} + \gamma_{21}W_j + \gamma_{22}W_j + \gamma_{23}W_j \ldots + u_{2j} \\
&\ldots\beta_{nj} = \gamma_{n0} + \gamma_{n1}W_j + \gamma_{n2}W_j + \gamma_{n3}W_j \ldots + u_{nj}.
\end{aligned} \tag{2}$$

This model differs from a traditional model in that it contains fixed effects (γs) and random effects (us). It is called a random intercepts and slopes (or mixed) model because both the level-one intercepts and slopes are allowed to randomly vary across neighborhoods and are modeled using level-two predictors (Ws). This model form was chosen because previous studies indicated that neighborhoods have different probabilities of abandonment (Morckel, 2014; Morckel, 2013), and it seems plausible that neighborhood-level effects differ by house-level characteristics.

Traditional models are created by entering all predictors into the model at one time or in blocks and removing those that are not statistically significant. But, because of the presence of random effects and potential cross-level interactions, multilevel models require a more complex model-building process. The process outlined here is a step-up approach to logistic modeling, similar to the one advocated by Luke (2004). First, an empty model is created with no predictors at either level. The purpose of this model is to estimate the overall probability of abandonment for the sample and to provide information about the proportion of total variability in abandonment that is attributable to neighborhood factors. This measurement is known as the intraclass correlation coefficient, or ICC (calculated as τ_{00} / [τ_{00} + 3.29], where τ_{00} is the variance component of the intercept u_{0j}, and 3.29 is the variance of the logistic distribution). If variability within neighborhoods is low, but variability between neighborhoods is high, the ICC will be high (Field, 2009).

Next, all level-one variables are entered into the model and their intercepts and slopes are allowed to vary.[2] Statistically insignificant variables are removed if their variances are also not statistically significant. If the ICC is high and residual variability still exists in the intercept ($p_{\tau 00} < 0.05$), the next step is to enter level-two variables as predictors of the level-one intercept. Doing so creates an intercept-as-outcome model, with main effects of the new level-two variables. Any variables that are not statistically significant are removed, provided they are not of interest in later cross-level interactions. Finally, for random effects with unmodeled variability (u terms with $p < 0.05$), level-two variables are added as predictors of these effects, creating cross-level interactions and a slopes-as-outcomes model. Once again, effects that are not statistically significant are removed if doing so reduces the deviance, with higher order terms removed first.

Other differences are notable between multilevel models and traditional regression models. Unlike traditional regression models with continuous dependent variables, parameter estimation in logistic, multilevel regression is based on principles of maximum likelihood and involves iterative estimation methods (O'Connell et al., 2008).[3] In addition, instead of pseudo R^2 statistics, model fit is assessed using deviance statistics (-2 log likelihood values) and information criterion values like AIC (Akaike Information Criterion). For brevity's sake, only the deviance will be used in this article. The deviance represents how poorly a model fits the data (that is, how far it "deviates" from a perfect model). If the deviance is reduced by a competing nested model (tested using a χ^2 difference test), the competing model is preferred (O'Connell et al., 2008). If nested models do not statistically differ, the model with fewer parameters is preferred for parsimony reasons.

Results

This section briefly demonstrates how the author arrived at the final model; it then presents the results of this model. The empty model indicates that the average probability of abandonment across all houses is 1.1 percent ($e^{-4.469} / [1 + e^{-4.469}] = 0.011$). The ICC for the model is 0.539 (3.844 / [3.844 + 3.29]), meaning that neighborhood-level factors account for 53.9 percent of the variability in housing abandonment. The second model added the level-one independent variables, all of which were statistically significant ($p < 0.05$ for all). The deviance was also reduced compared with the empty model ($\chi^2_{42} = 256{,}400.161 - 252{,}111.064 = 4{,}289.097$; $p < 0.05$). Because residual variability was still in the intercept ($p_{\tau 00} < 0.001$) and the ICC was high, level-two variables were added as predictors of the level-one intercept. This model reduced the deviance ($\chi^2_{9} = 252{,}111.064 - 251{,}655.988 = 455.076$; $p < 0.05$). Arson (N_Arson) was the only neighborhood-level variable that did not predict the intercept ($p = 0.289$); however, it was retained to avoid specification errors with later testing of cross-level interactions. The model with arsons retained had unexplained variability in the intercept ($\tau_{00} = 0.365$; $p < 0.05$), the slope for house-level tax delinquency ($p_{H\_Tax} < 0.001$),

[2] Because this study is exploratory and has a large sample size, the author permitted all slopes to vary. Estimation becomes more difficult with additional random effects; therefore, determining which slopes to vary should be based on the research questions and theory.

[3] Like those of O'Connell et al. (2008), the analyses presented in this article use full penalized maximum likelihood estimation for the coefficients and Laplace estimation for the deviances. A detailed discussion of estimation methods is beyond the scope of this article.

and the slope for house-level mortgage foreclosures ($p_{H\_Mfc} < 0.001$). Because of this remaining variability, all level-two variables were entered as predictors of the tax and mortgage foreclosures slopes (H_Tax and H_Mfc). Although this model reduced the deviance (χ^2_{18} = 251,655.988 – 251,593.033 = 62.955; $p < 0.05$), arsons at the house level were still not statistically significant, nor were most of the new level-two variables. Therefore, nonstatistically significant variables were removed one at a time, starting with the higher order effects and ending with neighborhood-level arsons, until the most parsimonious model was achieved.

Exhibit 2 shows the final model. It does not explain all the variability in the probability of abandonment (τ_{00} = 0.440; $p < 0.05$), or all the variability in the slopes for house-level tax delinquency and mortgage foreclosures (u_6 = 0.033; u_7 = 0.505; $p < 0.05$ for both). The model, however, is a significant improvement over the empty model, the model with only level-one predictors, and the intercept-as-outcome model. Thus, the model is the so-called final model because it is the best model obtainable with the present dataset. Other variables could be added in future studies to help explain remaining variability. In particular, it seems likely that the socioeconomic characteristics

Exhibit 2

Final Multilevel Model (1 of 2)

Fixed Effects	Coefficient	SE	Odds Ratio	t(df)	p
Intercept (β_0)					
Intercept (γ_{00})	– 15.251	1.403	0.000	– 10.865(373)	< 0.001
N_Value (γ_{01})	0.017	0.002	1.017	8.564(373)	< 0.001
N_Sale (γ_{02})	0.079	0.014	1.083	5.478(373)	< 0.001
N_Demo (γ_{03})	0.243	0.071	1.276	3.443(373)	< 0.001
N_Upkeep (γ_{04})	– 0.101	0.027	0.904	– 3.673(373)	< 0.001
N_Age (γ_{05})	0.009	0.002	1.009	5.463(373)	< 0.001
N_Tax (γ_{06})	0.029	0.008	1.029	3.400(373)	< 0.001
N_Mfc (γ_{07})	0.114	0.033	1.121	3.427(373)	< 0.001
N_Aband (γ_{08})	0.112	0.010	1.118	10.647(373)	< 0.001
H_Value (β_1)					
Intercept (γ_{10})	0.496	0.071	1.642	6.985(381)	< 0.001
H_Sale (β_2)					
Intercept (γ_{20})	0.839	0.056	2.313	14.865(381)	< 0.001
H_Arson (β_3)					
Intercept (γ_{30})	1.684	0.191	5.388	8.816(381)	< 0.001
H_Upkeep (β_4)					
Intercept (γ_{40})	1.868	0.081	6.477	23.074(381)	< 0.001
H_Age (β_5)					
Intercept (γ_{50})	0.483	0.060	1.621	8.054(381)	< 0.001
H_Tax (β_6)					
Intercept (γ_{60})	2.297	0.156	9.946	14.728(378)	< 0.001
N_Age (γ_{65})	– 0.003	0.002	0.997	– 1.996(378)	0.047
N_Tax (γ_{66})	– 0.018	0.007	0.982	– 2.485(378)	0.013
N_Aband (γ_{68})	– 0.018	0.007	0.983	– 2.567(378)	0.011
H_Mfc (β_7)					
Intercept (γ_{70})	2.612	0.256	13.627	10.209(378)	< 0.001
N_Age (γ_{75})	– 0.007	0.003	0.993	– 2.291(378)	0.023
N_Tax (γ_{76})	– 0.057	0.014	0.944	– 4.096(378)	< 0.001
N_Aband (γ_{78})	0.030	0.014	1.031	2.067(378)	0.039

Exhibit 2

Final Multilevel Model (2 of 2)

Random Effects	Variance	SD	df	χ^2	p
Intercept (u_0)	0.440	0.633	97	130.571	0.013
H_Value (u_1)	0.179	0.422	105	117.021	0.199
H_Sale (u_2)	0.117	0.343	105	124.783	0.091
H_Arson (u_3)	0.826	0.909	105	107.608	0.411
H_Upkeep (u_4)	0.225	0.474	105	109.098	0.372
H_Age (u_5)	0.185	0.431	105	121.872	0.125
H_Tax (u_6)	0.033	0.182	102	134.171	0.018
H_Mfc (u_7)	0.505	0.711	102	153.260	< 0.001

df = degrees of freedom. p = probability. SD = standard deviation. SE = standard error. t(df) = a test statistic and its associated degrees of freedom. χ^2 = chi squared statistic.

Notes: Deviance = 251,599.222. Parameters = 58. "H" represents house-level variables. "N" represents neighborhood-level variables.

of owners or residents would be relevant, because the ability to afford a property might influence the decision to abandon. Because it is difficult to obtain personal data at the house level, this article does not examine socioeconomic factors.

Model Interpretation. Because the intercept (γ_{00}) is the expected log-odds when all the predictor variables are zero, the negative coefficient for γ_{00} indicates that the probability of a house being abandoned when none of the characteristics (foreclosures, tax delinquency, poor property conditions, and so on) are present is virtually zero.[4] As for house-level variables, the model indicates that mortgage foreclosures are the strongest predictor of abandonment. A house that experiences a mortgage foreclosure is 13 times more likely to be abandoned than a house that does not, holding all other variables constant (Odds Ratio [abbreviated OR hereafter] = 13.627; $p < 0.001$). The effect of house-level mortgage foreclosures is also one of the most complex, given the presence of three cross-level interaction effects. The interactions indicate that the effect of a mortgage foreclosure is tempered by a neighborhood's age and tax delinquency status, but it is amplified by neighborhood abandonment. More specifically, the odds of abandonment for a house that experiences mortgage foreclosure decreases by 0.7 percent for every 1-percent increase in the number of homes built before 1945 (OR = 0.993; 100 [0.993 – 1] = -0.7 percent). Even when the house is in a neighborhood with all new houses, a house experiencing a mortgage foreclosure is still nearly 7 times more likely to be abandoned (-0.007 x 100 = -0.700; 2.612 – 0.700 = 1.912; $e^{1.912}$ = 6.767). A similar relationship holds between house-level mortgage foreclosures and neighborhood-level tax delinquency. The odds of abandonment for a house that experiences mortgage foreclosure decreases by 5.6 percent for every 1-percent increase in the number of homes that are tax delinquent (OR = 0.944; 100 [0.944 – 1] = -5.6 percent). This effect is opposite that of neighborhood abandonment (N_Aband), which increases the odds (OR = 1.031). If a mortgage foreclosure occurs in a neighborhood where 10 percent of the homes are abandoned, for example, the odds jump from 13 to nearly 19 times more likely to be abandoned (0.030 x 10 = 0.300; 2.612 + 0.30 = 2.912; $e^{2.912}$ = 18.394).

[4] This interpretation is true because zero has meaning for the independent variables. If a variable like square footage appeared in the model, it would have to be centered because zero has no practical meaning; a house cannot have zero square feet.

The next strongest effect is house-level tax delinquency. A house that is tax delinquent is nearly 10 times more likely to be abandoned than one that is not, holding all other variables constant (OR = 9.946). As indicated by the statistically significant interaction effects, however, this relationship is slightly tempered by neighborhood-level age (N_Age), tax delinquency (N_Tax), and neighborhood abandonment (N_Aband). All three variables have negative regression coefficients and odds ratios less than, but close to, 1 (OR_{N_Age} = 0.997; OR_{N_Tax} = 0.982; OR_{N_Aband} = 0.983).

The remaining house-level effects, which do not have cross-level interactions, are as follows: a house in poor condition is 6 times more likely to be abandoned than a house that is not (OR = 6.477); an arsoned house is 5.4 times more likely to be abandoned than a house that has not been arsoned (OR = 5.388); a house that has sold or transferred in the past year is 2.3 times more likely to be abandoned than one that has not sold or transferred (OR = 2.313); a house with a value that is less than the citywide median is 1.6 times more likely to be abandoned than a house above the median (OR = 1.642); and finally, a house built before 1945 is 1.6 times more likely to be abandoned than a newer house (OR = 1.621).

Of the neighborhood-level effects, demolitions have the greatest impact on the probability of abandonment (OR = 1.276). A 1-percent increase in the number of demolitions in a neighborhood results in a 27.6-percent increase in the odds of a house being abandoned (100 [1.276 – 1] = 27.6). The next strongest neighborhood effect is neighborhood abandonment, with a 1-percent increase resulting in a 12-percent increase in the house-level odds of abandonment (OR = 1.12). Similarly, a 1-percent increase in mortgage foreclosures increases the odds by 12 percent (OR = 1.12). Interestingly, a 1-percent increase in the number of homes in poor condition *decreases* the odds by 9.6 percent (OR = 0.904; 100 [0.904 – 1] = -9.6), while a 1-percent increase in the number of homes not sold or transferred in the neighborhood increases the odds by 8.3 percent (OR = 1.083). Finally, a 1-percent increase in the number of homes that are tax delinquent, valued at less than the median housing values, or built before 1945 increases the odds by less than 3 percent each (OR_{N_Tax} = 1.029; OR_{N_Value} = 1.017; OR_{N_Age} = 1.009).

Discussion and Conclusion

The title of this article poses the question of which scale (the house or the neighborhood) "matters more" when predicting abandonment. This question can be answered using multilevel modeling techniques because multilevel models allow for the same variables to appear at different scales in the same model. Furthermore, because odds ratios are an indication of effect size, the variables (and scale) with the largest odds ratios can be thought of as the ones that are most important when predicting abandonment. The large odds ratios for the house-level variables initially seem to indicate that the characteristics of a house matter more than the characteristics of a neighborhood. The answer to this question about scale, however, is more nuanced because the odds ratios for neighborhood-level variables are based on a 1.00-percent increase. This interpretation means that the effects of neighborhood-level variables are greater if one considers a threshold higher than 1 percent. Take, for example, property values, which has an odds ratio of 1.642 at the house level. At the neighborhood level, a 10-percent increase in the number of properties whose values are less than the median property value yields an odds ratio of 1.185 (0.017 x 10 = 0.17; $e^{0.17}$ = 1.185), which is less than the odds ratio of that variable at the house level. If 50 percent of properties in a neighborhood are valued at less than the median value, however, the odds ratio increases to 2.3 (0.017 x 50 = 0.85; $e^{0.85}$ = 2.340); and if all the properties in the neighborhood are valued at less than the median property value, the odds ratio increases to 5.5 (0.017 x 100 = 1.7; $e^{1.7}$ = 5.474), which is much higher than the odds ratio at the house level.

Exhibit 3 emphasizes this point by comparing the odds ratios at the house level with the odds ratios obtained with different percentages of the neighborhood-level variables for all variables in the study. As one can see from the exhibit, some of the odds ratios increase rapidly due to the exponentiation that occurs with logistic regression. Many quickly exceed the odds ratios at the house level, suggesting that, for stable neighborhoods (neighborhoods with low levels of the independent variables), the characteristics of a house matter more; however, for more distressed neighborhoods, neighborhood characteristics have a greater influence. There thus appears to be a tipping point after which neighborhood characteristics become more important when predicting the probability of a house being abandoned, although the exact point differs by variable. In addition, the ICC indicates that more than one-half of the variability is attributable to neighborhoods, further emphasizing that neighborhood characteristics are important to consider when addressing abandonment.

In sum, to create effective policies, the scale or scales at which the problem of interest operates should be identified. Although it is useful to create separate models to examine scale, this article demonstrates that true multilevel models are the preferred method. Failure to use multilevel models when the data are nested propagates the notion that the process of interest works the same way in different contexts—in this case neighborhoods—which is likely not true (Luke, 2004). In addition, the multilevel models in this article identify cross-level interaction effects. This shows how, had the nested nature of the data been ignored, different conclusions would have been reached. If a problem is ultimately a neighborhood-level problem, but policies are implemented at the house level, for example, it seems likely that the impact of the policies would be diluted at best. Further research is necessary to confirm this theory of spatial mismatch and policy ineffectiveness.

Exhibit 3

Comparison of Odds Ratios

Independent Variable (IV)	House-Level Odds Ratios	Neighborhood-Level Odds Ratios, Given the Following Increase in the IV				
		1%	10%	25%	50%	100%
Property values	1.642	1.017	1.185	1.530	2.340	5.474
Sales	2.313	1.082	2.203	7.207	51.935	2697.282
Arsons	5.388	NA	NA	NA	NA	NA
Demolitions	NA	1.275	11.359	434.850	189,094.090	> 1,000,000.000
Upkeep	6.477	0.904	0.364	0.080	0.006	< 0.001
Age	1.621	1.009	1.094	1.252	1.568	2.460
Tax delinquency	9.946*	1.029	1.336	2.065	4.263	18.174
Mortgage foreclosures	13.627*	1.121	3.127	17.288	298.867	89,321.723
Abandonment	NA	1.119	3.065	16.445	270.426	73,130.442

NA = not applicable. Variable removed from the model.

**Not including cross-level interactions.*

Notes: This table is for illustration purposes only. Not all levels are realistic for all variables.

Author

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3-D Residential Land Use and Downtown Parking: An Analysis of Demand Index

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Abstract

The need for downtown revitalization is a growing concern for community stakeholders who are attempting to make their communities more sustainable and minimize urban sprawl. One strategy to make the downtown more active is to increase the attractiveness of the downtown for street-level customers and residential development. Success in this strategy attracts more people to the downtown; however, the challenge is to provide adequate parking. This study examines parking and its spatial dimensions in downtown Laramie, Wyoming. A parking inventory of both on- and off-street parking revealed the uneven spatial distribution of parking in the downtown area. Street interviews provided information on length of parking, purposes for coming downtown, and the location of destinations once downtown. A three-dimensional land use inventory supplied detailed locations of all activities in each building and floor for the 28 blocks of downtown Laramie. A bubble analysis of each parking space identified the spatial dynamics of the downtown parking demand and its distributional inadequacy for downtown residents.

Introduction

The downtown of most cities is considered the heart of the community. Not only does the downtown have a substantial concentration of businesses and employment, it is also the cultural and social center of the community, with museums; historic sites; theatres; and social events such as festivals, parades, and ceremonies. The involvement of the people makes the downtown area a thriving pulse of the community. Wilson et al. (2012) examined the patterns of population change in metropolitan and micropolitan areas and found that metropolitan areas generally grew the fastest between 2000 and 2010. Along with this finding, Wilson et al. (2012) also concluded that downtown areas in the metropolitan counties had some of the fastest growth rates; for example, Chicago increased by 48,000 people within 2 miles of City Hall (the U.S. Census Bureau-designated center of the downtown area). Small towns, however, are experiencing some of the same types of population increases. The Census Bureau identified San Marcos, Texas, as one of the fastest growing communities in the United States, with a population increase of more than 20 percent between 2010 and 2013 (U.S. Census Bureau, 2014). Greenfield (2012) similarly identified that small towns are growing across the United States. The downtown areas are becoming the hallmark of regrowth and the core of the city (Glaeser, 2012). The trends in redevelopment of downtowns have been an ongoing process for the past 60 years, starting with the urban renewal projects in the early 1960s. Robertson (1999) identified a number of strategies to revitalize downtowns, specifically for small towns. In a study of 57 small-town development strategies, the following 9 strategies were identified by most of the communities: (1) historic preservation, (2) downtown housing, (3) waterfront development along with nightlife and entertainment, (4) new office development, (5) pedestrian improvements, (6) tourism, (7) traffic circulation changes, (8) Main Street approach, and (9) parking facilities and a convention center (Robertson, 1999). Several other studies demonstrated that it is imperative to reinvigorate the downtowns in communities (Faulk, 2006; Filion et al., 2004; Leinberger, 2005; Rypkema, 2003). The development of the downtown area provides a number of challenges for the local community, depending on the strategies it pursues.

A vibrant downtown is marked by mixed-use activities and a sense of place. These two characteristics are part of the increase in residential activities in downtowns (Birch, 2009; Cook and Bentley, 1986). The higher population densities in the downtown provide a potential market capture for retail, entertainment, and cultural activities (Ferguson, 2005). Wachs (2013: 1162) found that "[y]oung, highly educated professionals move downtown to consciously reject the suburban cul de sacs where they grew up. Millions of senior citizens of means are choosing to retire in central city locations increasingly served by Starbucks, Whole Foods, and Trader Joe's markets." In an earlier study by Filion et al. (2004) on the revitalized downtown areas, however, the most successful areas had several elements in common: university campus nearby, seat of government, and historical character. If the community does not have these characteristics, however, the downtown can be a central place for employment and provide housing options for the local citizens. Wachs (2013) believes a number of downtown development activities are enhanced by the importance of transportation connectivity. As important as connectivity is as an element in downtown development, the availability of parking for both customers and residents is even more critical. The American Planning Association (APA) report on off-street parking (Bergman, 1991: ii) states that "…there is tremendous citizen concern about the availability of parking, its effect on the transportation network, and, ultimately, on the quality of life in a community." With increasing population growth in downtown areas, the impetus to revitalize the downtown, and the concerns for parking and transportation, several factors need to be analyzed.

Objectives and Approach

This study examines downtown residential land use and its demand on parking. In the process of analyzing downtown residential parking demand, this research project has several objectives.

1. Locate and inventory all land uses in downtown Laramie, Wyoming.
2. Locate and inventory downtown Laramie's on- and off-street parking.

3. Create a spatial residential parking demand model based on the land uses within a set distance from each parking area.

4. Identify transportation and parking strategies that promote downtown residential development.

Unlike most land use studies and parking demand analyses, however, this study uses a different approach. First, the land use downtown is inventoried and analyzed using three-dimensional (3-D) spatial referencing. Each building downtown is inventoried floor by floor to record all land uses on each floor and their relative location on the floor. In the past, land use was recorded only for the first floor or a total count of land use was identified for a whole building without any spatial reference. Second, unlike most parking studies, which analyze the demand for parking based on the land use (ITE, 2010), the count of currently available off-street parking spaces, and the count of additional spaces needed to accommodate the new land use, this study assumes that the number of downtown parking spaces is fixed and that the probability of creating new spaces is low to none. Thus, this research attempts to calculate the parking demand generated by the land uses around each individual parking space and views demand from the parking space perspective, not from the land use perspective. This study is specifically concerned about downtown residential parking, its availability, and demand competition.

Parking demands generally are based on the zoning and the amount of parking required for each land use type within the zone. The Institute of Transportation Engineers (ITE) created a guide (2010) that presents the parking demand for more than 105 different land uses. Most transportation engineers, consultants, and planners use this guide to determine parking demands. The guide, however, was developed from studies of isolated land uses in suburban areas (ITE, 2010). To represent the full range of land areas, the fourth edition identifies five different area types: (1) central business district, (2) central city (not including the central business district), (3) suburban centers, (4) suburban, and (5) rural (ITE, 2010). The demand model used in this analysis used the available information only for the central business district or central city uses.

Parking Demands in Downtown Laramie, Wyoming

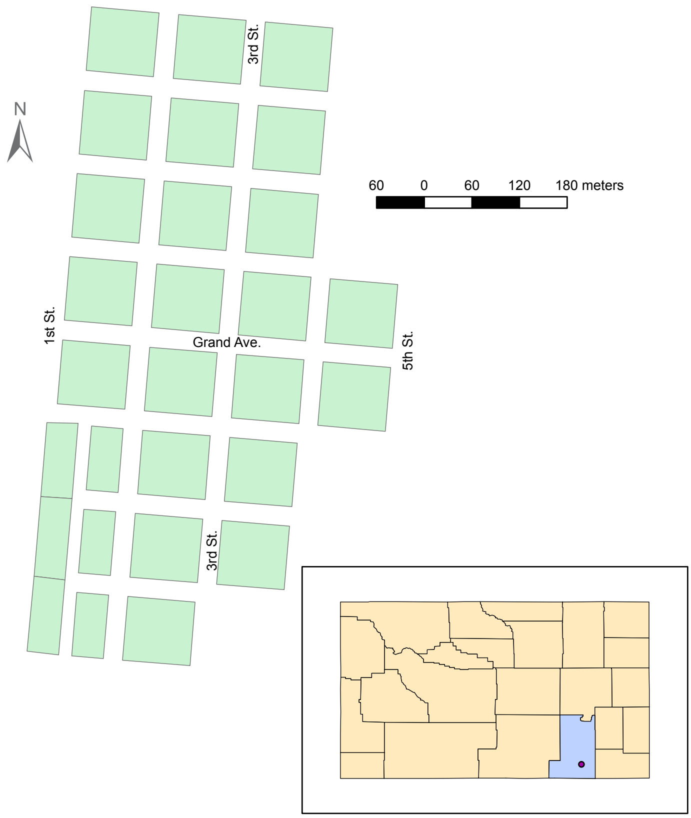
This study is concerned with residential parking demands in the Downtown Commercial (DC) zone district of Laramie, Wyoming. The DC zone district encompasses 25 blocks covering 29.6 hectares (73.1 acres; exhibit 1). Laramie is the third largest city in Wyoming, with an estimated 2013 population of 31,814 (http://quickfacts.census.gov). The home of the University of Wyoming (UW), Laramie has a fluctuating population but one of the most stable economies in a state noted for its boom-bust cycles of energy development. The city is attempting to encourage growth in the downtown area. In the City of Laramie's *Comprehensive Plan* (2007), a major goal for the downtown area is—

> Increase residential population in the Downtown through changes to the current zoning regulations to encourage mixed-use buildings and upper floor rental or condominium units. (City of Laramie, 2007: chapter 7, page 9)

Thus, an emphasis in the plan is to restructure planning policies and governmental regulations to lessen the barriers to downtown residential development.

Exhibit 1

Laramie's Downtown Commercial Zone, 2014



Note: The inset shows the location of Laramie on a map of Wyoming.

An understanding of the current downtown land use structure is critical to any development process. To assist in acquiring that knowledge, a complete inventory of land use downtown was completed. The inventory consisted of a complete survey of every building and every floor, identifying and recording the location of each individual activity. The use of 3-D spatial referencing made it possible to integrate the land use data into a Geographic Information System (GIS; Doner and Biyik, 2011). Overall, 36 different land uses in the 388 activity spaces were established, dominated by retail businesses and professional services (exhibit 2). Land use was recorded using a modified version of the North American Industrial Classification System (U.S. Census Bureau, 2013). The modifications included adding new codes for residential, parking lots, and vacant lands and buildings. Residential land use in Laramie's DC zone district totaled 133 units and consists primarily of second story apartments above office or retail businesses (exhibit 3). The area also has 14 homes, 1 converted five-story hotel with 36 apartments, and 1 five-story building with 16 apartments. The 14 homes are a mix of single-family dwellings and converted multifamily housing. The 2010 Census listed 297 people living in the DC zone district (http://www.census.gov). Laramie is a college town, however, and the capture rate of people listing Laramie as their primary residence could be suspect.

Exhibit 2

Downtown Laramie, Land Use, 2014

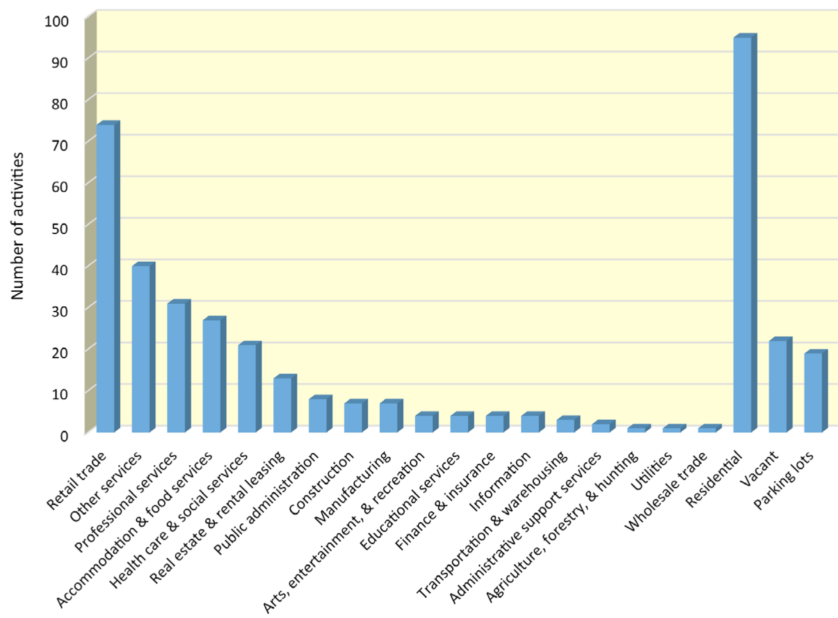
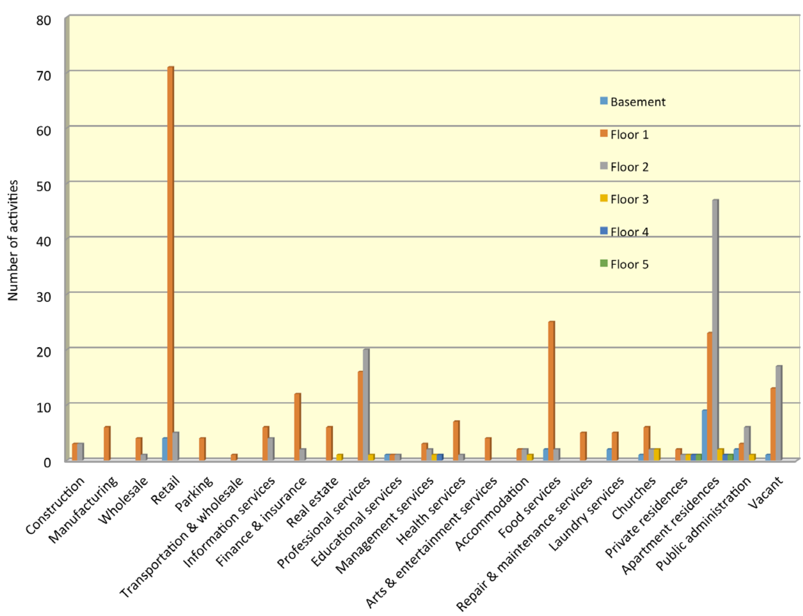


Exhibit 3

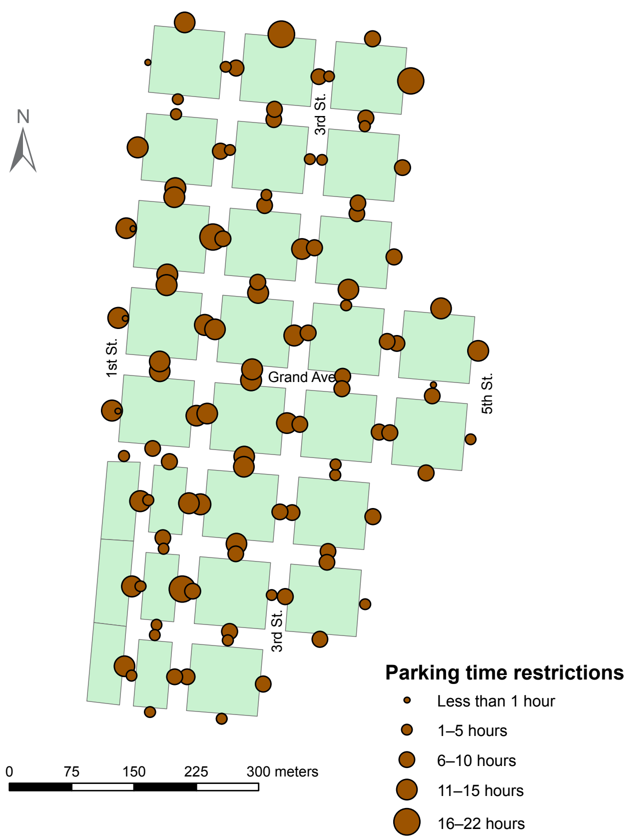
Downtown Laramie, Land Use by Floor, 2014



Parking has been a major issue in downtown development, with either not enough parking or too much (Jakle and Sculle, 2004). Parking is a major concern for expanding any residential activities downtown (Robertson, 1999). To alleviate some of the parking problems downtown, Edwards (1994) presented several strategies to alleviate the parking needs and to assist in small town downtown growth. The first step in the process, however, is to inventory and collect information on parking (Shields and Farrigan, 2001). To accomplish this task, a complete survey of both on- and off-street parking was completed in the DC zone district. Using a GPS, each on-street parking space was located and data were collected on its orientation, time restriction, and its handicap accessibility. Similarly, information collected for off-street parking included GPS location, time restriction, and ownership status (public, private, or business-related). Overall, 834 on-street parking spaces are available, with time restrictions varying from 15 minutes to unlimited (exhibit 4). Most of the parking downtown is limited to 2 hours (63.9 percent); however, some locations at the north and south ends of the downtown have no signage and thus have unlimited parking (4.0 percent).

Exhibit 4

Downtown Laramie, On-Street Parking, 2014



Although the on-street parking inventory was completed and the locations recorded, 64 percent of the 834 parking spaces had a 2-hour limit and would not be convenient for the downtown residents. The 220 spaces that did have all-day parking were generally some distance from the residence locations. A distance search function found that the average all-day parking spaces were 189.3 meters on average (standard deviation = 79.0 meters) from the residential units. This distance equates to slightly more than two city blocks from a unit. In the southeastern corner of the DC zone district, however, two multifamily housing units had building frontage adjacent to on-street parking with no signage.

Off-street parking has two areas: a larger parking lot and a small space on the backsides of buildings adjacent to an alleyway. Overall, 1,294 parking spaces are distributed across the DC zone district (exhibit 5), classified as public, private, or business-related (exhibit 6). Public off-street parking spaces are open to everyone and have a limited time span, whereas the private off-street parking spaces are signed as reserved parking for specific users—for either a specific apartment or business. The business-related parking spaces are those spots adjacent to a business without any specific restrictions; however, it is assumed those spaces are for the related business. If the spaces have signs, they usually identify the spaces as customer parking for the business.

Exhibit 5

Downtown Laramie, Off-Street Parking, 2014

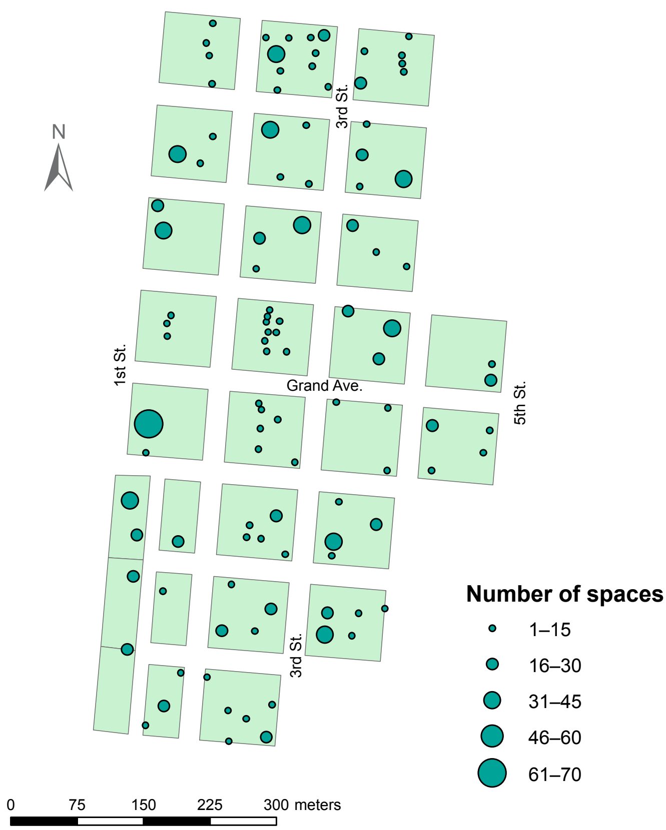
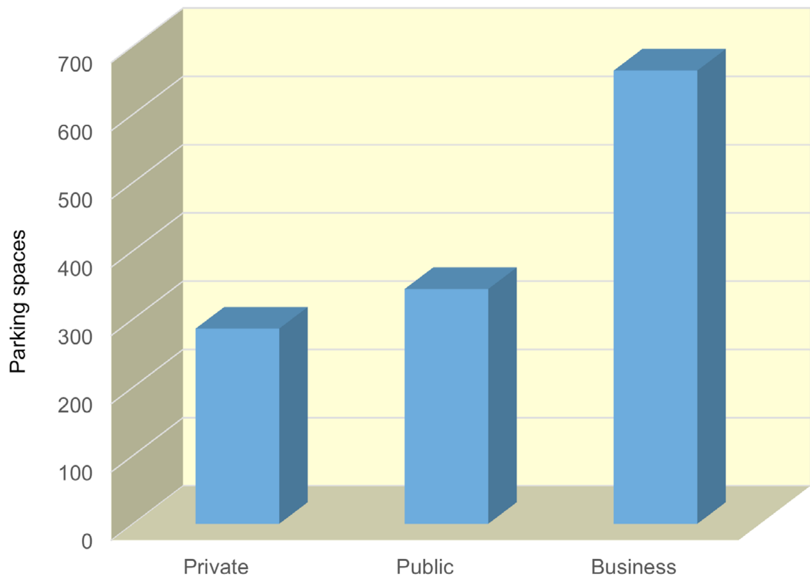


Exhibit 6

Downtown Laramie, Off-Street Parking, 2014



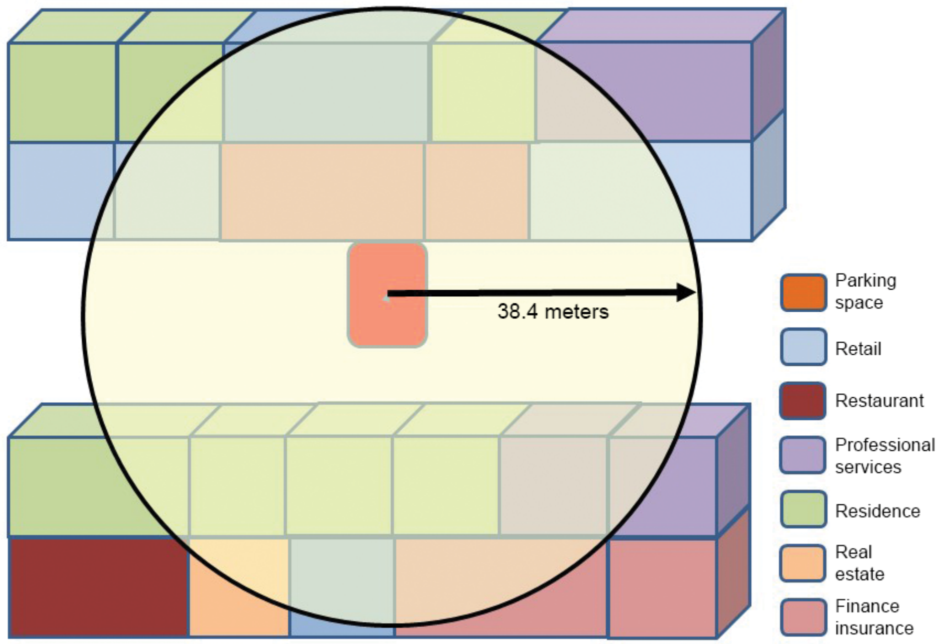
For the downtown residential inhabitants, two off-street parking options are available, either an assigned parking space or the use of public parking. Downtown Laramie does not have a parking garage or current on-street city permitting zones. As displayed in exhibit 5, most of the private parking spaces are at the rear of the residential units, within 15 meters of the dwelling unit entrance and exit. Of the residential units, 38 percent (51) do not have assigned overnight parking. To accommodate their parking demand, the residents have to use public parking spaces; thus, they are in competition with other parking space users—retail shoppers, restaurant and bar patrons, and so on. In addition, the public parking has time limits, either 2 hours or all day. The all-day parking, however, in most cases, does have a no parking restriction between 2:00 a.m. and 6:00 a.m.

Parking Space Demand Model

The basic parking space demand model is a bubble (exhibit 7). The radius of the bubble is the average distance a person walks to his or her destination; in this case, how far a resident walks to his or her residential unit. the model is a bubble because the capture area is three-dimensional; it encompasses all the land uses on every floor within that walking distance, including across the street and diagonally across corners. Using the ITE (2010) guidelines for central business districts and the central city, each land use parking demand can be identified and assigned to each downtown business. The demands are a ratio of the number of spaces per square footage of use; for example, office space—2.8 parked vehicles per 1,000 GFA (gross floor area). The Albany County Assessor's parcel data (Albany County, Wyoming Assessor's Office, 2013), which contains information on the square footage of each building downtown, was coupled with the land use inventory

Exhibit 7

Basic Parking Space Demand Model



data, which counted the number of floors in each building and determined the location of each land use. Thus, a calculated spatial demand for each parking space can be generated based on the radius of walking from the parking space and the parking generation of all of the land uses within that distance. The demand is strictly cumulative and is not weighted by day of the week, time of day, parking time restrictions, or vacancy rates. A complete parking study would capture this information, but a use and full vacancy rate analysis unfortunately was beyond the scope of this study.

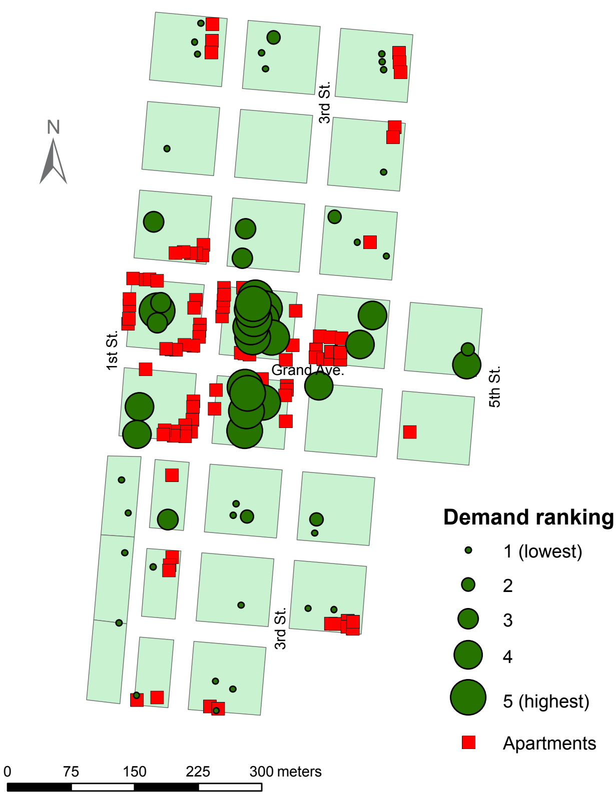
The walking radius is based on the responses from a random questionnaire conducted in March 2007 (Gribb, 2007). More than 280 individuals responded to an on-street parking survey that included questions concerning how long they parked, what the distance was to their first destination, how many additional destinations they had, and what the purpose was for each stop. The survey also included a number of questions concerning parking safety, aesthetics, and convenience. The average distance to the first destination was 38.4 meters, which in Laramie is nearly one-half of a block. This distance is considerably less than the 71.3 meters identified in Jakle and Sculle (2004), the distance people would walk from parking to shopping in a small town. With this information, a concentric circle search radius could be employed in ArcGIS (ESRI v.10.2) to capture the spatial parking demand for each type of off-street parking.

A simple additive calculation based on the search radius was performed in ArcGIS (ESRI v.10.2). After calculating the spatial demand for each parking space, the Jenk's natural breaks classification method (Jenks, 1963) was employed to create a demand ranking (1 = lowest, 5 = highest) to classify the spaces. The ranking method is a method to compare parking space demand, instead of using the actual demand index value. As would be expected, the parking spaces on the fringe of the DC zone district have the lowest demand rankings, whereas the parking spaces in the central portion of the downtown have some of the highest (exhibit 8). It is not a uniform distribution, however; some areas downtown do not have the same density of land uses and do not have multi-story buildings, thus creating a reduced parking demand.

In addition to calculating the spatial parking demand, a distance function was calculated to determine the average distance from each residential unit that did not have a private parking space to a public parking space. As mentioned previously, 51 residential units (38 percent) do not have assigned parking and, on average, the closest public parking is 148.9 meters (standard deviation of 63.2 meters), which is more than 1.5 blocks away. In addition, the available parking spaces within this distance generally had a ranking of 4 or 5, the highest demand classes (exhibit 8). Thus, the public

Exhibit 8

Downtown Laramie, Apartment-Off-Street Parking Demand, 2014



parking spaces that are available to the residential units are in high demand and may not necessarily be readily available. This issue is compounded by the fact that the vehicles have to be moved between 2:00 a.m. and 6:00 a.m. on select days.

Conclusion

A major complaint in most downtown areas is that not enough parking exists. Robinson (1999) in his different strategies for downtown revitalization identified parking as a major component to invigorating the downtown. Jakle and Sculle (2004) cautioned that too much or too little parking, however, could be a hindrance to downtown redevelopment. Shoup (2005) cautioned against free parking and time limits. It is not just the number of parking spaces, however, but also the type of spaces and any restrictions that may create a barrier to their use (Mukhija and Shoup, 2006). Laramie has nearly 2,130 parking spaces distributed between on- and off-street locations. Is this amount enough or too much? According to Litman (2006), most communities that follow a zoning standard for parking spaces have between 30 to 50 percent too much parking. Nearly 65 percent of the on-street parking is restricted to 2 hours, almost 25 percent of off-street parking is labeled private restricted, and another 51 percent is business-related parking. Thus, only about 25 percent of the 1,294 off-street parking spaces are available to the 51 housing units that do not have assigned or private parking.

Using a spatial parking demand index, it was possible to calculate and determine the distribution of parking demand by parking space. This method of demand analysis examines parking from the parking space perspective, not from the land use perspective. From the calculations, it was possible to determine that the available public parking spaces that are close to the residential units are in high demand and have time restrictions. The time restrictions present a major parking problem for nearly 34 percent of the residential units downtown. Manville (2013) found that development in downtown Los Angeles, California, was hampered by the parking requirements for residential units. By implementing an Adaptive Reuse Ordinance, it was possible to increase residential development in downtown Los Angeles. Litman (2006) also suggested that a variety of parking management strategies should be implemented. This same type of strategy could be employed in Laramie, by being creative in supplying parking to the one-third of the residents who do not have convenient access to parking.

Three other strategies for providing downtown parking are (1) shared parking spaces, (2) business-lease parking, and (3) on-street parking permits. APA published a document, *Flexible Parking Requirements* (Smith, 1983), that identified several methods in which daytime parking uses could be complemented by nighttime parking uses, thus eliminating the evening hour parking vacancies in those lots designed for daytime parking demands. The business-lease parking arrangement works in a similar manner: downtown businesses that have business-related parking spaces, of which 51 percent of the off-street parking is classified, could lease the spaces to downtown residential units based on vacancy rates or nighttime and daytime use rates. Finally, the city permit system would provide a permit for a fee to downtown residents to park in the on-street parking spaces beyond the 2-hour limit. This system has been implemented with great success in Amsterdam, which has a much higher density of downtown residents (van Ommeren, Wentink, and Dekkers, 2011).

In a completely different approach to the downtown development and parking problems, an investigation of alternative transportation options could be completed. The expansion of the Laramie/UW bus system could reduce the need for automobiles and their subsequent parking requirements and provide access to other areas in the city for the downtown dwellers. The bus system could conversely provide transportation for citizens from around Laramie to the downtown area, and they would not need parking. Creating a more extensive network of bicycle routes into and through the downtown would also provide the infrastructure for an alternative to the automobile and possibly reduce a barrier to more alternative transportation usage.

Downtowns are vital to the economic and social character of a community. Laramie's downtown is a vibrant place not only on football weekends, but also throughout the year because of its mixed use, residential capabilities, and availability of parking. As the downtown develops, it will be important to meet the needs of the citizens who live downtown along with the needs of the people visiting the downtown. A balance has to be created to meet the needs of these two groups so the dynamic power of the downtown continues into the future.

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Rethinking Food Deserts Using Mixed-Methods GIS

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Abstract

Food deserts—low-income neighborhoods with poor access to affordable, healthy food—have increasingly been seen as a driver of obesity and related health conditions in urban neighborhoods. Most current research uses an approach based on a Geographic Information System, or GIS, to identify food deserts using store locations, but data that link food environments to health outcomes have been inconsistent. This article outlines an alternative methodology that shifts from the proximity *of healthy food stores to the food-provisioning* practices *of neighborhood residents. Using a mixed-methods approach, this research relies on several data sources: (1) geographic tracking on daily mobility created using Global Positioning System, or GPS, software on a smartphone, (2) georeferenced photographs also created using smartphones, (3) food-shopping diaries and store receipts, and (4) semistructured qualitative interviews. The resulting analysis identified how factors ranging from perceived neighborhood disorder to available transit options shape decisions about how and where to get food. By more explicitly focusing on the food-provisioning strategies of low-income households and the factors that shape them, this research suggests potential pathways toward healthier, more livable cities.*

Introduction

British researchers first popularized the term *food desert* in the mid-1990s (Cummins and Macintyre, 1999; Wrigley, 2002). Since that time, it has become an increasingly common way to refer to neighborhoods where nutritious foods—most often defined as fresh produce and meats—are unavailable, of poor quality, or overly expensive. In the United States, several policy initiatives have been based on this research. Pennsylvania's Fresh Food Financing Initiative, which began in 2004, was one major response to this research, providing grants and loans to improve food-related infrastructure in areas with low food access (Pennsylvania Fresh Food Financing Initiative, 2014). Many of these funds were used to expand or create new supermarkets. President Barack Obama expanded this model at the federal level by creating the Healthy Food Financing Initiative (HHS, 2010). Along with the creation of these federal and state programs, several U.S. cities have created initiatives to improve food access in low-income neighborhoods, including the creation of a food policy task force by the U.S. Conference of Mayors (Boston Mayor's Office, 2012).

Current research on food deserts primarily makes use of an approach based on Geographic Information Systems (GIS)-based analysis that relies on the proximity of supermarkets to residential areas (Black, Moon, and Baird, 2014; Caspi et al., 2012). This methodology is conceptually clear and relatively easy to implement. It requires census data and a listing of major food retailers, both widely available, in addition to data on health outcomes such as body mass index, or BMI, or reported food consumption. Recent research shows little or no association between food deserts and these health outcomes, however, which puts into question the efficacy of this spatial analytical approach (Cummins, Flint, and Matthews, 2014; Lee, 2012).

This article describes an alternative methodology, one that moves from measures of food *proximity* to the food-provisioning *practices* of urban residents. This mixed-methods study combines Global Positioning System (GPS) data on daily mobility, food-shopping diaries, georeferenced photos, and semistructured qualitative interviews. It identifies the role of other major factors affecting food access, including perceived neighborhood disorder and store quality, the role of social networks, and the effect of available transit options. In contrast to approaches that privilege only objective analysis of geospatial data, this method is also more explicitly participatory, including the voices and perspectives of urban residents. It thus provides a useful lens on the daily food provisioning of urban households and the factors that shape them.

Measuring Food Access

Early research on food deserts mostly used market-basket studies, comparing the availability and price of goods across store types and neighborhoods (Block and Kouba, 2007; Cummins and Macintyre, 2002; Hendrickson, Smith, and Eikenberry, 2006). This research often documented discrepancies in food price and quality between lower and middle-to-upper-class neighborhoods. This labor- and time-intensive research limits analysis, however, because it usually assesses only a small number of neighborhoods. As a result, spatial analysis of food-store distribution across urban areas has become increasingly common (Apparicio, Cloutier, and Shearmur, 2007; Zenk, et al., 2005). In this approach, proximity to healthy food sources—most often supermarkets—is combined with measures of social deprivation, such as poverty level, racial composition, and/or vehicle access. The U.S. Department of Agriculture's (USDA's) own Food Access Research Atlas is arguably the most widely used example of this approach (USDA Economic Research Service, 2014). This online tool[1] provides an interactive national map showing the locations of all low-access, low-income census tracts, which are defined using only two variables: poverty level and distance to the nearest supermarket.

Spatial analytical approaches enjoy wide usage and reflect increasingly common use of geospatial data in "smart city" approaches to urban governance (Townsend, 2013). The relationship between neighborhood store environment and health and dietary outcomes is a tenuous one, however (Caspi et al., 2012). Some studies have shown that distance from place of residence to food stores

[1] http://www.ers.usda.gov/data-products/food-access-research-atlas.aspx.

is associated with food consumption habits (Gustafson et al., 2013; Hutchinson et al., 2012). Several studies have found little or no link between the two characteristics (Boone-Heinonen et al., 2011; Lee, 2012). One recent well-publicized study examined changes in residents' eating habits in a neighborhood targeted by the Pennsylvania Fresh Food Financing Initiative. Although residents were aware of their new neighborhood supermarket, their shopping and eating habits did not change significantly as a result (Cummins, Flint, and Matthews, 2014).

The inconsistency of these results questions the reliability of distance-based measures that rely on place of residence as a sole predictor of food-provisioning and consumption habits. Indeed, other studies have shown how distance is only one factor shaping food provisioning. In the late 1990s, USDA-sponsored research found that the supermarkets that food stamp clients used were more than twice as far from home as the closest supermarket (USDA Economic Research Service, 2009). Subsequent research has also demonstrated that low-income households often purchase food from stores outside their home neighborhoods (Clifton, 2004; Ledoux and Vojnovic, 2012; Shannon, 2014). Aside from distance, numerous other factors shape decisions about how and where to get food, including cultural preferences, perceptions of neighborhood safety, and store quality (Latham, 2003; Sampson, 2012; Zenk et al., 2011). By developing data sources that illustrate how individuals make use of urban food systems, rather than simply mapping the locations where food is available, research on food access can better identify neighborhood- and metropolitan-level factors that shape the ways residents procure food. The research outlined in this article provides a model of one such approach.

Critical GIS and Mixed-Methods Research

Several studies provide models for how to incorporate daily practices into geospatial analysis, many of them falling under the broad heading of critical GIS (O'Sullivan, 2006; Sheppard, 2005). Kwan (2008), for example, used travel logs and interviews with Muslim women soon after the terrorist attacks on September 11, 2001, to map how formerly routine daily trips to school and work became significantly shortened and filled with anxiety. Both Rogalsky (2010) and Matthews, Detwiler, and Burton (2005) used tracking and interview data to map the daily trips of welfare clients, showing how family commitments, shopping needs, and institutional demands meant regular long-distance trips, often using public transit, at a significant cost in both time and money. Knigge and Cope (2006) used grounded visualization, combining analysis of demographic data and participant observation within neighborhoods, to analyze the political battles over vacant lot space in Buffalo, New York. Critical GIS research is often more participatory in nature, prioritizing situated accounts over a supposedly objective and expansive analytical view (Pavlovskaya and St. Martin, 2007).

One primary contribution of critical GIS has been its mixed-methods approach. While some of these projects repurposed geospatial technologies for qualitative research (Cope and Elwood, 2009), others combined both quantitative and qualitative components in ways that preserve their respective strengths—breadth of view and analytical clarity in the case of quantitative work and the interpretative richness and nuance of qualitative approaches. Here, the use of mixed-methods provides a complex view of a world that is always just beyond our epistemological grasp (Elwood, 2009; Nightingale, 2003). Drawing on this work and combining quantitative and qualitative data on food-provisioning practices in complementary ways, the methodology described in the remainder of this article provides a richer understanding of the factors shaping food access at the household and neighborhood levels.

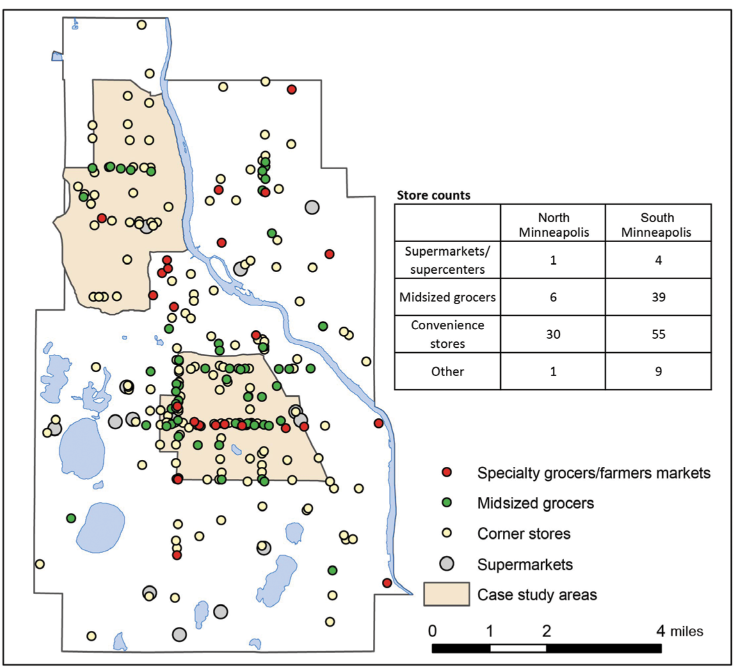
Study Context and Sampling

This research project, conducted in the Twin Cities (Minneapolis/St. Paul), Minnesota, was composed of two main sections. The first section used dasymetric mapping to analyze ZIP Code-level data on the Supplemental Nutrition Assistance Program (SNAP, formerly known as food stamps). I drew on these data to create disaggregated estimates of both client locations and benefit redemptions at SNAP-accepting retailers in neighborhoods with the highest concentration of SNAP clients. Two main findings emerged from this analysis. First, even in neighborhoods with a supermarket, a net "outflow" of SNAP dollars was evident, meaning that clients often traveled out of these areas to use program benefits. Second, midsized grocers (for example, discounters, ethnic retailers) accounted for a much larger proportion of benefit redemptions (31 percent of the total) within these neighborhoods than they did outside them (4 percent). More information on this section of this research is available in a related publication (Shannon, 2014).

The second section, which this article details, used case studies in two low-income neighborhoods in Minneapolis, using data on daily mobility, photographs of foods and stores used by study participants, and semistructured interviews. These two neighborhoods, north and south Minneapolis (exhibit 1), shared a high density of SNAP clients but differed demographically in significant ways (exhibit 2). North Minneapolis residents are largely White or African-American, with a smaller population of immigrant Hmong families from Southeast Asia. South Minneapolis also has

Exhibit 1

Case Study Neighborhoods and SNAP Food Retailer Locations, Minneapolis, Minnesota



	North Minneapolis	South Minneapolis
Supermarkets/ supercenters	1	4
Midsized grocers	6	39
Convenience stores	30	55
Other	1	9

SNAP = Supplemental Nutrition Assistance Program.

Exhibit 2

Study Area and Participant Demographics

	North Minneapolis	South Minneapolis	Twin Cities
Twin Cities demographics			
Population	44,535	59,874	3,318,486
Median age	28	29	36
Median household income ($)	32,730	32,524	79,922
Percent White	24	41	81
Percent African-American	50	26	7
Percent Asian American	14	3	6
Percent Hispanic	8	31	5
Percent with diploma	76	74	93
Percent with college degree	17	28	39
Percent SNAP households	34	24	8
Percent households with a car	76	71	92
Case study participants (N = 38)			
Total participants	18	20	
Median age	46	43	
Median household income ($)	15,684	11,400	
White	6 (33%)	8 (40%)	
African-American	8 (45%)	5 (25%)	
Hmong	4 (22%)	NA	
Hispanic	NA	7 (35%)	
High school diploma	15 (83%)	18 (90%)	
College degree	7 (39%)	6 (30%)	
SNAP recipients	12 (67%)	12 (60%)	
Access to a vehicle	9 (50%)	12 (60%)	
Male	5 (28%)	10 (50%)	
Female	13 (72%)	10 (50%)	

NA = data not available. SNAP = Supplemental Nutrition Assistance Program.
Sources: 2010 census; 2007–2011 American Community Survey

large White and African-American populations, along with immigrant households from South and Central America and East Africa. At the time of the study, south Minneapolis also had six times as many midsized to large food retailers (43 versus 7) as north Minneapolis. Although these two neighborhoods provided contrasting cultural and commercial landscapes, they shared high levels of economic hardship.

I used a quota sampling method in each neighborhood, recruiting roughly equal numbers of White, African-American, and immigrant populations (Hispanic populations in south Minneapolis and Hmong populations in north Minneapolis). A summary of study participants (N = 38) is provided in exhibit 2. These participants were recruited primarily through posting flyers in public spaces (for example, libraries, sign posts, neighborhood centers) along with advertisements on the online classified system Craigslist. In a few cases, participants heard of the study through word of mouth. Participants received a gift card in return for their completion in the study.

Study Methods

My study methods collected three broad forms of data from participants: (1) GPS tracks of daily mobility, (2) written and photographic diaries of food procurement, and (3) semistructured interviews about their activities during the 5-day study period. This length of time (2 weekend days and 3 weekdays) provided enough food-related trips for productive interview conversations without making the interviews overly burdensome. Many participants described their food shopping as a monthly pattern oriented around receipt of SNAP benefits, so while I considered study periods of up to 2 weeks, even these might not have been a fully representative sample. To investigate other possible food sources, I asked participants to describe any other food sources they used regularly and their reasons for doing so.

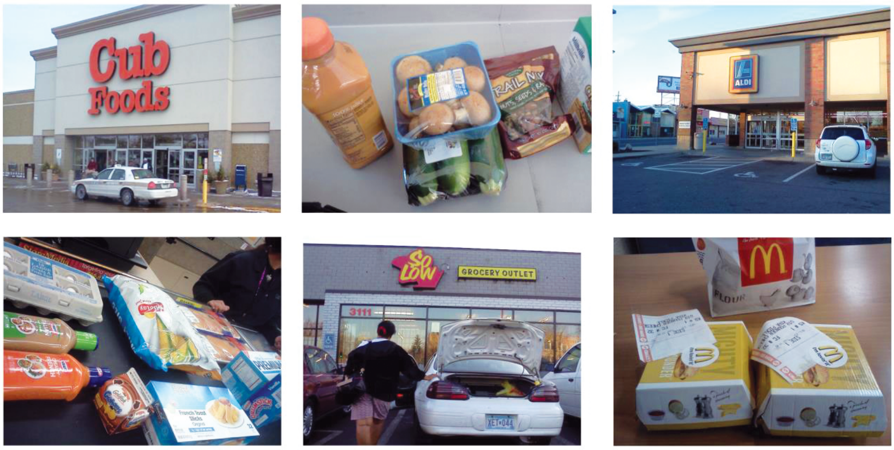
Study participants used Android smartphones to collect data on daily mobility and to take photographs of their food and food sources. The phone I chose, the LG Optimus T, had already been on the market for more than a year, reducing its price, but it had the needed hardware specifications. I registered these phones on a daily use plan with a major U.S. provider, meaning that a small fee was charged only on days the phones were in operation and that the phones would have unlimited service on those days.

The main function of these phones was collecting GPS data on daily mobility. It was difficult to find a suitable GPS-tracking application for Android. I used three applications during the course of the study, because my first choice was discontinued 1 month into the trial and the second option was unstable on the project phones. The final solution was FollowMee (https://www.followmee.com), a third party application that proved to be the most reliable and that provided data in a spreadsheet format easily transferred into GIS software. I set the application to record locations every 5 minutes, which allowed the phones to last a day on a single charge. This approach provided sufficient data to identify the general neighborhoods where individuals spent their time. Although GPS trackers provide greater temporal and spatial accuracy than phones, they add expense and require study participants to carry an additional device. The additional accuracy was also not necessary in this case. To protect privacy, I added noise to these GPS data, random numbers for both latitude and longitude that fell within a range of +/-167 meters (0.0015 decimal degrees). Visual tests showed that this approach made determining the location of home or workplaces significantly more difficult. I shared maps that demonstrate this additional uncertainty with participants in discussions of study risk before enrollment. For my final interviews for participants, I created and discussed a map of each participant's daily trips, using these data (see discussion in the following section).

Participants also used these smartphones to take pictures of food sources they used and the foods they procured during the study period. These images provided a ground-level view of these sites and created a visual link between food sources and the varieties of foods people purchased and gathered. Participants' food sources included workplace kitchens and friends' homes, along with supermarkets and restaurants (exhibit 3). Each phone automatically synced photos to an online storage service, enabling me to check the quality of images during the study period. Because smartphones automatically georeference photos, these photos could be placed on a map using software such as Google Earth. Although most participants had no trouble using the phone's camera, images did sometimes suffer from poor quality, primarily blurriness or low light for outside shots.

Exhibit 3

Participants' Photos of Food Sources and Purchased Foods



In addition to taking photographs, participants kept a written record of any food source used during the study period. This record included a shopping diary that listed store names and locations; information about when, how, and with whom they visited the stores; and how much money they spent. Although participants also had the option of using their smartphone to complete these diary records via an online form, all but one participant preferred the paper version. Participants also saved receipts from any food purchase made during the study period. The receipts verified store locations. Except in the case of sit-down and fast-food restaurants, the receipts were coded based on type of food purchased (for example, dairy, meats, dry goods, and produce). This approach provided detailed data for analyzing food-shopping patterns; I could summarize trip characteristics based on which products were purchased to determine food-shopping patterns.

Two interviews framed participation in the study. An initial interview, which lasted 20 to 30 minutes, included collecting participants' background information and providing them instructions for their role in the study. A second semistructured interview after the study period lasted 40 to 75 minutes. This interview had three sections. First, we examined the map of GPS data, and participants identified the main locations where they had spent time, talking about their daily routines. Second, participants described each food source they used, talking about their reasons for using the place and their impressions of it. Third, we spoke more generally about other food sources they did or did not use on an ongoing basis and the ways they thought their food options could be improved.[2] These interviews provided essential insights into factors shaping how and where these participants got food. For example, one woman traveled far across town to go grocery shopping rather than use the supermarket in her neighborhood, largely because of her limited walking ability and the direct bus route to this preferred store. Another woman gathered a group of friends for an early morning trip to a suburban Wal-Mart store to take advantage of their once-a-week meat specials. The details of these trips would have been difficult to discern using only GPS data.

[2] A full version of this interview protocol is available at https://www.scribd.com/doc/257040526/Closing-Interview-Schedule.

In keeping with previous research using active-interviewing strategies, the goal of both interviews was to develop a shared understanding of the factors shaping participants' food-provisioning strategies (Holstein and Gubrium, 1995). Indeed, when I asked participants for their thoughts about the study, the most common response by far was how much they had learned about their own food-provisioning habits through their participation. These interviews were coded inductively using the qualitative software NVivo. Codes were based on my research questions, including themes such as perceptions of distance, store quality, and quality of foods within different store types.

After an initial analysis of these data, I invited participants to a followup focus group in which they could respond to my initial conclusions. One focus group was held for each study area, and participants were offered a free meal for their participation. My initial results largely focused on the notable variety of stores participants used and the high number of trips they made to stores outside their neighborhoods. To me, these results demonstrated a significant degree of individual mobility, a finding that ran counter to existing research that focused only on the neighborhood environment. Participants pushed back against this interpretation, however, particularly in the north Minneapolis group. To them, their shopping patterns were direct effects of the high prices and low quality of foods in their local stores. Comparing their neighborhood stores to suburban locations, where prices and quality both were more favorable, several wanted to know how my research would improve what they saw as a clear injustice. These focus groups shaped my subsequent reporting on this research, which ultimately focused on the need to situate research and policy on food access within a broader framework of neighborhood disorder and segregation and on the need to strengthen transit systems.

Lessons Learned and Recommendations

GIS-based approaches to studying food accessibility document significant disparities in the food sources available to urban residents. Relying on measures of spatial proximity, however, fails to incorporate other important factors that shape food provisioning, including perceptions of the neighborhood environment and local stores and the resident's daily mobility. The alternative approach used in this study addresses this issue by using GIS as part of a mixed-methods approach. GIS and qualitative techniques were complementary in this case. GPS data on daily mobility and shopping diaries provided a full picture of participants' activities during the study period, providing ways to assess their daily activity space and visualize their food provisioning. Interviews and photographs contextualized this mobility, providing an "on the ground" perspective of the food sources participants used and their reasons for doing so.

Smartphones were a key technology in the study. They combined GPS tracking with the ability to take georeferenced photographs, both of which could be monitored in real time by syncing data through the phone's data plan to ensure I was aware of any ongoing technical problems. The phones could also be used to collect food-shopping diary entries from study participants, although only one participant did so in this case. Phones had sporadic technical problems. Finding reliable software to collect GPS data was one obstacle. Future research using this approach should confirm the availability of suitable software or consider budgeting for the development of a custom application. The inclusion of photographs in this study was useful, but many photographs were unfortunately of low quality (were blurry or had poor lighting). Phones with better cameras may have improved image quality through technologies like image stabilization. This project did not explicitly use the photo-voice method (Belon et al., 2014; Mahmood et al., 2012), but providing more instruction on how to use the cameras and encouraging participants to capture defining features of each food source would have borrowed elements of this approach that may have improved photo quality and usefulness.

The analysis of food environments is only one aspect of increasing reliance on spatial analytics in "smart city" initiatives (Townsend, 2013). This data-based approach to urban governance provides valuable insight on how policy initiatives can alter patterns of everyday life. As even this small-scale study suggests, however, the idea that a reliance on robust quantitative indicators produces a theory-free form of governance is fundamentally problematic (Anderson, 2008). The qualitative data developed in this project were essential to interpretation of both shopping diaries and GPS data. Through study interviews and focus groups, participants and I developed a shared understanding of the factors that shaped their food-provisioning behavior. The situated perspectives of neighborhood residents, not just their data, were needed (Haraway, 1988; Pavlovskaya and St. Martin, 2007). This mixed-methods approach thus provides one model for a participatory geospatial analysis of food access.

The growth of mobile GIS applications provides new opportunities for representing and understanding the everyday practices that form the rhythm of urban life. Future research can leverage this technology by exploring not just where food is, but where, how, and why urban residents draw on available food sources. This approach might use a smartphone application that city governments or nonprofit groups would custom design for their research. Targeted case studies in selected neighborhoods, similar to this project, might also prove useful. This small-scale study also generates broader research possibilities, such as analysis of existing transit data or citywide surveys of perceived store quality and neighborhood safety. Using this mix of methodologies to understand the everyday experiences of urban residents can thus suggest pathways to healthier, more livable cities.

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Spatializing Segregation Measures: An Approach To Better Depict Social Relationships

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Abstract

Segregation involves more than one population group, and segregation measures quantify how different population groups are distributed across space. One of the key conceptual and methodological foundations of segregation studies is to account for the potential of spatial interaction among two or more population groups across areal units. This foundation implies the need for a spatial approach to portray the spatial (and thus social) interaction among neighbors. In general, simple percentages (for example, percent Black) are not a measure of segregation. Because local spatial segregation measures did not emerge until recently, the objectives of this article are threefold: (1) to explain a spatial approach for measuring the level of segregation at the neighborhood (or local) level, (2) to demonstrate the deficiencies of using a percentage of racial/ethnic group as a measure of segregation, and (3) to clarify the appropriateness of two commonly used indexes of dissimilarity and diversity. Data from St. Louis, Missouri, and Chicago, Illinois, are used to discuss these three points.

Introduction

Residential segregation and the persistence thereof have long been topics of interest to a wide variety of academic disciplines (for example, sociology, demography, geography, political science, and public health) and to professionals or practitioners in multiple fields (for example, law enforcement, urban planning, and health service providers). Particularly in the United States, such phenomena have been viewed as a key factor of significant separation between White and Black residents.

Therefore, formulating potential solutions to reduce the levels of residential segregation have been considered as a major societal concern (for example, Anderson et al., 2003; Charles, 2003; Clark, 1986; Massey and Fischer, 2000; Taeuber, 1968; Williams, 1999; Williams and Collins, 2001). Note that all racial groups in this article refer to the non-Hispanic populations.

With a view to inform public policies and decisionmaking, however, the use of effective and meaningful segregation measures is fundamental and crucial to develop a reliable depiction and understanding of the social environment that different population groups experience in their place of residence (Johnston, Poulsen, and Forrest, 2014).[1] Since the publication of the review papers (for example, Massey and Denton, 1988; Massey, White, and Phua, 1996) that assessed several dozens of segregation measures, many more segregation measures have been introduced. Many of these newer measures are extensions or modifications of existing measures (for example, Feitosa et al., 2007; Reardon and O'Sullivan, 2004; Wong, 2008, 2002), but some are actually not measures of segregation (for example, Brown and Chung, 2006; Reibel and Regelson, 2007). The mushrooming in the number of segregation measures reflects that the concept of segregation is fluid, difficult to pin down, and multifaceted so that one or a few simple definitions are not capable of capturing its essence entirely. As a result, rather ineffective and insufficient ways of measuring segregation are evident in research and practice.

One major "malpractice" quite prevalent among studies focusing on neighborhood comparisons is using the percentage of racial and ethnic groups (for example, percent Black) as a measure of segregation to examine, for instance, the possible effects of residential segregation on academic performance (for example, Bennett, 2011; Card and Rothstein, 2007), home equity (for example, Deng, Ross, and Wachter, 2003; Kim, 2000), and health (for example, Inagami et al., 2006; Vinikoor et al., 2008). Census statistical units (tracts or block groups) have been used to denote the "neighborhoods" in most U.S. studies (including the six studies listed previously). Percentages, however, are not a measure of segregation (Johnston, Poulsen, and Forrest, 2007; Massey and Denton, 1988; Massey, White, and Phua, 1996; Reardon and O'Sullivan, 2004). A segregation measure needs to quantify how two or more population groups are distributed across space and to account for the potential of spatial interaction among population groups across areal units (Feitosa et al., 2007; Reardon and O'Sullivan, 2004; White, 1983; Wong, 2008, 2004, 2002, 1998, 1993).

Because the conceptual and methodological foundations of segregation studies have not been adequately translated into research and practice, the objectives of this article are threefold: (1) to explain a spatial approach for measuring the level of segregation at the neighborhood (or local) level, (2) to demonstrate the deficiencies of using a percentage of racial and ethnic group as a measure of segregation, and (3) to clarify the appropriateness of two commonly used indexes of dissimilarity and diversity. Data from two cities in the U.S. Midwest, St. Louis, Missouri, and Chicago, Illinois, are used to discuss such conceptual and methodological concerns.

[1] We do realize that measuring segregation should not be constrained to residential space only, but segregation in the residential space, nevertheless, has received the most attention.

Methods

In this section, we first provide an overview about how measures that depict segregation levels at the local or neighborhood level are formulated. Both aspatial and spatial versions of these measures will be discussed. Then, we apply these measures to study the two cities.

Segregation Measures

The dissimilarity index (*D*) and the entropy-based diversity index (*H*) are two common segregation indexes used to measure the unequal or differential distributions of population groups (that is, the evenness dimension of segregation). *D* was introduced by Duncan and Duncan (1955), and its use was advocated by Massey and his colleagues (Massey and Denton, 1988; Massey, White, and Phua, 1996). On the other hand, *H* was introduced by Shannon (1948a, b) or Theil (1972), depending on the fields of study (also referred to as the Shannon index or Theil index, respectively), and its use in segregation studies was advocated by White (1986) and Reardon and Firebaugh (2002).

Both *D* and *H* share a limitation and a shortcoming, however. First, they are global measures that summarize the condition of the entire region (for example, a city or a metropolitan area); thus, they fail to recognize the variations at the neighborhood (or local) scale (Feitosa et al., 2007; Reardon and O'Sullivan, 2004; Wong, 2004, 1996). Second, they are aspatial measures that do not account for the spatial relationships between areal units; thus, swapping the entire populations between areal units will not change the index values (Morrill, 1991; White, 1983; Wong, 2004, 1998, 1993). To address these two issues, Wong (1998) implemented the concept of composite population count to capture spatial relationships for modifying the global aspatial segregation indexes into local spatial segregation indexes (2008, 2002).

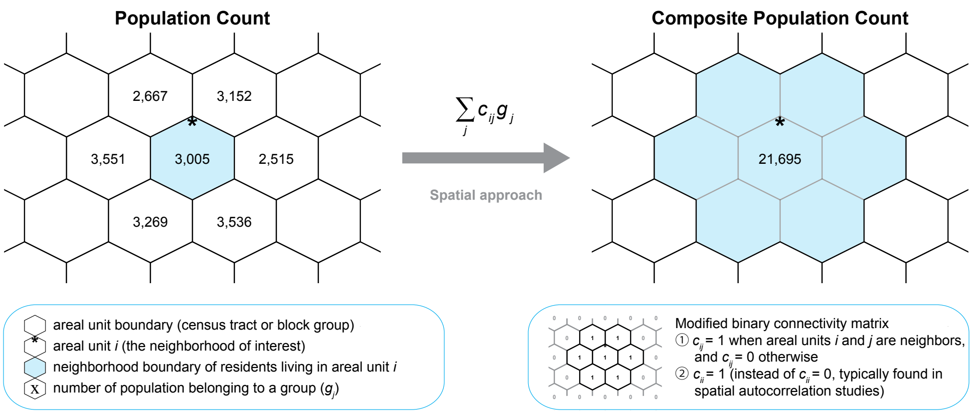
Borrowing the concept of modeling spatial autocorrelation, modifications of segregation indexes were achieved by adapting the function $c_{ij}(.)$ (Wong, 2008, 2002). Here, $c_{ij}(.)$ is the element of a (0, 1) matrix where $c_{ij} = 1$ indicates areal units *i* and *j* are neighbors, and $c_{ij} = 0$ otherwise; however, *i* can equal *j* and thus $c_{ii} = 1$. Therefore, the composite population count of group *G* in areal unit *i* (cg_i) is modeled as

$$cg_i = \sum_j c_{ij} g_j ,$$

where g_j is the population count of group *G* in areal unit *j*. In other words, a composite population count refers to the population count in areal unit *i* plus the population counts in its neighboring units *j*. This implicitly accounts for the spatial interaction of population groups across areal unit boundaries. Exhibit 1 illustrates how the function $c_{ij}(.)$ can be used to calculate the composite population count.

Exhibit 1

Illustration of the Concept of Composite Population Count



The concept and method of local spatial segregation measures did not emerge until recently (Wong, 2008, 2002). To explain the difference between aspatial and spatial segregation measures, specifications of the local aspatial dissimilarity index (D_i) and its spatial version (SD_i) along with the local aspatial diversity index (H_i) and its spatial version (SH_i) are given in the following discussion.

The local aspatial dissimilarity index (D_i) is defined as

$$D_i = \left| \frac{w_i}{W} - \frac{b_i}{B} \right|, \tag{1}$$

where w_i and b_i are the White and Black population counts in areal unit i, respectively, and W and B are the White and Black population counts for the entire study area, respectively. This index is the local aspatial version of the popular D. To derive the spatial version of this index, the local spatial dissimilarity index (SD_i), all population counts are replaced by their respective composite population counts—

$$SD_i = \left| \frac{cw_i}{CW} - \frac{cb_i}{CB} \right|, \tag{2}$$

where cw_i and cb_i are the composite White and Black population counts in areal unit i, respectively, and CW and CB are the composite White and Black population counts for the entire study area, respectively. This index is the local spatial version of the popular D.

The local aspatial diversity index (H_i) is defined as

$$H_i = -\sum_{k}^{n} \left(\frac{p_{ik}}{t_i}\right) \ln \left(\frac{p_{ik}}{t_i}\right), \tag{3}$$

where p_{ik} is the population count of mutually exclusive group k in areal unit i (for example, White, Black, Hispanic, … n), and t_i is the population count of total population in areal unit i. This index is the local aspatial version of the popular H. To derive the spatial version of this index, the local spatial diversity index (SH_i), all population counts are replaced by their respective composite population counts—

$$SH_i = -\sum_{k}^{n} \left(\frac{cp_{ik}}{ct_i}\right) \ln \left(\frac{cp_{ik}}{ct_i}\right), \tag{4}$$

where cp_{ik} is the composite population count of mutually exclusive group k in areal unit i (for example, White, Black, Hispanic, … n), and ct_i is the composite population count of total population in areal unit i. This index is the local spatial version of the popular H.

To demonstrate the use of these four local segregation indexes, they were computed in R (R Core Team, 2014) based on the 2005–2009 American Community Survey (ACS) data. Population counts by race and ethnicity at the census tract level were obtained for St. Louis (that is, St. Charles County, St. Louis County, and St. Louis City) and Chicago (that is, Cook County). Census tract data were used because they (unlike other areal units) are designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions (U.S. Census Bureau, 2014). Note that the 5-year ACS estimates are based on a larger sample size and, therefore, are more reliable than the 1- and 3-year estimates. Because census tract boundaries extend into rivers and include large ponds and lakes, such water bodies were removed when the total land area (in square kilometers) was recalculated in ArcGIS 10. The population and selected geographic characteristics of these two Midwestern U.S. cities are summarized in exhibit 2.

Exhibit 2

Selected Summary Statistics of Two Midwestern U.S. Cities: St. Louis and Chicago

	St. Louis	Chicago
Distance between cities[a] (km)	≈ 480	
Total land area[a] (km^2)	2,918	2,433
Census tracts[b]	340	1,327
Total population[b]	1,692,563	5,257,001
Non-Hispanic White[b] (%)	70.0	45.2
Non-Hispanic Black[b] (%)	23.3	25.3
Hispanic[b] (%)	2.4	22.5
Asian[b] (%)	2.6	5.6
Other racial and ethnic groups[b] (%)	1.7	1.4

km = kilometers.

[a] Derived from the Geographic Information System calculation by authors.

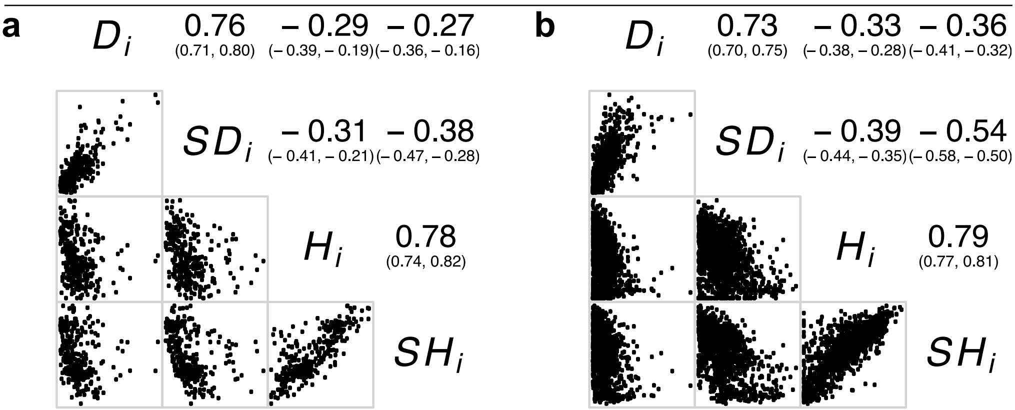
[b] Derived from the 2005–2009 American Community Survey.

Analysis

To examine the relationships of local aspatial and spatial segregation measures derived from the previous section (that is, D_i, H_i, SD_i, and SH_i), two separate correlation statistics (Friendly, 2002) were computed in R (Wright, 2012) for St. Louis (exhibit 3a) and Chicago (exhibit 3b). Correlations and scatterplot matrixes were used to display the relationships. The upper off-diagonal panels show the correlation coefficients with associated 95-percent confidence intervals (in parentheses), and the lower off-diagonal panels show the scatter plots.

Exhibit 3

Correlations of Local Aspatial and Spatial Segregation Measures in Two Midwestern U.S. Cities: (a) St. Louis and (b) Chicago

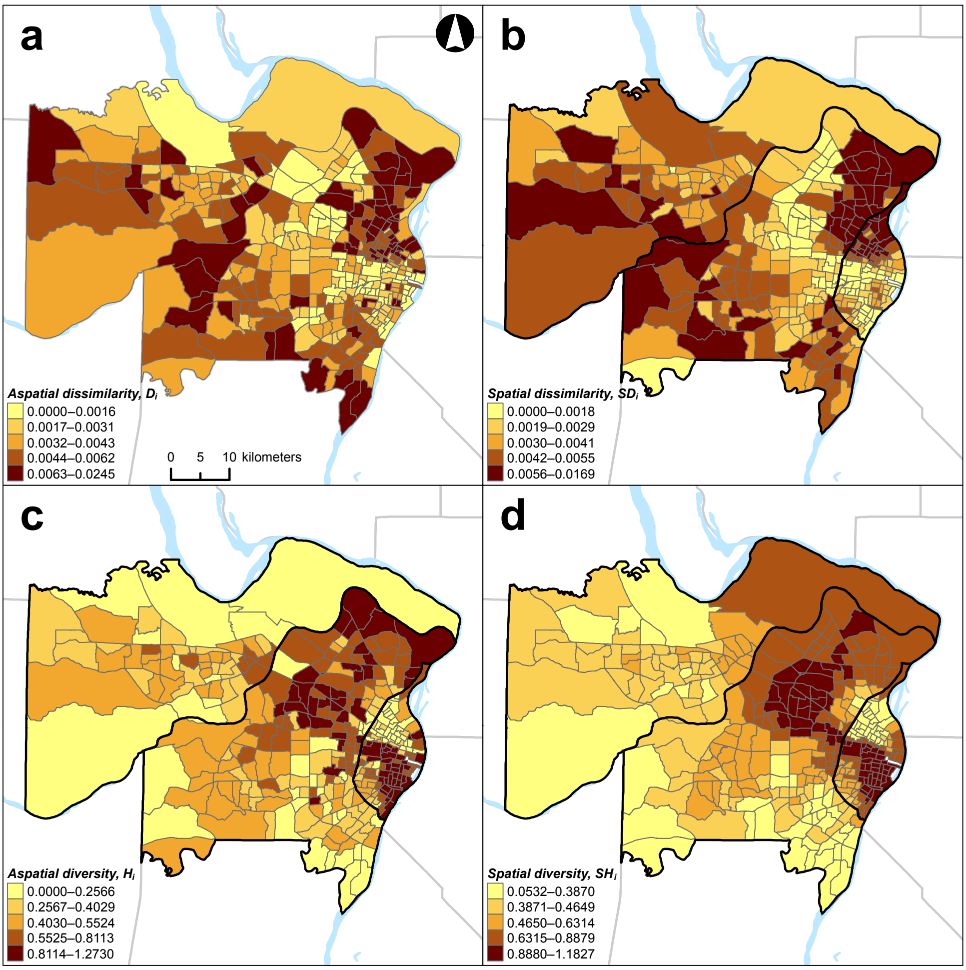


Note: Data represent 340 census tracts in St. Louis and 1,327 census tracts in Chicago.

As a way to understand the spatial patterns of racial and ethnic groups, the geographic distributions of local aspatial and spatial segregation measures are shown in maps for St. Louis (exhibit 4) and Chicago (exhibit 5). For demonstration purposes, the geographical distributions of percent White, Black, Hispanic, and Asian are also shown in maps for St. Louis (exhibit 6) and Chicago (exhibit 7). In these four maps, a quantile classification scheme was used to display the levels of segregation.

Exhibit 4

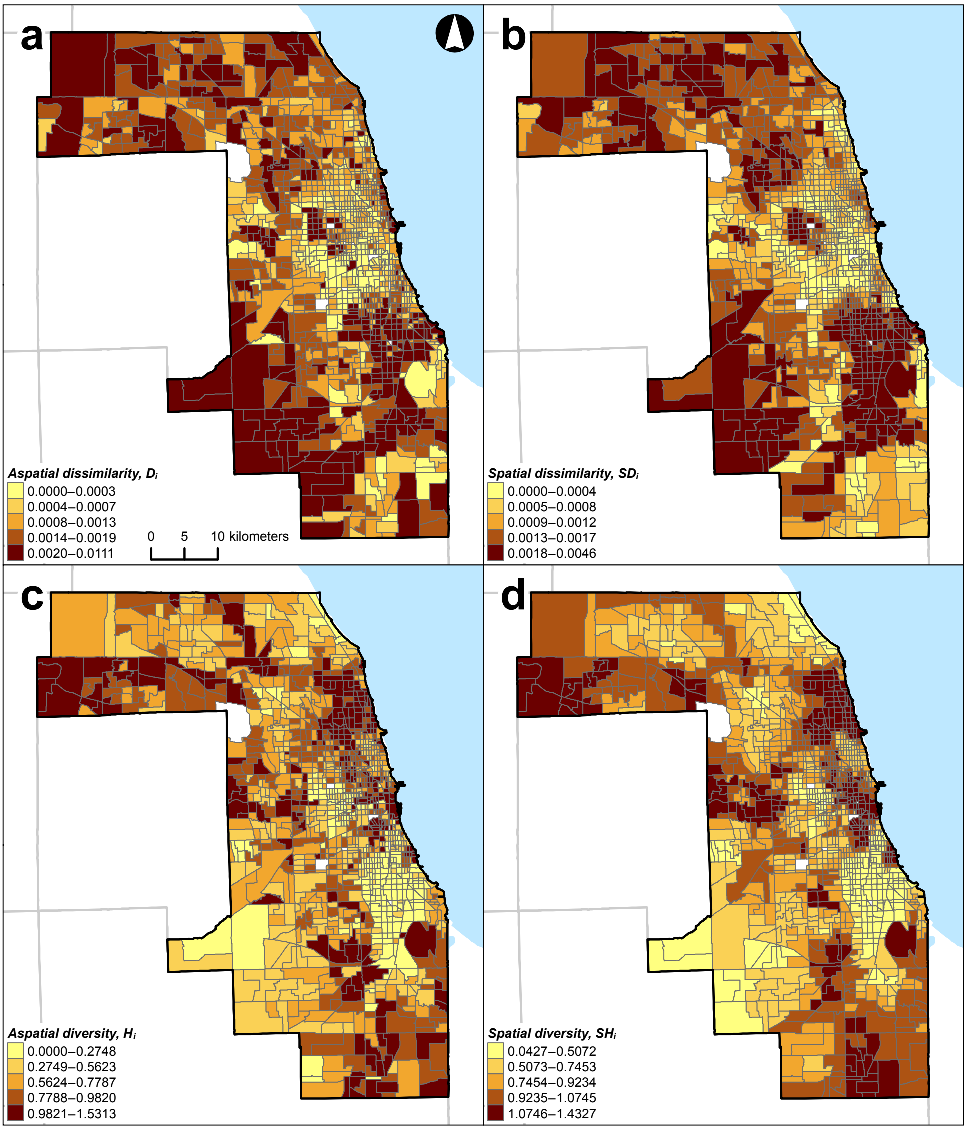
Geographic Distributions of Local Aspatial and Spatial Segregation Measures in St. Louis



Notes: A quantile classification scheme was used to display the levels of residential segregation. Data represent 340 census tracts.

Exhibit 5

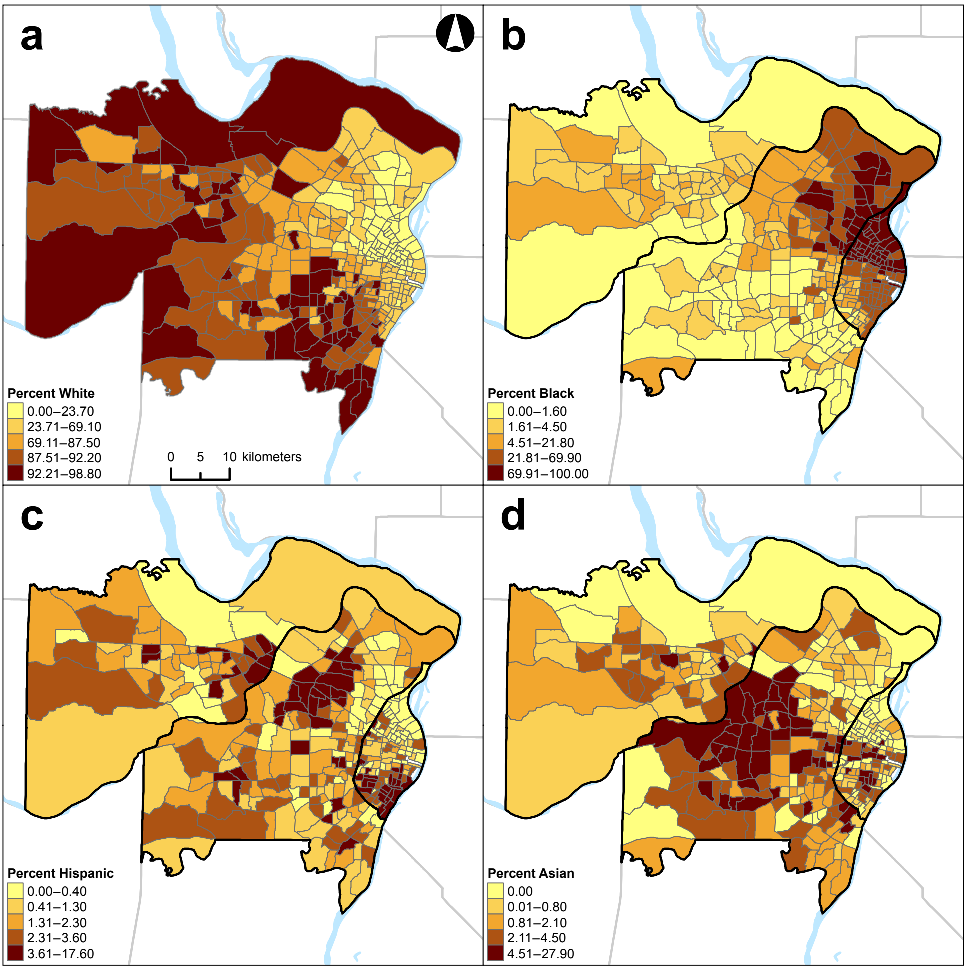
Geographic Distributions of Local Aspatial and Spatial Segregation Measures in Chicago



Notes: A quantile classification scheme was used to display the levels of residential segregation. Data represent 1,327 census tracts.

Exhibit 6

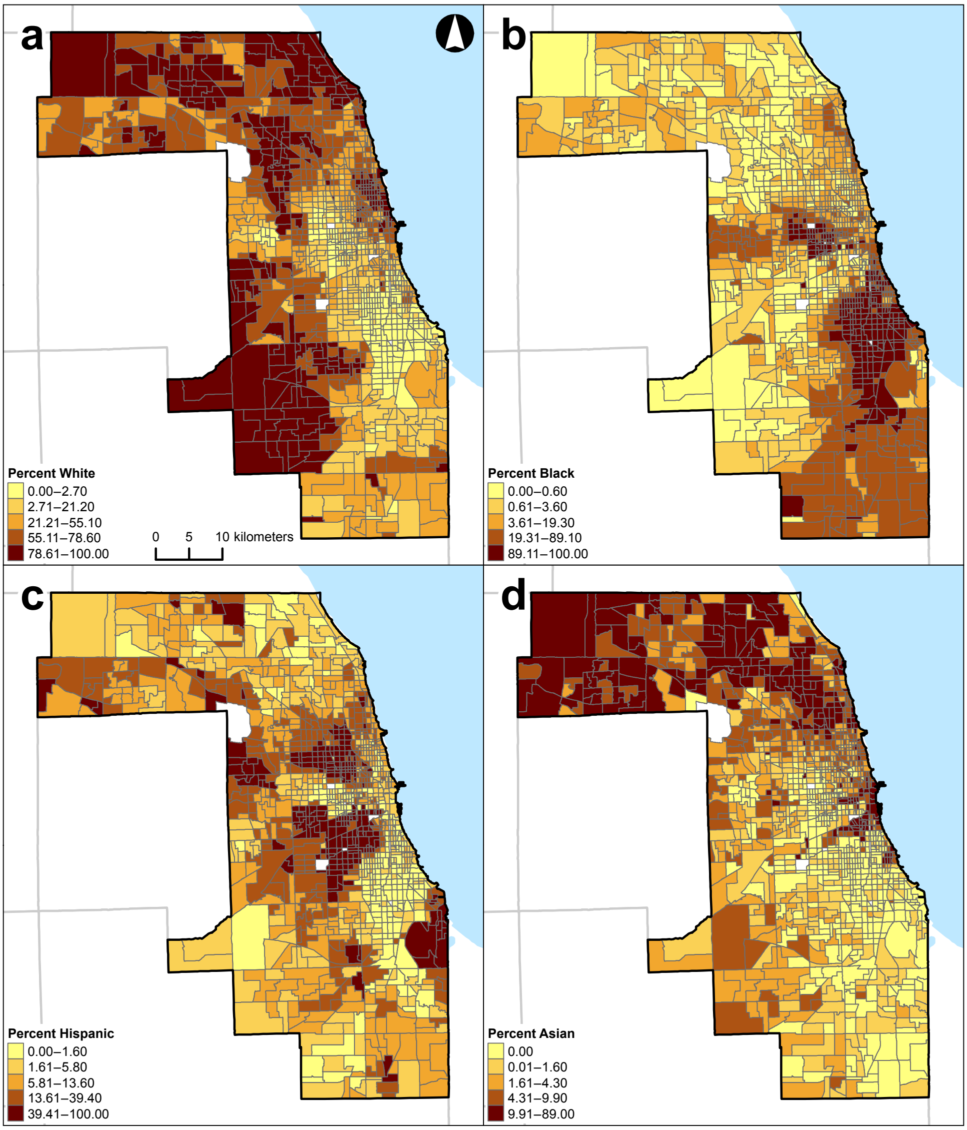
Geographic Distributions of Racial and Ethnic Groups Expressed as Percentages in St. Louis



Notes: A quantile classification scheme was used to display the levels of residential segregation. Data represent 340 census tracts.

Exhibit 7

Geographic Distributions of Racial and Ethnic Groups Expressed as Percentages in Chicago



Notes: A quantile classification scheme was used to display the levels of residential segregation. Data represent 1,327 census tracts.

Results

As illustrated in exhibit 1, the basic principle of the composite population count uses the function $c_{ij}(.)$ to remove the enumeration boundaries as the absolute barriers for intergroup interaction by aggregating population counts across adjacent (or contiguous) neighborhoods. Such operation provides a more realistic portrayal of the spatial (and thus social) interaction among neighbors in their place of residence than that of such interaction to occur only within the confined unit boundary (that is, colored cells on the right versus left).

The two Midwestern U.S. cities were examined because they are in the same geographic region with similar total areas, but they have different population characteristics (exhibit 2). In St. Louis, about 70.0 percent of the population was White and 23.3 percent was Black. In Chicago, however, the population was composed of fewer White residents relatively (45.2 percent), about the same proportion of Black residents (25.3 percent), and a larger proportion of Hispanic residents (22.5 percent). The proportion of the Asian population was slightly larger in Chicago (5.6 percent) than it was in St. Louis (2.6 percent).

Exhibit 3 displays the relationships between the local aspatial and spatial segregation measures in St. Louis (exhibit 3a) and Chicago (exhibit 3b). Overall, similar trends can be seen in the two cities. Comparing local aspatial segregation measures with their spatial counterparts, D_i and H_i are moderately and positively correlated with SD_i (r = 0.76 in St. Louis and r = 0.73 in Chicago) and SH_i (r = 0.78 in St. Louis and r = 0.79 in Chicago), respectively; scatterplot matrixes also suggest modest linear associations but relatively high degrees of variation between the two types of measures in the two cities. As explained previously, such differences are attributable to the incorporation of the function $c_{ij}(.)$ or the lack thereof (exhibit 1). Moreover, in comparison with dissimilarity and diversity measures, both D_i and SD_i are weakly, but negatively correlated (or not correlated) with H_i and SH_i ($-0.27 \leq r \leq -0.38$ in St. Louis and $-0.33 \leq r \leq -0.39$ in Chicago); the only exception here is that SD_i is moderately, but negatively, correlated with SH_i (r = -0.54) in Chicago.

Exhibit 4 (for St. Louis) and exhibit 5 (for Chicago) show that results of correlation analysis in exhibits 3a and 3b, respectively, are manifested spatially in the two cities. By comparing the geographical distributions of D_i with SD_i (4a versus 4b and 5a versus 5b), as well as H_i with SH_i (4c versus 4d and 5c versus 5d), it is clear that local aspatial segregation measures and their spatial counterparts do not exactly resemble similar spatial patterns; noticeably, SD_i (4b and 5b) and SH_i (4d and 5d) show much "smoother" spatial patterns and lower segregation levels than D_i (4a and 5a) and H_i (4c and 5c), respectively. In addition, neither the geographical distributions of D_i (4a and 5a) nor SD_i (4b and 5b) are the opposite of H_i (4c and 5c) and SH_i (4d and 5d). Put differently, areas with the highest (or lowest) values of D_i and SD_i do not always correspond to the lowest (or highest) values of H_i and SH_i in the two cities.

As emphasized earlier, percentages of racial and ethnic groups should not be used as a measure of segregation, because the geographical distributions of percent White, Black, Hispanic, and Asian cannot quantify how different population groups are distributed across areal units. For example, in St. Louis, areas with higher percentages of White (exhibit 6a), Black (exhibit 6b), Hispanic (exhibit 6c), and Asian (exhibit 6d) residents coincide in the central, northwestern, and lower eastern parts of

St. Louis. Similarly in Chicago, areas with higher percentages of White (exhibit 7a), Black (exhibit 7b), Hispanic (exhibit 7c), and Asian (exhibit 7d) residents coincide along the shore of Lake Michigan and in the northern, central, and southern parts of Chicago. Taken together, a higher percentage of a racial/ethnic group could refer to both a racially/ethnically dominated and diverse (or integrated) neighborhood in the two cities. More importantly, simple percentages can capture the within-unit relationships, but they cannot capture the between-unit relationships as modeled in spatial segregation measures. Despite their simplicity, both exhibits 6 and 7 demonstrate that the percentage of racial/ethnic groups is not an appropriate measure of segregation (Johnston, Poulsen, and Forrest, 2007; Massey and Denton, 1988; Massey, White, and Phua, 1996; Reardon and O'Sullivan, 2004).

Discussion

A series of correlation and visual analysis of St. Louis and Chicago (exhibits 3 through 7) leads to two main conclusions: (1) local spatial segregation measures (SD_i and SH_i) produce a "smoother" spatial pattern and lower segregation levels than their aspatial counterparts (D_i and H_i, respectively), and (2) the two-group-based dissimilarity measures (D_i and SD_i) do not capture the local variation of segregation as the multiple-group-based diversity measures (H_i and SH_i) do (aspatial and spatial alike). These results, in turn, highlight two important remarks about the measurement of segregation.

For the first remark, the difference between aspatial and spatial approaches to measure segregation reflects the recent methodological achievements. Most segregation indexes introduced in the early era of developing segregation measures are aspatial in nature (for example, Morrill, 1991; White, 1983; Wong, 1993). A typical example used to demonstrate the aspatial nature is a checkerboard pattern in which each cell is dominated by only one group and cells are arranged in a spatially alternate manner. Calculating D for such a pattern produces a value of 1, indicating perfect segregation. Clustering together all cells that belong to one group, creating a perceivably more segregated pattern, will also produce a D value of 1. The bottom line is that D does not consider the spatial relationship of population distribution and, thus, exaggerates segregation levels. A similar demonstration can be conducted for H. To overcome this limitation, existing measures were modified to incorporate spatial information into the formulations so that these spatial versions of the indexes consider the spatial distributions of different population groups.

A common approach is to include populations in the neighboring units when evaluating the population characteristics of a unit (Feitosa et al., 2007; Reardon and O'Sullivan, 2004; Wong, 2008, 2002). Doing so implicitly allows for the mixing of neighboring populations, removing the artificial boundaries between units in separating the populations. Both Reardon and O'Sullivan (2004) and Feitosa et al. (2007) adopted the fancy concept of a spatial kernel to derive the weights to count populations in the neighboring units toward the reference unit. The kernel implements the distance decay concept so that population at and near the reference unit will be counted more and populations in farther away units will be counted less. Nevertheless, the basic principle of using the simplistic composite population count (Wong, 2008, 2002) or the elegant spatial kernels is the same. Because local spatial segregation measures (compared with their aspatial counterparts) provide a more realistic portrayal of the spatial (and thus social) interaction among neighbors, future studies should consider using local spatial segregation indexes.

Regarding the second remark, the difference between dissimilarity and diversity measures (aspatial and their spatial versions alike) warns that a careful consideration is needed before choosing the segregation index in future studies. Both *D* and *H* measure the evenness dimension of segregation. From a conceptual standpoint, these two measures are the inverse of each other (Massey and Denton, 1988; Massey, White, and Phua, 1996). Such an expectation does not generally hold, however (exhibits 3 through 5). *D* has become one of the most popular measures of segregation.[2] The popularity of *D* is, in part, induced by its easy calculation and interpretation. Also, the use of *D* was popularized by the strong endorsements from Massey and his colleagues (Massey and Denton, 1988; Massey, White, and Phua, 1996).[3]

Despite many desirable properties, the use of *D* in segregation studies has long been criticized for its inconsistencies with the notions of segregation (for example, Reiner, 1972; Winship, 1978; Zelder, 1972). In fact, Cortese, Falk, and Cohen (1976) demonstrated some of the systematic biases in *D* nearly four decades ago. More recently, a major concern of *D* raised by White (1983) is that the measure is insensitive to the spatial arrangement of population distribution. Simply put, by swapping the populations in any two subareas (for example, neighborhoods) within a larger region (for example, a city or a metropolitan area), the value of *D* will not change; *D* is influenced only by the population mix within each areal unit and does not consider who are "next" to each other. On the other hand, *H* has been determined to be a superior measure. It conceptually and mathematically satisfies the desirable decomposition properties for handling multiple population groups in segregation studies (Reardon and Firebaugh, 2002; White, 1986). Because *H* is global and aspatial in nature, future studies should consider using its local spatial version (that is, SH_i).

In summary, local spatial segregation measures produce "smoother" spatial patterns at lower segregation levels than their aspatial counterparts, and the dissimilarity measures cannot handle multiple-group comparisons as effectively as the diversity measures. For these reasons, the use of SH_i (instead of SD_i) is recommended to measure the unequal or differential distributions of racial and ethnic groups (that is, the evenness dimension of segregation) in future studies.

Limitations

Two challenges should be considered when using SH_i in future studies. First, SH_i captures only the evenness dimension of segregation that Massey and Denton (1988) claimed to be the most important dimension of segregation. It fails to evaluate another important and distinct dimension of segregation, however—isolation (that is, the potential interaction of population groups; Johnston, Poulsen, and Forrest, 2007; Reardon and O'Sullivan, 2004). The isolation index (P^*) (Lieberson, 1981) has been regarded as the standard index to measure isolation. Wong (2008, 2002) introduced the local spatial version of P^*, denoted as the local spatial isolation index (S_i). Although the detailed explanation of S_i is beyond the scope of this article, SH_i and S_i should be used to reflect the evenness and isolation dimensions of segregation, respectively.

[2] A search on http://www.scholar.google.com (on September 16, 2014) showed that the paper by Duncan and Duncan (1955) has been cited 1,898 times.

[3] A search on http://www.scholar.google.com (on September 16, 2014) showed that these seminal review papers together have been cited 1,911 times (1,731 and 180 times, respectively).

Second, SH_i (as well as all spatial segregation indexes) is influenced by the boundary or edge effect. Such effect introduces bias into the identification of spatial distribution and the parameter estimates of spatial processes (Griffith, 1983). Several solutions have been proposed, but none can fully solve the problem (Griffith, 1987, 1980). One rather simple practical solution, which was not implemented in this study, is to include a buffer zone around the study area. Because the function $c_{ij}(.)$ adopted to implement the concept of composite population involves only the immediate neighboring units (Wong, 1998), a buffer zone including the first order adjacent units along the study area will be sufficient for using SH_i to measure the level of segregation.[4]

Conclusion

The use of effective and meaningful segregation measures holds the key to examining the possible (that is, adverse, protective, or null) effects of residential segregation on its residents (Johnston, Poulsen, and Forrest, 2014). Otherwise, only limited (if not biased) knowledge can be gained to formulate potential solutions to reduce the levels of segregation, and then to inform public policies and decisionmaking. A gap between the conceptual and methodological achievements in segregation studies and their implementations in different fields is quite prevalent, however, especially among those focusing on neighborhood comparisons.

From a critical point of view, the continued uses (or misuses) of ineffective and insufficient segregation measures will substantially undermine the purposes of research and their potential contributions to inform public policies and decisionmaking. Hence, future research needs to build on the conceptual and methodological foundations of segregation studies established by demographers, geographers, and sociologists.

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[4] Because the $c_{ij}(.)$ function can be implemented differently (for instance, including higher order neighbors), the buffer size should be adjusted accordingly to contain the edge effect.

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Increasing the Accuracy of Urban Population Analysis With Dasymetric Mapping

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Abstract

Many types of urban policy analyses, particularly those relating to exposure to hazards or accessibility to resources, rely on accurate and precise spatial population data, although such data are not always available. Dasymetric mapping is a technique for disaggregating population data from one set of source spatial units to a finer resolution set of target spatial units through the use of an ancillary dataset, typically land use, zoning, or similar nominal datasets related to population distribution. Dasymetric mapping operates by employing weights that capture both the relative areas of the target spatial units and the relative population densities of the different nominal ancillary classes, and it is typically implemented in Geographic Information System, or GIS, software. An example application demonstrates the efficacy of the dasymetric approach by comparing census tract-level and dasymetric data in an assessment of the population living in proximity to hazardous air pollutant releases in Philadelphia, Pennsylvania, using block-level data as a validation dataset.

Introduction

Many types of urban policy analyses rely on accurate and precise spatial population data. Of particular note are analyses of exposure and accessibility, where one must assess the population in proximity to, or overlapping with, some geographic feature. Examples of such analyses include the estimation of population exposed to natural and technological hazards, such as flooding or air pollution. Other relevant research applications concern access to amenities and resources, such as recreation facilities, health centers, nutritious food, or employment opportunities.

Although the U.S. Census Bureau provides high-resolution demographic data for the United States, certain variables may be available only over coarser spatial units, such as census tracts.

Other population-related datasets, such as disease incidence data, may be limited to distribution at a coarse spatial resolution for purposes of privacy protection. In many developing nations, population data at a fine resolution are not available at all, because many countries do not have the resources to invest in census infrastructure. In addition, in all these cases, population data are likely to be available aggregated to spatial units that are derived by convenience of enumeration or are a reflection of administrative or political jurisdiction boundaries and, consequently, are unlikely to capture the nature of the actual population distribution. Thus, the development of small-area estimates for urban population data remains a challenge in both developed and developing nations.

Dasymetric mapping is a technique for estimating population in small areas in situations where one has access to population data aggregated only at a relatively coarser scale (Mennis, 2009). It uses ancillary data, an additional dataset related to the distribution of population but distinct from it, to disaggregate population data from one set of spatial units to another set of smaller spatial units. The formal principles of dasymetric mapping were initially developed for a Russian mapping project in the early 20th century (cf. Petrov, 2012) and were introduced to English-speaking audiences in a series of articles appearing in the 1920s and 1930s, most notably in an article by Wright (1936). The dasymetric mapping technique, however, was little known outside cartographic circles until the widespread availability of Geographic Information System (GIS) software and digital data products that could serve as ancillary data, such as those derived from remotely sensed imagery, spurred the growth of dasymetric mapping algorithms and applications beginning in the 1990s through the present.

Dasymetric mapping more recently has been employed for a wide variety of applications that benefit from high spatial resolution population data, including environmental justice (Mennis, 2002), public health (Maantay, Maroko, and Porter-Morgan, 2008), crime (Poulsen and Kennedy, 2004), and historical population estimation (Gregory and Ell, 2005). It has also been used to create national-level, high-resolution population datasets (Bhaduri et al., 2007).

The purpose of the present article is to describe dasymetric mapping, its theoretical basis, and its implementation using GIS software. As an illustration of dasymetric mapping and its application to urban analysis, an example is presented for Philadelphia, Pennsylvania, where tract-level population data are disaggregated to sub-tract-level spatial units. These data are then used for an analysis of population residing in close proximity to facilities releasing hazardous pollutants to the atmosphere. The tract and the dasymetric data are then compared with an analogous analysis using census block-level data for accuracy assessment.

The Dasymetric Mapping Technique

Dasymetric mapping can be considered a form of areal interpolation, the transformation of data from one set of spatial units to another set of spatial units; for example, the assignment of population originally encoded in U.S. counties to a set of watershed boundaries. The original set of spatial units is referred to as *source zones* and the set of destination spatial units is referred to as *target zones*. The simplest approach to areal interpolation is areal weighting, which assumes a homogeneous distribution of the data within the source zones. Thus, data are apportioned to the target zones based on the proportional area that each source zone contributes to each target zone.

A particular case of areal interpolation occurs when the target zones are formed by the geometric intersection of the source zones with another—ancillary—polygon data layer, so that the target zones spatially nest perfectly within the source zones, and each source zone can be disaggregated into one or more target zones. Areal weighting in this case implies that given a target zone f nested within a source zone g, such that $f \in g$, then the population of the source zone can be distributed to its constituent target zones based on the area ratio (AR) of each target zone, where $AR_f = A_f / A_g$, and where A is area. The target zone population can then be estimated as $\hat{y}_f = y_g AR_f$, where $\hat{y}_f$ is the estimated count of the target zone and y_g is the population of the host source zone (Goodchild and Lam, 1980).

Dasymetric mapping can be viewed as an extension of areal weighting in which the ancillary dataset overlaid with the source layer is typically an area-class map, which exhaustively tessellates a region into nominal classes that are related to the distribution of the variable being mapped. Thus, dasymetric mapping incorporates not only the relative proportion of the contributing area of each target zone but also its ancillary class to redistribute data from the source zone to its constituent target zones. As such, dasymetric mapping employs not only the area ratio but also a density ratio among the ancillary classes to make target-level estimates. If we formally consider an ancillary class c associated with target zone f, the density ratio (DR) can be defined as $DR_c = (\hat{D}_c)/(\sum \hat{D}_c)$, where $\hat{D}_c$ is the estimated density of the ancillary class c. The total fraction (TF) integrates the area ratio and density fraction into a single term, where

$$TF_{fc} = \frac{AR_f DR_c}{\sum_{f \in g}(AR_f DR_c)} \quad . \tag{1}$$

The target zone population can then be estimated as

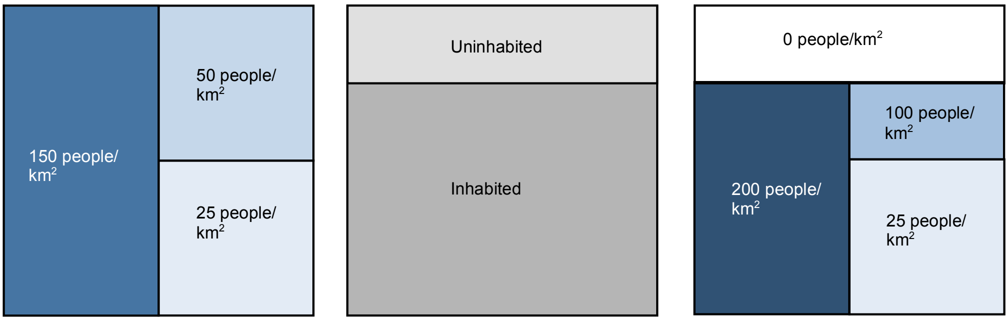
$$\hat{y}_f = y_g (TF_{fc}). \tag{2}$$

Note that the sum of the population of each source zone is maintained in the dasymetric output (Tobler, 1979), because the area ratio and density ratio both sum to 1 for each source zone. The value of $\hat{D}_c$ can be set by the analyst through his or her own expert knowledge (Eicher and Brewer, 2001) or it can be estimated by sampling the variable values of source layer zones that are spatially coincident with different ancillary data classes (Mennis, 2003). Values of DR_c can also be set directly by the analyst without setting the values of $\hat{D}_c$ in cases in which one is knowledgeable about only the relative densities among the classes.

By far the most common ancillary dataset used in dasymetric mapping of population is land use or land cover data, often derived from classified remotely sensed imagery. The most basic dasymetric mapping implementation involves the use of such ancillary data to simply distinguish between inhabited and uninhabited land area; for instance, by distinguishing between developed regions and those occupied by water or barren land. In this case, all population in a source zone bisected by uninhabited and inhabited land would be allocated to the land classified as inhabited, leaving the remaining portion of the source zone with zero population. Exhibit 1 illustrates this principle of dasymetric mapping using a schematic diagram. A set of source zones with observed population densities is shown on the left, with an ancillary land cover data layer used in the dasymetric

Exhibit 1

Illustration of the Binary Method of Dasymetric Mapping: Source Zones (left), Ancillary Layer (middle), and Target Zones (right)



km² = square kilometers.

mapping shown in the middle. The resulting dasymetric map is shown on the right, where all the population of a source zone with both inhabited and uninhabited regions is apportioned to the inhabited region. Thus, the population density of the inhabited regions of a source zone increases and is conversely held to zero in the uninhabited regions.

This general principle can be easily extended to the use of other ancillary datasets besides land use/cover, including road density data (Reibel and Bufalino, 2005), zoning- and parcel-level data (Maantay, Maroko, and Herrmann, 2007), address point data (Zanderbergen, 2011), unclassified remotely sensed spectral values (Holt, Lo, and Hodler, 2004), and scanned raster reference maps (Langford, 2007). In addition, as equation 1 indicates, the technique can accommodate not only two ancillary classes with DR_c values of zero (uninhabited) and one (inhabited) but also multiple classes with values ranging continuously between zero and one, so that population can be allocated in a more complex manner than by simply distinguishing between inhabited and uninhabited regions.

Demonstration

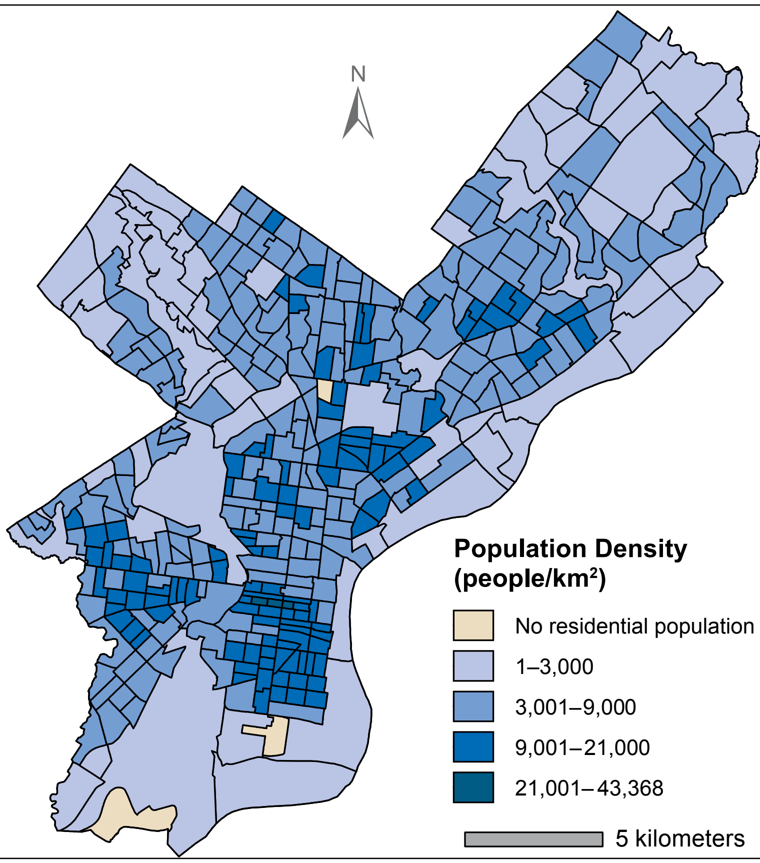
As a demonstration of the dasymetric mapping for small-area estimation of urban population, dasymetric mapping is used to estimate population data for the city of Philadelphia, mapped to the census tract level at sub-tract spatial units. Tract-level data and dasymetric mapping-level data are then compared in an analysis of the population at risk of air pollution to illustrate how dasymetric mapping can be used for urban analysis. Population data at the census block level are used as a validation dataset to compare the analytical results of the tract- and dasymetric-based measurements of population exposure. Note that this analysis is intended strictly for purposes of illustration of the dasymetric approach and is not intended to address issues of environmental exposure to air pollutants in Philadelphia, which would require a more thorough analysis.

Data and Implementation

Total population derived from the 2010 Census at the tract and block levels were acquired from the Census Bureau American Factfinder website. These data include 384 tracts (18,872 blocks) with a total population of 1,526,006 (exhibit 2). Ancillary data related to population distribution in Philadelphia are necessary to facilitate the dasymetric mapping. For this purpose, zoning data for Philadelphia were acquired from the City of Philadelphia. These polygon data encode allowable land uses and building restrictions, coded as the following zoning classes: high-density residential, low-density residential, commercial/residential mixed use, commercial nonresidential, industrial nonresidential, parks and other related nonresidential land uses, and nonresidential transportation infrastructure. These classes were aggregated to reflect low-density residential, high-density residential (including commercial/residential mixed use), and nonresidential areas (exhibit 3).

Exhibit 2

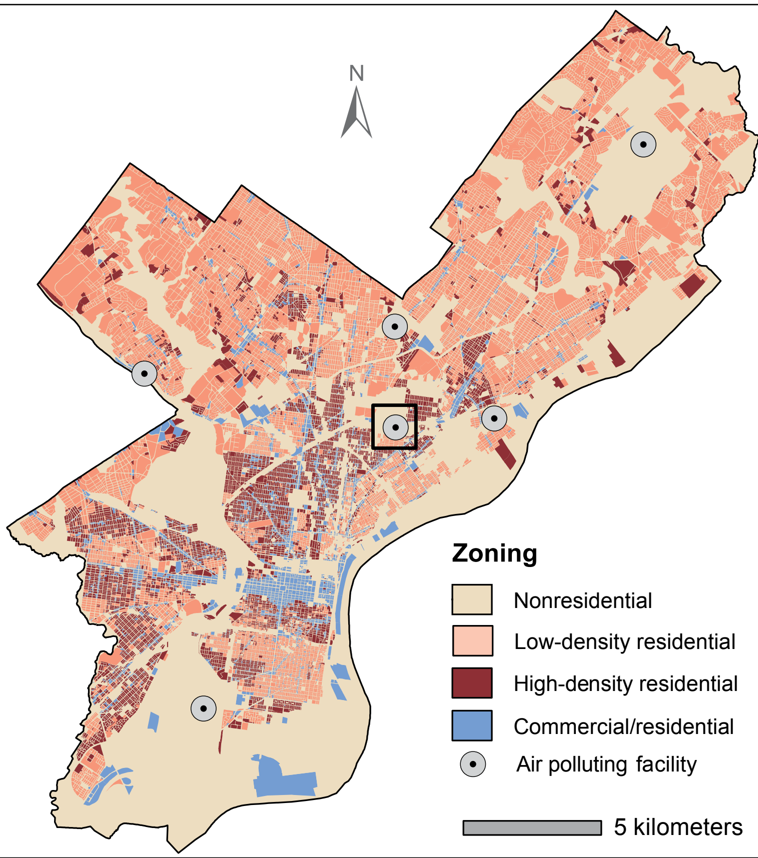
Map of Population Density by Tract in Philadelphia



km² = square kilometers.
Source: U.S. Census Bureau, with calculations by the author

Exhibit 3

Map of Zoning Classes Used As Ancillary Data in the Dasymetric Mapping: Nonresidential, High-Density Residential, and Low-Density Residential



Note: The locations of air polluting facilities are also included.
Source: City of Philadelphia, with calculations by the author

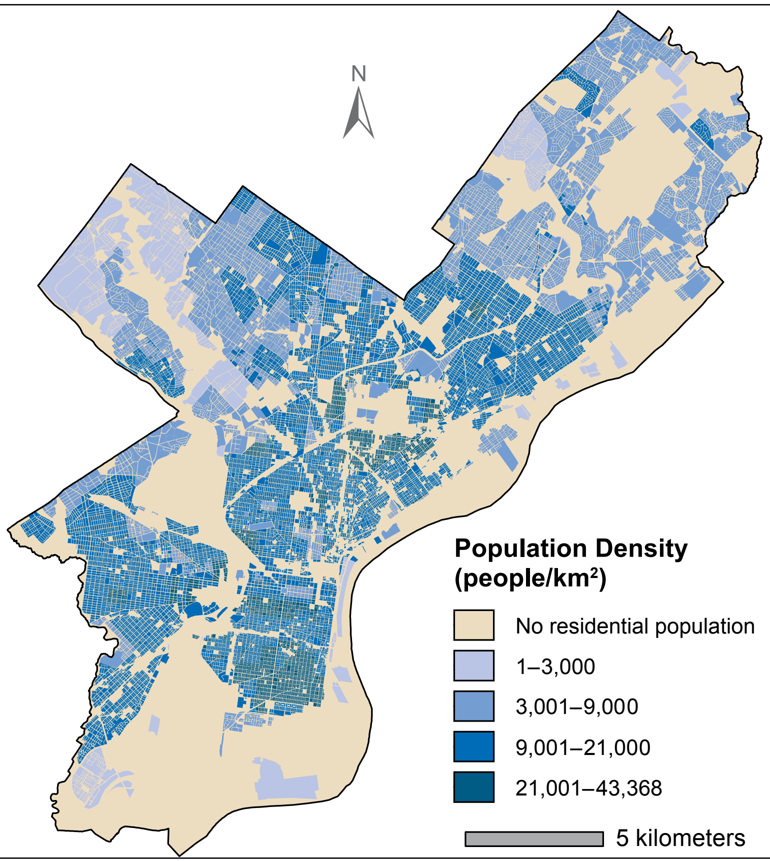
GIS software was used to process the data, perform the dasymetric estimation, and implement equations 1 and 2. The tract layer and the ancillary zoning layer were intersected to produce a target layer composed of 30,271 polygons. Each term in equation 1 was then calculated and stored in a field in the target layer attribute table. The area ratio (AR_f) was calculated as the ratio of the target zone area to its host source zone (tract) area. The density ratio for the spatial ancillary zoning class data (DR_c) was set to values of 0.30 for low-density residential areas, 0.35 for both the high-density residential areas and the commercial and residential mixed-use areas (typically downtown apartment buildings with stores located on the first floor), and 0.0 for the other nonresidential zoning classes. Although these values are acknowledged as being somewhat arbitrary, they reflect the exclusion of population from nonresidential areas of the city and also the greater concentration of population in high- versus low-density residential zoning classes.

The value for $AR_f DR_c$ was calculated and encoded in another field in the target layer attribute table. Using a summarize function in the GIS, the sum of all target layer polygons' $AR_f DR_c$ value was calculated for each individual tract, and these data were joined onto the target layer attribute table. The TF_{fc} value—that is, the ratio of each target polygon's $AR_f DR_c$ to the sum of all $AR_f DR_c$ in that target polygon's host tract—was then calculated and stored in another field in the target layer's attribute table. Finally, the population value for each target polygon was calculated according to equation 2 by multiplying the host tract population by the TF_{fc} for each target polygon.

The resulting dasymetric map of population density is shown in exhibit 4. One can clearly see that the precision of population distribution is far higher in the dasymetric map as compared with the tract-level map. The tract-level map has only three small tracts that have no residential population, whereas the zoning map clearly shows large areas of the city that are nonresidential. The dasymetric map prohibited population from the areas zoned nonresidential and allocated the remaining population to the residentially zoned areas. Areas zoned high-density residential and commercial and residential were allocated population at a greater proportion as compared with low-density residential zoned land, after accounting for differences in the area of the target polygons.

Exhibit 4

Dasymetric Map of Population Density in Philadelphia



km² = square kilometers.
Source: Calculations by the author

Calculating the Population Located Near Air Polluting Facilities

As a way of illustrating the utility of the dasymetric mapping, a relatively simple analysis is conducted of the population located near facilities releasing pollutants to the air. Data on the locations of facilities releasing or disposing of more than 10,000 pounds of hazardous air pollutants on site in 2010 were acquired from the U.S. Environmental Protection Agency's Toxic Release Inventory Program. Six facilities were mapped (exhibit 3) and population counts were tallied within a series of distances from the facilities, using the tract, block, and dasymetric data population maps. First, the total populations of the six tracts, blocks, and dasymetric polygons that contained the six facilities were calculated. Then, those tracts, blocks, and dasymetric polygons within 0.25 kilometer of a facility were selected, those within 0.5 kilometer of a facility were selected, and so on up to 1.0 kilometer from a facility.

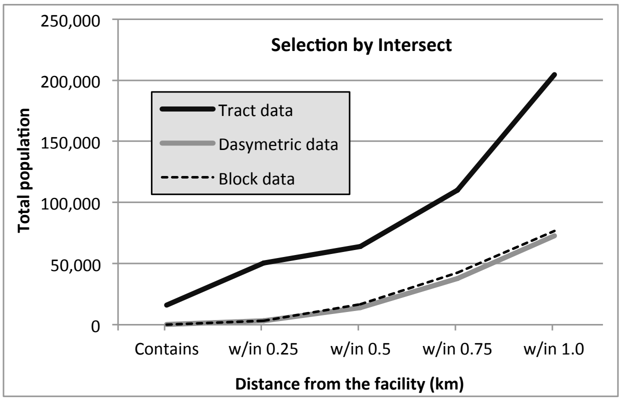
Two prominent GIS-based methods of selecting polygons within a certain distance of a set of point features were employed (Mennis, 2003). The first method, referred to as the *intersect* method, selects all those polygons that overlap the distance buffer. So, for example, a tract for which any portion of the tract falls within the specified distance of a facility would be selected as being within that distance of that facility. The second method, called the *centroid* method, selects only those polygons whose geometric center falls within the buffer distance.

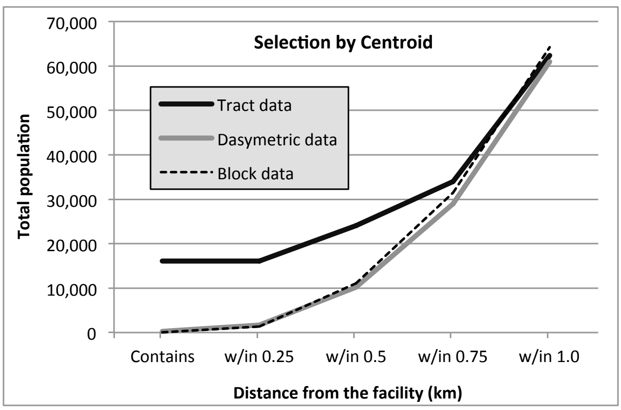
Exhibit 5 shows two graphs indicating the differences among the tract-level, block-level, and dasymetric-level population calculations, with total population shown on the y-axis for each measured distance from the each facility. The graph at the top shows the results for the intersect method of polygon selection and the bottom graph shows the results using the centroid method. For both methods of selection, the tract-based calculations clearly tend to overestimate the total population nearby as compared with the dasymetric-based calculations. For the intersect method of selection, the difference between the tract data and the dasymetric data increases with increasing distance. At a distance of 1 kilometer, the tract-level population estimate is nearly three times the dasymetric-level estimate. This pattern occurs because the number of tracts under consideration increases substantially as the distance from a facility increases—because the tract data are a much coarser resolution than the dasymetric data, the area considered within any given distance of a facility using the intersect method is much larger using the tract data as compared with the dasymetric data.

For the centroid method, the maximum difference between the tract and dasymetric datasets is observed at distances nearest to the facilities. At a distance of 0.25 kilometer, the tract-level population estimate is nearly 10 times the dasymetric-level estimate. As the distance increases, the estimation of the total populations for the different datasets tends to converge at a distance of approximately 1 kilometer. The reason for this can be observed in exhibit 6, which shows a closeup view of the facility in the bolded box in exhibit 3, where the bolded circle and cross-hatch pattern show the area within 0.5 kilometer of the facility. The tract data on the left indicate that the facility lies nearly at the intersection of three separate tracts; thus, the calculation of the population at risk, using data derived from the host tract, is likely to be inherently inaccurate, because air pollutants would likely spread across tract boundaries. The dasymetric data on the right shows a far greater spatial variation in population distribution, where it is clear that most of the area within 0.5 kilometer of the facility is nonresidential. Indeed, the entire population within the 0.5-kilometer distance is concentrated in the southern portion of the buffer.

Exhibit 5

Graphs of the Total Population Within Certain Distances of the Air Polluting Facilities Using the Tract, Block, and Dasymetric Population Data

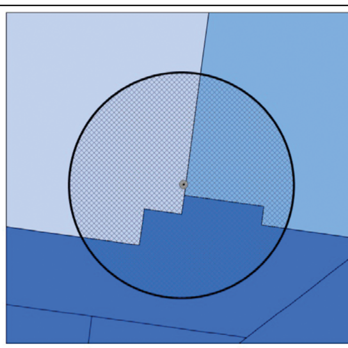


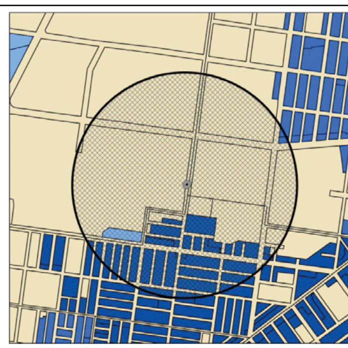


km = kilometer. w/in = within.

Exhibit 6

A Visual Comparison of the Tract (left) and Dasymetric (right) Population Data Within 0.5 Kilometer of the Air Polluting Facility Shown in the Box in Exhibit 3





Importantly, for both the intersect and centroid selection methods, the graph lines for the block-level data closely mirror those of the dasymetric data. Indeed, it is very clear visually that the tract-level data for both methods substantially overestimate the population within a given distance of a facility, whereas the dasymetric data provide a far more accurate depiction.

Conclusion

This article outlines the general principles of dasymetric mapping and offers a demonstration of its efficacy in urban population analyses. The use of coarse resolution population data relative to the scale of analysis, or the use of population data aggregated to spatial units unrelated to the actual distribution of population, can result in inaccurate assessments of urban population exposure and accessibility. Dasymetric mapping offers substantial potential for improving estimates of population exposure and accessibility through the estimation of population at a much finer scale, through the integration of often publicly available ancillary data. In addition, the basic principles of dasymetric mapping are relatively easy to implement in many commercial and open-source GIS software packages.

More sophisticated approaches to dasymetric mapping that rely on regression, kriging, and iterative algorithms have also been developed (for example, Leyk, Nagle, and Buttenfield, 2013; Liu, Kyriakidis, and Goodchild, 2008). Research suggests, however, that, although the accuracy of dasymetric mapping is dependent on the nature of the algorithm and ancillary data source, even relatively simple efforts to incorporate ancillary data into dasymetric population estimation typically result in significant improvements in population estimations over areal weighting (Langford, 2013; Zanderbergen and Ignizio, 2010). Thus, urban analysts with even basic knowledge in GIS should be able to effectively implement and benefit from dasymetric mapping.[1]

Acknowledgments

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[1] The dasymetric mapping technique described here was implemented in two publicly available scripts for ArcGIS (Environmental Systems Research Institute, Inc.). The first was implemented by Rachel Sleeter at the U.S. Geological Survey (Sleeter and Gould, 2007) and is available at http://geography.wr.usgs.gov/science/dasymetric/. The second was implemented by Torrin Hultgren (Mennis and Hultgren, 2006) and is available at http://enviroatlas.epa.gov/enviroatlas/Tools/Dasymetrics.html. Responsibility for the use and application of the dasymetric mapping scripts and their products lies with the user.

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An Integrated Framework To Support Global and Local Pattern Assessment for Residential Movements

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Abstract

Residential mobility is a defining characteristic of society in the United States. A 2003 U.S. Census Bureau migration report highlights that more than 22 million people were characterized as domestic migrants between 1995 and 2000. Understanding resulting patterns is important because it provides insights on rationale for movement and for housing, services, and supporting infrastructure implications. The method for facilitating pattern identification and exploration of movements unfortunately is lacking. It is often the case that migration and movement are considered in aggregate terms—between cities and counties in a state or region. Individual behavior reflective of a movement trajectory is therefore masked in various ways. Survey evidence also indicates that residential movements of short distance—for example, those occurring within a city or county—reflect the greatest proportion of total migrations. To address limitations, this research proposes a framework integrating spatial analytical methods to support pattern analysis for individual movements, relying on detailed information of origin and destination change. The framework can explore the patterns at both the global and local levels. The framework is designed using various visual analytic interfaces coupled with statistical evaluation and significance testing, representing both exploratory and confirmatory assessment. The integrated framework is applied to study residential movement involving 2,636 housing changes in Franklin County, Ohio, and effectively estimates some special global and local patterns from those events.

Introduction

Residential mobility is a defining characteristic of U.S. society today. Studies of residential changes can enable better understanding of how humans and the environment engage in mutual interactions in different places and at different scales. For the researchers, including geographers and urban planners whose major interest is to comprehend and design better urban environment, it is especially meaningful to examine the effect of a collection of residential movements, if such spatial data are available, as a way of studying the immediate changes in the composition of many urban neighborhoods. The information associated with change of residence can also provide insights into the mechanism under which urban structure constrains residential choices. Therefore, residential movement is an important issue.

Research on residential movement has been carried out for more than a century (Quigley and Weinberg, 1977; Ravenstein, 1885) and is still of broad interest to researchers today (Dieleman, 2001; Rae, 2009). A major part of those research attempts was rooted in cartographic technique and gradually has developed to spatial data visual analytics, in which computational tools have been extensively involved (Andrienko et al., 2008; Rae, 2009; Ravenstein, 1885; Tobler, 1987). The disadvantage of spatial data visual analytics is its incapability for confirmatory hypothesis testing in spatial pattern identification.

On the other hand, the confirmatory analyses actually have been applied into movement pattern since the 1960s. Depending on mathematical and statistical methods, those works essentially transformed the spatially complex form of movements into manageable geometry and so focused more attention on the movements' spatial pattern (Adams, 1969; Brunsdon and Corcoran, 2006; Fotheringham and Pitts, 1995; Morrill, 1963). The disadvantage of those works is that they were excessively focused on the "global map" or general "law." Meanwhile, such method is heavily based on aggregated data.

Compared with the study based on aggregated data at the macro level, it is actually more important for geographers and urban planners to understand the pattern of residential movement at the micro scale with individual records, because the pattern can directly and accurately illuminate the change of social composition in a county or city. The difficulty with such perspective shifting is the significant raising of data size. With hundreds and thousands of individual movement records, significant patterns can be masked (Andrienko et al., 2008). Taken with redesigned visual analytics, however, statistical methods might prove efficient and effective for exploring and evaluating patterns in mass movement data. Exploratory spatial data analysis (ESDA)-based studies recently have recognized this necessity, and researchers have suggested possibilities for combining visual analytics and statistical methods (Thomas and Cook, 2005). As yet, a systematic framework has not been developed that reflects this necessity, synthesizing both confirmatory and exploratory approaches.

Method

Generally speaking, spatial patterns refer to the specific spatial configuration or arrangement of features of interest over space (Chou, 1995). Insights into the characteristics of spatial patterns result in knowledge of the dynamics of spatial processes (Getis and Boots, 1978).

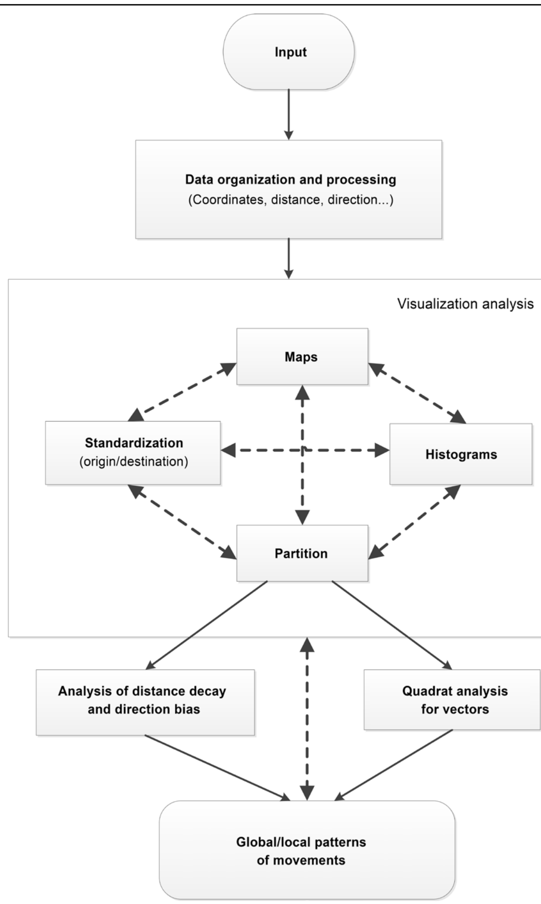
Movement data are records of spatial trajectory for tracking behavior over space or, more abstractly, as a directional line with fixed length. In geometry, such form of a trajectory is essentially a vector of distance and direction. Based on this perspective, the spatial pattern in residential movements can refer to a spatial arrangement of the dual components: moving distance and moving direction. Distance is a basic means for measuring the space separating objects; it is also used to quantify the possible intensity of a relationship and interaction between geographical events. The distribution of moving directions is a reflection of urban evolution. Research in spatial arrangement of moving directions within a city can be used to examine whether a specific planning strategy has been effective in generating movements toward certain areas (Quigley and Weinberg, 1977). A research difficulty is figuring how to analyze the features of distance and direction simultaneously.

The proposed framework is to resolve this difficulty by both exploratory and confirmatory approaches.

Exhibit 1 illustrates a proposed framework with general structure for data analysis. First, the movement data records are processed and converted into a standard format. Using the manipulated

Exhibit 1

Conceptual Framework of the Proposed Toolkit



data, visualization-based analysis is then performed, incorporating exploratory data analysis using multiple interfaces. Based on visual analytics, quantitative examination is included to test visually detected patterns at both the global and local scales.

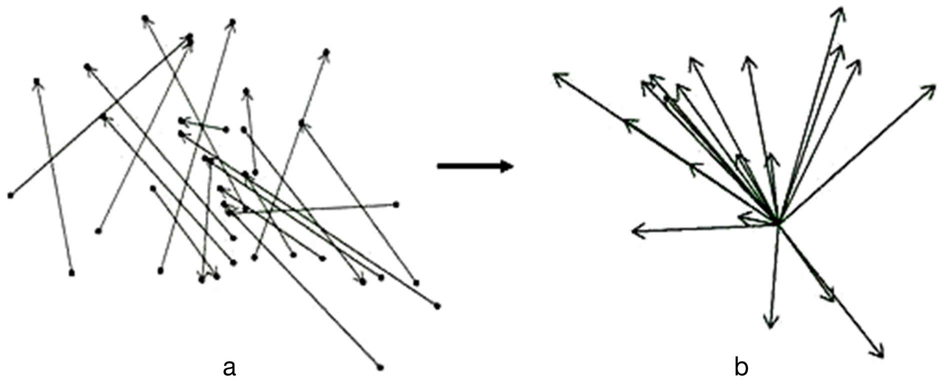
Standardization of Movement Data

A unique method of data standardization is suggested here as the first step for pattern analysis: moving all the vectors' origin or destination to an identical center while maintaining distance and direction. The effect is shown in exhibit 2.

The standardized movements intuitively provide a more direct and clear illustration of the distribution of distances and directions. Distances are abreast with each other from the same start, and directions are arranged in a uniform circle to form something like a rose. In this standardized interface, potential patterns in the arrangement of distances and directions cannot be easily masked. Thus, patterns in the distances and directions can be simultaneously illustrated.

Exhibit 2

Movement Data Standardization



Notes: (a) All the vectors are distributed at their original locations over the area before the standardization step. (b) All the vectors' origins are moved to an identical center while maintaining their distances and directions.

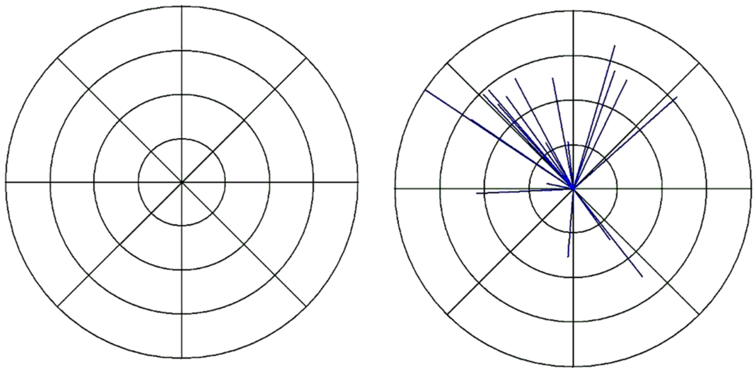
Exploratory Analysis Interface

Given the standardized movement data, one can imagine that they are distributed along a series of circular sections. The width for each circular section represents a unit range of length away from the established center. Further, each circular section can be separated into several equal fan sectors based on a directional range. Based on this idea, as shown in exhibit 3, a partition scheme is possible.

Based on the partition scheme over standardized vectors, a color gradation is applied to each section to enable visual understanding. The darkness of color in each section is in accordance with the counts of endpoints in this section. The more endpoints in a particular section, the darker the fill color.

Exhibit 3

A Partition Scheme for Standardized Vectors



Notes: (a) The partition scheme is generated by identical distance and direction intervals; concentric circles surrounding an established center partition the vectors by equal length interval (the radius of the largest circle equals the largest vector length), and homocentric rays from the center partition the vectors by equal angle interval. (b) The partition scheme is set over standardized vectors.

Statistical Analysis of Movement Patterns

Because the partitioned scheme parallels the quadrat analysis interface, a type of statistical testing, the goodness-of-fit metrics, can be applied to examine whether the actual distribution of distance and direction follows a theoretical pattern. Such a method is also meaningful for exploring the pattern for a specific subset of movements and for testing whether this subset possesses a pattern that is similar to or different from the global pattern. Using this kind of comparison, it is possible to explore whether community dissimilation or mixture is occurring in a city or region.

In practice, the number of endpoints from the entire data (global) and the subset (local) in each section is counted respectively. It follows that the global counts for each section can be compared statistically with the local number, by linear regression analysis. The counts for the local data are treated as the dependent variable and the counts for the entire data are treated as the independent variable. Then, the regression function is—

$$L_i = (a \times G_i) + b + \varepsilon_i, \tag{1}$$

where L_i equals the counts of the endpoints for local data in section i, G_i equals the counts of the endpoints for entire data in the same section i, a and b are the regression parameters, and ε_i is the regression error for the section i. The similarity between global and local patterns can be tested by the coefficient of determination, R-square, of the linear regression model. Here, R-square indicates the proportion of the local pattern "explained" by the global pattern. The lower the R-square value, the less consistency exists between local and global patterns.

Distance Decay and Directional Bias

That locations separated by shorter distances are more related has been globally examined and has become a fundamental theory for spatial science, the theory of "*Distance Decay*" (Fotheringham and

O'Kelly, 1989; Taylor, 1975). Given this global theory, within a study area, more residential movements will reasonably be expected with short distance than with longer movements. The question is how to quantitatively measure the frequency of movements with specific moving distances. Taylor (1975) has given two model categories and five specific expressions for describing the quantitative relationship between the moving distance and the movement intensity.

1. Single-log models $f(d) = d^m$.

Square root exponential: $\log I = a - (b \times \sqrt{d}\,)$ (2)

Exponential: $\log I = a - (b \times d)$ (3)

2. Double-log models $f(d) = \log^m d$.

Normal: $\log I = a - (b \times d^2)$ (4)

Pareto: $\log I = a - (b \times \log d)$ (5)

Log-normal: $\log I = a - [b \times (\log d)^2]$, (6)

where I is the intensity of movements, d is the distance, and a and b are regression parameters to be estimated. Among these five specific forms, the issue to resolve is which one, if any, would best describe the distance decay tendency in observed behavior. Different estimates and values in parameters may help reveal information associated with moving behaviors. The estimation relies on a statistical test, such as R-square or P-value. The test can be formalized as—

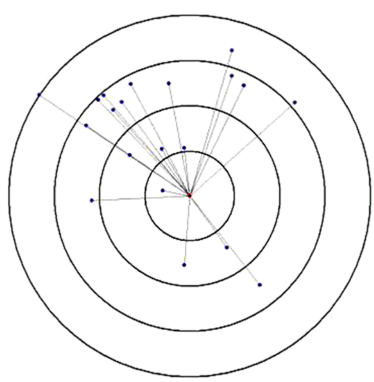
$\lambda_x \leftarrow g_x\ (I,d)$, (7)

where λ_x is a test index (that is, R-square or P-value) used for evaluating the regression equation $g_x\ (I,d)$.

In the standardized interface, intensity of movements is equivalent to intensity of endpoints; thus, movement intensity is derived based on endpoints within different distance ranges. Exhibit 4 illustrates this consideration.

Exhibit 4

Interface for Investigating Global Distance Decay Tendency



Intensity I_i is calculated based on the counts of endpoints and the area of each circular section. The series of intensities, then, is examined based on their relationship to the radius of the corresponding circular section d_i.

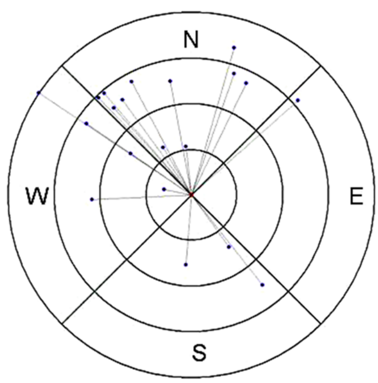
To detect the potential directional variation in distance decay, each circular range is separated into different directional sections. Exhibit 5 is showing an example in which each circular range is directionally partitioned into north, south, east, and west sections.

Then, the five specific forms of decay models are examined with respect to each directional section.

The similarity or difference between models for global decay and directionally partitioned decay can be evaluated by comparing the confidence intervals of regression parameters. Because the interest is decay tendency, the evaluation needs to focus on only the slope parameter b in a regression model. After a regression model for global data has been derived, $y = \alpha + \beta x + \varepsilon$, a confidence interval with a specific significance level for the slope parameter β can be derived as well (β_{min}, β_{max}). Then, the slope parameter b_i (i represents the four directions respectively) in the regression model for each directional partition is tested for whether $b_i \in (\beta_{min}, \beta_{max})$. If the test derives a positive result, it indicates that the two regression models possess a significantly similar slope. In practical terms, $b_i \in (\beta_{min}, \beta_{max})$ means that the data located within the i directionally partitioned data zone possess a similar decay tendency as the entire dataset. The global regression model for distance decay can be appropriately used to describe the decay tendency for movements along a specific direction.

Exhibit 5

Interface for Investigating Distance Decay Over Different Directions

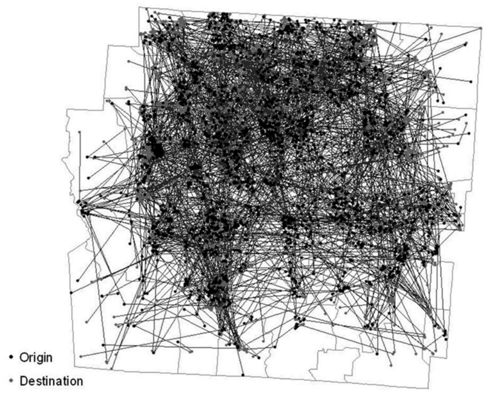


Application

To test those functions in the framework, 2,363 residential changes, which were derived from 39,232 residential transactions of home sales and purchases in Franklin County, Ohio, from October 2004 to April 2006, are geocoded as matched pairs in a Geographic Information System, or GIS, database. The 2,363 records are regarded as 2,363 movement vectors, as shown in exhibit 6.

Exhibit 6

The 2,363 Residential Movements in Franklin County, Ohio



According to a series of reports by the Mid-Ohio Regional Planning Commission, from 2000 to 2030 the northwest region of Franklin County is planning for more employment opportunities and increased economic growth. Thus, cities in the regions surrounding U.S. Highway 33, including Dublin, Upper Arlington, and townships in the northwest part of Franklin County, will likely attract more residents. Because the research data are derived from residential changes from 2004 to 2006, it is reasonable for the planners from the Mid-Ohio Regional Planning Commission who made the regional planning strategies for Franklin County to assume that the patterns of those residential movements will reflect aspects of planned behavior. To assess observed behavior, this application will therefore use the framework to thoroughly explore patterns in the 2,363 residential movements.

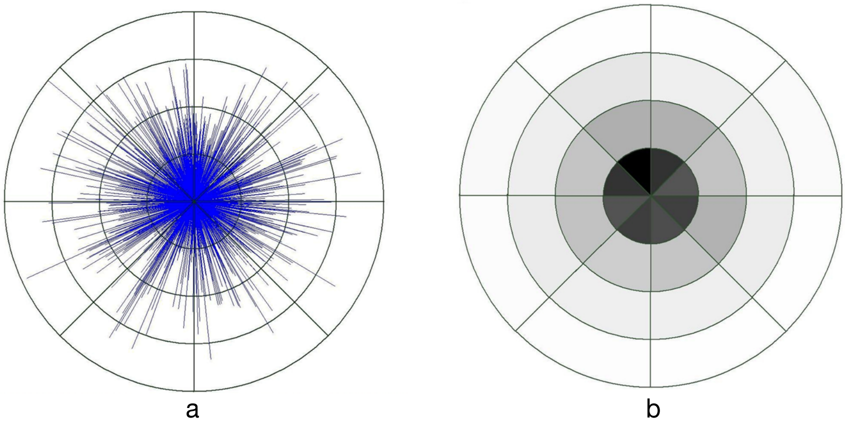
Exploratory Analysis of Distance and Direction

To get more meaningful insights about spatial pattern for these residential movements, visual analytics are used. Following the procedures of vector standardization and the partition scheme introduced previously, a visual display for the distribution of the dual features is created. This scheme with standardized data offers an integrative version for the two spatial features, as illustrated in exhibit 7.

The counts of endpoints in each distance-direction section of the partition scheme reflect the number of movements for a corresponding distance and direction range. The counts of endpoints, or the frequencies of movements, can be visually illustrated by color gradation. By reading the color gradient tendency, the general pattern for the 2,363 movements becomes more evident. The eight sections of the innermost circle are much darker than those for any peripheral section, suggesting that distance decay is a dominant pattern in residential changes. For the distribution of directions, an imbalanced pattern is clear, which suggests a tendency for more residential changes to be oriented toward the northwest.

Exhibit 7

Partition Scheme Over the Standardized Vectors (a) and the Color Gradient Showing Endpoint Density (b)



Directional Bias in Distance Decay Tendency

To further explore the directional bias in distance decay for the 2,363 residential movements, the relationship between intensity of movements and moving distance is explored. Exhibit 8 illustrates the interface for such exploration.

Exhibit 8

Visual Analytics Exploring Movement Intensity (a) and Moving Distance (b)

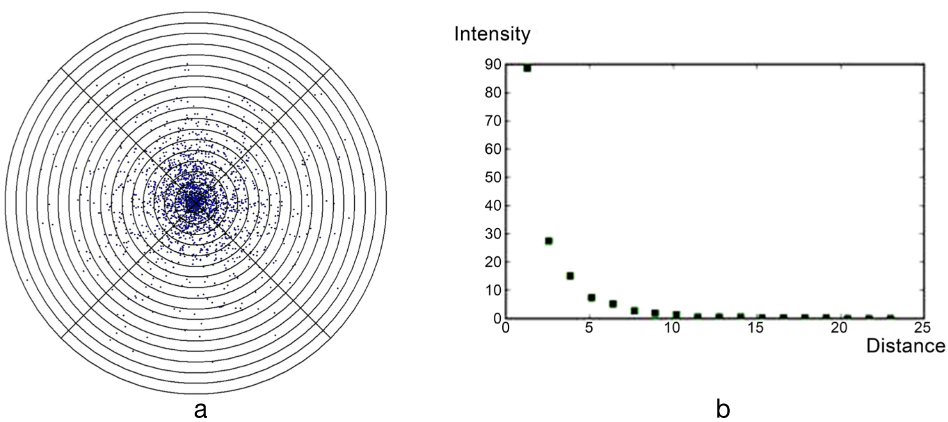


Exhibit 8 also illustrates the global relationship between intensity of endpoints in each distance rings (without considering the directional partitions) and the radius of each distance circle.

Based on such an interface, the framework further estimates that, for all the movements, the most appropriate regression function is the *exponential* equation, because it has the highest R-square value, 0.9757. Thus, the function used for describing the global distance decay tendency is established as—

$$I = \exp\,[4.273 - (0.384 \times d)]. \tag{8}$$

Such exploration is conducted for data that have been categorized into different directional zones as well. Exhibit 9 summarizes the quantitative descriptions of distance decay for the four directional zones. It is interesting to researchers to notice that *square root exponential* function is most appropriate for each of the four directions, but none of them follow the same trend as the global tendency. The *square root exponential* function mathematically results in a more gradual rate of decay than the basic *exponential function*. This result actually indicates that the decay tendency is faster globally than it is for any of the directional zone subsets considered.

The framework further compares the global decay to the directionally partitioned decay statistically. To implement this comparison, the global pattern must be modeled by the *square root exponential* function in accordance with the model for each partitioned subset. A *square root exponential* regression equation for the global pattern is—

$$I = \exp\,[7.503 - (2.377 \times \sqrt{d}\,)], \tag{9}$$

with an R-square value of 0.964, which means this model can also appropriately summarize the global distance decay tendency. The test is to evaluate whether the value for the global slope, -2.377, is significantly different from the slope for each of the directionally partitioned subsets. Exhibit 10 summarizes the confidence interval (with 95-percent significance level) of the global slope as well as the slope of each partitioned subset.

Exhibit 9

Estimated Distance Decay Functions for Movements in Each of the Four Directional Zones

Directional Zones	Function	R-Square
North	$I = \exp\,[5.576 - (2.166 \times \sqrt{d})]$	0.987
South	$I = \exp\,[5.395 - (2.162 \times \sqrt{d})]$	0.974
East	$I = \exp\,[5.390 - (2.123 \times \sqrt{d})]$	0.963
West	$I = \exp\,[5.293 - (2.060 \times \sqrt{d})]$	0.983

Exhibit 10

Slope Values of Regression Models for Global and Local Datasets

Global	95% Confidence Interval		East	West	North	South
	Lower	Upper				
– 2.377	– 2.621	– 2.134	– 2.123	– 2.06	– 2.116	– 2.162

Exhibit 10 clearly shows that the slope values for the north, east, and west subsets are not within the 95-percent confidence interval (-2.621, -2.134) of the global slope. This result indicates that the decay tendency for the north, east, or west partition is significantly (with 95-percent significance level) different from the globally estimated decay tendency. While the globally estimated tendency indicates a sharper decay slope, the decay tendency for the north, east, and west partitions is significantly smoother. So, if the globally based model is used to describe the pattern of distance decay for the entire set of movements, such a directional effect cannot be appropriately captured.

Pattern Comparison Between Global and Local

Exploration of whether the pattern for a subset of the data is consistent with the global pattern can help reveal whether residential changes lead to social differentiation in a city or region. As an example for such exploration, the 20 richest census tracts are considered locally interesting. Then, the residential movements with their destinations located inside these 20 census tracts are selected to form a sample subset. A research question is: "Is the distribution of distances and directions for those movements with destinations in the richest neighborhoods significantly similar to the respective distributions for all movements in Franklin County?"

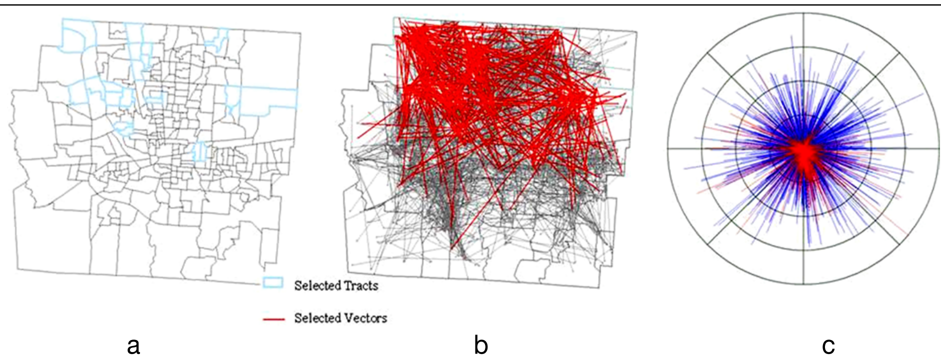
In exhibit 11a, highlighted polygons are the 20 richest census tracts in Franklin County. In exhibit 11b, the movements whose destinations fall within the 20 census tracts are highlighted. This sample contains 538 movements. Exhibit 11c is similar to exhibit 7 but the vectors are standardized by destinations. Those highlighted vectors correspond to the selections in exhibit 11b.

Researchers in this study noticed that most of the highlighted vectors are oriented toward the north, because 18 of the 20 selected tracts are in the northern portion of Franklin County.

Further, based on the comparison metrics introduced previously, the framework tests the significant similarity or difference between the local pattern of the 538 selected movements and the global pattern of all the data by *linear regression* model. Exhibit 12 summarizes the counts of endpoints with respect to the entire (global) and subset (local) movements in each partition section.

Exhibit 11

Selected Movements With Destinations in the 20 Richest Census Tracts



Notes: Exhibit 11a highlights the 20 richest census tracts in Franklin County, Ohio. Exhibit 11b highlights the movement vectors whose destinations fall within the 20 census tracts. Exhibit 11c standardizes the vectors in exhibit 11b.

Exhibit 12

Counts of Endpoints in the Partitioned Sections for Entire Data and Subset Data

Circle Order	Global or Local Counts	NNE	ENE	ESE	SSE	SSW	WSW	WNW	NNW
First inside circle	Global	201	179	212	265	214	177	199	186
	Local	35	30	55	92	57	43	47	28
Second inside circle	Global	51	64	62	84	83	63	81	61
	Local	7	5	22	34	23	14	12	6
Third inside circle	Global	17	21	18	27	17	16	20	17
	Local	0	1	4	5	3	3	7	1
Outside circle	Global	3	4	7	2	2	6	2	2
	Local	0	0	2	0	1	1	0	0

ENE = east-northeast. ESE = east-southeast. NNE = north-northeast. NNW = north-northwest. SSE = south-southeast. SSW = south-southwest. WNW = west-northwest. WSW = west-southwest.

Note: Each row of the table records the counts in each distance circle, starting from the NNE corner and progressing in clockwise order.

Then, to estimate the relationship between the global and local patterns, the framework derives a linear regression function as follows.

$$Local = -2.02 + (0.255 \text{ x } Global), \quad (10)$$

with a coefficient of determination (R-square value) of 0.87. This R-square value indicates that the two patterns, in general, are statistically similar. In short, the local pattern, which is for the subset of movements with their destinations in the richest regions of the study area, is similar to the global pattern for the complete set of 2,363 residential changes.

Summary

Through a series of analyses, the framework facilitates pattern exploration for the 2,363 residential movements in Franklin County, Ohio. At the global level, distance decay has been confirmed as a significant tendency, but the framework also quantitatively detects that a single equation derived from the entire dataset is not able to fully describe characteristics in the distance decay tendency, because the directional bias is also established as a significant effect. For these northwest-oriented movements, the slope for their distance decay tendency is not as steep as the general trend.

The framework also facilitates investigation of local characteristics associated with the identified movement patterns as well. The research examines movements into the richest 20 census tracts in Franklin County. Their movement pattern is established and compared with the global pattern. The framework confirms that the local pattern is actually similar to the global. This finding indicates that these "rich" residential movements did not exhibit a significant difference in spatial behavior from the complete set of movements in this research.

Conclusion

This research introduces a framework consisting of a series of functions and methods for exploratory and confirmatory examination of spatial patterns from mass residential movements at a micro scale. The spatial pattern of movement in this research is treated as the arrangement of distances and directions over space. Then, to efficiently detect patterns from mass movements, the framework provides ways to visually standardize movements. Based on standardized movements, a partition scheme is introduced. The distribution of movement distance and direction can then be qualitatively, as well as quantitatively, investigated. By using such an analytical process, movement patterns for 2,363 residential changes within Franklin County, Ohio, have been evaluated. Further, local deviations associated with subsets of movements can be identified from global movements. This technology has been used to examine patterns for 538 movements from the complete dataset. The successful application has confirmed the effectiveness of the proposed framework.

Some future developments can be made for improvement. First, some functions of the framework should be more objective for achieving statistically robust insights; for example, the size of the distance-directional interval in the partition scheme. Second, temporal dimensions should be included for analysis as well, because the distribution of residential movements over time can also suggest insights into how humans and the environment interact. Such developments indicate that this framework can exhibit additional strength for effectively and efficiently detecting information from mass residential movements.

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Spatial Experiences: Using Google Earth To Locate Meanings Pertinent to Sense of Place

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Abstract

Using aerial images that enable research participants, during an interview, to discuss and locate points of spatial significance in their community represents an innovative approach to place-based research. This method allows for participants to discuss spaces relative to their associated meanings and enables researchers and community planners to understand the makings of place in a particular community. This article discusses how researchers and planners can use Google Earth to organize and spatially reference qualitative data to allocate community members' subjective meanings of particular spaces and landscapes. The article includes examples from the Dominican Republic to outline the suggested approach.

Introduction

"…to experience a geographical place, it seems, is the want to communicate about it" (Ryden, 1993: 19). Maps provide users and researchers copious information by detailing places relative to one another; however, perceptions of human experiences often remain unnoticed in maps. Researchers use mental maps to better visualize people's experiences and to understand how people view their world to seek meanings not necessarily visible (Relph, 1997; Ryden, 1993; Wise, 2014). Google Earth represents a contemporary and innovative approach to seeking meanings and insight into everyday spaces and places and to locating and reinforcing understandings of sense of place and sense of community. The approach outlined in this article can be useful for community planners to get a sense of how people engage with and interact in particular spaces and places to better inform future decisionmaking. Using aerial images during the interview process provides research participants the ability to spatially identify and discuss points of spatial significance in a particular community. Cognitive mapping exercises, in which researchers use Google Earth to reference data gathered from identified points on the map and subsequent interviews, therefore enable interviewees to characterize pertinent discourse regarding experiences, perceptions, and imaginations, which can all be referenced spatially. Using Google Earth as a tool to organize and spatially reference qualitative data will enable researchers to allocate subjective meanings of particular landscapes with which members of a community interact frequently. Moreover, enabling researchers to understand the makings of place in a particular community further integrates sociological and geographical understandings.

The conceptual and practical method of data collection presented in the following section was piloted in the Dominican Republic as part of a wider ethnographic study. Interviews were held with members of the community using Google Earth images to encourage interviewees to discuss significant spaces and places in the community while the researcher referenced these points. Subsequent data collected during field conversations and participant observations can also be stored along with interview data in placemarks to efficiently organize and spatially reference a wider collection and range of data.

Theoretical Framework

Geographers and planners attempt to understand people's perceptions and experiences in and of the spaces, places, and landscapes with which they socially interact. Lynch's (1960) work on social psychology concerning structure, identity, and meaning has provided foundational conceptual insight on place and social perceptions. Furthermore, this insight concerns how individuals evaluate spaces, places, and landscapes. Mental maps and imaging practices intentionally rely on individuals' psychological perceptions of social spaces. Lynch (1960: 6) noted "…there may be little in the real object that is ordered or remarkable, and yet its mental picture has gained identity and organization through long familiarity." Lynch's (1960) typologies for interpretation involve paths, edges (for example, perimeters or boundaries), nodes (points), landmarks, and element interrelations. Similarly, Sack (1997), writing from a geographical standpoint, conceptually complements Lynch's approach, suggesting that to understand places researchers should address social relations—adding supplemental meaning to paths, edges, and nodes. Sack (1997: 155) suggested "…awareness is the capacity to see things not only from our own partial and personal perspective but also from other points of view." Documenting points on Google Earth maps also enables researchers to consolidate multiple points of view spatially—which is the main point this article will suggest and show.

In reiterating mental mapping approaches, this technique has been a core approach of behavioral geographers, who pioneered humanist thought (Madaleno, 2010). Researchers who have conducted mental mapping exercises have attempted to explore lived experiences to uncover people's cognitive perceptions, understandings, and images of particular places (Downs and Stea, 2005; Fenster, 2009; Gould and White, 1986; Madaleno, 2010; Smiley, 2013; Wise, 2014). Moreover, mental mapping endeavors have offered researchers insight into cognitive perceptions of, for example, globalization (for example, Madaleno, 2010), relative locations (for example, Gould and White, 1986), local landscapes (for example, Wise, 2014), migration (Kusek and Wise, 2014), and why people travel particular routes (for example, Wood, 1978). Building on concepts offered from mental maps, using Google Earth images provides the researcher and the interviewee the opportunity to identify and spatially reference points during discussions. Participants identify actual sites on aerial images instead of drafting from memory, as they would in more traditional mental mapping techniques. Seeing and identifying particular spaces and places evoke memories, and the narratives that participants communicate supply meaning of lived experiences, offering insight into sense of place. The objective of this article is to challenge researchers to look beyond what is inherently visible. This approach provides the potential for researchers and planners to further gain from new knowledge offered by local residents. Such data may offer new or alternative perspectives on contested spaces or landscapes and can offer insight into existing social divisions to better inform future planning or community development.

Google Earth in Research

The epistemological and methodological rationale of this approach reflects on organizing and spatially referencing experiences of fieldwork and interview data. According to Sui (2004), approaches using nascent technologies encourage researchers to seek supplemental meanings of spaces, places, and landscapes. Google Earth enables researchers to conduct spatial analyses of landscapes, with the ability to zoom in on specific site locations and identify cultural and physical features based on the elements of recognition—such as shape, size, pattern, tone, texture, shadows, site, association, resolution—brought in from remote sensing (see Lillesand, Kiefer, and Chipman, 2008). Applying a spatial technology such as Google Earth to studies on sense of place represents a unique and innovative approach not only to advance the collection of data, but also to efficiently organize and spatially reference data gathered through interviews, conversations, and participant observations.

Beyond using this technology in physical and geological sciences, geographers and urban/regional planners use remote sensing technologies in research to interpret cultural landscapes. Hong (2003), for example, incorporated aerial imaging with ethnographic research, arguing that remote sensing technologies are advancing cultural landscape interpretations. The use of Google Earth supports inductive social and cultural research relating to the area of qualitative Geographic Information System (GIS) and remote sensing (Bender et al., 2005; Cope and Elwood, 2009). Google Earth has even been referred to as "desktop archaeology" (Kennedy, 2009). It has become a tool to assist social science researchers, but mainly through spatial observations and interpretations (for example, Brunn and Wilson, 2013; Kennedy and Bishop, 2011; Lisle, 2006). Street View, where available, enables the researcher to navigate farther along paths and into certain areas identified by interviewees (Brunn and Wilson, 2013). In terms of storing and referencing data, features embedded in Google Earth enable researchers to view historical images; measure distances; and create placemarks, lines, and polygons to store data, similar to storing data in GIS attribute tables.

Although this approach is inherently ethnographic, ethnographies aim to understand people's everyday lives and sense of place (Watson and Till, 2010). Ethnography is a snapshot of a community's everyday cultural practices, in which researchers take on some proximate role to immerse themselves with a group's natural setting. With ethnographic studies, which are observational and participatory, social and cultural researchers spend an appropriate period of time living alongside a local group of people to engage in and reflect on daily activities. Participant observations help researchers and planners understand community identity in terms of how people interact with their environment, surroundings, sociopolitical situations, and cultural landscapes (Basso, 1996;

Watson and Till 2010). Although ethnographic methods are rigorous, they challenge researchers to critically evaluate and write about social phenomena in addition to understanding everyday meanings and situations in a local community. Although ethnography was pioneered in anthropologic inquiry, "…geographers have brought our discipline's theorizations of space, place, scale, landscape, and environment to develop further understandings of spatial processes and concepts in ethnography" (Watson and Till, 2010: 122). In this regard, Google Earth is a tool to help ethnographers locate these spatial data, because the use of this readily available technology can bring snapshots of fieldwork locations into a new perspective.

Applying Google Earth technology to research presents an alternative dynamic in human (cultural and social) geography methodology, assisting with visual ethnographies of space and place. Google Earth captures clear images of the landscape—particularly over time—and enables cultural and social geographers to discuss and identify meanings with local members of the community by assessing meanings imprinted in the landscape or sites of social activity—each pertinent to sense of place. It enables people to recognize spaces and places of significance and engage with landscapes and sites in the community in a different way. It may also provide researchers the opportunity to see how spaces and places connect and link, because people will speak from experience, and researchers and community planners then will be challenged to connect and relate the narratives presented. This approach provides participants another way to link their cognitive memory with spaces and places of familiarity; participants can trace memories and experiences in certain spaces on the images for input into placemarks (or lines and polygons) in Google Earth back in the computer lab. Cope and Elwood (2009: 1) noted that such geographically based technologies can be used to store "non-cartographic forms of spatial knowledge, such as emotion," as a way of pinpointing and consolidating data—the images presented in the following section illustrate this approach. Each point marked in Google Earth will have a particular association, and the data referenced offer researchers and planners much insight into how people interact in their local settings. Therefore, in line with the main points put forth in this article, Google Earth becomes a database for storing and referencing experiences. Ground-truthing is often necessary to capture experiences that cannot be interpreted only from images. Collecting photographs is another way of referencing spatial images in places where Street View is unavailable, such as in the case of rural areas of the Dominican Republic (the use of GPS-enabled cameras or video recorders is easily spatially referenced in Google Earth or GIS). Analyzing the landscape involves critically reporting on features; spatial designations; and how, where, and why people gather in certain locations. This approach offers much insight and meaning for social scientists, geographers, and planners. In this regard, the landscape becomes the stage on which broader narratives need to be explored (Basso, 1996; Manzo and Devine-Wright, 2014), and interpretations add insight to meanings of community involvement and sense of place.

Using Google Earth To Spatially Reference Sense of Place

This section provides an example of how Google Earth can be used during the interview process to complement narrative ethnographic research and cognitive mapping exercises. Having Google Earth images during interviews enables the researcher to map and locate points discussed when asking participants to identify significant spaces and places in the community. Approaches will differ based on location and access, but researchers can either have printed images, which may limit discussions to the printed frame, or conduct interviews with Google Earth open to enable the interviewee to navigate and to help document and reference data. In the context presented previously, the objective of this approach is to consolidate and spatially reference meanings associated with social spaces and places, because such insight offers perspective into what is not always inherently visible. Interviews make experiences visible, because data gathered during the interview process are often not available otherwise. In general, interviews fill voids, and Google Earth becomes a tool to spatially reference interview data.

Visual reference points that spark cognitive memories during interviews help participants elaborate on past experiences and social activities—based on space and place. Participants may refer to positive experiences in particular spaces, where interactions and community building have occurred. Sometimes people relate to a particular incident or physical feature in the landscape. These memories can also be unsettling to participants, because they may identify an area that is off limits because of a crime or an area of the city or town that is associated with some negative connotation. Nevertheless, experiences are spatially referenced to exact site locations. This insight enables researchers to see (new) meanings significant to community and identity formation—or sense of place.

The pilot-study example was conducted in a rural community in the Dominican Republic. As noted, this method was tested as part of a wider ethnographic study in which the researcher spent one semester residing in Villa Ascension de Caraballo (hereafter, Villa Ascension) as a volunteer assisting with community development. Residing in a community and observing everyday life and activities enable researchers to elaborate and reflect on participants' responses to add value to the meaning being communicated and to add supplemental depth. To gather a representative sample, participants were selected based on a range of age, gender, employment, and role in the community. Each participant involved was presented with a laminated Google Earth image of Villa Ascension and markers; they were asked to locate important community spaces on the map. After the participants identified spaces and places on the laminated image, the interviewer used the marked map to guide the semistructured interview about the meanings of identified spaces and places in relation to their actual significance to the participants and the community. Exhibits 1 and 2 are digitized examples of locations identified or circled on the Google Earth transparencies. Participants had the freedom to discuss experiences and relate to social activities in these spaces, offering insight into the making of places.

This approach represents a visual qualitative mapping method that engages participants with their local geography and adds meanings to the places where they reside. Researchers and planners can critically evaluate meanings that emerge to better understand everyday perceptions and uses of space. It is important to note specific visible features recognized by each participant and to complement insight from local community members with data collected from observations, queries, and conversations during research. Bringing together a wide range of data helps a researcher fill the void of what is not visible. Certain elements in an image may take on alternative meanings that should not be assumed, so for clarity the researcher must facilitate a discussion with each participant regarding why certain spaces or places were identified.

Exhibit 1

Example 1 of Community Spaces Identified As Important in Villa Ascension de Caraballo, Dominican Republic

Exhibit 2

Example 2 of Community Spaces Identified As Important in Villa Ascension de Caraballo, Dominican Republic

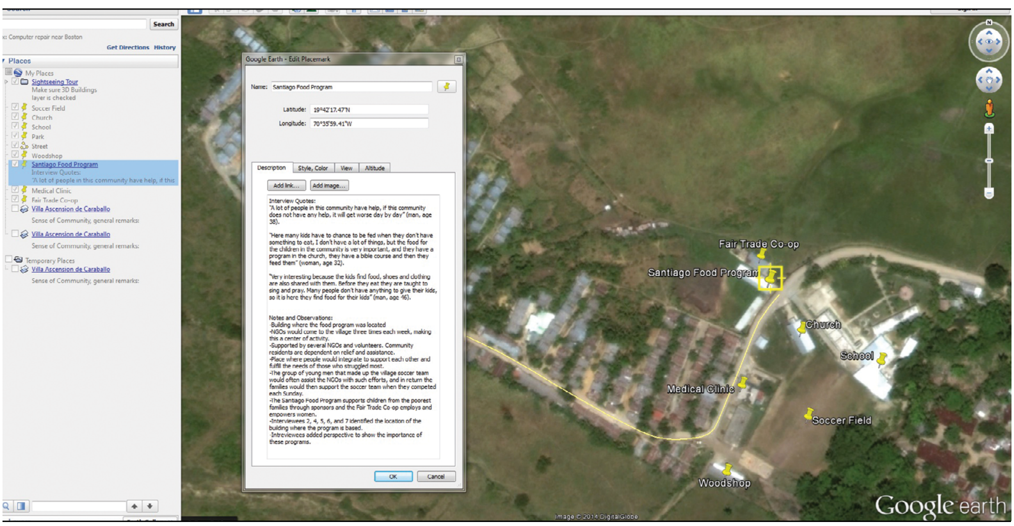
As mentioned previously, placemarks, a Google Earth feature, enables the researcher to store data on specific spaces and places from interviews or observations in placemark textboxes. The researcher can also add images and links, as necessary; can edit data entered into each placemark by selecting "properties"; and can save data as .kmz files that can be edited at a later time. For the pilot study conducted in Villa Ascension, interviewees were asked to identify the five points in the community they deemed most significant to sense of place and sense of community. Exhibit 3 identifies all the points discussed by those who participated in this study. Exhibit 4 shows one of the points and the corresponding spatially referenced interview data. Each placemark has embedded latitude and longitude coordinates, which can then be easily spatially referenced in GIS. Using

Exhibit 3

Google Earth Placemarks Identifying All Locations Identified As Important by Study Participants in Villa Ascension de Caraballo, Dominican Republic

Exhibit 4

Example of Spatially Referenced Data From Participant Interviews in Villa Ascension de Caraballo, Dominican Republic



digitizing commands, the researcher can then identify the points discussed by participants (see exhibit 3) and add supplemental data from the interview to an attribute table (exhibit 4). Entering qualitative data into Google Earth or GIS is an efficient way to organize and spatially reference interviews or photographs collected to inform the analysis and assess similarities or differences in understanding spaces and place.

Concluding Remarks

The data entered into Google Earth placemarks are useful for academic researchers to engage with the meanings embedded in significant spaces and places identified by members of a local community. Such data are also useful for planners who are seeking insight into the effect of new community buildings, parks, or spaces based on location. Google Earth is a tool for storing and spatially referencing qualitative data collected in the field as a means for understanding particular spaces and places. The wider purpose of this method and approach is to produce and store new local knowledge from community participants to consult, or inform, when planning new projects. This article not only is relevant to understanding people's perceptions of place and community in urban areas but also offers insight into how to strategically plan for and promote community development by enabling participants to spatially reference their experiences. Using easily and readily accessible technologies such as Google Earth encourages researchers to fully develop practical understandings of spatial interactions and to georeference meanings in actual locations. Moreover, Google Earth promotes the underlying spatial emphasis of this work to gather, identify, and locate data to make sense of place more visible and spatially informed, which makes it relevant to social science researchers and community planners.

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Small Stories in Big Data: Gaining Insights From Large Spatial Point Pattern Datasets

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Abstract

With the onset of big data, it is now relatively easy to gain access to a wide variety and great magnitude of data sources. Data, however, do not necessarily equate to useful insights and meaningful analysis. In this article, we outline a specific step-by-step approach to gaining insight into the spatial footprint of online, point-based data—in this particular case, data from the popular social media service Twitter.

Introduction

A key aspect of current research directions in urban studies is that researchers are inundated by both a flurry of "big" datasets and persistent writing about the importance of that data deluge. From cellphone records to open government datasets and online social media shared using application programming interfaces (APIs), the topic of big data—both in terms of possible applications and critique—is ever more present.

The relative ease with which a researcher can gain access to a variety of new data sources, however, does not necessarily mean that insights from those data can be achieved as easily. Putting aside key questions of what an indicator actually measures (an issue present in various forms across datasets), researchers are also confronted with the fact that many trusted analytical and mapping methods cannot be directly applied in standard ways to spatial *big* data. To partly alleviate this issue, we outline a step-by-step approach to gaining insight into the spatial footprint of online big data—in this particular case, the popular social media service Twitter. As with most geosocial online data (for example, Foursquare check-ins, geotagged Flickr photos), tweets are stored as spatial points with a longitude and latitude coordinate pair and a variety of other metadata (timestamp, text, images, activity records, etc.) that can be leveraged to gain useful insight on the spatial distribution of daily life (Poorthuis and Zook, 2014). It should be noted that the approach outlined in this article would also be applicable to large spatial point pattern datasets generated from other, more traditional, sources.

So Much Data… Now What?

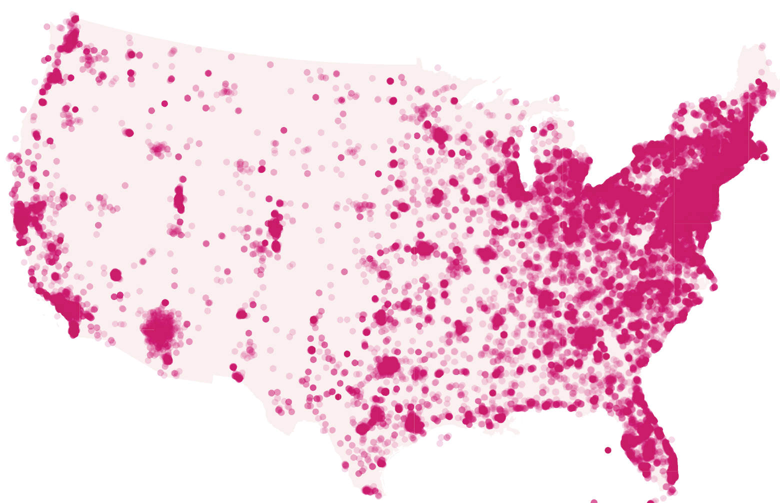
In principle, anyone with an interest in geosocial online data and some programming skills can access a wide range of APIs made available by almost every major social media platform. Although this article does not address the techniques for API access, tutorials and code are widely available. Moreover, those without the prerequisite technical skills can acquire ready-made datasets through third party vendors, such as Gnip. In stark contrast with the situation facing social science research for most of the 20th century, today we certainly do not suffer from a lack of data. For example, the Dolly project at the University of Kentucky has been collecting all geotagged tweets in the world since June 2012—totaling more than 9 billion data points, and counting. Even small subsets of such data, from people talking about receiving a flu shot to people tweeting about their favorite beer brands, yield many thousands of data points.

Instead, the pressing problem that presents itself is how to gain *meaningful* insights from such large collections of spatial points. Although research may take any number of approaches (Crampton et al., 2013), an early step is to simply map or visualize these data in ways that reveal the presence (or absence) of underlying spatial processes and distributions.

The easiest approach for visualizing the spatial distribution of data—in this case, tweets from Hurricane Sandy (Shelton et al., 2014)—is, quite literally, putting the points on the map (exhibit 1). This relatively straightforward one-to-one plotting of data points on a map presents two specific

Exhibit 1

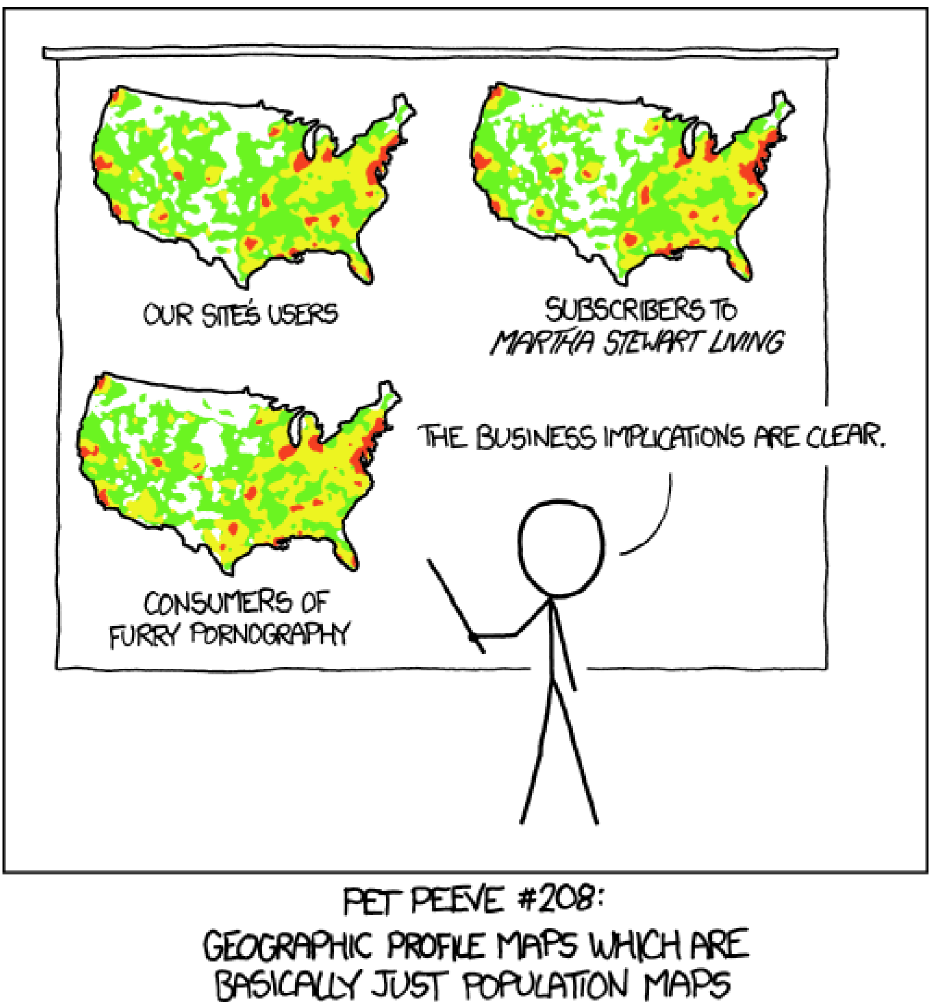
Overplotting—Too Many Points To Distinguish Clear Spatial Patterns



problems. First, such maps suffer from "overplotting": many overlapping points obscure each other and make it difficult to assess the total number of points in each area. Second, even if the problem of overplotting were solved, these patterns largely mimic population density: in the case of Twitter, more tweets are generally sent from densely populated areas because these locations simply have more Twitter users. This second problem is very much prevalent in maps of online phenomena and even reached modest Internet fame after Randall Munroe devoted a popular XKCD comic to it (exhibit 2). In the next sections, we walk through a step-by-step approach that first addresses the problem of overplotting by aggregating individual points to a hexagonal lattice. It subsequently provides a solution to correct for this population density "mirroring" by normalizing raw counts through the calculation of an odds ratio.

Exhibit 2

Population Density?



Source: Reprinted from http://xkcd.com/1138/

Fixing the Overplotting Problem

A range of common cartographic and geographic information science, or GIScience, approaches can solve the problem of overplotting. The first is to make each data point slightly transparent. This approach is fine with only a small number of overlapping points but, in the case of big geodata, we are often confronted with hundreds of points overlapping in one location, while other locations have only one or two points. Another approach would be to visually "explode" overlapping features, slightly offsetting their position to prevent overlap. Again, this approach works well with smaller datasets (John Snow's classic cholera map is a prime example of this approach [Snow, 1855]) but is not well suited for large datasets.

Another way to address the issue of overplotting is generating what is colloquially called a "heatmap." Techniques such as kernel density estimation or kriging are used to create a (smooth) density surface. A major caveat, however, is that these techniques interpolate or "smooth" values in between actual data points and thus assume that the underlying spatial processes are continuous. This caveat applies to many natural phenomena, such as temperature and precipitation, but is more problematic when applied to social phenomena. This caveat is especially the case on an urban scale in which stark differences in demographics, retailing, and so on, are often present between neighborhoods or even from block to block. Although heatmaps are visually pleasing (and hence popular), they are not necessarily the most appropriate technique for gaining meaningful insight from online social media data.

A more suitable approach is to aggregate individual points to larger areas or polygons. These areas could be administrative regions, such as census tracts or counties, or they could be arbitrary spatial areas, such as rectangles, circles, or hexagons. Unless the final goal of the analysis is to compare the point data under study with other datasets that are available only for certain administrative units, aggregating to a lattice of arbitrary areas (such as hexagons) has two specific advantages from an analytical perspective. First, administrative units often have varying sizes. For example, counties in the western part of the United States, in general, are much larger than their eastern counterparts. The larger counties not only have a higher chance of having more points inside their border, but they also stand out much more visually. Aggregating to a regular lattice of rectangles or hexagons, in which every area has the exact same size, solves this problem. Second, such a lattice enables us to address, although not solve per se, the Modifiable Areal Unit Problem (MAUP) by intentionally modifying the size of the rectangles or hexagons. This can be done to test whether the spatial patterns indeed change due to MAUP or simply to choose the "best" cell size based on the underlying phenomenon (see Wilson, 2013, for an example of the consequences of changing areal units).

Creating a Hexagonal Lattice

Hexagonal lattices have seen a recent surge in popularity within online mapping, but they are more than just the latest fad—they have a few distinct advantages over rectangular grids. First, in cartographical terms, rectangular cells are more distracting. The eye is drawn to the horizontal and vertical grid lines, making it more difficult for the reader of the map to distinguish spatial patterns

(Carr, Olsen, and White, 1992). Second, in analytical terms, hexagonal lattices have a higher representational accuracy than square or rectangular grids (Burt, 1980; Scott, 1988), meaning that they represent the underlying point pattern more closely. The hexagon is the highest sided regular polygon that can still be used to tessellate (that is, cover a surface without gaps or overlap), and, as such, it is closest to the ideal of a circle. The closer a polygon is to a circle, the closer its border points are to its center, which partly explains the higher representational accuracy.

As such, the first practical step in generating a hexagonal lattice is to aggregate up from the original point pattern. This aggregation can be done quite easily in Arcmap[1] and QGIS[2] or using R (R Core Team, 2014). Given the power of R and its relative newness to geospatial analysis, we include code snippets used for generating the maps in this article. More extensive (and commented) code with some sample data is available at https://github.com/atepoorthuis/smallstoriesbigdata.

```
library(sp)
tweets <- read.csv("tweets.csv", colClasses=c("latitude"="numeric",
    "longitude"="numeric"))
coordinates(tweets) <- c("longitude", "latitude")
proj4string(tweets) <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs"
hex <- HexPoints2SpatialPolygons(spsample(tweets, n=3000, "hexagonal"))
```

At this point we read a dataset of tweets from a .csv file, point to the longitude and latitude columns for the spatial coordinates, set a projection, and then generate a hexagonal grid over the same spatial extent. A key variable in this code is the number of cells in the lattice (3,000 in this example), but this number can be readily changed to explore how changes in cell size affect the resulting visualization. After we have produced a hexagonal lattice, we can then simply spatially join each individual tweet to a grid cell.

```
tweets$hex <- over(tweets, hex)$id
```

We take this intermediate step of adding the identifier of the corresponding grid cell to each individual tweet, because it also allows for the flexibility of sampling down power users (Poorthuis and Zook, 2014). Within most online social media, a power law, or close approximation, can be found in which a few users contribute by far the most content (Clauset, Shalizi, and Newman, 2009). If we wanted to correct for that effect, we could, for example, randomly sample down active users to a maximum of 5 data points (or some other selected value) per grid cell.

```
library(data.table)
tweets.dt <- data.table(tweets)
tweets.dt[,sample(.I, if(.N > 5) 5 else .N), by=list(u_id, hex)]
```

After that, it is just a matter of counting the number of tweets per grid cell and visualizing the results.

```
tweets.dt[,tweets=.N, by=list(hex)]
```

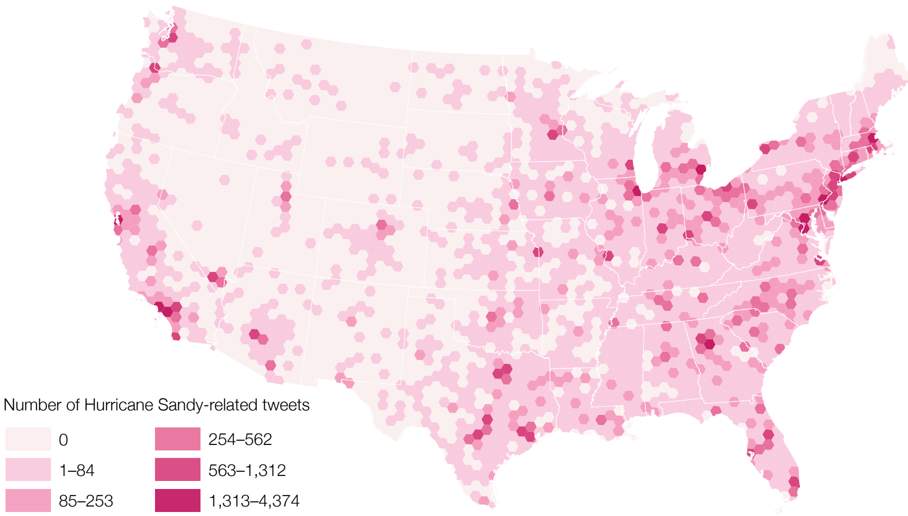
[1] http://www.arcgis.com/home/item.html?id=03388990d3274160afe240ac54763e57.

[2] http://michaelminn.com/linux/mmqgis/.

An example of this step in the process is provided in exhibit 3, which shows the spatial pattern of tweets related to Hurricane Sandy sent in October 2012 (Shelton et al., 2014).

Exhibit 3

Aggregation to Hexagons



Normalizing the Cells Using an Odds Ratio

Although aggregating to hexagons solves the problem of overplotting, to a large extent, the resulting spatial pattern still follows very closely the distribution of population. Given that this dataset is derived from social media, this problem is to be expected. We are, after all, still looking at the raw count of the number of tweets, which is heavily influenced by how many people happen to live in each hexagon.

A fortunate side effect of the aggregation to polygons is that it becomes much easier to normalize each raw count. For conventional data, we would likely choose to normalize a phenomenon by simply dividing raw counts by the total population or, for example, the area of each polygon. In the case of online social media data, this approach has two specific disadvantages. First, the approach yields a ratio that becomes difficult to understand; for example, what does 15 tweets per square mile or 100,000 people actually mean? Second, the total population might very well not be the same as total tweeting population.

Instead, we calculate an odds ratio, which is slightly more sophisticated but has the great advantage of allowing us to normalize by any other variable, and the resulting ratios are easy to interpret (Edwards, 1963). In the case of social media data such as Twitter, it often makes sense to normalize by a random sample of all tweets that stands in as a proxy for the total tweeting population rather than the total population in and of itself. By using the total tweeting population, we can visualize the distribution of a phenomenon within social media use, rather than the popularity of a social media service within the overall population. The formula for the odds ratio is—

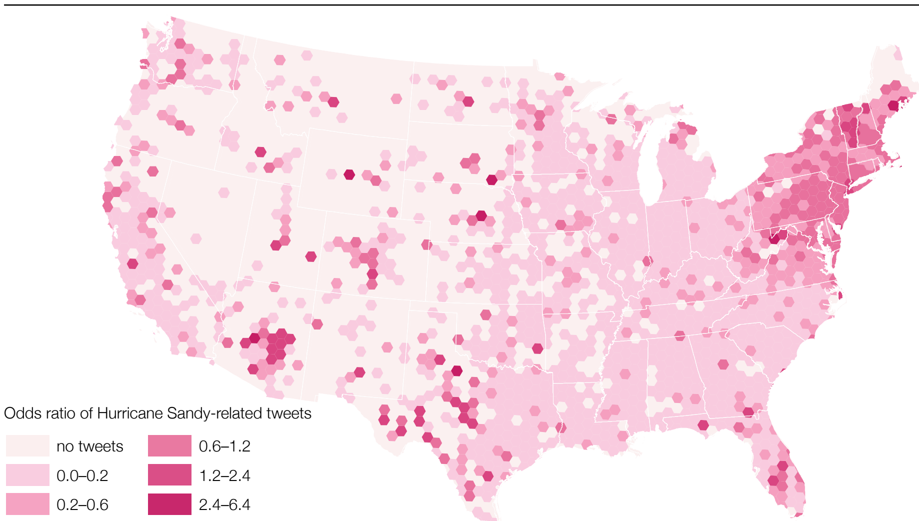
$$OR = \frac{p_i / p}{r_i / r} , \tag{1}$$

where p_i is the number of tweets in hexagon i related to the phenomenon of interest (for example, flu shot tweets or tweets related to a certain beer brand) and p is the sum of all tweets related to that phenomenon in all hexagons. r_i is the number of random tweets in hexagon i and r is the sum of all random tweets in all hexagons. We choose a random sample of all tweets at this point, but one could easily substitute other variables—for example, active Internet users or possibly another point-based phenomenon aggregated to the same hexagonal lattice.

The resulting ratio has a midpoint of 1. At that midpoint, as many data points related to our phenomenon of interest as we would expect are present based on that random sample of all tweets. Values lower than 1 indicate we have fewer points of interest than expected, and vice versa. For example, an odds ratio of 0.5 means that we find only half as many points of interest as we expected, and a value of 2.0 means we find twice as many points as we expected, based on the total population. We can easily calculate this odds ratio in R (see result in exhibit 4).

Exhibit 4

Basic Odds Ratio



```
randomTweets <- read.csv("random.csv", colClasses=c("latitude"="numeric",
    "longitude"="numeric"))
coordinates(randomTweets) <- c("longitude", "latitude")
proj4string(randomTweets) <- "+proj=longlat +ellps=WGS84 +datum=WGS84
    +no_defs"
randomTweets$hex <- over(randomTweets, hex)$id
randomTweets.dt <- data.table(randomTweets)
randomTweets.dt[,random=.N, by=list(hex)]
hex.join <- merge(tweets.dt, randomTweet)
hex.join[,OR:=(tweets/sum(tweets))/(random/sum(random)),]
```

Small Numbers Problem: Confidence Intervals

When the odds ratio for each hexagon is visualized, we finally start to gain a meaningful understanding of the spatial pattern. Furthermore, we have now solved the issue around population density that the XKCD comic pointed out so vividly. One last problem remains, however: areas with only a few tweets have wildly varying odds ratios. In exhibit 4, this variation can be clearly seen in sparsely populated states such as Wyoming and Montana. This issue is mostly the result of the small numbers problem. Simply put, areas with only a small number of tweets show a high degree of variance. This makes sense: an odds ratio based on two tweets of interest versus three random "population" tweets is less "reliable" than the same ratio based on 200 tweets of interest versus 300 random tweets. We can thus calculate a confidence interval for each odds ratio to gain an indicator of reliability (Bland and Altman, 2000; Morris and Gardner, 1988).

$$OR_{CI} = e^{\ln(OR) \pm z \times \sqrt{\frac{1}{p_i}+\frac{1}{p}+\frac{1}{r_i}+\frac{1}{r}}}, \quad (2)$$

where z is the z-score of the chosen confidence level (for example, $z = 1.96$ for 95 percent confidence level).

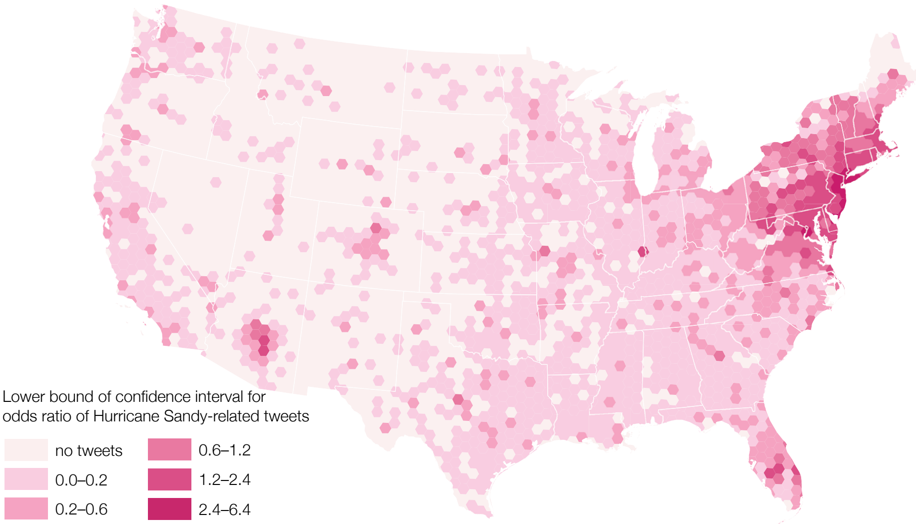
We can use this approach to calculate both the upper and lower bounds of the confidence interval but, if we are interested only in significant instances of higher odds ratios, we can calculate and visualize the lower bound only. This approach would enable one to say, for example, the value in hexagon *I* is *at least* 1.5, with 95 percent confidence. To calculate this value in R, we only have to adapt the formula (the last line of the previous code snippet) a little bit.

```
hex.join[,ORlowerconf:=exp(log(OR)-1.96*sqrt(1/tweets+1/sum(tweets)+1/
    random+1/sum(random))),]
```

When we visualize this lower bound of the confidence interval for the odds ratio, we get to the final step in our approach, seen in exhibit 5, which results in a clear—and in this case, expected—spatial pattern largely following the areas most affected by Hurricane Sandy (see Shelton, 2014, for a more indepth discussion of this pattern).

Exhibit 5

Lower Bound of Confidence Interval for Odds Ratio



Source: Reprinted from Shelton (2014)

Final Considerations

The approach outlined in this article starts with an arguably noisy and large set of point-level data derived from social media. Using aggregation to a hexagonal lattice and subsequent normalization and calculation of an odds ratio with confidence intervals, we go from a raw view on the data (exhibit 1) to a clear spatial pattern (exhibit 5). Although we have used a random "population" sample to normalize in the example, this approach is flexible; thus, the same approach can be used to directly compare two different point datasets (for example, artists versus bankers) or different time periods of the same dataset.

Furthermore, in many cases, this step will be only the first in a more indepth spatial analysis, especially because the hexagonal lattice is a very suitable input for further analysis with subsequent spatial statistical techniques (for example, cluster detection or spatial regression models).

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Sustaining Homeownership After Delinquency: The Effectiveness of Loan Modifications by Race and Ethnicity

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Abstract

As mortgage foreclosures spiked beginning in 2007, federal policymakers focused on loan modifications as a primary tool for preventing foreclosure and initiated programs to increase the number and effectiveness of loan renegotiations. Yet, loan modifications are largely undertaken at the discretion of private loan servicers and are not as transparent as lender mortgage decisions. Systematic differences are possible in the types of loan modifications that borrowers receive. To be specific, borrowers of color may be receiving less favorable modification terms than comparably situated White borrowers. Because the terms of a loan modification influence the likelihood that a borrower will be able to retain his or her home, it is important to understand who gets what kind of modification and whether that modification succeeds in preventing foreclosure.

This study uses data on a national sample of approximately 42,000 privately securitized subprime loans originated between 2004 and 2006 to examine modification types and foreclosure outcomes by race and ethnicity. We find no evidence of significant differences in modification types across borrowers; indeed, we find that Black, Hispanic, and Asian borrowers receive slightly larger reductions in monthly payments than comparably situated non-Hispanic White borrowers. The results also reveal that loan modifications that entail payment reductions reduce the likelihood of redefault and foreclosure 1 year after modification. This finding is consistent across all racial and ethnic demographic

Abstract (continued)

groups. The research suggests that federal efforts to incentivize modifications have helped keep borrowers in their homes, but the research also reveals the need for additional research into servicing and loss-mitigation practices and their role in sustaining homeownership during periods of economic distress.

Introduction

The recent foreclosure crisis and the resulting erosion of family wealth and neighborhood stability have raised critical questions about the policies and programs that are needed to sustain homeownership. While policy has focused on consumer protections in the mortgage lending market and the terms by which borrowers access credit, an equally important focus is what happens after loan origination. Mortgage-servicing, collections, and loss-mitigation practices should be central to the dialogue around how to promote homeownership while reducing the costs of foreclosures on borrowers, communities, and the overall U.S. economy.

Compared with the vast research and literature about mortgage loan application and origination outcomes, however, mortgage-servicing practices have received fairly little research attention. One barrier to studying loan servicing and loss-mitigation practices is that mortgage modifications are largely at the discretion of loan servicing firms, and modification terms and outcomes are not as systematically transparent as loan application approvals and denials. This lack of information stands in stark contrast to the highly transparent process used to track mortgage loan application approvals and denials under the Home Mortgage Disclosure Act (HMDA). In addition, the process of modifying a loan is highly individualized, time consuming, and "more art than science."[1] As a result, consumer advocates have raised the concern that the loan modification process could unfairly burden historically underserved borrowers—especially those who lack experience and knowledge of dealing with a lending institution. For example, borrowers who do not speak English or who may distrust banking institutions may fail to pursue a loan modification, or they may not be able to negotiate the best modification terms. Race or perceived race could also serve as a proxy that servicers use for decisionmaking on modifications, especially if these borrowers are deemed less sophisticated, more time consuming, and, therefore, more costly to serve. Understanding whether modification outcomes are different by race or ethnicity is especially important given the disparate impact of the foreclosure crisis on Black and Hispanic households (Bocian et al., 2011) and the role that homeownership plays in the racial wealth gap (Oliver and Shapiro, 2006).

[1] As quoted in Andrews and Witt (2009: 1): "It's more art than science," said Guy Cecala, publisher of *Inside Mortgage Finance*. "Who knows whether the borrower will default, what the value of the property is, what will happen to home values," he said. "I'm skeptical of all of it."

In this article, we use a unique dataset that merges national data on the loan performance of subprime home mortgages from more than 100 servicers with data on borrower demographics reported as part of HMDA. With these data, we are able to examine national trends in loan modification types by borrowers' race and ethnicity and to assess the subsequent outcomes of those modified loans for a large sample of subprime loans. Previous research to date has not found racial disparities in the incidence of loan modifications (Been et al., 2013; Collins and Reid, 2010), but these studies have not examined the changes in loan terms by race, nor have they assessed whether differences in modification terms lead to different rates of redefault after.

Our findings suggest that, conditional on a loan having modified terms, there are no significant racial or ethnic differences in the types of modifications that borrowers receive. In fact, we find that controlling for a range of borrower, loan, and housing market characteristics, minorities are equally likely to receive a loan modification that involves lowered interest rates or principal balances. When we examine the amount of change in monthly payments, we find that Black, Hispanic, and Asian borrowers are all more likely to receive a slightly larger reduction than White borrowers, although the amount is small. In terms of the effectiveness of loan modifications, we find that modifications reduce the likelihood of subsequent redefault and foreclosure, and that the terms of the modification influence its effectiveness, even after controlling for a wide range of variables. We do not find significant differences in redefault rates across racial or ethnic groups.

This study proceeds as follows. The first section following this introduction provides a brief background on the evolution of federal loan modification policies, including the federal Home Affordable Modification Program (HAMP). The second section reviews the existing literature on loan modifications, focusing on studies that have examined modification outcomes by race and ethnicity. The third section describes our data and methodology and provides descriptive statistics for our sample. The fourth section presents our findings. The article concludes with the implications of this research for public policy and suggests avenues for future research.

Evolution of Loan Modification Efforts

Since the start of the foreclosure crisis in 2007, mortgage servicing has garnered increased attention for its role in processing mortgage delinquencies. As the interface between borrowers and investors, servicers are often the ones that make the decision to either grant a loan modification or start foreclosure proceedings. Mortgage loan servicers[2] have a number of options open to them in response to a borrower in default: approve a loan modification, offer an alternative such as a short sale, or pursue a foreclosure. Servicers may pursue these options simultaneously, or even encourage borrowers to submit modification applications and then fail to act on the application, request extensions and more data, or require that the borrower initiate the entire process again sometime down the road.

[2] Although a mortgage loan may be serviced by a third party or by a lender, we use the term "servicer" to indicate the party responsible for reporting to lenders and investors in a security about the status of each loan each month.

In addition to significant variation in the loan modification process, loans can be modified in multiple ways, and not always in ways that are favorable to the borrower. A common form of loan modification occurs when a servicer adds payment arrears to the total loan balance and then calculates a new monthly payment that will amortize the increased balance during the life of the loan. This type of modification generally increases the monthly payment amount and the overall amount of debt (White, 2009a, 2009b). A second type of modification—generally used on adjustable rate mortgages (ARMs)—is to freeze the interest rate and not permit it to reset at a higher rate. With a third type, a servicer can permanently reduce the interest rate on a loan to reduce the monthly payment, while leaving the balance of the mortgage the same. Finally, a servicer can choose to reduce the loan balance or principal, which reduces the overall amount of the loan. A principal reduction is believed to be particularly beneficial to homeowners whose house values are significantly lower than the amount of their mortgage, commonly referred to as being "under water."

Recent research has suggested significant heterogeneity among servicers in terms of the types of resolutions they offer to borrowers (Agarwal et al., 2012). Early loan modification efforts were solely proprietary and voluntary in nature, and they did little to help delinquent borrowers. As the foreclosure crisis extended into 2008, prompting a large-scale recession and high rates of unemployment, pressure mounted on the federal government to scale up efforts to modify loans and prevent foreclosures. In February 2009, the U.S. Department of the Treasury (hereafter, Treasury) rolled out the federal government's landmark foreclosure prevention initiative, the Making Home Affordable (MHA) program, which included the Home Affordable Modification Program (HAMP). HAMP was designed to overcome barriers to loan modification by encouraging servicers to bring loan payments in line with borrowers' incomes (GAO, 2014). Under the program, eligible borrowers work with the servicer to reduce their monthly payment to 38 percent of their income, and then HAMP provides a government subsidy to further reduce the payment to 31 percent. Servicers also receive an upfront fee of $1,000 for each modification, plus "pay for success" fees on performing modified loans of $1,000 per year for up to 5 years, thus providing servicers a financial incentive to initiate modifications that help keep borrowers in their homes.[3] Borrowers are eligible for a HAMP modification on first lien loans for owner-occupied properties with an unpaid principal balance of less than $729,750, originated on or before January 1, 2009.

Since its launch, HAMP has been revised several times to extend its reach and effectiveness. For example, as high unemployment persisted and housing prices nationally continued to fall, HAMP added features to try to address the situation of unemployed homeowners and underwater borrowers. Still, the program has struggled to reach its intended scale. As of November 2013, 1.3 million borrowers had received modifications under HAMP, fewer than Treasury's initial estimate of 3 to 4 million (GAO, 2014). In addition, since peaking in early 2010, the monthly volume of new modifications made under the program has largely trailed off. Despite

[3] HAMP also provides a bonus incentive of $1,500 to lenders/investors and $500 to servicers for modifications made while a borrower is still current on mortgage payments but at imminent risk of default. To help servicers make a determination if a modification would help to protect the investors' interests in the loan, HAMP uses a standardized net present value, or NPV, model to compare expected cashflows from a modified loan to the same loan with no modification, using certain assumptions.

not reaching its volume target, some evidence shows that HAMP has been successful in extending beneficial terms to struggling homeowners. The program has led to significant reductions in payments—an average of $544 each month, or approximately 40 percent of their premodification payment—for borrowers who obtained relief (Treasury, 2014), and a study in New York City found that HAMP modifications outperformed non-HAMP modifications after 1 year (Voicu et al., 2012). In addition to HAMP modifications, the Office of the Comptroller of the Currency (OCC) estimates that an additional 2 million homeowners have received proprietary modifications (OCC, 2014), although very little is known about the terms of these modifications.

Although OCC and Treasury release regular reports on loan modification activity and redefaults, still only a few studies have examined the factors that influence the effectiveness of modifications in a multivariate framework, and even fewer studies consider differences across demographic groups. This study helps to fill that gap. In the next section, we review the existing literature on loan modifications, focusing specifically on studies that seek to understand loan modification trends by borrowers' race and ethnicity.

Literature Review

Although, in theory, the borrower and investor are each better off if a foreclosure is avoided, in practice, it has proven to be much more difficult to modify loans. Research has identified several institutional factors that may influence servicer practices, including servicer incentives and capacity, mortgage securitization and the associated pooling and servicing agreements, information asymmetries, and lack of borrower contact (Adelino, Gerardi, and Willen, 2013; Cordell et al., 2010; Eggert, 2007; Gelpern and Levitin, 2009; Levitin and Twomey, 2011; Piskorski, Seru, and Vig, 2010).

One of the biggest barriers to modifying loans has been the lack of incentives for servicers. Loan modifications are costly: they are labor and time intensive and cannot be easily automated. Unlike the costs associated with foreclosure, neither the labor nor the overhead costs associated with modifications are billable back to investors (Levitin and Twomey, 2011). If the modified loan redefaults before the servicer has recouped the cost of the modification, then the modification is a money loser for the servicer. As a result, until HAMP was put into place, most servicers had very little financial incentive to undertake loan modifications. Moreover, very few servicers invested in either the staff or the technological capacity to respond to the volume of distressed borrowers at the height of the foreclosure crisis (Cordell et al., 2010).

Researchers have also posited that the investor pooling and servicing agreements (PSAs) that govern privately securitized loans may limit a servicer's ability to offer a loan modification. Although PSAs vary for different mortgage pools, in general, they require servicers to manage the loans in a way that maximizes the returns to the investor. A loan modification may be more difficult for servicers to undertake if they need to consider multiple investors with competing interests (Cordell et al., 2010). A handful of papers have found that loans in private-label securities were less likely to be modified than loans held in portfolio (Agarwal et al., 2011; Been et al., 2013; Piskorski, Seru, and Vig, 2010). In contrast, Adelino, Gerardi, and Willen (2013) argued that no differences in loan modification rates exist between loans held in portfolio and those held in private-label securities. The extent to which securitization influences modifications is still unclear, however, because all four of these studies use different data, methods, and model specifications, making it difficult to compare results.[4]

A third explanation for differences in modification rates may lie in individual servicers' institutional responses to the foreclosure crisis. One option for a servicer is to implement a highly automated process of default management, which enables the servicer to keep the costs of managing delinquencies low (Levitin and Twomey, 2011). In contrast, other servicers have created loss-mitigation units to work with distressed borrowers, often in concert with housing counselors or foreclosure prevention specialists. Experts have also described the renegotiation process as "more art than science"; ex ante it is difficult to know whether a modification will actually lead to a cure or whether it merely postpones delinquency (Adelino, Gerardi, and Willen, 2013). Given that a significant percentage of loans self-cure, servicers must also make a judgment as to whether the modification is really necessary for any individual borrower. The extent to which the servicer is willing to invest in staff and time to perfect this "art" may lead to different determinations about the benefits of offering a borrower a modification and on what terms.

All these factors have material effects for a borrower who is seeking to obtain a loan modification and stay in his or her home. Borrowers have very little control over the ownership or administration of their loan after origination, however; they cannot decide whether their loan will be securitized, who their servicer will be, or what contractual provisions will govern the servicing of their loan (Levitin and Twomey, 2011). Consumer rights regarding loss mitigation are fairly narrow, and the process by which loss-mitigation decisions are made is often opaque. As a result, advocates and housing counselors have raised the concern that the loan modification process may lead to unequal outcomes for certain protected classes (California Reinvestment Coalition, 2011). For example, race or perceived race could serve as a proxy that servicers use for decisionmaking on modifications, especially if these borrowers are deemed more time consuming and, therefore, more costly to serve.

In this article, we contribute to a growing literature on the effectiveness of loan modifications and specifically build on studies that examine loan modification terms and subsequent loan performance for different racial and ethnic groups. The lack of public data on individual loan modifications, coupled with the fact that most loan performance datasets do not include any information about the borrower with the exception of a FICO™ credit score, means that we still have a limited understanding of whether loan modifications help prevent foreclosures, and, if so, for whom.[5] Given the importance of homeownership for asset building and community development, research on how to improve outcomes in the default resolution process is especially relevant for public policy.

Empirical studies that have examined the effectiveness of loan modifications have found that the terms of the modification are important in predicting redefault. In one of the first studies

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[4] For a discussion of the points of contention and differences in methodology, see Adelino, Gerardi, and Willen (2013).

[5] Treasury released the first loan-level data on HAMP in 2011. Mayer and Piven (2012) attempt to use these data to identify racial differences in modification outcomes, although in 79 percent of active permanent modification records and 82 percent of trial modification records no information on borrower race or ethnicity is in the data file.

to examine loan modification terms, White showed that most pre-HAMP modifications typically increased a borrower's monthly payment and the principal owed on the loan (White, 2009a, 2009b). He argued that the high redefault rates of early modifications reflected the fact that the loan renegotiation process did little to increase the affordability of the mortgage. Subsequent studies have shown that the most successful loan modifications are those that result in a significant decrease in either the monthly payments or the principal of the loan (Cordell et al., 2009; Cutts and Merrill, 2008; Haughwout, Okah, and Tracy, 2010; Quercia and Ding, 2009). Quercia and Ding (2009), for example, found that loans with greater payment reductions have lower redefault risks and that loans have an even lower risk of redefault when payment reduction is accompanied by principal reduction. The authors suggest that, among the different types of modifications, the principal forgiveness modification has the lowest redefault rate. Cutts and Merrill (2008) similarly showed that the success rate of modified loans varies by the amount of arrearage capitalized into the loan modification; they found a direct relationship between a lower arrearage and a lower redefault rate.

Missing from these studies, however, is an analysis of how these factors might differ for different types of borrowers. Four studies post-crisis have used loan performance datasets merged with HMDA and other data sources to examine differences in loan modification rates by borrowers' race and ethnicity.[6] None of these studies found significant disparities in loan modification outcomes for Black or Hispanic borrowers. In an early study on loan modifications, Collins and Reid (2010) examined data on subprime and Alt-A loans originated in 2005 in California, Oregon, and Washington, analyzing loan modification outcomes through 2010. The results for these three states showed no evidence of lower modification rates for minority borrowers than for White borrowers, conditional on being delinquent.

The other three studies focused on borrowers' outcomes in New York City, which has data systems that enabled the authors to build comprehensive datasets with a large number of control variables. In the first study, Been and her colleagues (2013) used a sample of first lien, prime, and subprime mortgages in New York originated between 2004 and 2008 and found that the race or ethnicity of the borrower has no significant impact on the likelihood that a seriously delinquent loan was modified between 2008 and 2010. They also found that neighborhoods with large shares of Black residents are more likely to receive modifications (even after controlling for other neighborhood-level factors that might influence delinquent loan outcomes). Chan et al. (2014), using a sample of subprime and Alt-A privately securitized loans originated in New York between 2003 and 2008 observed through 2010, found a higher loan modification propensity for Black and Hispanic borrowers, after controlling for a wide range of factors. In the third study, Voicu and his colleagues (2011) used a sample of New York loans from the OCC Mortgage Metrics database (which covers nine of the largest mortgage

[6] A couple of studies before the foreclosure crisis examined the influence of borrowers' race on postdelinquency outcomes. For example, using a large sample of Federal Housing Administration (FHA) loans, Ambrose and Capone (1996) investigated whether racial differences influence the resolution of loans that enter default. They found that minority borrowers remain in default longer than White borrowers, suggesting that lenders may actually have been more lenient toward minority borrowers. They also found that the foreclosure rate is consistent for both minority and White borrowers, conditional on being delinquent. These previous studies relied almost exclusively on FHA data, however, and do not include other factors (for example, credit score or equity position) that might influence postdelinquency borrower outcomes.

servicers) and found that HAMP loans are more effective at preventing default than proprietary loan modifications, after controlling for a wide range of variables. While they found that borrowers who receive HAMP modifications are less likely to redefault compared with those who receive proprietary modifications, Voicu et al. (2011) also found that the borrower's race or ethnicity is not significantly correlated with the odds of redefault.

As Collins and Reid (2010) pointed out, however, it is hard to use datasets on loan performance to determine whether racial or ethnic differences influence the incidence of loan modifications, because the data do not enable researchers to see the number of borrowers filing applications to have their loan modified. Without application data, determining differences in the incidence of modifications ultimately is difficult. A study by Mayer and Piven (2012) used the publicly released HAMP data to assess whether racial minorities and Hispanics, women, and low-income homeowners benefited equally from HAMP. They concluded that race, ethnicity, gender, and income have "very little" impact on borrowers' successful participation in HAMP. A subsequent study conducted by the General Accounting Office (GAO) using nonpublic HAMP data on four servicers found some differences in the incidence of HAMP modifications across protected classes, but these differences were, in large part, because of differences in servicers' determination of borrowers' eligibility related to their debt-to-income ratio and the completeness of their modification request (GAO, 2014).

In this study, we seek to extend the research on racial and ethnic heterogeneity in loan modifications to include the modification terms borrowers receive. We also follow borrowers to observe differences in borrower repayment outcomes after modifications are made. This question is crucial, because, if modifications merely delay foreclosure, they may actually make lenders and borrowers (who are making payments under the modification) worse off. If redefault rates are systematically higher for borrowers of color who have received modifications, it would suggest that additional policies may be needed if the goal is to help these borrowers resolve their delinquency and sustain homeownership.

Methodologically, we present this analysis using a national sample of subprime and Alt-A mortgages originated at the peak of the subprime lending boom that are being serviced by a wide range of bank and nonbank servicers. This study is the only one to date to use merged loan performance data to study modifications at the national level through December 2012 (covering the peak period during which modifications were made). Although our sample still covers only a segment of the mortgage market, we believe that expanding the geographic and historical coverage of the analysis adds valuable new empirical evidence to our understanding of loan modifications and their effectiveness. We provide further details on the data in the next section.

Data and Methods

For this analysis, we created a unique dataset that merges loan-level data on subprime home mortgages that are managed by Corporate Trust Services (CTS) with loan-level data on borrowers from the HMDA. This merged dataset enables us to analyze whether differences in loan modification terms are influenced by the race and ethnicity of the borrower and to assess the extent to which these modifications are successful in preventing subsequent redefault.

CTS is a subsidiary service of Wells Fargo Bank, N.A. (hereafter, Wells Fargo) that provides investment vehicles administered by the bank. The CTS data cover privately securitized mortgages for which Wells Fargo serves as the trustee, including mortgages with different interest rate structures, purposes, property types, and lien statuses (Quercia and Ding, 2009; White, 2009b).[7] The database includes loans originated as early as the 1980s, tracks performance until the loan is paid off or foreclosed upon, and includes more than 4 million individual loans. Although Wells Fargo serves as the trustee for these investor pools, the data include loans from more than 100 servicers across the country, including large bank servicers such as Bank of America Corporation and J.P. Morgan Chase & Co. and nonbank servicers such as Ocwen Financial Corporation and Nationstar Mortgage Holdings, Inc. (Goodman and Lee, 2014). The top 20 servicers in our data cover bank and nonbank servicers, and they include 7 out of the 10 largest servicers in terms of market share in 2013 (Goodman and Lee, 2014). The largest servicer in the CTS data handles more than 13 million loans, while the smallest has approximately 70,000 loans in its portfolio. The data also reflect a broad range of servicer quality as ranked by Moody's Corporation credit rating services, including servicers who scored an SQ1, which represents strong combined servicing ability and stability, and SQ4, which represents less-than-average servicing ability and stability (Moody's Investor Service, 2014).

Each monthly loan record contains the borrower's FICO credit score, loan-to-value (LTV) ratio at origination, the last 12 months of delinquency history, the property ZIP Code, the type of loan, and the original and current balance of the loan. Importantly for this study, the CTS data include a modification indicator, which represents all permanent loan modifications and equals one for every period after the loan is modified. The reports also have information about the loan balance, mortgage payment, and interest rate, before and after modification, which enables us to identify whether total mortgage debt, interest rate, or mortgage payments are changed for individual homeowners.

The CTS dataset, however, does not include any information on the borrower's race or ethnicity. For this reason, following methods used by other researchers, we merge the CTS data with loan-level HMDA data (Ding, 2013; Ding et al., 2012). HMDA data provide information on the race and ethnicity of the borrower, his or her income, and the geographic location of the property securing the loan. To match the data, we sort CTS and HMDA loans into the census tracts of the purchased property using a geographic crosswalk file.[8] Within each census tract, we match loan originations on the following variables: origination date, loan amount, lien

[7] These investor report files are available at https://www.ctslink.com.

[8] One challenge in merging these data is relating U.S. Postal Service (USPS) ZIP Codes (the scale of the CTS data) to Census Bureau geographies (the scale of the HMDA data). We used the MABLE/Geocorr12: Geographic Correspondence Engine to allocate loans in ZIP Codes to corresponding census tracts. Details about the crosswalk are available at the Missouri Census Data Center, http://mcdc.missouri.edu/websas/geocorr12.html. For robustness, the authors also tested other available crosswalks (for example, the HUD/USPS ZIP crosswalk file), but the match rate did not improve.

status, and loan purpose.[9] Only loans that provide for a direct match on these variables are included in the resulting sample. We were able to match 69.2 percent of the unique loans in the servicing record to HMDA applications. We compare the sample means of CTS matched loans against those that were not matched and find no significant differences in the average loan amount, the borrower's FICO score, or whether the loan had an adjustable interest rate.[10] In addition, we compare the demographic distribution of the CTS sample against the demographic distribution of subprime loans in HMDA and find that the proportions of non-Hispanic White, Black, Hispanic, and Asian borrowers are similar across the two datasets.

The sample used in this study consists of all first-lien mortgages for owner-occupied, single-family residences originated in 2004, 2005, and 2006 (as the market shifted in early 2007, nonconforming subprime loans were no longer being added to the CTS database); we limit the data to loans that were active but at least 60 days delinquent as of June 2009.[11] We drop observations that went into bankruptcy during the panel and loans that were prepaid in the first period of observation. We also remove loans with an original balance of more than $1 million, because they are arguably a different subset of loans.[12] We observe modifications and loan performance through December 2012. Data on modifications from the OCC show that the volume of modifications peaked in early 2010 and then declined throughout 2011 and 2012, meaning that our sample captures the period during which most modifications were made (OCC, 2014). Because our interest in this study is to understand the relationship between modification types and redefault for different types of borrowers, we focus our analysis on 42,000 modified loans and consider only permanent, not trial, modifications.

Using cross-sectional linear probability models, we examine the performance of these loans from June 2009 through December 2012, at periods 6 and 12 months after modification, controlling for a wide range of loan, borrower, and housing market characteristics.[13]

We create additional variables to distinguish between different types of modifications. We construct two indicator variables, "interest rate decreased" and "loan balance decreased," that equal 1 if the rate decreased or the balance decreased, respectively.[14] To assess the extent of payment relief, we calculate the percentage change in the interest rate and monthly payment ("payment change") before and after modification. We also create an indicator variable that assesses whether

[9] The matching procedure was completed while one of the authors was at the Federal Reserve Bank of San Francisco, providing access to the nonpublic HMDA data, which include origination date. CTS loans were matched to HMDA on site, and then all identifying HMDA variables (including loan number) were deleted from the matched record, resulting in a CTS data file with race/ethnicity and income attached to each loan record, but no ability to regenerate the origination date or link the CTS records to the public HMDA file.

[10] Other studies that have used matching to merge HMDA data with loan performance records employ a probability matching technique so data on loans with multiple matches are not lost (Bocian et al., 2011). To date, no research has compared and contrasted these methods and the strengths and weaknesses of the different approaches.

[11] We chose to focus on delinquent loans because borrowers who receive modifications without being delinquent may differ from distressed borrowers in important and distinct ways.

[12] Dropping loans over $1 million results in a loss of about 0.5 percent of observations.

[13] Using a cross-sectional model design versus a panel structure did not change our substantive findings, so we present the cross-sectional results to ease interpretation.

[14] The data do not enable us to see whether the decline in the balance is related to principal forbearance or forgiveness.

a loan was "HAMP-eligible." Although we cannot directly see which loans were modified under HAMP, this HAMP-eligible variable includes loans that (1) were modified after the launch of HAMP, (2) had an unpaid principal balance of less than $729,750, (3) had an interest rate reduction that did not bring the interest rate to less than 2 percent (the HAMP interest rate floor), and (4) were ARMs but converted to fixed-rate mortgages after modification (in other words, ARMs that remained ARMs after modification were excluded).

The control variables in our analysis include the borrower's race and ethnicity, the borrower's income, the borrower's FICO score at origination, a no-documentation indicator, a prepayment-penalty indicator, and the combined loan-to-value (CLTV) ratio. We coded the race and ethnicity variables in the HMDA data based on the primary applicant as "Black/African-American" (Black), "Hispanic/Latino" (Hispanic), "Asian/Hawaiian/Pacific Islander" (Asian),[15] and "non-Hispanic White." The variables that capture the borrower's race and ethnicity, income, and FICO score are measured at the time of origination; one significant limitation of these data and most data that report loan performance is the inability to assess how changes in the borrower's income or FICO score over time influence either the probability of default or the success of modification.[16] We take a log transformation of income in the models because borrower income is not normally distributed. To account for changes in the housing market, we use monthly data from Zillow at the ZIP Code level and calculate relative house price changes for each loan, enabling us to see the effect of a borrower's equity position on modification terms or the likelihood of cure. All our models also include metropolitan statistical area (MSA)-level fixed effects to account for other market-level conditions that may influence modification terms or redefault.

Exhibit 1 presents summary statistics for the CTS sample of modified loans. The descriptive means for these variables are measured at origination with the exception of "HAMP eligibility," which is determined at the time of modification. For purposes of this study, it is noteworthy that the sample is demographically diverse. Although the plurality of borrowers is non-Hispanic White (48 percent), the sample also includes 22 percent Black borrowers, 28 percent Hispanic borrowers, and 4 percent Asian borrowers. Most loans (62 percent) listed a male borrower as the primary applicant. The average credit score of borrowers in the sample was 613, which is generally considered to be subprime (consistent with the fact that these are subprime and Alt-A loans that are bundled into private-label securities). The average applicant income at origination was $85,790. Focusing next on loan characteristics, we find that the average loan balance at origination was $241,265, with a mean LTV ratio of 83.48 percent. Most loans were ARMs (69 percent), with an average interest rate of 7.37 percent. Approximately one out of four modified loans were HAMP eligible, suggesting that a fair number of loans in our sample underwent proprietary modifications.

[15] Also includes a small percentage of Native American and other races.

[16] Although a borrower's race and ethnicity should be static characteristics and not change between origination and modification, researchers who have analyzed the HAMP data have found that the race and ethnicity associated with a loan can change. For example, at modification it may be the coapplicant who interfaces with the lender. Lenders may have also made assignment errors, either at origination or at time of modification. In addition, researchers have noted the high degree of nonreporting of race/ethnicity data in HMDA (Wyly and Holloway, 2002).

Exhibit 1

Summary Statistics for the CTS Sample of Modified Loans

Borrower Characteristics		Loan Characteristics	
Black	0.22	ARM	0.69
	(0.41)		(0.46)
Hispanic	0.28	Loan balance	241,265
	(0.45)		(155,010)
Asian	0.04	HAMP-eligible	0.25
	(0.19)		(0.43)
Non-Hispanic White	0.48	CLTV ratio	83.48
	(0.50)		(12.77)
Male	0.62	Interest rate	7.37
	(0.49)		(1.74)
FICO™	613		
	(73)		
Applicant income	85,790		
	(88,660)		

ARM = adjustable-rate mortgage. CLTV = combined loan-to-value. HAMP = Home Affordable Modification Program.

Notes: N = 42,374. Data include all loans originated between 2004 and 2006 that were modified before December 2012. Means reported for period 1 (December 2006). Standard deviations are in parentheses. Black, Hispanic, Asian, non-Hispanic White, and male are based on Home Mortgage Disclosure Act data. FICO™ is credit score at the time of origination. Applicant income is applicants' income at time of application. ARM = 1 for adjustable rate mortgages. HAMP-eligible is determined at the time of modification.

Source: Corporate Trust Services

One significant limitation of the CTS data is its coverage of the mortgage market—in particular, the lack of coverage of prime loans and loans held by banks in portfolio. Nevertheless, given that subprime mortgages account for a significant share of all foreclosures and that most subprime loans that led to the crisis were privately securitized, this sample provides important insights into the performance of loan modifications for this segment of the market. Also, given the potential that modifications are more challenging among privately securitized loans (meaning loans not managed by Fannie Mae, Freddie Mac, or Ginnie Mae), this sample is particularly relevant for policymakers. Finally, one other strength of this data and study is their national coverage; as noted previously, other studies that have examined detailed loan modification outcomes by borrower race and ethnicity have tended to focus on borrowers in New York City (Been et al., 2013; Voicu et al., 2012) or in select states (Collins and Reid, 2010). Expanding the analysis to a national sample of loans enables us to determine the extent to which these more geographically targeted findings on loan default resolutions by race and ethnicity are nationally representative. As we argue in the conclusion, however, additional research is needed to develop a better understanding of servicing practices across the entire mortgage market, especially because existing studies also cover different time periods and mortgage market segments.

Findings

In this section, we present the results of our analysis. First, we assess whether Black, Hispanic, and Asian borrowers receive less aggressive loan modifications, contingent on receiving a modification. Second, we explore the effectiveness of loan modifications in preventing re-default, again with a focus on differences across racial and ethnic groups.

Loan Modification Terms by Race and Ethnicity

Because the success of modification is likely shaped by the type of modification a borrower receives, it is important to understand whether, conditional on modification, different borrowers receive differently structured modifications. In exhibit 2, we present three separate models to assess whether racial or ethnic differences influence the type of modification received. The

Exhibit 2

Models Examining the Likelihood of Receiving a Modification With Interest Rate, Loan Balance, or Payment Reductions

Dependent Variable	Linear Probability: Interest Rate Decreased	Linear Probability: Loan Balance Decreased	Ordinary Least Squares: Payment Change
Black	0.005	0.008	– 0.011**
	(0.005)	(0.005)	(0.004)
Hispanic	– 0.005	– 0.002	– 0.025***
	(0.005)	(0.005)	(0.004)
Asian	– 0.005	0.005	– 0.015*
	(0.011)	(0.010)	(0.007)
ARM	0.074***	0.035***	– 0.070***
	(0.006)	(0.005)	(0.003)
Income (logged)	0.006	0.009*	0.003
	(0.004)	(0.004)	(0.003)
HAMP-eligible	0.426***	0.038***	– 0.156***
	(0.005)	(0.004)	(0.003)
House price change	0.037**	– 0.215***	0.122***
	(0.012)	(0.013)	(0.008)
More than 60 days behind before modification	0.024***	– 0.010	– 0.003
	(0.006)	(0.005)	(0.004)
Total Observations	33,383	33,383	29,896

ARM = adjustable-rate mortgage. HAMP = Home Affordable Modification Program.

**p < 0.05. **p < 0.01. ***p < 0.001.*

Notes: Interest rate decreased and loan balance decreased are dummy variables regarding the type of modification. Payment change reflects the change in monthly payment before and after modification, recorded in percentage terms. Black, Hispanic, and Asian are based on Home Mortgage Disclosure Act data. Non-Hispanic White is the excluded group. ARM is a dummy for an adjustable rate mortgage. Income (logged) is at the time of application. HAMP-eligible is determined at the time of modification. House price change measures the difference in house prices at the ZIP Code level between date of modification and origination. More than 60 days behind before modification marks the delinquency status the month before modification. The model also controls for FICO™ credit score and combined loan-to-value ratio quartiles, a no-documentation dummy, a prepayment penalty dummy, and metropolitan statistical area-level fixed effects.

Source: Corporate Trust Services

first two columns present the findings from a linear probability model assessing whether a modification entailed (1) a reduction in the loan interest rate and (2) a reduction in the loan principal or balance. The third column presents an ordinary least squares model in which the dependent variable is the percent change in the monthly mortgage payment. In addition to the variables in the exhibit, each model controls for FICO and CLTV quartiles, the percent change in house prices at the ZIP Code level from origination to modification (logged), the borrower's income at origination (logged), a no-documentation indicator variable, a prepayment penalty indicator variable, and MSA-level fixed effects.

Importantly, we find very few differences in the likelihood of either interest rate reductions or balance decreases by race or ethnicity. Compared with White borrowers, Black, Hispanic, and Asian borrowers are equally likely to receive a modification that decreases the interest rate or principal balance, after controlling for a wide range of factors. When we examine the amount of change in monthly payments, we find that Black, Hispanic, and Asian borrowers all receive a slightly larger reduction in their monthly payments than White borrowers. The differences are slight, however, with the difference ranging from a 1.1-percent greater decrease in monthly payments for Black borrowers to 2.5 percent for Hispanic borrowers.

In terms of the other control variables, we find that loans with adjustable interest rates are more likely to result in interest rate and principal balance decreases and also a greater decrease in the monthly payments. We find that higher income borrowers are slightly more likely to receive a modification that entails a principal decrease, but again the effect is small. We also find that living in ZIP Codes with lower house price declines (or house price increases) between origination and modification significantly decreases the likelihood of a borrower receiving a principal reduction, but it increases the likelihood of the borrower receiving a lowered interest rate and a greater reduction in monthly payments. For some servicers, a rising market may change their net present value, or NPV, calculation and reduce the likelihood that they would be willing to forgo principal. We also find that borrowers who are more than 60 days delinquent at the time of modification are slightly more likely to see interest rate reductions than borrowers who are only 2 months behind on their payments; however, serious delinquency appears to have no effect on the likelihood of principal decreases or the amount of payment relief the borrower is offered.

The model also shows that the HAMP-eligible indicator variable has a significant, positive effect on the type of modification a borrower receives. Conditional on receiving a modification, borrowers who fit within HAMP-eligibility criteria—including receiving their modification after HAMP was launched—are more likely to receive an interest rate or principal reduction on their loan. They also receive a much greater decrease in their monthly payments—on average, borrowers who could have received a HAMP modification see their monthly payments go down 15.6 percent compared with borrowers who receive a modification before HAMP was launched or who may not be eligible because their loan balance is too high.

Modifications and Loan Performance

Our second assessment relates to the effectiveness of loan modifications and whether the modifications granted have been successful at keeping borrowers in their homes. We begin by examining differences in loan performance in a descriptive framework. Exhibit 3 displays summary statistics for our sample of modified loans in the top panel and, for a comparable sample of nonmodified loans in the CTS data, in the bottom panel.[17] Approximately 22 percent of the delinquent loans in our sample were modified between December 2006 and December 2012. Without controlling for other borrower or loan characteristics, we find that modification rates are higher for Hispanic and Black borrowers; approximately 33 percent of Black borrowers and 25 percent of Hispanic borrowers received a loan modification compared with 19 percent of Non-Hispanic White borrowers and 17 percent of Asian borrowers. Most loan modifications involve a rate reduction; 80 percent of all modifications include some form of interest forgiveness, with an average reduction of monthly payments of 29 percent. In contrast, only 18 percent of modifications include a reduction in the loan balance. Consistent with other studies, in these descriptive results, we do not find significant racial or ethnic differences in the types of modifications received. Overall, the incidence of various loan modification types and terms are remarkably consistent across racial and ethnic categories. We also find that approximately

Exhibit 3

Comparing Outcomes for Delinquent Loans With and Without Modifications, by Race and Ethnicity

	White	Black	Asian	Hispanic	Other	Total
Delinquent loans with modification						
Number of delinquent loans	20,506	9,267	1,549	10,568	484	42,374
Percent of delinquent loans modified	0.19	0.33	0.17	0.25	0.23	0.22
Interest rate decreased	0.79	0.81	0.81	0.80	0.82	0.80
	(0.41)	(0.40)	(0.39)	(0.40)	(0.39)	(0.40)
Loan balance decreased	0.16	0.20	0.18	0.20	0.15	0.18
	(0.36)	(0.40)	(0.38)	(0.40)	(0.36)	(0.38)
Percent payment change	– 0.27	– 0.30	– 0.29	– 0.31	– 0.28	– 0.29
	(0.24)	(0.24)	(0.24)	(0.24)	(0.22)	(0.24)
Ever foreclosed	0.33	0.32	0.26	0.28	0.35	0.31
	(0.47)	(0.47)	(0.44)	(0.45)	(0.48)	(0.46)
Delinquent loans, no modification						
Number of delinquent loans	86,863	19,227	7,403	31,657	1,600	146,750
Ever foreclosed	0.33	0.42	0.38	0.49	0.42	0.38
	(0.47)	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)

Notes: Means reported, with standard deviations in parentheses. Interest rate decreased and loan balance decreased are dummy variables regarding the type of modification. Percent payment change reflects the change in monthly payments before and after modification, recorded in percentage terms.

Source: Corporate Trust Services

[17] The nonmodified sample includes loans originated between 2004 and 2006 that were at least 60 days delinquent and active in June 2009 but that were not modified between December 2006 and December 2012.

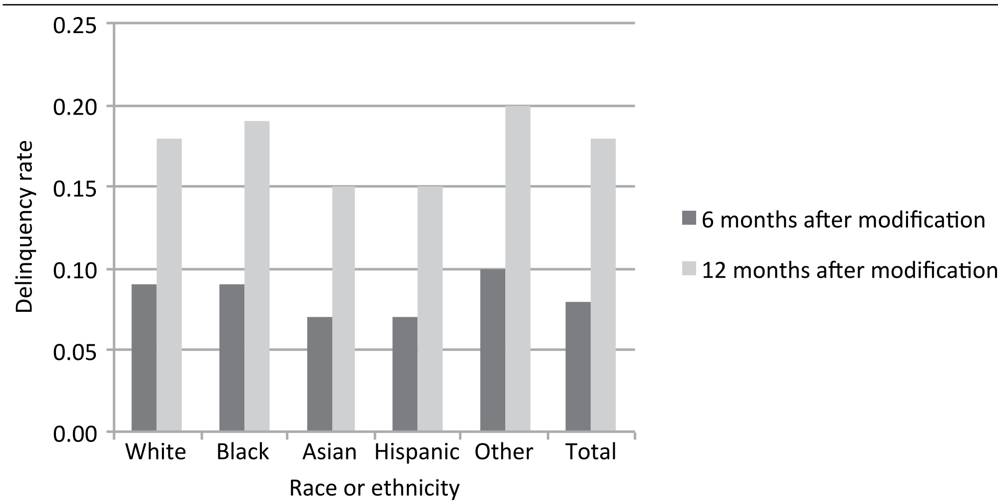
one-third of modified loans end in foreclosure, despite the modification.[18] Asian borrowers have the lowest levels of foreclosure after modification (26 percent), with White, Black, and borrowers classified as "Other" having slightly higher foreclosure rates than average.

For comparison, in the bottom panel of exhibit 3, we present the foreclosure rate for loans that were 60 days or more delinquent but not modified during our observation period. Overall, modified loans perform better than unmodified loans; 38 percent of unmodified loans in our sample end in foreclosure. The data also show that modifications reduced the foreclosure rate for minority borrowers, but not for non-Hispanic White borrowers. For instance, 42 percent of Black borrowers who did not receive a modification lost their home to foreclosure compared with 32 percent of Black borrowers who received a modification. In contrast, the foreclosure rate for non-Hispanic White borrowers is similar for delinquent loans that underwent modification and those that did not.

In exhibit 4, we examine serious delinquency rates for modified loans by race and ethnicity, measured at 6 and 12 months after modification. Approximately 7 percent of loans have missed at least three payments 3 months after modification (and are therefore 90 or more days late). Within a year, nearly 18 percent of borrowers have missed at least three payments. In comparison with White and Black borrowers, Asian and Hispanic borrowers have slightly lower rates of being 90 or more days delinquent, at 6 months and 1 year after modification.

Exhibit 4

Percent of Modified Loans That Returned to Seriously Delinquent Status 6 and 12 Months After Modification



Source: Corporate Trust Services

[18] The foreclosure rate is measured at the last period of observation, either when the loan ends in foreclosure or in December 2012.

Although these descriptive statistics can help reveal overall trends in loan performance after modification, they do not control for borrower, loan, or housing market characteristics that might influence the likelihood that a borrower can continue to pay his or her mortgage, even with a modification. For this reason, we explore the effectiveness of loan modifications in a multivariate framework. Exhibit 5 presents a cross-sectional linear probability model that assesses loan performance 6 and 12 months after modification. As with the previous models, nonreported controls include FICO and CLTV quartiles, a no-documentation indicator variable, a prepayment penalty indicator variable, house price changes at the ZIP Code level from the time of modification to 6 or 12 months after origination, and MSA-level fixed effects.

Focusing first on differences by race and ethnicity, we find that only Black borrowers are slightly more likely to experience delinquency than White borrowers after receiving a modification. Specifically, 12 months after modification, Black borrowers are more likely to be 60 days delinquent, but the size of the effect is small. We also find that Hispanic borrowers are slightly less likely to be at least 30 days delinquent 6 months after modification. Overall, after controlling for a wide range of factors, we find very little variation in the effectiveness of modifications by race or ethnicity. Borrowers with higher incomes at origination are slightly less likely to become delinquent or go into foreclosure after modification.

HAMP eligibility also reduces the likelihood of redefault. Modifications that were HAMP eligible reduce the likelihood of foreclosure after 12 months by 6 percent, even after controlling for a wide range of other characteristics. We do not find a significant effect of house price changes on the likelihood of redefault; in part, this may be because of the fact that we are measuring house price change between the month of modification and 6 or 12 months later, which results in smaller differentials than our previous measure of house price change, which captured the higher price levels among loans originated before 2007 and the subsequent rapid drop in values during the crisis.

Perhaps counterintuitively, we find that borrowers who are seriously delinquent (90 days or more) at the time of modification are less likely to redefault after modification. Although this finding may in part be due to a selection effect (for example, servicers may be effectively identifying borrowers who need a modification to stay in their homes), it also suggests that modifications can be effective even for borrowers who are several months behind in their payments. In terms of the modifications themselves, we find that interest rate reductions tend to reduce delinquencies (this is consistent at both 6 and 12 months after modification), but that only principal forgiveness reduces the likelihood of foreclosure a year after modification. When we run the same model but control for the percentage change in monthly payments, we find that a decrease in monthly payments reduces the likelihood of redefault and foreclosure across the board (exhibit 6). As we discuss in the conclusion that follows, these results point to the importance of understanding both the nature of modifications and the outcomes that are tracked post-modification to assess which modifications are the most effective at keeping borrowers in their home over the long term.

Exhibit 5

Models Examining the Role of Modifications in Subsequent Loan Performance, Interest Rate and Loan Balance Changes

	After 6 Months				After 12 Months			
	30 or More Days Behind	60 or More Days Behind	90 or More Days Behind	Fore-closure	30 or More Days Behind	60 or More Days Behind	90 or More Days Behind	Fore-closure
Black	0.001	0.002	– 0.003	– 0.006	0.010	0.017*	0.004	– 0.005
	(0.007)	(0.006)	(0.005)	(0.003)	(0.009)	(0.008)	(0.007)	(0.006)
Hispanic	– 0.016**	– 0.010	– 0.006	– 0.005	– 0.015	– 0.001	– 0.003	0.003
	(0.006)	(0.005)	(0.005)	(0.003)	(0.008)	(0.007)	(0.007)	(0.005)
Asian	– 0.015	– 0.010	– 0.007	– 0.002	– 0.005	– 0.007	– 0.004	– 0.001
	(0.013)	(0.011)	(0.009)	(0.006)	(0.016)	(0.015)	(0.014)	(0.010)
Male	0.013*	0.007	0.004	0.004	0.012	0.006	0.001	0.005
	(0.005)	(0.004)	(0.004)	(0.003)	(0.006)	(0.006)	(0.005)	(0.004)
Loan balance decreased	0.006	0.016*	0.014*	0.008*	0.001	0.002	– 0.002	– 0.019***
	(0.008)	(0.007)	(0.006)	(0.004)	(0.010)	(0.009)	(0.009)	(0.006)
Interest rate decreased	– 0.039***	– 0.032***	– 0.027***	– 0.004	– 0.042***	– 0.044***	– 0.039***	0.004
	(0.006)	(0.006)	(0.005)	(0.003)	(0.008)	(0.007)	(0.007)	(0.005)
More than 60 days behind before modification	– 0.097***	– 0.079***	– 0.058***	– 0.028***	– 0.111***	– 0.110***	– 0.105***	– 0.061***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.008)	(0.007)	(0.006)	(0.004)
ARM	0.011*	0.011*	0.009*	0.001	0.014*	0.015*	0.018**	0.007
	(0.005)	(0.005)	(0.004)	(0.003)	(0.007)	(0.006)	(0.006)	(0.004)
Current balance	0.074***	0.060***	0.050***	0.022***	0.095***	0.083***	0.076***	0.040***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.009)	(0.009)	(0.008)	(0.006)
Income (logged)	– 0.025***	– 0.022***	– 0.016***	– 0.008*	– 0.024**	– 0.022**	– 0.021**	– 0.015**
	(0.006)	(0.005)	(0.004)	(0.003)	(0.008)	(0.007)	(0.007)	(0.005)
HAMP-eligible	– 0.101***	– 0.079***	– 0.059***	– 0.032***	– 0.147***	– 0.136***	– 0.121***	– 0.056***
	(0.005)	(0.004)	(0.003)	(0.002)	(0.007)	(0.006)	(0.005)	(0.004)
House price change (6 months after modification)	0.026	– 0.017	0.018	– 0.003	—	—	—	—
	(0.057)	(0.048)	(0.042)	(0.029)	—	—	—	
House price change (12 months after modification)	—	—	—	—	– 0.040	– 0.017	– 0.008	– 0.042
	—	—	—	—	(0.050)	(0.046)	(0.043)	(0.032)
Total observations	27,973	27,973	27,973	27,940	22,645	22,645	22,645	22,411

ARM = adjustable-rate mortgage. HAMP = Home Affordable Modification Program.

$^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

Notes: Model—Linear probability. Additional controls include a no-documentation dummy, a prepayment penalty dummy, metropolitan statistical area-level fixed effects, and FICO™ credit score and combined loan-to-value ratio quartiles. Black, Hispanic, and Asian are based on Home Mortgage Disclosure Act data. Non-Hispanic White is the excluded group. ARM is a dummy for an adjustable rate mortgage. Income (logged) is at the time of application. Interest rate decreased and loan balance decreased are dummies equal to 1 if the loan interest rate or principal balance, respectively, was reduced with the modification. HAMP-eligible is determined at the point of modification. More than 60 days behind before modification marks the delinquency status the month before modification. House price change is measured as the difference in house prices between 6 or 12 months after modification and the time of modification.

Source: Corporate Trust Services (CTS)

Exhibit 6

Models Examining the Role of Modifications in Subsequent Loan Performance, Monthly Payment Changes

	After 6 Months				After 12 Months			
	30 or More Days Behind	60 or More Days Behind	90 or More Days Behind	Fore-closure	30 or More Days Behind	60 or More Days Behind	90 or More Days Behind	Fore-closure
Black	0.005	0.005	0.001	– 0.004	0.008	0.017*	0.006	– 0.003
	(0.007)	(0.006)	(0.005)	(0.004)	(0.009)	(0.008)	(0.008)	(0.006)
Hispanic	– 0.018**	– 0.012*	– 0.007	– 0.005	– 0.021**	– 0.008	– 0.009	0.002
	(0.006)	(0.005)	(0.005)	(0.003)	(0.008)	(0.007)	(0.007)	(0.005)
Asian	– 0.020	– 0.016	– 0.010	– 0.003	– 0.026	– 0.018	– 0.011	– 0.004
	(0.013)	(0.010)	(0.009)	(0.006)	(0.016)	(0.015)	(0.014)	(0.010)
Male	0.014**	0.008	0.005	0.005	0.006	0.001	– 0.001	0.004
	(0.005)	(0.004)	(0.004)	(0.003)	(0.007)	(0.006)	(0.006)	(0.004)
Payment change	0.305***	0.207***	0.153***	0.054***	0.356***	0.299***	0.251***	0.124***
	(0.014)	(0.012)	(0.010)	(0.008)	(0.018)	(0.016)	(0.015)	(0.011)
More than 60 days behind before modification	– 0.099***	– 0.078***	– 0.058***	– 0.029***	– 0.111***	– 0.112***	– 0.106***	– 0.060***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.008)	(0.007)	(0.006)	(0.004)
ARM	0.003	0.007	0.004	– 0.003	0.007	0.007	0.010	0.000
	(0.006)	(0.005)	(0.004)	(0.003)	(0.007)	(0.007)	(0.006)	(0.005)
Current balance	0.048***	0.040***	0.037***	0.017***	0.081***	0.071***	0.067***	0.038***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.010)	(0.009)	(0.008)	(0.006)
Income (logged)	– 0.014*	– 0.014**	– 0.012**	– 0.007*	– 0.021**	– 0.019**	– 0.019**	– 0.015**
	(0.006)	(0.005)	(0.004)	(0.003)	(0.008)	(0.007)	(0.007)	(0.005)
HAMP eligible	– 0.009	– 0.014**	– 0.011*	– 0.014***	– 0.040***	– 0.043***	– 0.042***	– 0.019***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.008)	(0.007)	(0.007)	(0.005)
House price change (6 months after modification)	– 0.040	– 0.068	– 0.002	– 0.010	—	—	—	—
	(0.060)	(0.050)	(0.042)	(0.029)	—	—	—	—
House price change (12 months after modification)	—	—	—	—	– 0.110*	– 0.088	– 0.075	– 0.078*
	—	—	—	—	(0.055)	(0.050)	(0.046)	(0.035)
Total observations	24,926	24,926	24,926	24,905	19,657	19,657	19,657	19,481

ARM = adjustable-rate mortgage. HAMP = Home Affordable Modification Program.

$^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

Notes: Model—Linear probability. Additional controls include a no-documentation dummy, a prepayment penalty dummy, metropolitan statistical area-level fixed effects, and FICO™ credit score and combined loan-to-value ratio quartiles. Black, Hispanic, and Asian are based on Home Mortgage Disclosure Act data. Non-Hispanic White is the excluded group. ARM is a dummy for an adjustable rate mortgage. Income (logged) is at the time of application. Interest rate decreased and loan balance decreased are dummies equal to 1 if the loan interest rate or principal balance, respectively, was reduced with the modification. HAMP-eligible is determined at the point of modification. More than 60 days behind before modification marks the delinquency status the month before modification. House price change is measured as the difference in house prices between 6 or 12 months after modification and the time of modification.

Source: Corporate Trust Services (CTS)

Conclusions

Confronted with a rising number of foreclosures, the federal government launched HAMP in 2009, with the goal of increasing the scale and impact of loan modifications. Since then, concerns have emerged about whether loan modifications are successful at preventing foreclosure and whether racial or ethnic differences influence who benefits from a modification. Using a sample of national subprime and Alt-A loans, we find no evidence of racial disparities in the types of loan modifications received. Overall, race or ethnicity is not a significant factor in predicting loan modification terms. The one exception is in the area of monthly payment reductions; we find that Black, Hispanic, and Asian borrowers receive modifications that entail a greater reduction in monthly payments than non-Hispanic White borrowers, although the additional amount of payment relief is small. These findings stand in stark contrast to the literature on mortgage originations, which has revealed persistent differences in loan outcomes by race and ethnicity in terms of loan pricing and terms (Avery, Brevoort, and Canner, 2006; Bocian, Li, and Ernst, 2008; Nichols, Pennington-Cross, and Yezer, 2004).

Our findings on the effectiveness of loan modifications are more mixed. We find that modifications do reduce the likelihood of delinquency and foreclosure, and that substantive differences in the effectiveness of modifications are very little across racial and ethnic groups. HAMP-eligible modifications (those that were made after HAMP was officially launched and that met loan amount criteria) display significantly lower subsequent rates of delinquency and foreclosure, as do modifications with reductions in monthly payments. These findings suggest that the focus of HAMP on the affordability of payments may facilitate better borrower outcomes than earlier voluntary modification efforts in which monthly payments would often increase (White, 2009a, 2009b). Because we cannot directly observe HAMP versus proprietary modifications, however, the direct impact of HAMP remains an important avenue for future research. Another important question for future research is whether the modification terms (for example, interest rate reductions) will remain in place and contribute to the sustainability of the loan beyond the 1 year we can observe.

Beyond the primary questions driving this study, several other issues are raised by this research. First, the models show that the affordability of monthly payments is a key factor influencing redefault, suggesting that affordability concerns are an important component of any loss-mitigation program. Under HAMP, interest rate reductions are required to be in place only for 5 years. As loans modified under HAMP revert to premodification interest rate levels in the coming years, some borrowers will have recovered from the recession sufficiently to manage these increased payments. Other borrowers, however, may need ongoing attention from servicers to develop alternative payment arrangements or to even sell the property to avoid default. The needs of borrowers with modified mortgage loans will require additional capacity from servicers and deserve ongoing oversight by regulators. Future research should also focus on racial and ethnic differences as borrowers reach the 5-year limit of their loan modifications.

Second, housing counseling has been an emphasis of the response to rising foreclosures, as evidenced by the National Foreclosure Mitigation Counseling Program. This program is associated with increased rates of loan modifications for troubled borrowers (Collins and Schmeiser, 2013; Collins, Schmeiser, and Urban, 2013; Mayer et al., 2009). Existing datasets on loan performance, including the one used in this study, unfortunately do not include information about whether borrowers received counseling either prepurchase or during the loan renegotiation process. The role of counseling needs to be considered in any review of policies responding to borrowers in distress as policymakers consider ways to stimulate loan workouts in other markets, particularly the student loan market, which has garnered increased attention in recent years.

Third, our research demonstrates that not all loan modifications are successful, and we believe that a lot can still be learned about which types of modifications and post-purchase interventions are the most effective at sustaining homeownership. As with other research focused on loan modifications, our study is limited in its coverage of the mortgage market; existing datasets generally either focus on one market segment (for example, subprime and Alt-A loans as with the CTS) or do not include a specific loan modification flag, requiring that researchers make assumptions about which loan changes are because of a modification. Increased transparency in servicing practices and better publicly available data on loan modification terms and outcomes by race and ethnicity (and by income and gender) for the entire mortgage market would increase our ability to assess the relative strengths and weaknesses of different loan modification practices and develop policies to better assist borrowers who face mortgage distress. HMDA, and the role it played in increasing transparency about mortgage applications, offers one potential model. Servicers could be required to disclose loan modification terms and borrower characteristics using a similar annual reporting mechanism as is used for home mortgage loan applications. Evidence is emerging that simply enforcing reporting requirements might shift servicer behavior (Collins and Urban, 2014).

Finally, our finding that one-third of modified, subprime loans still end in foreclosure raises the larger question of how to reduce the vulnerability of lower wealth and lower income households in the homeownership market. The Consumer Financial Protection Bureau and the reforms enacted by the Dodd-Frank Wall Street Reform and Consumer Protection Act expand consumer protections while limiting the ability of financial institutions to engage in high-risk lending practices. Mortgage terms are not the only predictors of the sustainability of homeownership, however. Borrowers of color, especially those who have lower incomes or who work in lower skilled jobs, may face increased risk and income volatility associated with structural changes in the labor market (Reid, 2014). In addition, lower income homeowners have a smaller financial cushion with which to withstand the impact of negative life events, such as unemployment or serious illness, or to meet unanticipated repair costs (Mallach, 2011). For these borrowers, loan terms may not be the only, or even the most important, factor influencing the sustainability of homeownership. Although transparent and effective guidelines for loan servicing are critical, greater emphasis and funding for policies that provide post-purchase support can help to ensure that borrowers of color are able to stay in their homes and experience the potential benefits of homeownership.

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Departments

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- *Foreign Exchange*

Data Shop

Data Shop, a department of Cityscape*, presents short articles or notes on the uses of data in housing and urban research. Through this department, the Office of Policy Development and Research introduces readers to new and overlooked data sources and to improved techniques in using well-known data. The emphasis is on sources and methods that analysts can use in their own work. Researchers often run into knotty data problems involving data interpretation or manipulation that must be solved before a project can proceed, but they seldom get to focus in detail on the solutions to such problems. If you have an idea for an applied, data-centric note of no more than 3,000 words, please send a one-paragraph abstract to david.a.vandenbroucke@hud.gov for consideration.*

Data Sources for U.S. Housing Research, Part 2: Private Sources, Administrative Records, and Future Directions

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This article is the second of a two-part article about data sources for U.S. housing research. The first part, which appeared in the previous issue of Cityscape *(Volume 16, Number 3), addressed public sources.*

Abstract

For practitioners and policymakers to make a serious attempt to affect housing policy, they must cite evidence-based research. Part 2 of this article summarizes many of the private sources of housing data for researchers that can provide such evidence. It then summarizes the challenges of using administrative records (AR) and proposes to construct new data sources by marrying survey data with AR and by constructing synthetic databases. The article concludes with a brief discussion of some data issues.

Introduction

The basis for good housing policy is evidence-based research, and the only way to do good research on housing is to base that research on appropriate data. Whereas part 1 of this article focused on government data sources for U.S. housing statistics, part 2 describes private data sources and administrative records (AR). It concludes with suggestions for future data production activities and mentions two unresolved data issues.

Private-Sector Data Sources

The National Association of Realtors® (NAR) and the National Association of Home Builders (NAHB) both issue housing affordability indexes (the latter is known as the NAHB/Wells Fargo Housing Opportunity Index). Such an index typically indicates whether a family with median income can afford the median-priced existing single-family home at prevailing mortgage rates (NAR uses the national median income and NAHB uses the U.S. Department of Housing and Urban Development's [HUD's] Area Median Incomes).

National Association of Realtors

NAR also provides monthly data series that track housing market sales: monthly sales volumes for existing homes by region, monthly sales volumes for single-family and cooperative apartments, monthly sales inventories of existing single-family and condominium homes, and the monthly pending home sales index (a forecast of existing home sales in the subsequent 1 to 2 months).

National Association of Home Builders

On a subscription basis, NAHB also offers 43 sets comprising various data series of interest to its constituency. These sets include data on building material prices (for example, framing lumber), employment, and permits. NAHB surveys multifamily developers and property managers to produce a Multifamily Production Index and a Multifamily Vacancy Index.

Mortgage Bankers Association

For subscribers, the Mortgage Bankers Association Weekly Applications Survey offers a comprehensive analysis of mortgage application activity. Historical index data are available back to the original start date of the survey in 1990. The survey's 15 indexes cover fixed-rate, adjustable-rate, conventional, and government loans for purchases and refinances.

RealtyTrac

RealtyTrac® Inc. has a website with foreclosure listings covering more than 2 million default, auction, short-sale, and bank-owned homes. Access is available for subscribers, and bulk downloads can be licensed. RealtyTrac describes its data as covering more than 100 million homes in 2,200 counties, accounting for 85 percent of all properties in the largest 200 metropolitan areas in the United States. For each property, RealtyTrac provides detailed housing characteristics (equity, foreclosure details, comparable sales and listings, trends, lot size, square footage, price, and year built) and sales history (historical loan positioning, loan-to-value ratio, loan amount, estimated market value, property information, default amount, owner name, trustee, and lender name). HUD and the U.S. Census Bureau began joint research using these records matched to the American Housing Survey (AHS). RealtyTrac is distinct from other companies providing online foreclosure information in that it has historical data back to 2005 and provides analytic reports.

Other Sources of Information

Companies such as CoreLogic, Inc., Black Knight Financial Services, Inc., and Zillow can provide basic property tax data, including parcel boundaries, for a large subset of the United States. As CoreLogic notes—[1]

> CoreLogic is the nation's largest provider of advanced property and ownership information, analytics and solutions. Our databases cover more than 99 percent of the U.S. properties. CoreLogic obtains property records, tax assessments, property characteristics, and parcel maps from tax assessors and county recorders offices across the nation. This information is combined with flood, demographics, crime, site inspection neighborhood, document images and other information from proprietary sources to further enrich our databases.

Zillow provides property-level data, including historical sales price and year, taxes, and number of bedrooms and bathrooms; demographic data at the city and neighborhood level; and neighborhood information, including the Zillow Home Value Index, median single-family home and condominium values, and average tax rates. The Census Bureau is looking into whether such commercial data sources can reduce the cost of updating the Master Address File (MAF).

MPF Research analyzes the rental housing market for clients. The company advertises that, "With exclusive access to a completely unique data source and a solid foundation of sound statistical methodologies, MPF Research publishes 72 individual apartment market reports covering the top 100 markets nationally."[2] MPF Research presents little about its methodology on its website.[3]

The National Council of Real Estate Investment Fiduciaries (NCREIF) is a cooperative organization that publishes information provided by its members. Its website indicates that, "NCREIF was established to serve the institutional real estate investment community as a non-partisan collector, processor, validator and disseminator of real estate performance information."[4] NCREIF bases its reports on its database of all-equity properties begun in 1977. In 2013, NCREIF has information on "approximately 30,000 properties historically, and approximately 10,000 current properties. NCREIF collects 67 data fields each quarter that consist of financial information such as Market

[1] Quoted from http://www.corelogic.com/solutions/property-information-analytic-solutions.aspx.

[2] Quoted from https://www.realpage.com/mpf-research/?src=AdWords&medium=PPC&campaign=AdGroupName&Network=Search&kw=mpf&gclid=CNfo5ayInsMCFdgKgQodtj0AmQ.

[3] They note at https://www.realpage.com/mpf-research/methodology/ that "Data collected in the MPF Research quarterly survey is collected through various sources. Where available, MPF Research can incorporate data from RealPage software products. MPF Research also collects data through direct relationships with management companies, through telephone surveys, and through e-mail surveys that are completed by apartment community owners or managers."

[4] Quoted from https://www.ncreif.org/about.aspx.

Value, [Net Operating Income], Debt, and [Capital Expenditures], as well as descriptor data such as Property Type and Subtype, Number of Floors, Square Footage, Number of Units, and Location" (NCREIF, 2013–2014: 2). It also publishes the NCREIF Property Index (NPI), "which is a quarterly index tracking the performance of core institutional property markets in the U.S." (NCREIF, 2013–2014: 2), and the NCREIF Transaction-Based Index (NTBI)—"The NTBI is an equal-weighted transaction and appraisal index while the NPI is a value weighted index calculated using appraised values" (NCREIF, 2013–2014: 7). Using a subset of the included properties, NCREIF also publishes the NCREIF Timberland and Farmland Property Indices and provides other products to its clients such as a quarterly property index trends analysis report and operations data categorized by "four subcategories within income and eight categories within expense, as well as four capital expenditures subgroups" (NCREIF, 2013–2014: 3).

The Promise and Challenge of Administrative Records

Researchers have probably reached the limits of what government survey data collection can accomplish. As federal budgets get tighter, fewer surveys (and reduced sample sizes) are likelier than increased coverage of topics or additional samples to provide separate information for more metropolitan areas. That likelihood suggests that a fruitful area for federal statistical agencies to create value added is to take advantage of existing AR data sources; that is, data collected primarily or exclusively for administrative purposes rather than for research, also known as *third party data*. As the HUD *Research Roadmap* points out—

> Research has shifted toward administrative data for three reasons:
>
> 1. Administrative records offer much larger sample sizes for full populations, which support more compelling research designs and research into important but relatively rare events.
>
> 2. Administrative files often have an inherent longitudinal structure that enables researchers to follow individuals over time and address policy questions.
>
> 3. Administrative data are less likely than survey data to suffer from high and rising rates of nonresponse, attrition, and underreporting. (HUD, 2013: 3)

Harnessing the power of these data through web-based information systems and geospatial analysis and matching these data with survey and administrative data from other agencies will provide the foundation for the next generation of evidence-based policymaking.

One particularly important area for investigation is the use of AR for improving the Census Bureau MAF. Improving the MAF—the basis for all Census Bureau household survey samples—will yield benefits to all such surveys and to the next decennial census. Under an agreement with the Census Bureau, the U.S. Postal Service (USPS) already provides a copy of its Delivery Sequence File (DSF) twice a year, and each DSF is used to update the MAF. The Census Bureau is investigating the use of National Change of Address files for improving the MAF.

Two other key components of MAF updates associated with the decennial census—address canvassing to determine ground truth and local updates—can be brought further into the digital age. Efforts under way through the Census Bureau Geographic Support Systems Initiative will establish links to counties and large cities that can provide periodic electronic updates to their address files. The Census Bureau currently has no plans to run the Local Update of Census Addresses program as an ongoing program rather than a once-a-decade program. True partnership between the Census Bureau and state and local governments to improve the address list should be a two-way street.

Through an interagency agreement with USPS, HUD receives counts of total and vacant business and residential addresses in the United States at the ZIP+4 geographic level. HUD uses these data for a variety of purposes, including researching neighborhood change, tracking disaster recovery, gauging the foreclosure crisis, analyzing housing markets, and measuring the effect of HUD funding on communities. HUD also makes the vacancy data available at the census tract level to government and nonprofit organizations through a permitted-user sublicense agreement.

HUD collects information on the tenants in HUD-subsidized housing in its Public and Indian Housing Information Center (PIC) system and its Tenant Rental Assistance Certification System (TRACS). Local program administrators use form HUD-50058 to submit data to the PIC system and form HUD-50059 to provide HUD with tenant data for TRACS. PIC data contain longitudinal information on families living in public housing or receiving tenant-based housing vouchers, whereas TRACS data contain longitudinal information on families living in project-based Section 8 housing. HUD uses these data in several ways and provides them for research purposes to other government agencies that promise confidentiality protection.[5] Mast provides the following information about PIC.

> The PIC system has quarterly entries for each family receiving HUD rental assistance starting in 1995. Data are available on income, rent, and a large number of other household and PHA [public housing agency] characteristics. …
>
> The PIC data system is transaction based. The most common transactions are (1) admissions, (2) annual [reexaminations], (3) interim [reexaminations] due to changes in eligibility factors such as income or family size, (4) moves, and (5) exits from the program. The system captures the most recent transaction at the end of each quarter. If multiple transactions for a household occur during a quarter, only the most recent is available. If no transaction occurs during a quarter, the family's entry is a duplicate of the entry for the previous quarter.
>
> Rent contracts are effective for 1 year and most households have only one transaction per year. Therefore, most changes are made annually, not quarterly. (Mast, 2012: 60)

The HUD Office of Policy Development and Research produces annual tabulations from the PIC/TRACS data called Picture of Subsidized Households (the most recent is for 2009). As the website notes, "Picture of Subsidized Households describes the nearly 5 million households living in HUD-subsidized housing in the United States [providing] characteristics of assisted housing units and residents, summarized at the national, state, public housing agency (PHA), project, census tract, county, Core-Based Statistical Area and city levels as downloadable files."[6] A 5-percent sample of the

[5] For examples of research using the HUD-PIC extract file, see Lubell, Shroder, and Steffen (2003); Mills et al. (2006); Olsen et al. (2005); Shroder (2002); and Tatian and Snow (2005).

[6] Quoted from http://www.huduser.org/portal/datasets/picture/yearlydata.html#download-tab.

microdata is available to qualified researchers. In addition, as mentioned previously, the 2011 AHS collected data from a supplementary sample of HUD-subsidized units selected from PIC/TRACS.

The Federal Financial Institutions Examination Council (FFIEC) collects data from lending institutions related to the enforcement of mortgage regulations. The Home Mortgage Disclosure Act (HMDA) was enacted by Congress in 1975 and was implemented by Federal Reserve Board Regulation C. On July 21, 2011, the rule-writing authority of Regulation C was transferred to the Consumer Financial Protection Bureau. Regulation C requires lending institutions to report public loan data to assist in—

- Determining whether financial institutions are serving the housing needs of their communities.
- Siting local public-sector investments so as to attract private investment to areas where it is needed.
- Identifying possible discriminatory lending patterns.

HMDA initially required reporting of the geographic location of originated and purchased home loans. In 1989, Congress expanded HMDA data to include information about denied home loan applications and the race, sex, and income of applicants and borrowers. In 2002, the Federal Reserve Board amended the HMDA regulations to require lenders to report price data for certain higher priced home mortgage loans and other new data. For each transaction, with some exceptions, the lender reports data about—

- The loan (or application), such as the type and amount of the loan made (or applied for) and, in limited circumstances, its price.
- The disposition of the application, such as whether it was denied or resulted in a loan origination.
- The property to which the loan relates, such as its type (single-family or multifamily) and location (including the census tract).
- The applicant's ethnicity, race, gender, and income.
- The sale of the loan (if applicable).

This regulation applies to certain financial institutions, including banks, savings associations, credit unions, and other mortgage-lending institutions. FFIEC also collects similar data from private mortgage insurance companies on a voluntary basis and is responsible for administering the regulations to implement the *Community Reinvestment Act of 1977*,[7] "intended to encourage depository institutions to help meet the credit needs of the communities in which they operate."[8]

Several countries maintain housing registers—a list of all housing units and their characteristics—that can form the basis for housing analysis. For example, Denmark established its first housing register in the 1880s for the city of Copenhagen. As Christensen noted—

> The [Danish] Building and Housing Register (BBR) was established in 1977. Since 1981, BBR has been updated annually by the municipalities. Before 1981, data on housing

[7] Public Law 95–128.

[8] Quoted from http://www.ffiec.gov/cra/default.htm.

> conditions were collected as part of nationwide census of all households in Denmark that took place every fifth year. The first nationwide census including housing information took place in 1955. BBR consists of national data concerning building and housing. The purpose of the register is to describe the total housing stock and individuals' housing conditions and is used for administrative purposes. …
>
> There are good opportunities to carry out research on Danish housing conditions. The key data in BBR are of high quality and go back in time so longitudinal analyses can be executed. Furthermore, BBR can be matched with other registers so it is possible to make detailed analyses of tenant composition over time. In particular, analyses that compare individuals over time living in different segments of the housing market, e.g. ownership, social housing sector, and private sector, provide unique knowledge of individuals' living and housing conditions. (Christensen, 2011: 106, 108)

No U.S. housing register exists, however. The closest approximation is MAF, which is confidential under federal law.[9] Under Title 13, however, MAF can be accessed for research that also benefits the Census Bureau (through its network of Research Data Centers). The MAF contains little information other than the address and associated census geography, but it can be linked to many Census Bureau household surveys.

The public property records in the United States that are the basis for property taxes are also potential data sources. Because these records are assembled at the municipal level, however, they are of varying quality, such as might result from delays in reassessment. Companies such as Zillow aggregate these records to offer services to the public for specific addresses. Researchers may be able to access these records for their own research.

Promising Techniques for Creating Additional Data Sources

While the data in AR datasets are interesting and useful, their value can be enhanced for research purposes.

Linking

One method that can enhance the value of existing data is to link datasets together. In this section, I describe a recent effort (Andersson et al., 2013, in which I participated) that linked together decennial census data, unemployment insurance AR on earnings, and HUD administrative data on subsidies to create a new database for housing research.

Andersson et al. (2013) and ongoing research focus on a difficult research issue—analyzing how children's housing affects their earnings in early adulthood. Andersson et al. developed a frame of households and children from the internal version of the 2000 decennial census. The short form provided a set of demographic variables that can be used to control for observable characteristics of parents and children. It also provided the residential location of households in 2000, which Andersson et al. linked to neighborhood characteristic variables (aggregates of the long-form data

[9] *Code of Federal Regulations*, Title 13.

to the block group and census tract levels). Next, they used person identifiers developed at the Census Bureau to link the parents and children to HUD-PIC, the administrative data file of housing assistance recipients described previously. The HUD-PIC file covered 1997 through 2005; it was used to identify each year a parent or child was in subsidized housing and whether they were in public housing or received a housing voucher enabling them to live in private-sector housing.

Finally, Andersson et al. used the unique person identifiers to link the children in the sample to earnings records for 2008 through 2010 (and parents to their income for the entire period). The Census Bureau Longitudinal Employer-Household Dynamics (LEHD) dataset provides earnings records for more than 130 million workers each quarter from the mid-2000s onward.[10] Those records provided a measure of labor market outcomes for 1.8 million children who were ages 13 to 18 in 2000 in low-income families—a sample size sufficient to present results disaggregated by race and Hispanic origin, gender, and housing subsidy program, while controlling for neighborhood conditions such as poverty level. When the initial analysis is complete, analysis with the file can be expanded to other topics, such as residential mobility and intergenerational earnings mobility.

Synthetic Data

One key problem with using the American *Housing* Survey for housing analysis is the relatively small sample sizes in any one location (metropolitan area), though the sample sizes appear adequate for national analysis. One key problem with using the American *Community* Survey (ACS) for housing analysis is the relatively few questions asked about housing and neighborhood physical, social, and economic characteristics. Is there any way to combine the strengths of the two surveys to enhance the data available for housing analysis?

Recent work by Reiter and others suggests it is possible to create a (partially) synthetic dataset that combines AHS and ACS using exact matches and modeling.[11] Synthetic datasets are created based on a multiple draws from a derived joint distribution of variables; that distribution is based on observed data relationships. Fully synthetic datasets create all variables this way, whereas partially synthetic datasets retain survey observations for some variables and impute other variables.

[10] LEHD is a partnership between the Census Bureau and all 50 states and the District of Columbia; it produces public use data tabulations (Quarterly Workforce Indicators and an interactive web-based commuting analysis tool, OnTheMap) that are widely used by state and local governments. At its core are two AR files provided by states on a quarterly basis: (1) unemployment insurance (UI) wage records, giving the earnings of each worker at each employer; and (2) employer reports giving establishment-level data, also known as the Quarterly Census of Employment and Wages. The coverage is roughly 96 percent of private, nonfarm wage and salary employment. LEHD is in the process of integrating data on self-employed individuals and independent contractors that are not covered in the UI files but that are available from the Census Bureau Business Register, which contains the universe of all businesses, including all sole proprietorships, on an annual basis (whether the sole proprietor has employees or is a nonemployer). In addition, the LEHD project has acquired personnel records from the U.S. Office of Personnel Management so that federal workers are now also tracked in LEHD. See also Abowd, Haltiwanger, and Lane (2004).

[11] Partially synthetic public use datasets have already been developed for selected Census Bureau surveys (the Survey of Income and Program Participation, the Longitudinal Business Database, the LEHD dataset of AR, and ACS group quarters data) to permit release of additional microdata without jeopardizing the confidentiality of respondents. For other examples and discussions of partially synthetic data, see Abowd and Lane (2004); Abowd and Woodcock (2004, 2001); Kennickell (1997); Little (1993); Little, Liu, and Raghunathan (2004); Reiter (2005a, 2005b, 2005c, 2004a, 2004b, 2003); and Reiter and Mitra (2009).

Many AHS demographic, economic, and housing variables also appear in ACS and can therefore be used for modeling the joint distributions. Because the precise location of the unit is known, when operating within a confidential environment, one can also link census tract characteristics from the 2000 long form and ACS. Those additional variables could help in developing imputation models.

It appears likely that enough exact-matched cases are available to enable researchers to form decent imputation models. From 2000 through 2012, 16.6 million ACS interviews were completed, mostly at unique addresses.[12] In 2011, approximately 132 million housing units were in the United States; thus, ACS cases represent approximately one-eighth of all housing units (although a small fraction of ACS housing units will have been demolished by 2011). One-eighth of the 2011 AHS sample size of 180,000 units yields more than 20,000 units in the 2011 AHS that had been in the 2000–2012 ACS. Of course, not all these matches are possible, because some AHS cases are added each survey year to account for new construction, so previous AHS sample sizes were smaller (although one can use both the national AHS files and the metropolitan area AHS files), and some matching variables will be missing.

Analysts can derive models for selected AHS characteristics that are not included in ACS by examining the relationships between AHS variables that are also in ACS and those that are not. These models can then be used to create the synthetic AHS variables for ACS households—both those in the exact match universe and those only in ACS. Multiple imputations are typically done to reduce potential bias from any one draw from the joint distribution. The validity of the imputations can be tested by reference to the actual values for the exact matches, and it seems wise to focus on imputing only a few critical housing measures.

Some Data Issues

The previous section discussed some promising techniques for enhancing existing datasets for housing research. Some problems remain, however. One of these problems is undercoverage of housing units by the sampling frame that the Census Bureau uses for its household surveys. To the extent that units at the edge of habitability, or more likely units that are the result of conversion or subdivision (such as a converted garage) are missed, the statistics we use to describe our housing stock will be biased. A second type of problem is the development of new types of living quarters, such as congregate housing. As the population ages, more and more people are living in developments that cater to their needs, including housing units that do not have kitchens (because meals are provided centrally). How we should measure their growth depends on how we allow the definition of habitable housing to vary, and whether we can adequately add them to our sampling frame.

Another problem is that we measure the same concept in multiple ways and in multiple surveys. A prime example is the vacancy rate. On AHS, the definition of a vacant housing unit is quite similar to that used in the Housing Vacancy Survey.

> A housing unit is vacant if no one is living in it at the time of the interview, unless its occupants are only temporarily absent. In addition, housing units where all the occupants have a usual residence elsewhere are grouped with vacant units. … For vacant housing

[12] Duplicates can be treated as independent observations, because they will be matched to different AHS observations.

> units that are not intended by their current owners for year round use (seasonal and migratory), the respondent was asked whether the construction and heating of the housing unit made it suitable for the unit to be occupied on a year-round basis. A housing unit is suitable for year-round use if it is built as a permanent structure, properly equipped, insulated, and heated as necessitated by the climate.[13]

This definition differs from the definition of a vacant housing unit used in the American Community Survey, however, because of the ACS residence rules.

> The basic idea behind the ACS current residence concept is that everyone who is currently living or staying at a sample address is considered a current resident of that address, except for those staying there for only a short period of time. For the purposes of the ACS, the Census Bureau defines this short period of time as less than 2 consecutive months (often described as the 2-month rule). Under this rule, anyone who has been or will be living for 2 months or less in the sample unit when the unit is interviewed (either by mail, telephone, or personal visit) is not considered a current resident. This means that their expected length of stay is 2 months or less, not that they have been staying in the sample unit for 2 months or less. In general, people who are away from the sample unit for 2 months or less are considered to be current residents, even though they are not staying there when the interview is conducted, while people who have been or will be away for more than 2 months are considered not to be current residents. The Census Bureau classifies as vacant [a housing unit] in which no one is determined to be a current resident. (U.S. Census Bureau, 2009: chapter 6)

The implications for measuring vacancy rates derive from the ACS interview methodology. First, a questionnaire is mailed out and, starting in January 2014, a solicitation to respond is sent via the Internet as well. This questionnaire is followed about 1 month later by a telephone followup (if a phone number can be obtained), and then, for a sample of nonrespondents, about 1 more month later by a personal visit. A unit that might have been vacant at the original date of interview (month 1) may well become occupied at month 3, when the household is interviewed, yielding a lower vacancy rate than might otherwise be recorded. Thus, it is likely that vacancy rates measured by ACS differ from those measured by household surveys and from the decennial census (which uses yet a different methodology).[14]

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[13] Quoted from http://www.census.gov/housing/ahs/files/, Appendix A: 31–32.

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New York City Housing and Vacancy Survey (NYCHVS): http://www.nyc.gov/html/hpd/html/pr/vacancy.shtml and http://www.census.gov/housing/nychvs/about/.

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HUD, Public and Indian Housing Information Center (PIC) system and Tenant Rental Assistance Certification System (TRACS): aggregate data (A Picture of Subsidized Households) at http://www.huduser.org/portal/datasets/assthsg.html; a 5-percent microdata sample from those systems for researchers at http://www.huduser.org/portal/pumd/index.html.

U.S. Postal Service, Vacancies: Aggregate data quarterly at the census tract level for government and not-for-profit researchers from HUD at http://www.huduser.org/portal/datasets/usps.html.

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Connecting Address and Property Data To Evaluate Housing-Related Policy

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Abstract

Housing conditions can vary greatly from one property to the next, but housing characteristics often are measured at different geographic units because of data limitations. This article discusses the process of connecting address-level datasets to create meaningful analyses at the property level in the absence of a comprehensive address-to-parcel crosswalk. To demonstrate this process, the authors describe linking child lead screening, lead property compliance, foreclosure, and tax assessors' property records for a U.S. Department of Housing and Urban Development-funded Lead Technical Study in four Rhode Island core cities. Using the linked data analysis, robust property-level findings can lead to an effective evaluation of policies that affect properties, particularly for urban communities with high proportions of multifamily housing.

Introduction

Connecting existing datasets to conduct policy evaluation is a smart way to make the best use of available resources. Administrative datasets across multiple domains contain addresses and can be linked to gain insight regarding housing conditions and policy. In some situations, however, researchers prefer data about entire properties to address-level data when describing housing issues. Many multiunit residential properties have more than one address and, when researchers try to collect information about all residential units within properties, address listings are often insufficient. This concern is particularly evident for analysis in urban communities, where a high proportion of the housing stock contains more than one unit.

Robust statewide data systems ideally would exist and would enable researchers and city administrators to easily link address-specific data to property-level data. In Rhode Island, as we suspect in many other states, that ideal is not yet the reality. Therefore, extensive preparatory work was completed to conduct a property-level analysis of childhood lead exposure, lead compliance certificates, and foreclosures in four Rhode Island cities. In this article, we discuss the process of connecting a variety of separate address-level datasets with unique variables and coding systems. We provide background information that defines the study's purpose and describe how we created a master lookup table, matched our datasets to it, and analyzed the data. We also share the lessons we learned from this effort.

Context

The 2005 Rhode Island Lead Hazard Mitigation Act requires owners of nonowner-occupied properties built before 1978 (when residential lead-based paint was banned in the country) to comply with a series of actions aimed at reducing lead exposure. These requirements include attending a lead hazard awareness class, inspecting rental properties, providing tenants information about lead hazards and a copy of the inspection report, responding to tenants' concerns about any lead hazards, fixing lead hazards, and using lead-safe work practices when performing any maintenance. After the owners comply with the requirements, they receive a Certificate of Conformance, which needs to be kept current.[1]

For this U.S. Department of Housing and Urban Development-funded study, we sought to evaluate outcomes associated with the Rhode Island law. We identified the number of residential properties that were in compliance with the law, whether lead-exposed children were more likely to reside in noncompliant homes, and whether foreclosure had an impact on lead exposure and compliance. The analysis centers on lead exposure and other risks that are likely to pervade entire structures, and the unit of analysis was at the property level rather than address level. In addition, the law has implications for property owners, which bolsters the rationale for a property-based approach. We studied four cities in Rhode Island that have high risks of substandard housing concerns and lead-exposed children: Central Falls, Pawtucket, Providence, and Woonsocket (Healthy Housing Collaborative, 2012). The first results of our analysis, in which we compared blood lead levels of children with a property owner's compliance with and exemption from the Lead Hazard Mitigation Act and which included a summary of the methods that we used, were recently published and received notable press coverage in local media (Rogers et al., 2014).

Preparing the Data

In the four cities we studied, most residential properties have two or more units (U.S. Census Bureau, 2014), and many of those properties have more than one street address. Thus, to obtain

[1] State of Rhode Island General Assembly. 2003. Chapter 23-24.6 Lead Poisoning Prevention Act.

accurate property-level counts, we first determined which distinct addresses were part of the same property and then, based on the knowledge of all addresses for each property, aggregated all the address data from various sources to the property level. For example, if three children were exposed to lead at one address and two at another, but those addresses were both part of the same multi-family property, that property housed five lead-exposed children.

Creating a Master Lookup Table

To overcome the obstacles associated with having multiple addresses per property, we created a crosswalk tool called the master lookup table, or MLT, which links each address to its property identifier code as well as other basic descriptive data about the property. Our method for creating the MLT differed between Providence and the other three cities. For Providence, the largest city in the state, the MLT was developed to be a more robust resource (as described further in the Providence MLT Online Tool section that follows). Two key pieces that enabled the work for Providence were (1) the availability of an up-to-date parcel shapefile, which identifies the plat and lot numbers for properties and the size and shape of the parcel of land, and (2) a cooperative relationship with the city tax assessor's office. Having staff members with Geographic Information System (GIS) experience and interns to assist in the time-consuming portions of creating a reliable MLT were also integral to the process.

Another indispensable resource for this work was a dataset of all addresses for occupied and unoccupied structures in Rhode Island, which was initially developed for the emergency 911 telephone and response system. These addresses are available through the state's GIS data website as a point shapefile (Rhode Island Geographic Information System, 2014). In ArcGIS software, we were able to join the Providence parcel data shapefile with the emergency 911 addresses to create a citywide map of all properties. To increase accuracy, we consulted paper maps from the tax assessor's office and, on occasion, staff members physically visited properties to verify the address-to-property crosswalk. Today, where available, Internet-based streetview maps can serve to validate addresses or other property information by zooming in on the address in question. Parcels with more than one street address can be easily identified through this combination of data—any address that matches to a given parcel identifier is then linked to that parcel.

For Central Falls, Pawtucket, and Woonsocket, addresses from the emergency 911 point shapefile were standardized and matched to parcel records from each city's taxroll records. This process resulted in separate files specific to each municipality. The geocoded shapefile associated with the emergency 911 addresses served as a good starting point for identifying all the properties in each municipality. Inaccuracies and differences in completeness in these data continue across municipalities, however, and so we would not suggest relying solely on this source. For example, some cities' records include parcel identifiers in the file, but many do not. Furthermore, because the shapefiles are point data, rather than polygons, they provide no sense of the size and shape of property lines in relation to one another in the city.

The next step in our data preparation entailed actively looking for multiunit properties that were likely to have multiple addresses. Within each city, we selected the tax class that corresponds with two- to five-family properties and, for each address, added 2 and subtracted 2 from the street number to create fields representing what would be the next address to the left or right of the property. If those addresses matched an existing address in the data, we discarded them, but, if they did not, we kept them as potential matches to expand the coverage of the MLT. If address numbers were recorded as ranges, we split them up to create multiple address records from the original.

Adding the municipality-specific datasets into one master file was the final step. To avoid any loss of data that could arise if plat and lot numbers overlapped in different cities, we created a city-specific parcel identifier field called “CKEY.” The identifier field concatenated a two-letter abbreviation of the city name—CF (Central Falls), PA (Pawtucket), PR (Providence), and WN (Woonsocket)—and the parcel identifier code: the plat and lot numbers. For example, if the plat and lot numbers for a property in Providence were 1 and 1, the CKEY would have been PR 1-1.

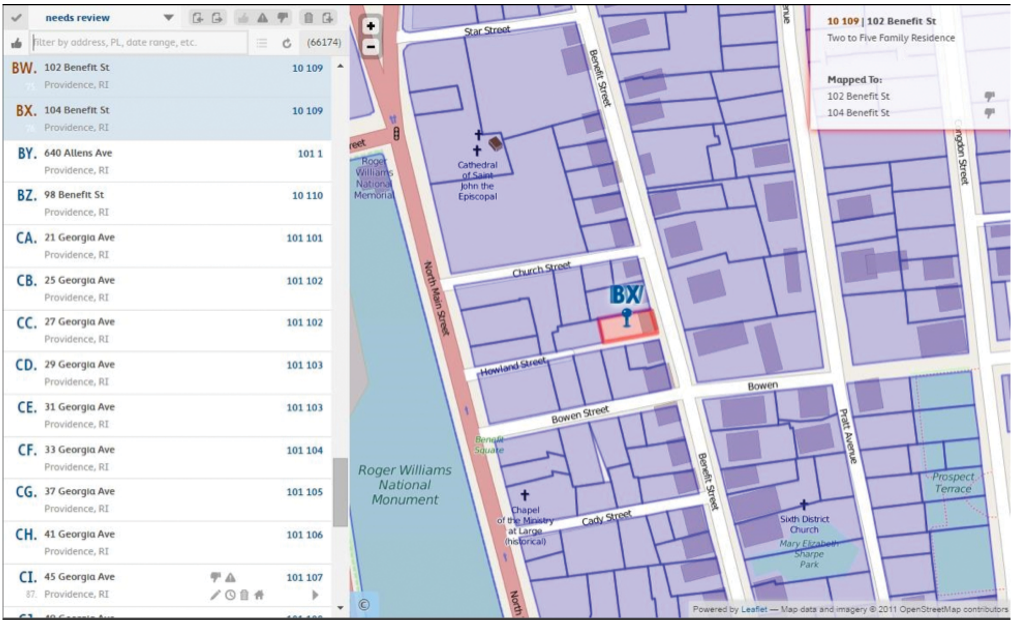
The most basic version of the MLT file contains all residential addresses, the municipality, and the corresponding CKEY, with all text in uppercase lettering to ensure standardization. The basic structure of the file is provided in the appendix. Variables that can be included as needed in the MLT include address number, tax class category, property type, and year built—essentially, any descriptive attribute that is unlikely to change regularly. Because the MLT is focused on linking addresses to parcels, each address within a city should be listed only once and addresses should not match to more than one plat and lot. Parcel identifiers can have duplicates, however, because when they match to more than one address, they are listed in separate rows in the table. The MLT created for the Lead Technical Study currently contains more than 100,000 address-to-parcel linkage records, with about 65 percent of those in Providence.

Providence MLT Online Tool

A secondary outcome of the MLT effort was the creation of an online tool that enables the user to import addresses to tag with parcel identifiers or download lists of addresses and parcels. It also enables registered users to modify records when new information is available or errors are found. See exhibit 1 for a visual example of how the MLT acts as a crosswalk between addresses and parcels. This online version was created using Leaflet, an open-source resource for interactive maps. Although the tool is currently available for Providence only and is a private website that requires a login, the concept is replicable.

Exhibit 1

Providence Master Lookup Table



Note: This screenshot of the master lookup table website provides an example of the interactive nature of the online tool. By clicking on records BW and BX, a pin shows up on the map. By clicking on the parcel, a box in the top right corner of the screen provides details about the property type, property owner (suppressed), and addresses associated with the particular parcel identifier.

Connecting the Data

After the MLT was complete, the next steps involved gathering the various datasets necessary to answer the research questions and then linking them together.

Study Datasets

Using the MLT for the four cities in the analysis, we linked city tax assessors' datasets, two lead compliance certificate datasets (from the Rhode Island Department of Health [HEALTH] and Rhode Island Housing Resources Commission), blood lead screening surveillance data from HEALTH, and foreclosure deeds datasets. Taxroll data provided the details needed to identify if a property was subject to the law, including year of construction and the owner's address. The lead compliance certificate records were integral to the policy evaluation, which aimed to assess whether outcomes differed based on having a certificate. Lead screening records provided the primary outcome variable—blood lead level screening results—and the address at the time of each screening. Rhode Island law mandates that healthcare providers screen all children for lead twice by age 3 and report the results, so the lead screening dataset covers most young children in the state. Foreclosure deeds allowed for compliance and lead exposure comparisons at properties being considered for possible foreclosures.

Each dataset used different formatting of address, unit, and property records. With the exception of the taxroll and foreclosure records, parcel identifier codes often either contained obvious errors or were completely missing in the datasets analyzed. The lead compliance certificate datasets had errors and missing records for the parcel identifier fields. The screening surveillance data records included only patient address fields, which were subject to data entry errors. In some cases, addresses included post office box addresses, which are not useful for this work because they do not indicate the physical address of residence and thus were excluded. Standardizing the addresses was essential.

Preparation for Matching

To prepare the existing address-level datasets, we ensured that any addresses conformed to the same format as the MLT. Geocoding the addresses (we used ArcGIS software) is a good way to begin the process, because it can correct some spelling errors or other inconsistencies automatically. Further editing required reviewing all addresses for errors, stripping any unit designations out of the addresses (apartment numbers, floor numbers, and so on), making sure public housing and similar complexes were in the same format, and standardizing common abbreviations such as "N" instead of "North." To match the format of the MLT, we also ensured that any text was all upper case. We used statistical software to clean up the datasets after geocoding, which systematized the process, because the syntax can be adapted to apply to each dataset and reused when new data need to be processed. We used IBM SPSS Statistics software, but other statistical packages would serve the same purpose. Each type of data we prepared for analysis had one file that contained address and municipality fields.

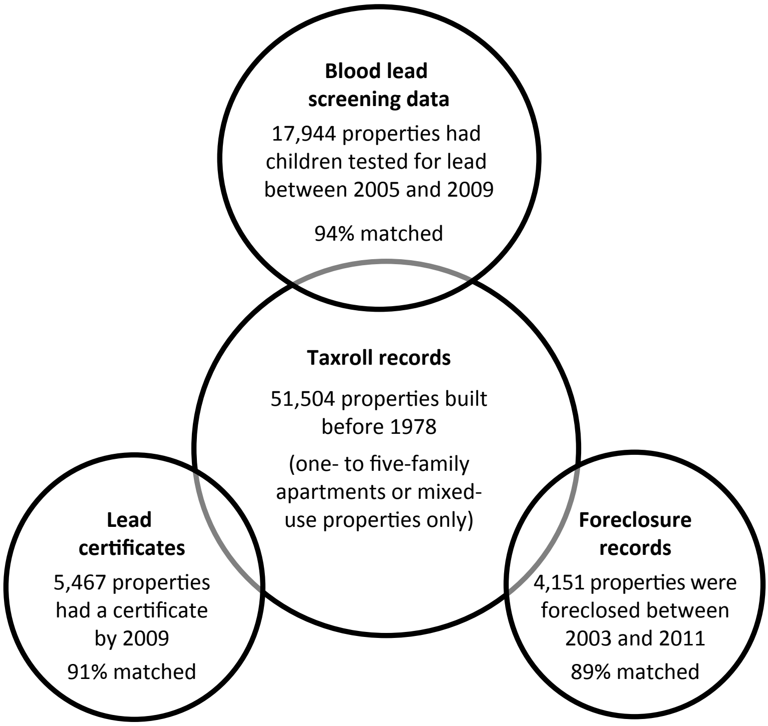
Matching

When the separate data files were fully prepared, we could match the addresses in the datasets for analysis to the addresses in the MLT. To avoid any complications with duplicate addresses across municipalities, the files were matched based on two variables: address and municipality. Matching one file per city at a time to the MLT records for that city could also avoid duplicative addresses. By processing all the address-level data through the MLT, we ensured that the addresses in each of the various datasets correspond to the same properties. Matching to the MLT resulted in each file containing the CKEY parcel identifier field.

After all the files contained a CKEY field, one main property-level analysis file could be created. The taxroll file at the CKEY level served as the base file to match the other property data. For the purpose of the Lead Technical Study, a subset of residential properties built before 1978 was selected—one- to five-family properties, apartments, and mixed-use properties—based on the corresponding codes in the taxroll data. Properties were then classified as either owner- or nonowner-occupied. We aggregated the address-level taxroll, foreclosure, and lead certificate records to the parcel level using the CKEY variable and matched the files to the taxroll. New fields indicated if a property had lead certificate records, any foreclosures, or was exempt from the law. See exhibit 2 for example match rates based on the foreclosure analysis from 2005 through 2009.

Exhibit 2

Properties That Matched Through the Master Lookup Table



Note: The match rates report the percentage of properties in the dataset from which they originate that matched the properties in our pre-1978 taxroll records.

The way we handled the lead screening data differed slightly depending on the unit of analysis. To prepare the lead screening data after matching it with the MLT, we analyzed one record for each child. If a child matched to more than one property, we kept one record per child per property. For the child-level analysis, we matched the property-level file of taxroll, foreclosure, and lead certificates data to the lead screening file to describe the property where the child was living and focused on the first result per child per property. For the property-level analysis, we aggregated the number of children who had screening records at a given address and identified whether one or more children's maximum test results were considered elevated. Thus, conducting analysis with these methods allowed for flexibility at the aggregation level.

Analyzing the Data

The crosswalk provided by the MLT helped create datasets that could be analyzed with relative ease at various levels of aggregation. For the analysis that led to the *American Journal of Public Health* article (Rogers et al., 2014), we focused mainly on outcomes at the child level and could account for children who lived in different properties or multiple children who lived at one property. We identified whether children who lived in properties that became compliant had declines in blood lead levels, and we described the burden of lead exposure in exempt properties. For work outside the scope of the journal article, we investigated outcomes at the property level to describe how many properties housed one or more lead-exposed children, comparing lead exposure in compliant and noncompliant properties as well as between exempt and nonexempt properties. These property-based findings were presented to stakeholders and at conferences. Finally, we analyzed children's lead exposure by whether the property where they lived had been foreclosed on within a certain amount of time. When new data become available, these methods can be repeated to keep stakeholders updated on the status of associations of interest.

Discussion

Investing the effort to match data with the methods described in this article has numerous advantages, especially in urban communities with high proportions of multifamily properties. In many cases, administrative datasets that are relevant to housing and health will have address records, but not parcel identifiers. A data crosswalk such as the MLT provides not only a way to link disparate datasets but also rich layers of information to analyze. Without preparing a comprehensive property-level lookup table, a much higher proportion of data would be lost because of nonmatching. In addition, without translating data from address- to property-level status, count, proportion, or density calculations for a given area could mislead readers. The data are particularly misleading at smaller geography levels, such as census blocks and neighborhoods; the differences between property and address information can be meaningful.

The techniques employed to create the MLT and use it as a data-matching system could benefit researchers conducting analysis at the property level in other cities in the absence of established integrated data systems. The tool supported the evaluation of outcomes associated with housing policies—work that would have otherwise been unfeasible given the data landscape. Although the effort associated with having to conduct this work one municipality at a time could make a statewide analysis burdensome, the ability to target at-risk communities and, in some cases, at-risk properties has been valuable to stakeholders in Rhode Island. In summary, ensuring that linkages between property data are accurate and meaningful can lead to meaningful results. Those robust analyses can, in turn, guide policymakers to evaluate housing-related policies more effectively.

Appendix

Exhibit A-1

Fields for Master Lookup Table

Field	Type	Description	Case
SRC	text	Source of address and/or parcel information	
CKEY	text	Parcel level id# with 2-letter municipal code	
LOCATION	text	Original address	Proper
RNG	text	“Y” if multiple address records were created from original address	
ADDR_NUM	text	Address number	
ADDR_X	text	Address number extra (1/2, R, etc.)	Upper
ADDR_NAM	text	Address street name	Upper
ADDR_TYP	text	Address type	Upper
ADDR_SFD	text	Address suffix direction	Upper
PAR_ADDR	text	Full address formatted	Upper
ADDR_NMB	number	Address number	
ADDR_STR	text	Street name and type	Upper
CITY	text	Municipality name	Proper

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Industrial Revolution

Every home makes compromises among different and often competing goals: comfort, convenience, durability, energy consumption, maintenance, construction costs, appearance, strength, community acceptance, and resale value. Often consumers and developers making the tradeoffs among these goals do so with incomplete information, increasing the risks and slowing the adoption of innovative products and processes. This slow diffusion negatively affects productivity, quality, performance, and value. This department of Cityscape *presents, in graphic form, a few promising technological improvements to the U.S. housing stock. If you have an idea for a future department feature, please send your diagram or photograph, along with a few well-chosen words, to elizabeth.a.cocke@hud.gov.*

Glass-Modified Asphalt Shingles for Mitigation of Urban Heat Island Effect

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Abstract

This study aims to use recycled glass cullet (broken or waste glass suitable for remelting) and titanium dioxide powder in asphalt shingles to increase a roof's solar-reflectance index while maintaining high performance levels. The study also uses cullet-modified asphalt shingles to alleviate the harmful effects of the urban heat island, and it evaluates the reduction in heating and cooling loads when the new class of asphalt shingles is used.

The Status Quo

The urban heat island (UHI) phenomenon is becoming increasingly intense as summertime temperatures continue to rise. In the United States, many cities with a population of 1 million or more experience an annual mean air temperature of 1.8 to 5.4 °F (1 to 3 °C) warmer than its surroundings (EPA, 2014). Elevated temperatures during the summertime lead to thermal discomfort, human health issues, and increased consumption of energy for cooling purposes. Development of the Earth's surface and the use of high-solar-radiation-absorbing materials, including asphalt roof shingles, are causes of UHI effect, especially in areas with a high density of buildings and urban structures. The surface temperatures of a traditional asphalt roof system may reach upwards of 160 °F on a 90 °F day (NRCA, 2013), thus intensifying UHI phenomenon.

Asphalt shingles are true composites made from a variety of materials, including fiberglass or organic felt, asphalt binder, mineral filler, and aggregate granules. By weight, shingles may be made of 80 percent mineral and rock, and, despite being called asphalt shingles, asphalt represents a very small yet important element of the material (Leavell, 2006). In an attempt to continue to use asphalt shingles while mitigating UHI phenomenon, this research project proposes the use of a new type of asphalt shingles that contains recycled cullet coated with light-colored titanium dioxide (TiO_2) powder in place of the mineral filler.

Experimental Program

Implementing sustainable materials into current manufacturing processes can reduce costs, conserve energy, and lower pollution. For a material to be considered sustainable, it should be cost efficient to the consumer and perform comparably or better than conventional materials. As an approach for mitigating the harmful effects of UHI, the use of cullet in the production of asphalt roof shingles has the potential to become a cool-roof strategy.

The objective of this study is to test the hypothesis that the use of recycled glass increases the solar-reflectance index (SRI) without affecting the performance of asphalt roof shingles. To evaluate the feasibility of using recycled glass in this application, the engineering properties of cullet were measured and compared with conventional aggregates used in the production of asphalt roof shingles. Laboratory samples were then prepared and the solar-reflectance properties and strength characteristics of conventional and recycled-glass roof shingles were measured.

Laboratory results showed that the use of recycled glass (see exhibit 1) as a replacement to standard ceramic-coated black roofing granules on the top surface of asphalt shingles resulted in an increased SRI. Further, the addition of white pigment TiO2 powder (anatase ultrafine particles passing mesh #320), which is mixed and applied with the surface granules, improved reflectance values to a level that met the cool-roof threshold. Results also showed acceptable tear strength for the laboratory-manufactured shingles.

Exhibit 1

Recycled Glass Shingle Produced in the Laboratory

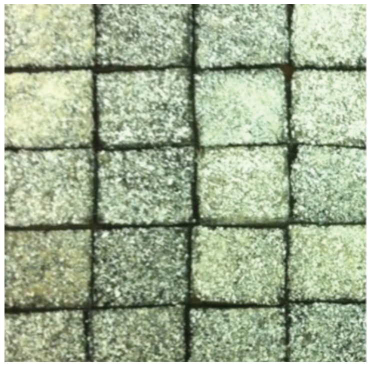


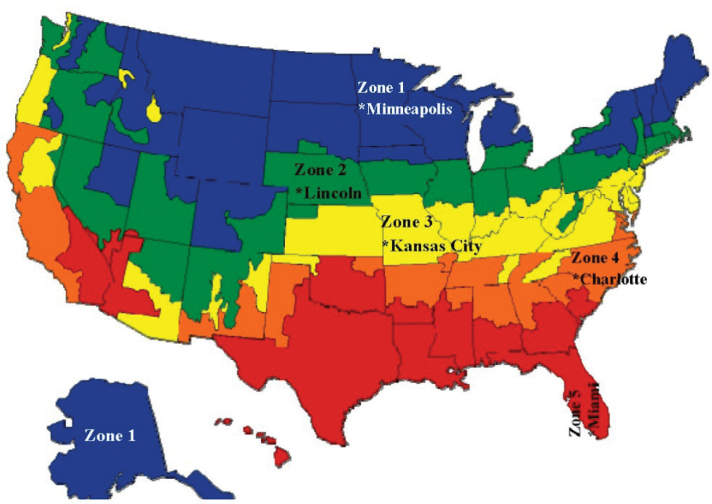
Photo courtesy of Marwa Hassan

Quantification of Energy Benefits

A three-dimensional (3-D) transient finite element (FE) model was developed and validated to quantify energy savings provided by the proposed recycling process under various climatic conditions. Simulations were carried out for three cities located in three of the five climate zones in the United States. The U.S. Energy Information Administration (EIA) categorized the climate regions in the United States into five main zones based on the last 30-year average heating degree days (HDD) and cooling degree days (CDD) (EIA, 2011; NOAA, 2012). Exhibit 2 shows the five main climate zones in the United States. For this study, Zones 3, 4, and 5 were simulated. The three cities representing each region were Kansas City, Missouri, for Zone 3; Charlotte, North Carolina, for Zone 4; and Miami, Florida, for Zone 5.

Exhibit 2

Climate Zones in the United States



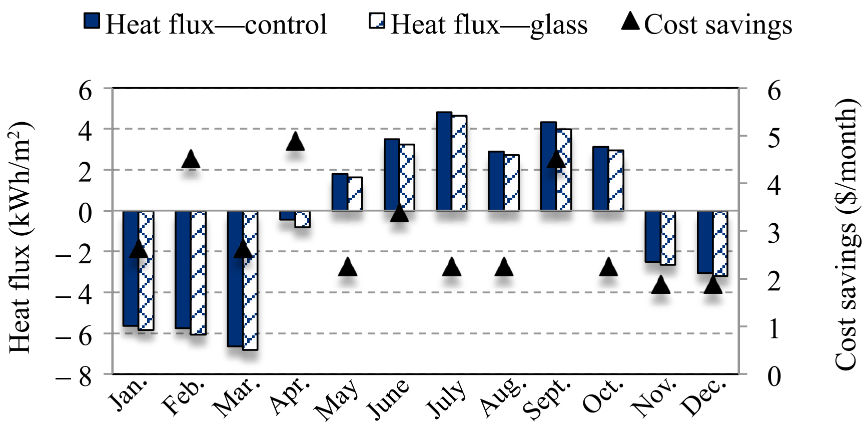
Source: http://energyiq.lbl.gov/EnergyIQ/tooltips/CBClimateMap.html?width=650&height=700

Results for each of the climate zones are shown in exhibits 3, 4, and 5. Exhibit 3 shows the monthly heat flux for a simulated two-floor building's attic in Kansas City—the first simulation using the proposed shingles and the second simulation using conventional shingles—as well as the monthly cost savings in energy consumption. The expected total energy savings per year is approximately $35.

Exhibit 4 shows the monthly heat flux for a simulated two-floor building's attic in Charlotte—the first simulation using the proposed shingles and the second simulation using conventional shingles—as well as the monthly cost savings in energy consumption. The expected total energy savings per year is $62.

Exhibit 3

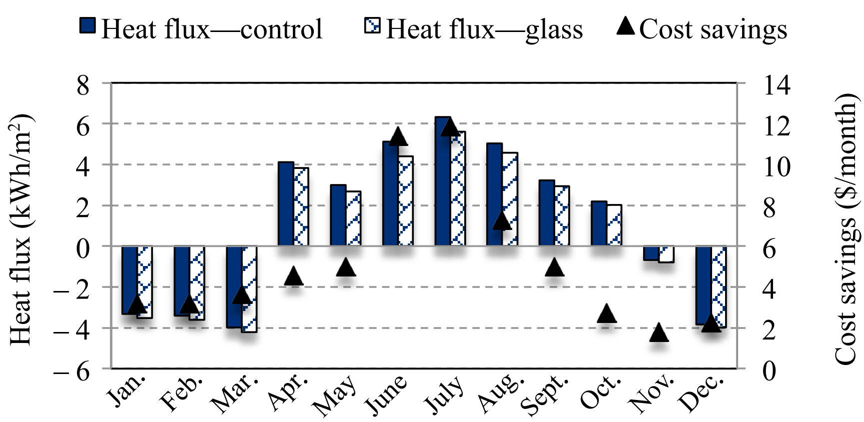
Simulated Heat Flux and Energy Savings for Kansas City, Missouri—Zone 3



kWh/m² = kilowatt-hour per square meter.

Exhibit 4

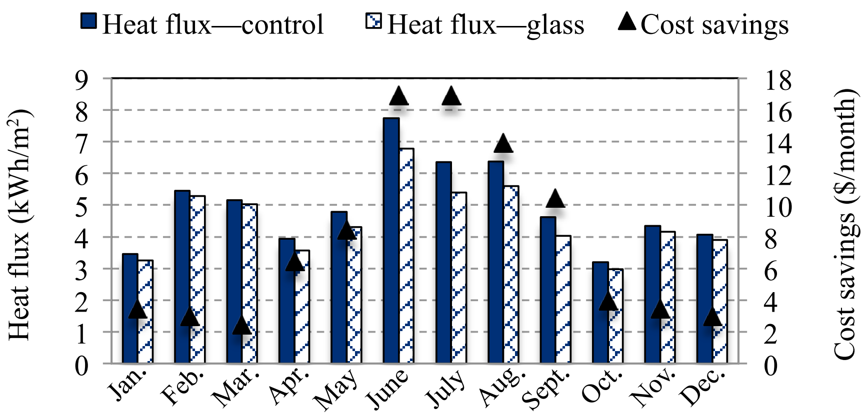
Simulated Heat Flux and Energy Savings for Charlotte, North Carolina—Zone 4



kWh/m² = kilowatt-hour per square meter.

Exhibit 5

Simulated Heat Flux and Energy Savings for Miami, Florida—Zone 5



kWh/m² = kilowatt-hour per square meter.

Exhibit 5 shows the monthly heat flux for a simulated two-floor building's attic in Miami—the first simulation using the proposed shingles and the second simulation using conventional shingles—as well as the monthly cost savings in energy consumption. The expected total energy savings per year is approximately $93.

As demonstrated by the FE results, more energy savings are attained in warmer climates. This technology is very well suited for use in Miami and locations with similar hot weather in the United States.

Conclusions and Recommendations

From the results of this study, we learned that cullet can be successfully blended with conventional materials to produce a sustainable asphalt shingle that has a solar-reflectance property that is 25 percent greater than conventional materials without compromising performance. This shingle design was patented and proven to result in significant annual energy savings especially in hot climate zones, including Florida and Louisiana.

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Foreign Exchange

Foreign Exchange, a department of Cityscape, *reports on what the U.S. Department of Housing and Urban Development's Office for International and Philanthropic Innovation has learned about new departures in housing and development policy in cities and suburbs throughout the world that might have value if applied in U.S. communities. If you have a recent research report or article of fewer than 2,000 words to share in a forthcoming issue of* Cityscape, *please send a one-paragraph abstract to lawrence.j.handerhan@hud.gov.*

Measuring U.S. Sustainable Development

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Abstract

In recent decades, such global institutions as the United Nations (U.N.) have promoted sustainable development, loosely defined as improving the human condition without compromising the ability of future generations to meet their needs. In its advocacy, the U.N. has called for the crafting of measures to benchmark current conditions and mark progress toward the overall goal. As national and subnational governments have undertaken these activities, they have also been involved in developing a wide range of monitoring tools, especially defining indicators reflective of their distinctive programs in this arena. The work of the Partnership for Sustainable Communities (PSC), an alliance between the U.S. Department of Housing and Urban Development, the U.S. Department of Transportation, and the U.S. Environmental Protection Agency, founded in 2009, provides an example of this phenomenon. Working with researchers from the University of Pennsylvania Institute for Urban Research and funded by the Ford Foundation, the PSC has launched the Sustainable Communities Indicator Catalog described in this article.

Introduction

Public and private decisionmakers in the 21st century are fashioning sustainable development policies and programs in response to a variety of global concerns that include climate change, resource depletion, economic downturns, high levels of poverty, wasteful settlement and urbanization patterns, and a scarcity of adequate, affordable housing and basic services. They assume that human settlement activity has lasting effects on the well-being of individuals and society and understand that sustainable development is an ongoing process, not a "fixed state of harmony" (Hardi and Zdan, 1997: 9). In their choices of policies and programs, decisionmakers adhere to the so-called Brundtland Commission's interpretation of sustainable development to improve the human condition to meet current needs without compromising the ability of future generations to meet their needs, an idea refined at the Rio Earth Summit in 1992 and further developed at the Rio +20 Conference in 2012. *The Future We Want*, the outcome document of the 2012 meeting, defined sustainable development as working for poverty eradication, changing unsustainable patterns of consumption and production, and promoting inclusive and equitable economic growth (U.N., 2012).

Notably, *The Future We Need* called for the formulation of sustainable development goals, targets, and indictors to be applied to all nations (U.N., 2012). This declaration would call for broadening and extending an earlier setup, the soon-to-expire Millennium Development Goals that applied to only the developing countries. Thereafter, the United Nations (U.N.) initiated a 3-year deliberative process to develop a post-2015 development framework of sustainable development goals, targets, and indicators to be presented for U.N. General Assembly approval in September 2015. By the early spring of 2015, U.N. member states had made much progress toward agreeing, in principle, to 17 goals with associated targets and were deeply involved in determining indicators that the U.N. Statistical Commission agreed to deliver by March 2016.

General Background on Sustainable Development

Over the years, much work has been done to strengthen the research, policy, practice, and subsequent evaluation of sustainable development. Many believe that progress has been sluggish, however, and attribute the slow adoption of the paradigm to political resistance, limited financial resources, and such technical issues as the absence of scientifically valid and credible indicator systems (Evans and Steven, 2011; UNCTAD, 2011).

Experts agree that "sustainable development is perhaps the most challenging policy concept ever developed" (Hak, Moldan, and Dahl, 2007: 2), noting that it receives support generally when characterized broadly as "not cheating your kids" (Bell and Morse, 2010: 5) but less agreement when it comes to putting it into operation with a working definition. Competing views emerge. Some hold that sustainable development "is like truth and justice," ideas "not readily captured in precise definition," because their meanings "can vary greatly from individual to individual and between societies" (Bell and Morse, 2010: 11), therefore preventing its implementation; others insist that despite its being a complex concept in which the interplay of various factors has a wide variety of outcomes, it is manageable. Others reference physical and social scientists who regularly deal with value-affected, complex systems by breaking them down to individual components, examining how each component works, first, in isolation and, later, together (Bell and Morse, 2010). For this latter group, sustainable development can have clear, workable definitions; be implemented through congruent and coherent policy and programs; and be evaluated via transparent, evidence-based measures.

Until 2009, the United States had a spotty record in these matters; not only did it lack a national sustainable development agenda, but also it had no associated evaluation system. As a consequence, many municipalities, some states, several advocacy groups, and a number of private corporations undertook their own sustainable development programs and assessments. The lack of guidance, however, meant their conceptual framing and definitions ranged widely, with some emphasizing the environment (for example, Baltimore City Office of Sustainability, 2010, 2009; Siemens AG, 2012) and others giving weight to other factors (Birch, 2011; City of New York, 2011; Epstein, 2008; ICLEI, 2010, 2009).

The Partnership for Sustainable Communities

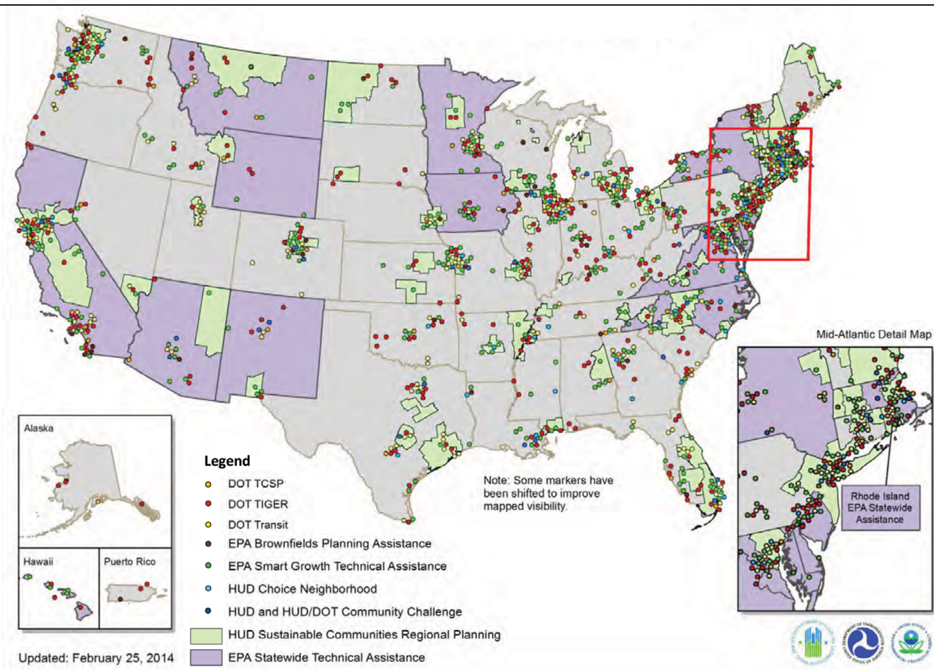
In 2009, the federal government acted to devise a national sustainable development agenda by forming the Partnership for Sustainable Communities (PSC), an innovative, interagency agreement among the U.S. Department of Housing and Urban Development (HUD), the U.S. Department of Transportation (DOT), and the U.S. Environmental Protection Agency (EPA; PSC, 2014). The PSC defined its vision of sustainable development through iteration and the use of six Livability Principles for policy and program guidance (PSC, 2014).

The Livability Principles, with their call for improvements in the built environment, define sustainable communities as those that "give Americans more housing choices, make transportation systems more efficient and reliable, reinforce existing investments, protect the environment, and support vibrant and healthy neighborhoods that attract businesses and jobs" (PSC, 2014: inside cover). The principles call for providing more affordable housing, energy-efficient and less polluting transportation alternatives, and aid to strengthen existing communities. In effect, they favor dense, mixed-use settlement patterns underpinned by economic agglomeration, qualities that decades of research (and continuing research) by urban planners and economists show are key elements of sustainability and lend themselves to measurement and evaluation (Birch and Wachter, 2006; Boarnet et al., 2011; Ewing and Cervero, 2010; Ewing, Greenwald, and Zhang, 2011; Feiden and Hamin, 2011; Kahn, 2006). Although other agencies are engaged in sustainable development projects, PSC stands out for its clear framing of a specific, comprehensive, and operationalized sustainable development agenda.

To advance this work, the agencies publicized the work in digital and print media (for example, DOT dedicated a section of its website http://www.dot.gov/livability/) or created special offices (for example, EPA created the Office of Sustainable Communities [OSC]). Within 2 years, the effort became more tangible through the awarding of funding based on the Livability Principles, the issuing of publications and supporting research, and advances in communication (for example, creation of a dedicated website http://www.sustainablecommunities.gov/). Between 2009 and 2014, PSC agencies awarded grants valued at $4.6 billion to more than 1,000 grantees (PSC, 2014). (See exhibit 1.)

Exhibit 1

Location of PSC Grantees



As of February 2014, the Partnership agencies have received more than 9,800 applications for assistance, requesting almost $122 billion. The Partnership has been able to fund 1,066 projects in all 50 states, the District of Columbia, and Puerto Rico with approximately $4.6 billion, representing just over 10 percent of applications.

DOT = U.S. Department of Transportation. EPA = U.S. Environmental Protection Agency. HUD = U.S. Department of Housing and Urban Development. PSC = Partnership for Sustainable Communities. TCSP = Transportation, Community, and System Preservation Program. TIGER = Transportation Investment Generating Economic Recovery.

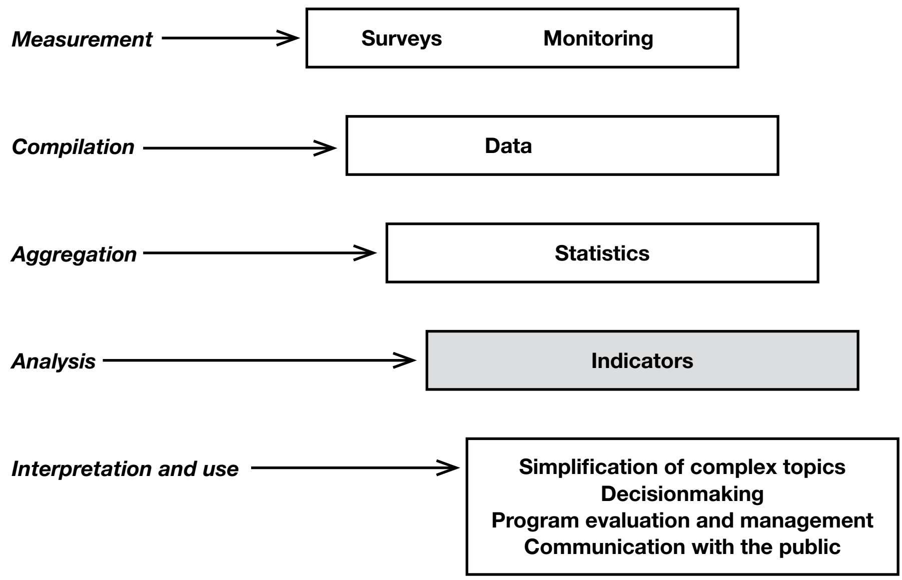
Source: Reprinted from "Partnership for Sustainable Communities," http://www.sustainablecommunities.gov/sites/sustainablecommunities.gov/files/docs/partnership-accomplishments-report-2014-reduced-size.pdf

As originally conceived, however, PSC's approach had one weakness: it did not have an associated, easily employed mechanism for evaluation to benchmark and measure progress toward the desired settlement patterns. As is well known, public policy evaluation helps define and refine a common vision; encourages the creation and regular updating of information; underlines and reinforces progress or demonstrates weaknesses, failings, or false (null) hypotheses or assumptions of a given policy or program; and supports a wider public understanding of the enterprise under consideration (Hak, Moldan, and Dahl, 2007). Although many evaluation techniques exist (for example, quasirandomized studies, case studies, benchmarks, surveys, and questionnaires), the use of indicators has become the commonly accepted approach in assessing sustainable development (Bell and Morse, 2008; Hak, Moldan, and Dahl, 2007). Exhibit 2 illustrates the place of indicators in public policy; employed correctly, they perform the functions listed in the bottom box of the exhibit.

Over time, PSC agencies worked to remedy the evaluation gap. By 2014, they offered three important tools to help communities evaluate their programs: (1) the Location Affordability Index (http://www.locationaffordability.info) estimates the percentage of a family's income dedicated to

Exhibit 2

Place of Indicators in Public Policy



Source: Adapted from Briggs (2003)

the combined costs of housing and transportation in a given location; (2) the Sustainable Communities Hot Report (http://thedataweb.rm.census.gov/TheDataWeb_HotReport2/EPA2/EPA_HomePage2.hrml), which integrates publicly accessible data by county on eight indicators (for example, mean travel time, housing costs of more than 30 percent of income, unemployment);[1] and (3) the Sustainable Communities Indicator Catalog (SCIC) (http://www.sustainablecommunities.gov//indicators), which is a searchable database of 31 core indicators that allows communities to select their own set, provides instructions for their calculations, and includes examples of places employing them.

Developing a U.S. Sustainable Communities Indicator Catalog

Thinking about developing a sustainable development indicator system for the United States had two sources. First, from its inception, the PSC has devoted attention to this topic (Argilagos, 2010). Second, exchanges at UN-HABITAT's World Urban Forum (WUF) 6 in Rio de Janeiro, Brazil (March 2010) stimulated interest at HUD on the topic. After WUF 6, HUD Deputy Assistant Secretary Ana Marie Argilagos, then Director, Office of International and Philanthropic Affairs, spearheaded a study group to explore the development of sustainable development indicators for

[1] The hotspot aggregates information from the American Community Survey; U.S. decennial censuses 1990, 2000, and 2010; the U.S. Department of Labor's Quarterly Census of Employment and Wages and State Occupational Projections; and the U.S. Census Bureau's Local Employment Dynamics.

the United States. The group, which met regularly through 2010 and 2011, posited that, for the most part, individual sustainability indicators existed, but group members needed to resolve the issue of how to select those that would be appropriate for the United States in the 21st century.

To this end, representatives from the American Planning Association and the University of Pennsylvania's Penn Institute for Urban Research (Penn IUR) volunteered to undertake preliminary research, an effort whose results are detailed by Birch and Lynch (2012), Lynch (2011a, 2011b, 2010), and Lynch et al. (2011) in several articles and presentations. In summary, Birch and Lynch (2012) reported the methodology and results of the researchers' inventory and analysis of representative indicator systems. It shows how they measured and evaluated individual indicators via several assessment tools (SMART [specific, measurable, accessible, replicable, timely], demand, pressure response, and multifactor versus single factor) and against two metrics: the traditional dimensions of sustainability (equity, economics, and environment) and later against the PSC's Livability Principles.

On the basis of this work, the Ford Foundation provided funding to the Penn IUR to undertake further development of an indicator system for use by the PSC. Working with PSC representatives, the Penn team devised and executed a five-step process to arrive at an appropriate evaluation system (exhibit 3).

Exhibit 3

Sustainable Development Indicator Process

OECD = Organisation for Economic Co-operation and Development. WB = World Bank.

Thus, in creating the SCIC, Penn IUR built on its research from previous years and consulted closely with representatives from PSC agencies, with Office of Sustainable Communities grantees, and with other stakeholders and experts. The researchers tested more than 100 indicator systems encompassing more than 400 indicators. In addition, the team developed 14 potential use cases to demonstrate the variety of users and their needs (exhibit 4). In March 2013, DOT hosted an expert workshop and, in May 2013, the Lincoln Institute of Land Policy held a second workshop for expert consultation. The Penn IUR team received additional feedback after presenting to professional associations in the United States and abroad, including the 2013 Federal Reserve Community Development Conference, the Organisation for Economic Co-operation and Development (OECD), the Urban Affairs Association, and others. It shared experiences with others developing indicator systems, including the OECD, which launched its *Better Life Index* in June 2104 and Arcadis's recently released Sustainable Cities Index (Arcadis, 2015; OECD, 2014).

In conjunction with this process, two critical decisions emerged that would drive the effort: first, the decision to use existing in-use indicators wherever possible; second, the decision to develop a flexible, searchable, web-based platform to offer wide choices to different types of communities. The decision to employ indicators that have already been used derived from two practical considerations. First, in-use indicators have a track record. Second, these in-use indicators are often (but not always) supported by scholarly research. Having the ability to refer to the reports or even other users of specific indicators enhances users' ability to tailor a system. The decision to make users' choice determine the choice of indicators from a limited list recognizes that different types of places, whether they are cities, counties, regions, or states, have varying goals in their pursuit of sustainability. Notably, this is the same approach being recommended by the high-level expert group, Sustainable Development Solutions Network, to the U.N. Statistical Commission for the indicators for soon-to-be-approved Sustainable Development Goals (Sustainable Development Solutions Network, 2015; U.N. ECOSOC, 2015).

Exhibit 4

A Use Case Example

Organization Type: Submunicipal Organization

User: Planner in a community-based Healthy Neighborhoods Coalition

Areas of Interest: Promoting biking and walking

Use Case:

The community planner for a Healthy Neighborhoods Coalition is developing a program to promote walking and biking as healthy, inexpensive, and sustainable modes of transportation. To that end, the planner is interested in measures that will provide a baseline and enable the organization to track bike and pedestrian travel and infrastructure in the future. The organization is relatively small, with a low technical capacity, and the planner has many other programs and responsibilities. Indicators need to be easy to understand and the data easy to collect at the neighborhood level.

The SCIC is fully operational and can be viewed on the PSC website (http://www.sustainablecommunities.gov/). Included are 11 tip sheets to assist users, the catalog, and links to communities in which the indicators are in use.

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