Measuring Urban Attitudes Using Twitter: An Exploratory Study

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Justin B. Hollander
Tufts University

Henry Renski
University of Massachusetts, Amherst

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Abstract

The goal of this working paper is to introduce a new breed of powerful software tools and social media data that can be used to study the attitudes of people in urban places. In particular, the paper reports on the work of the Urban Attitudes Lab, where a research project experimented with using microblogging data in conjunction with a mix of quantitative and qualitative methods, including content analysis and advanced multivariate statistics, to study the urban experience and draw implications for public policy. The research used propensity scoring to develop matched pairs of mid-sized U.S. cities in the Northeast and Midwest, where the most significant difference between each pair is that of population decline. This resulted in a group of 50 declining cities matched with 50 growing/stable cities. Over 300,000 Twitter posts were collected over the course of two-months, each analyzed for either positive or negative sentiment. After running difference of means tests, we found that sentiment in the declining cities does not differ in a statistically significant manner from stable and growing cities. These findings suggest that real opportunities exist to better understand urban attitudes through sentiment analysis of Twitter data.

Keywords: urban and regional planning, computerized, GIS, stakeholders, urban

About the Authors

Justin B. Hollander is associate professor in the Department of Urban and Environmental Policy and Planning at Tufts University. His research and teaching is in the areas of shrinking cities, Big Data, brownfields, and the intersection between cognitive science and the design of cities. Most recently, he co-authored *Cognitive Architecture: Designing for How We Respond to the Built Environment* (Routledge, 2015) and is the author of three other books on urban design and planning.

Department of Urban and Environmental Policy and Planning
Tufts University
97 Talbot Avenue
Medford, Massachusetts 02155 USA
tel: (617) 627-3394
fax: (617) 627-3377
email: justin.hollander@tufts.edu
http://www.tufts.edu/~jholla03
http://sites.tufts.edu/ualab
Twitter: JustinHollander

Henry Renski is an associate professor in the Department of Landscape Architecture and Regional Planning at the University of Massachusetts, Amherst and Director of the UMASS Center for Economic Development. He teaches courses in state and local economic development policy, quantitative methods, and Geographic Information Systems. His research interests include regional influences on entrepreneurship, the influence of technology on spatial development patterns, changing knowledge and skill requirement in the labor force, industrial cluster analysis, applied analytical methods, and the evaluation of state and local economic development policy.

Department of Landscape Architecture and Regional Planning
109 Hills North
University of Massachusetts
111 Thatcher Road, Ofc 1
Amherst, MA 01003-9357
Tel: (413) 545-2255
Email: hrenski@larp.umass.edu

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Measuring Urban Attitudes Using Twitter: An Exploratory Study

Introduction

With support from the Lincoln Institute, Dr. Hollander and Dr. Renski have been working with Tufts students at the Urban Attitudes Lab (Department of Urban and Environmental Policy and Planning at Tufts) to explore ways in which Twitter can be used to better measure urban attitudes. The first section of the report provides a brief overview of relevant literature, the next section offers an introduction to the tools we employed in this analysis. This is followed by the methods and results from our study "Resident Sentiment in Declining Cities: A Comparative Analysis of Twitter Posts," and we end the report with a conclusion, suggestions for research future, and a discussion about the implications of this study.

Review of the Literature

Assessing well-being

Well-being may be a far more important way to assess the status of a community or society than the economic indicators that are usually employed (Diener and Seligman, 2004). Diener and Seligman (2004) argue that well-being is much more predictive of worker productivity, mental and physical health, and social and community relationships than is economic status. However, it is a necessarily imprecise task to try to measure or even define something as subjective as well-being. Diener and Seligman (2004) define well-being as "peoples' positive evaluations of their lives, includes positive emotion, engagement, satisfaction, and meaning" (p.1). They point out that while economic factors do influence well-being, social relationships and physical health have a greater impact (Diener and Seligman, 2004). Van Kamp, Leidelmeijer, Marsman, and De Hollander (2003) describe a similar concept, "quality of life", as the overlap of human community, natural environment, and economics. On an individual scale, self-reported "well-being" can be measured with a survey or questionnaire, but this would be cost-prohibitive to administer on a large scale (Quercia, Ellis, Capra, and Crowcroft, 2012). Fortunately, studies have found that results of sentiment analysis of social media content correlate strongly with self-reported life satisfaction for individuals (Kramer 2010). This can also be applied to communities or even whole countries: Kramer (2010) used a sentiment analysis of Facebook posts to measure "Gross National Happiness" over time. Quercia et al. (2012) took this a step further and found a strong relationship between overall sentiment detected from Twitter data and economic status at the community and neighborhood level.

Microblog sentiment analysis

As an emerging field, the analysis of microblog data as a means of gathering information about social issues has both strengths and weaknesses. It is a relatively fast and low-cost method of collecting freely volunteered opinions in real time from a wide range of the public on a wide range of topics. This is much simpler, cheaper, and faster than conducting surveys or interviews, for example. However, there are also limitations to consider. Use of social media to express opinions and sentiment is much more pervasive among certain age groups and among those who have more access to smartphones and computers than it is among other groups. A Pew Research Center report from 2012 found that only 15% of adults in the United States used Twitter, and these individuals were most likely to be between the ages of 18 and 29 and live in urban areas (Smith and Brenner 2012). Mislove, Lehmann, Ahn, Onnela, and Rosenquist (2011) additionally found that Twitter users were significantly more likely to be male and live in densely populated areas. There are socioeconomic, linguistic, and cultural factors that may also impact use of social media. Thus, any social media or microblog data collected in this way cannot be said to be a random sample of the population to be studied, and it is important to be aware that key demographic groups may be underrepresented (Hollander, Graves, and Levanthal 2014).

Uses of sentiment analysis

Sentiment analysis is a quasi-qualitative analytical method, a form of content analysis that can be applied to large data sets including social media data sets. Unlike traditional content analysis, in which a researcher reads through a document and codes certain words and phrases, sentiment analysis is a more automated process, using a sentiment dictionary and a computer program to analyze large data sets.

Sentiment analysis of microblogging data has been used to consider social issues in a variety of studies. For example, sentiment analysis can be used to assess the public mood in response to events. Bollen, Mao, and Pepe (2011) conducted a Twitter sentiment analysis in which they considered nationwide sentiment over a 6-month period in 2008. They calculated a daily mood for their entire pool of data and correlated that with external events such as elections and holidays. Several other studies have compared microblogging sentiment analysis with the results of elections (Gordon 2013; O'Connor, Balasubramanyan, Routledge, and Smith 2010). Of special interest are those studies in which sentiment analysis has been used to compare different geographic areas. For example, Quercia et al. (2012) compared sentiment analysis of Tweets geotagged to different areas of London, and found a strong correlation between expressed positive sentiment and higher socioeconomic variables for each area. A number of other studies have also used geotagged tweets to look at differences between different geographic areas (Mearns et al. 2013; Mitchell, Frank, Harris, Dodds, and Danforth 2014; Lovelace, Malleson, Harland, and Birkin 2013; Antonelli et al. 2014; Balduini et al. 2013; Bertrand, Bialik, Virdee, Gros, and Bar-Yam 2013).

Urban applications of microblog sentiment analysis

Our research falls within the category of urban applications of sentiment analysis. While the field is still new, Twitter sentiment analysis has been applied successfully to urban studies and urban planning topics. Antonelli et al. (2014) and Balduini et al. (2013) look at Twitter as a way to assess reactions to city-scale events, while MacEachren et al. (2011) apply similar methods to crisis management. Bertrand et al. (2013) apply sentiment analysis to Tweets from New York City to see how sentiment varies within different areas of the city and changes over time. Lovelace et al. (2014) consider a very small scale, comparing how many visitors frequent different museums in Yorkshire, England based on Tweets about the museums or Tweets sent from the geographic locations of the museums. Geotagged tweets have also been used track movement of people over time (Fujisaka, Lee, and Mumiya 2010) and to determine land use in urban environments (Frias-Martinez, V., Soto, Hohwald, and Frias-Martinez, E. 2013). However, the majority of these studies use only the quantitative data available from Twitter, rather than qualitatively analyzing the content of specific Tweets. One of the most comprehensive of these studies which does use sentiment analysis is that of Mitchell et al. (2013), which looks at happiness between states and urban areas within the United States and compares their sentiment analysis results to a number of other indicators of well-being, such as Gallup polls and gun violence rates. One of their more interesting findings was that areas with higher numbers of Tweets per capita tend to have less positive sentiment. They also correlated happiness from sentiment analysis with census data and found a strong correlation between cities with a higher percentage of white, married, higher-income residents and cities with higher happiness scores (Mitchell et al. 2013).

Hollander et al. (2014) produced a qualitative study of Twitter content to study attitudes relating to child and family policies and other urban issues within a specific urban area. This study is the closest in structure and scope to our research goals, and uses the specific qualitative sentiment analysis methods that we are using, applied to an urban planning-related topic. We will be basing our methods and approach heavily on their study.

Application of Urban Attitudes Software

Urban Attitudes is a data mining and text analysis tool we developed in 2013. With support from Lincoln, we have used the software to conduct several research projects.

The software supports the following operations:

- analyze a large variety of text files; and
- download Tweets from Twitter filtered by locations.

Downloading Tweets

The program requires a set of tokens from Twitter to download Tweets. This can easily be obtained by signing up on Twitter. Currently the program supports downloading Tweets based on geographical locations. The user needs to provide the NE and SW latitude and longitude coordinates which serve to define a bounding box from which the Tweets are downloaded. Based on specific requirements, the program can be upgraded to download Tweets by keywords, hashtags, usernames, et cetera. In other words, Tweets can be downloaded according to any of the filters offered by the Twitter API.

Based on current requirements, the present version downloads the following fields of a Tweet: User ID, Username, Text, Longitude, Latitude, Language, Created at.

The program can be tweaked to download a great deal more information about each Tweet. The full list of the fields can be found here.

Analyzing for Sentiments

The sentiment analyzer currently scans each Tweet for keywords defined in a dictionary, rated according to their sentiment with an integer. The program comes with a default dictionary based on AFINN.

The AFINN dictionary was developed by Finn Årup Nielsen, and ranks words on an ordinal scale ranging from +5 to -5. For example, "abusive" is given a score of -3, while "satisfied" is given a score of +2. The latest version of AFINN has 2,477 words, and is capable of capturing variants of words such as recognizing "loooooove" as "love." It has been used in multiple research studies to date, including an analysis of tweets emanating from New Bedford, MA between February 9, 2014 and April 3, 2014 (Hollander, Graves, and Leventhal 2014), identification of anti-vaccine sentiments from tweets (Brooks 2014), evaluation of more than 5,000 advertisements in business magazines (Abrahams, Coupey, Zhong, Barkhi, and Manasantivongs 2013), and as part of a model predicting fluctuations in global currency markets (Jin et al. 2013).

The score of each sentiment word is summed up for every tweet and the net score gives a measure of the sentiment present in a dataset. The analysis can be performed in conjunction with parameters that allow Tweets to be filtered by date-time stamp, presence of keywords, and other factors. This is a useful feature to have, especially if you wish to analyze Tweets by topic/hashtags or other indicators. In addition, the program also allows any text file to be analyzed with an inbuilt text analyzer, which is similar to the Tweet analyzer.

The sentiment analyzer allows for scanning by wildcards, whereby defining words with a '*' following a sequence of characters and a corresponding score enables the program to score all words with that pattern to be scored the same. For example, kind* scans for kind, kindly, kinder, etc. and assigns the same score to every iteration of the associated sentiment.

Future Additions

The program can be upgraded to mine data from all social networking and rating sites, which provide public APIs to access their data, and can be customized to analyze them. Possible additions include support for Yelp, Foursquare, and Facebook.

Resident Sentiment in Declining Cities: A Comparative Analysis of Twitter Posts

This study investigates whether the residents of declining cities are more prone to negative sentiment than residents of growing or stable cities, based on an analysis of a sample of anonymous Twitter posts from a variety of cities. This section begins with some context on the shrinking cities phenomena and then presents the methods and results from a study we conducted.

The Shrinking Cities and Smart Decline Literature

In conventional urban policy and planning practice, there is a stigma against losing population. Beauregard's (2003) seminal *Voices of Decline* documented the overwhelming negativity associated in popular culture with population loss. If a city loses population, it is widely considered to be "dying," so to speak. If a city grows, it is a winner and is thriving. These powerful, entrenched perceptions have engendered a discourse that shapes the way investment and public policy decisions are made.

However, a new discourse revolving around the implementation of smart decline practices has gained attention as an alternative framework for thinking about population decline. Popper and Popper (2002) define smart decline as "planning for less—fewer people, fewer buildings, fewer land uses" (23). The clearest practical example of smart decline is their proposal to establish a Buffalo Commons in severely shrinking parts of the Great Plains (Matthews 2002 [1992]). The Poppers' research (1987) found that the preservation of a large portion of the Great Plains as "somewhere between traditional agriculture and pure wilderness" offered "ecologically and economically restorative possibilities" (Popper and Popper 2004, 4). Vergara (1999) proposed an American Acropolis in downtown Detroit to preserve the scores of abandoned skyscrapers. He saw cultural benefit in establishing a park at the site to attract visitors to walk the crumbling streets. Also, Clark (1989) encouraged the preservation of declining areas as vacant, arguing that these areas could be greened for "parkland and recreational spaces" (143)—a suggestion echoed recently by Schilling and Logan (2008).

Community leaders in Youngstown, Ohio (which has lost half of its population since 1950) adopted this smart decline approach with a new municipal Master Plan to address its remaining population of 74,000 (U.S. Census 2008). In the Plan, the city came to terms with its substantial population loss and called for a "better, smaller Youngstown," focusing on improving the quality of life for existing residents rather than attempting to regrow the city to its former magnitude (City of Youngstown 2005; Hollander 2009). The New York Times Magazine recognized the city's plan as one of the most creative ideas of 2006.

Greenberg and Schneider (1996) showed through survey research that such abandoned buildings and vacant lots, along with crime, are the most influential factors in determining resident perceptions of the quality of their neighborhoods. In-depth interview research in neighborhoods with major abandoned structures has further confirmed that eliminating physical blight generally makes people happier and improves their opinions of their neighborhoods (Bright 2000; Hollander 2009). Smart decline provides a path for shrinking cities to effectively deal with their abandoned buildings and vacant lots as part of a broader strategy of managing depopulation.

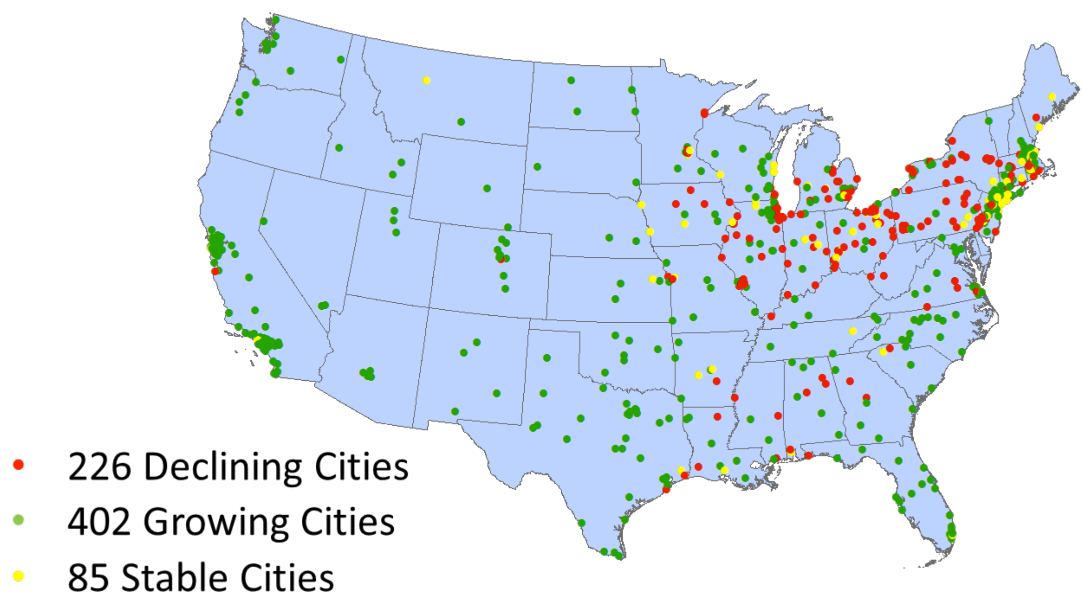
The critical paradox of the shrinking city is that, as demand for real estate falls, so do property values, thus decreasing tax revenues (Glaeser and Gyourko 2005). Diminished fiscal capacity translates to fewer services (for example, less fire protection) or poorer quality services (for example, lower teacher-to-student ratios). Smart decline interrupts this cycle of deterioration by reducing the excess supply of homes, roads, and other infrastructure, relative to a smaller population (Koziol 2006; Schwarz and Rugare 2008; Weichmann 2008). Smart decline balances the scales, reducing the size and scale of the city to match its lower population. While overall economic conditions in a shrinking city may continue to worsen, a timely smart decline strategy should be able to reduce municipal expenditures to a lower level, concomitant with a city's new, smaller size.

Fiscal stability is one thing, but what about the quality of life for those left behind by depopulation? In economics, the happiness literature has been growing and is viewed by some as a surrogate for quality of life (where employment, income levels, and other economic indicators have traditionally been used) (Bruni and Porta 2007; Easterlin 2002; Frey and Stutzer 2002). In one such research project, overall life satisfaction was examined at the municipal level to test for differences among German cities with varying population trajectories. The study found that overall life satisfaction for those cities that shrunk from 1990–2005 was not any lower than growing cities; in some domains, life satisfaction was even higher for residents of shrinking cities (Delkin 2008). Life satisfaction is also closely tied to overall sentiment, as discussed in the second section of this report.

Research Design: Selecting Candidate Cities

We focus our attention on mid-sized declining cities, defined as municipalities (incorporated places and county subdivisions) with populations between 30,000 and 250,000 in 1970 that have experienced population loss of more than 5 percent over the past 40 years. 226 cities met these criteria (Figure 1).

Figure 1: Candidate Mid-Sized Cities



To truly understand whether it is perceptions of decline that may lead to observed differences in resident sentiment, and not associated conditions such as poverty or demographic differences, we will compare our sample of Tweets from declining cities to a set of matched cities that have not experienced substantial population loss. Just over 400 cities had 40-year population growth rates in excess of 5 percent, a standard we are tentatively using to define growth (Figure 1). Another

85 had stable growth, with population growth rates in between -5 and 5 percent. Stable cities typically do not face the kind of negative stigma associated with decline. We therefore combined growing and stable communities into a single comparison group (growing/stable cities) in order to focus attention on differences with unambiguously declining cities.

There are clear differences in the geography of municipal growth and decline (Figure 1). All but a handful of declining cities are located in the Northeast and Midwest. Growing cities tend to be in the West and South. This reflects the continued snow-belt to sub-belt shift of American settlement patterns, coupled with the de-industrialization of the U.S. economy. It also reflects the generally fixed municipal boundaries in Northern states, juxtaposed with the possibility of land annexation in the South and the West. To reduce the potentially confounding influence of these and other regional differences, we decided to restrict our analysis to mid-sized cities in the Northeast and Midwest. This reduces the candidate city pool to 196 declining cities and 221 growing/stable cities.

Propensity Score Matching

We use a process known as propensity score matching to identify the most suitable matches to our sample of declining cities. Propensity score matching follows a two-step process. It first estimates a binary logistic regression model (logit) to "predict" whether a city is growing/stable or declining based upon a comprehensive set of explanatory variables. These are factors that may explain possible place variation in resident sentiment apart from growth or decline, such as demographic composition, income and poverty, public health conditions, and access to natural amenities (Table 1). Other variables were considered, but dropped in the final model specification due to a lack of unique variation. A summary of our logistic regression model results are included in Appendix Table 1.

Table 1: Variables Used for Propensity Score Matching

Source	Measure	Geographic Level
Census Bureau, American Community Survey, 2009-2013		Place/County Subdivision
	Total Population (in 000s)	
	Population share, under 18 years old	
	Population share, 18 to 24 years old	
	Population share, 65 and older	
	Percent Black or African American	
	Percent Hispanic (any race)	
	Percent Foreign Born	

High School Dropout Rate	
Share of Adults (25+) with graduate degrees	
Median Household Income in Past Year ($000s)	
Poverty Rate	
Unemployment Rate	
Gini index of Income Inequality	
Centers for Disease Control, National Vital Statistics System	County
Age-Adjusted Mortality Rate	
USDA ERS, Natural Amenities Index	County
Mean January Temperature	
Area covered by water (log)	
Annual number days of sunlight	
Degree of topographical variation	
USDA ERS, 2013 Rural-Urban Continuum Codes	County
Large Metro (Counties in metro areas of 1 million population or more)	
Mid-Sized Metro (Counties in metro areas of 250,000 to 1 million population)	

The second step of the matching process uses the predicted probabilities from the logit models to develop propensity scores—a single metric for each city that summarizes the overall degree of similarity of different communities among the included independent variables. These scores are then fed into an algorithm that identifies the most appropriate match for each candidate declining city. We use an optimizing algorithm (i.e. ps_match_multi SAS macro) that minimizes the overall difference between the set of selected declining cities with a matching set of growing/stable cities (Fraeman, 2010). Some cities cannot be adequately matched and are thus eliminated from further analysis. The analyst chooses a threshold (caliper) that defines the acceptable degree of similarity. A smaller caliper produces fewer, but more closely similar, matches. A larger caliper results in a larger sample size that may be more generalizable to the full population of cities, but at the expense of internal comparability. We decided to err on the side of fewer, better matches, considering the computational burden of collecting and analyzing tweets for large numbers of cities. Our final data set includes 100 cities: 50 declining cities and 50 growing/stable cities (Figure 2). The list of selected of cities is provided in Appendix Table 2.

The ultimate purpose of matching is to produce a reduced set of cities that are balanced (that is, equivalent) on key characteristics. Prior to matching, the candidate populations of declining and growing/stable cities were unbalanced, with statistically significant differences in their average propensity scores (Table 2). On the whole, declining cities tend to be smaller, with a population comprised of more children and senior citizens, but fewer young adults. African Americans comprise a much larger share of the residents of declining cities in the Northeast and Midwest, although they have fewer foreign-born and Hispanic residents, most likely because immigration is a major factor contributing to growth. Declining cities also have higher poverty rates, lower household incomes, higher mortality rates, more high school drop-outs, and fewer graduate-degree holders. Declining cities are generally similar to growing/stable cities in terms of natural amenities, with the exception of average annual days of sunlight.

Figure 2: Final set of 100 Study Cities

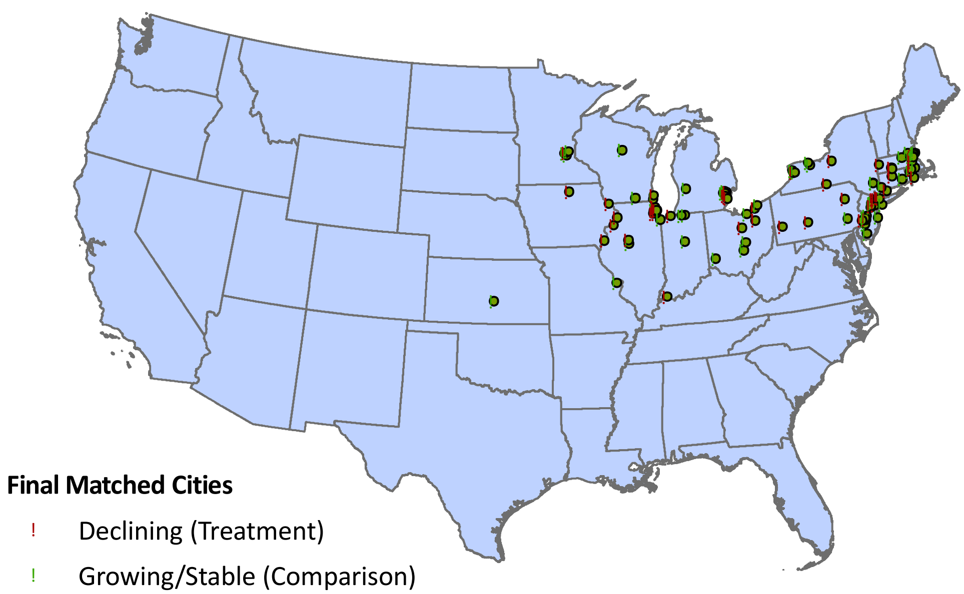


Table 2: Difference of Means, Characteristics of Declining vs Growing/Stable Cities, Pre-Matching

	Growing/Stable	Declining	Difference	Pr < t
Propensity Score	0.3	0.7	0.44	0.00
Population (in 000s)	73.1	49.5	-23.60	0.00
Population share, under 18 years old	22.6	23.5	0.86	0.02
Population share, 18 to 24 years old	12.0	10.2	-1.80	0.01
Population share, age 65 and older	13.1	14.5	1.42	0.00

Percent Black or African American	8.4	18.2	9.79	0.00
Percent Hispanic (any race)	12.9	7.7	-5.14	0.00
Percent foreign born	16.0	9.4	-6.59	0.00
High school dropout rate	12.2	13.9	1.64	0.02
Share of adults with graduate degrees	13.4	10.5	-2.91	0.00
Median Household Income (in 000s)	59.5	48.6	-10.84	0.00
Poverty rate	14.4	19.4	4.95	0.00
Unemployment Rate	9.2	12.1	2.82	0.00
Gini index of income inequality	0.44	0.45	0.00	0.36
Age adjusted death rate	691.8	764.9	73.09	0.00
Mean January temperature	25.7	25.9	0.16	0.75
Area covered by water (log)	6.0	6.2	0.14	0.38
Average annual days of sunlight	139.7	128.1	-11.58	0.00
Degree of topographical variation	7.2	7.0	-0.16	0.76

Our matched set of declining and growing/stable cities is far more balanced (Table 3). There are no longer any significant differences in average propensity scores, nor in any of the remaining 18 variables. This does not mean that the matching cities are identical, but rather that the set of declining cities is, on the whole, similar in these characteristics to the comparison group of matched growing/stable cities. Therefore, we can continue on to the next stage of the analysis with some level of confidence that any observed differences in Twitter sentiment are due to decline, and not the overall socio-demographic composition of the city itself. We further acknowledge that Twitter users are not reflective of the general population and may differ in their sentiment toward their community. It is possible that there are unmeasured systematic differences in the composition of Twitter users in declining versus growing/stable cities, but, lacking characteristics of individual users, we cannot be sure.

Table 3: Difference of Means, Characteristics of Declining vs Growing/Stable Cities, Post-Matching

	Growing/Stable	Declining	Difference	Pr <= t
Propensity Score	0.5	0.5	0.0	1.00
Population (in 000s)	54.8	53.4	-1.4	0.79
Population share, under 18 years old	23.0	22.5	-0.5	0.41
Population share, 18 to 24 years old	9.4	9.4	0.1	0.87
Population share, 65 and older	14.8	14.9	0.1	0.89
Percent Black or African American	10.2	9.3	-0.9	0.73
Percent Hispanic (any race)	9.4	7.6	-1.8	0.40
Percent foreign born	13.0	12.0	-1.0	0.60
High school dropout rate	12.1	11.0	-1.0	0.47
Share of adults with graduate	13.6	14.7	1.1	0.62

degrees				
Median Household Income (in 000s)	61.1	60.9	-0.2	0.97
Poverty rate	13.6	13.6	0.1	0.96
Unemployment Rate	9.8	9.3	-0.5	0.47
Gini index of income inequality	0.4	0.4	0.0	0.26
Age adjusted death rate	716.8	717.2	0.4	0.98
Mean January temperature	26.1	25.5	-0.6	0.50
Area covered by water (log)	6.3	6.2	-0.2	0.54
Average annual days of sunlight	135.1	131.9	-3.2	0.40
Degree of topographical variation	6.4	7.8	1.4	0.17

Monitoring Sentiment through Twitter Posts

With the final sample of declining and matching cities selected, the next stage of the analysis was to identify bounding coordinates for each city, and to capture the Tweets posted within these bounds using our Urban Attitudes program. The Urban Attitudes program tracks a sample of geographically identified (or "geo-tagged") tweets that fall within a specified rectangle (see Appendix Figure 1 for an example). First, we collected the historic (1980) shapefile boundaries for each city from the US Census Bureau TIGER files. Using static historic municipal boundaries ensures that we are tracking a consistent area regardless of possible annexations or other changes in municipal boundaries. We then used ArcGIS to determine a bounding rectangle for each city. Because we are limited to bounding rectangles, the sampled area does not perfectly match the municipal jurisdictional boundaries. We purposely set our bounding rectangles at the outmost edges of each municipality. This ensures coverage of the entirety of the city, although it also means that we also include some areas outside the historic municipal jurisdictions. We then convert the vertices of the southwestern and northeastern corners of the bounding rectangle into point locations as indicated by their latitude and longitude coordinates. These coordinates are entered into the Urban Attitudes program for tracking purposes.

We collected tweets from the 100 sampled cities over the roughly two-month period from May 21, 2015 to July 24, 2015. We determined that this was a minimally acceptable timespan to distinguish durable and consistent differences in community sentiment, from that induced by temporary and/or one-time events. Over 309,000 individual tweets were collected during this period, ranging from a high of 12,593 for Bristol, PA to a low of 446 tweets collected for Burlington, IA. We then conducted a basic sentiment analysis of captured tweets using the AFINN sentiment dictionary (see details in Section II of this report).

Each city was analyzed separately, with the Urban Attitudes program reporting a number of summary statistics for each. This included an overall score for each city based upon the number and relative intensity of positive and/or negative words of all tweets. The summary measures also include the number of positive and/or negative tweets. A tweet is deemed positive if its overall sentiment score is more positive than negative. From these basic indicators we constructed four analytical metrics: the ratio of positive to negative scores, the ratio of positive to negative tweets, the percentage of positive tweets, and the percentage of negative tweets. The two ratio metrics had heavily skewed distributions, and thus were transformed by natural logarithms to normalize the data prior to analysis. The percentage-based measures were already quasi-normal and required no additional transformation.

Results

We use simple difference of means tests to determine whether, on average, Twitter sentiment in our sample of declining cities is significantly different than sentiment in our comparison cities (Table 4). We found no such differences. The Positive to Negative Score ratio shows that twitter users in declining cities are slightly more positive than growing/stable cities. But the differences are too small to be meaningful. The same is true for the Positive to Negative Tweet Ratio, which only considers whether the overall Tweet is positive or negative and does not consider the relative intensity of sentiment words within each tweet. Regardless of location, Twitter users tend to be generally positive in their sentiment, with twice as many positive tweets as negative. Residents of declining cities are slightly less prone to post positive tweets, and have similar rates of posting negative tweets. But again, none of these differences are statistically significant.

Table 4: Difference of Means, Resident Sentiment, Declining vs. Growing/Stable

	Means				
	Declining	Growing/ Stable	Difference	T-score	Pr(T<=t), two-tailed
Positive to Negative Score Ratio	2.59	2.43	0.16	0.705	0.483
Positive to Negative Score Ratio (ln)	0.84	0.82	0.01	0.141	0.888
Positive to Negative Tweet Ratio	2.22	2.15	0.07	0.542	0.589
Positive to Negative Tweet Ratio (ln)	0.75	0.74	0.01	0.139	0.890
Percent Positive Tweets	39%	40%	-0.01	-1.235	0.220
Percent Negative Tweets	19%	19%	-0.01	-0.571	0.570

One possible caveat is that actual differences are obscured by tweets that do not truly reflect resident attitudes or opinions. Many tweets are commercial solicitations. Most commonly, these are job announcements, which alone comprised 17% of all the tweets captured. It is likely that these tweets contain little sentiment, and thus may pull the results toward the middle (i.e. more neutral).

To test the sensitivity of our results, we re-ran the difference of means tests filtering out tweets that were job announcements as denoted by hash-tag (#) that include key words, such as #Jobs, #Job, #Hiring, and the like. It was difficult to clearly identify other forms of commercial solicitation, as they lack a set of consistent and common hash-tag keywords to aid in their identification. Again, we find no significant differences in the implied sentiment of Twitter posts in declining cities as compared to peer cities. Filtering reduced the number of both "positive" and "neutral" posts, resulting in slightly lower Positive to Negative Ratios, a lower percentage of positive tweets, and a slight increase in the percentage of negative tweets. But the relative differences between declining and growing/stable cities remains consistent.

Table 5: Difference of Means, Resident Sentiment, Declining vs. Growing/Stable, Filtered

	Means				
	Declining	Growing/ Stable	Difference	T-score	Pr(T<=t), two-tailed
Positive to Negative Score Ratio	2.17	2.02	0.15	0.827	0.411
Positive to Negative Score Ratio (ln)	0.67	0.65	0.02	0.250	0.803
Positive to Negative Tweet Ratio	1.88	1.81	0.07	0.646	0.520
Positive to Negative Tweet Ratio (ln)	0.75	0.74	0.01	0.139	0.890
Percent Positive Tweets	37%	38%	-0.01	-1.113	0.269
Percent Negative Tweets	21%	22%	-0.01	-0.742	0.460

Conclusion

Given the literature discussed above and the popular notions of how decline is linked to negative outcomes, it is striking to see that sentiment in declining cities do not differ in a statistically significant manner from stable and growing cities. This study uses a statistical matching technique to identify cities that are a close match on many socio-economic attributes, all save for the pace of population growth or decline over the past 30 years. We found that there is no meaningful difference in how Twitter users in mid-sized declining cities express their overall sentiment, as compared with users located in growing or stable cities after accounting for social and demographic differences.

The research has important implications for public policy. It suggests that population decline itself may not contribute to lower overall sentiment levels, which means local, state, and federal agencies ought to better explore how decline does impact neighborhoods and overall community well-being. Growth can also be disruptive, especially if not properly managed, and may stir up negative feelings among residents just as much as decline. The research also gives some evidence that population decline may be better managed in some places versus others. As shown in Appendix Tables 3 and 4, shrinking cities like Bristol, PA and Newport, RI had higher overall sentiment than growing and stable cities like Lexington, MA and Poughkeepsie City, NY. Officials in a declining city with low sentiment (such as Bridgeport, CT) might consider how they can more to emulate another declining city, like Bristol, PA where people are generally pleased.

This research suggests that rich opportunities exist for employing microblogging data in urban social science research. Our exploratory use of sentiment analysis also proved to be useful and enlightening, though clearly not without its problems. We caution not to over-infer the results from a sample population of Twitter users to reflect the sentiment of the general public. Twitter users are not a representative sample. According to a 2015 survey conducted by the Pew Research Center, 23% percent of the adult internet users use Twitter (Duggan 2015). While we do not know the precise characteristics of the users included in our study, in general Twitter users tend to be younger, more highly educated, urban, and have higher earnings than the general public. Twitter users are also slightly more likely to be male and are disproportionately comprised of African Americans and Hispanics. So while perhaps not necessarily representative of the general public, the population of Twitter users is still very large and reflects the opinions of demographic groups that are of critical interest to urban planners and policy makers alike. A further limitation is that our analysis covers only mid-sized cities in the Northeast and Midwest, which we track for a relatively short period of time. A more robust analysis would measure sentiment over a longer time period in order to distinguish fleeting moods and opinions that may be tied to particular events from real, and sustained, differences between cities.

In conclusion, we find that, with appropriate care and caution, Twitter data can be properly harnessed to answer critical research questions of interest to land use, planning, and urban policy makers and encourage others to continue to experiment with these novel data sources.

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Appendix

Appendix Table 1: Summary, Logistic Regression Results

Number of Observations	417
Number Declining	196
Number Growing/Stable	221

	Intercept only	Intercept with Covariates
AIC	578.585	397.989
SC	582.618	482.684
-2 Log L	576.585	355.989

Parameter	Estimate	Standard Error	Pr > ChiSq
Intercept	-8.366	3.582	0.020
Total Population (000s)	-0.024	0.005	<.0001
Population share, under 18 years old	-0.008	0.071	0.914
Population share, 18 to 24 years old	-0.049	0.041	0.230
Population share, age 65 and older	0.217	0.069	0.002
Percent Black or African American	0.058	0.017	0.001
Percent Hispanic (any race)	-0.040	0.024	0.102
Percent Foreign Born	-0.029	0.024	0.224
High School Dropout Rate	0.090	0.062	0.144
Share of Adults (25+) with graduate degrees	0.111	0.043	0.010
Median Household Income in Past Year ($000s)	0.008	0.021	0.718
Poverty Rate	0.136	0.057	0.016
Unemployment Rate	0.063	0.076	0.402
Gini index of Income Inequality	-12.619	6.410	0.049
Age-Adjusted Mortality Rate	0.009	0.003	0.000
Mean January Temperature	-0.071	0.034	0.038
Area covered by water (log)	0.241	0.106	0.023
Annual number days of sunlight	0.080	0.031	0.010
Degree of topographical variation	0.000	0.008	0.971
Large Metro (vs. small metro or non-metro)	0.550	0.263	0.037
Mid-Sized Metro (vs. small metro or non-metro)	0.324	0.246	0.189

Appendix Table 2: List of Sampled Cities

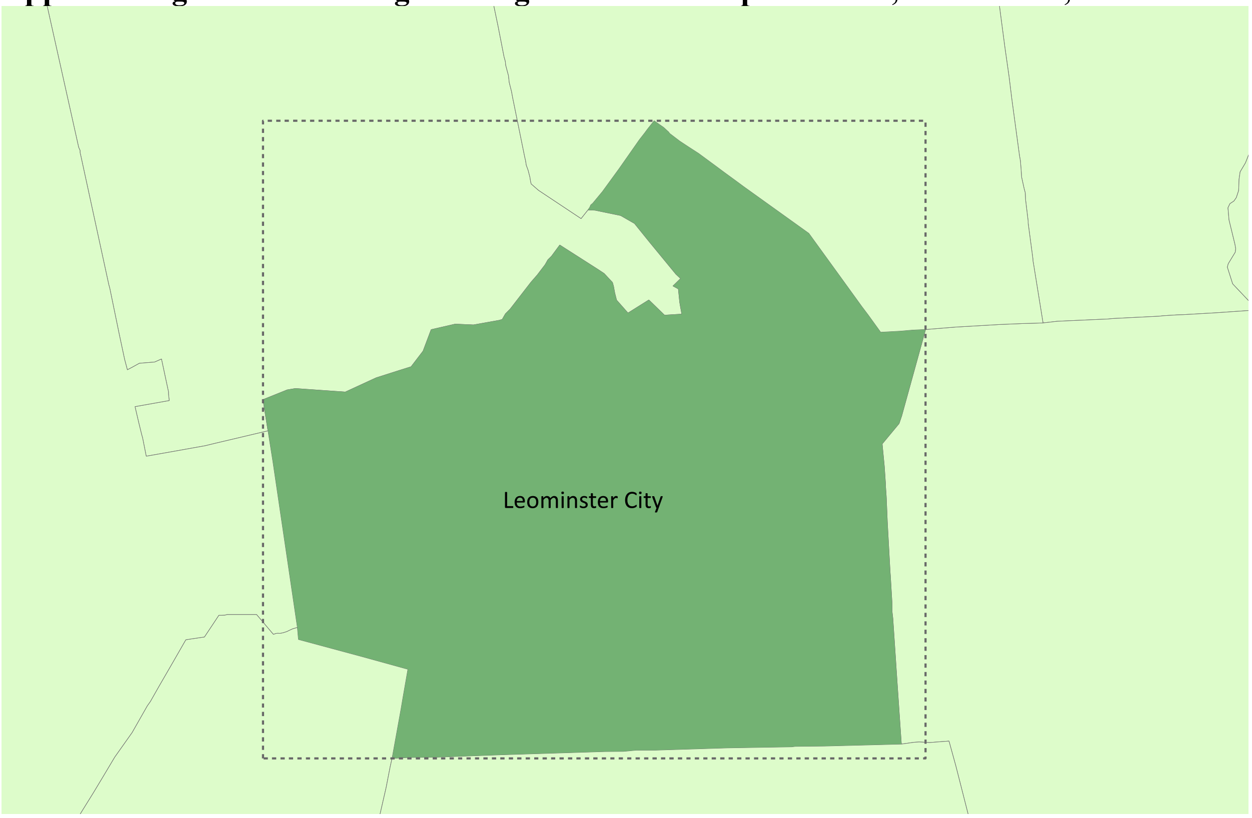
Declining Cities

Abington, PA	Elmira , NY	Oak Park, IL
Allen Park, MI	Euclid, OH	Park Ridge, IL
Altoona, PA	Evanston, IL	Pawtucket, RI
Arlington, MA	Evansville, IN	Peoria, IL
Barberton, OH	Fair Lawn , NJ	Pittsfield, MA
Bayonne , NJ	Hartford, CT	Racine, WI
Bergenfield , NJ	Highland Park, IL	Ross, PA
Bridgeport, CT	Mamaroneck, NY	Royal Oak, MI
Bristol, PA	Mansfield, OH	Salina, NY
Burlington, IO	Mason , IO	Skokie, IL
Cheektowaga , NY	Medford, MA	Somerville, MA
Chicopee, MA	Melrose, MA	Springfield, MA
Clinton, IO	Michigan, IN	St Louis Park, MN
Dearborn Heights, MI	Moline, IL	Westfield , NJ
Dubuque, IO	Newport, RI	Wilkes Barre, PA
Eastchester, NY	Newton, MA	Wyandotte, MI
Elmhurst, IL	Norwood, MA	

Growing / Stable Cities

Amherst , NY	Greece, NY	Newark, OH
Beverly, MA	Hutchinson, KS	Norwich, CT
Bloomfield, MI	Janesville, WI	Peabody, MA
Bloomington, MN	Kenosha, WI	Pekin, IL
Brick , NJ	Kokomo, IN	Plainfield , NJ
Brighton, NY	Lancaster , NY	Poughkeepsie City, NY
Brookline, MA	Lancaster, OH	Poughkeepsie Town, NY
Calumet , IL	Leominster, MA	Reading, PA
Chelsea, MA	Lexington, MA	Roseville, MN
Cherry Hill , NJ	Livingston , NJ	Southfield, MI
Cranston, RI	Long Beach, NY	St Charles, MO
Danbury, CT	Lowell, MA	Taunton, MA
Des Plaines, IL	Mentor, OH	Vineland , NJ
Elkhart, IN	Middle, OH	Wausau, WI
Elyria, OH	Middle, PA	West Orange , NJ
Ewing , NJ	Minnetonka, MN	Wyoming, MI
Farmington Hills, MI	Mishawaka, IN	

Appendix Figure 1: Bounding Rectangle for Tweet Capture Area, Leominster, MA



Appendix Table 3: Study Sample Sentiment Scores, Declining Cities

City	Sentiment Words	Positive Score	Negative Score	Pos. / Neg. Score Ratio	Total Tweets	Sentiment Tweets	Positive Tweets	Negative Tweets	Pos. / Neg. Tweet Ratio
Abington, PA	452	2654	-1660	1.60	2283	1172	855	523	1.63
Allen Park, MI	487	3632	-3298	1.10	3320	1818	1210	971	1.25
Altoona, PA	268	1699	-675	2.52	1366	689	531	258	2.06
Arlington, MA	192	969	-360	2.69	682	359	270	127	2.13
Barberton, OH	212	598	-441	1.36	484	295	206	147	1.40
Bayonne , NJ	376	2810	-1116	2.52	3088	1155	843	459	1.84
Bergenfield , NJ	191	726	-535	1.36	673	332	232	155	1.50
Bridgeport, CT	592	7780	-8983	0.87	9386	4213	2664	2281	1.17
Bristol, PA	571	19804	-3141	6.30	12406	6853	6139	1186	5.18
Burlington, IO	116	466	-111	4.20	324	162	136	49	2.78
Cheektowaga , NY	654	7186	-5951	1.21	7201	3670	2435	1838	1.32
Chicopee, MA	541	4200	-2998	1.40	3668	1964	1352	974	1.39
Clinton, IO	127	577	-131	4.40	363	198	165	60	2.75
Dearborn Heights, MI	596	5423	-4173	1.30	6888	2662	1839	1256	1.46
Dubuque, IO	344	1899	-1099	1.73	1854	834	609	385	1.58
Eastchester, NY	298	1484	-591	2.51	1398	603	460	217	2.12
Elmhurst, IL	302	1602	-670	2.39	1115	590	465	237	1.96
Elmira , NY	163	440	-274	1.61	416	198	147	94	1.56
Euclid, OH	669	10331	-9574	1.08	7797	4621	3120	2481	1.26
Evanston, IL	605	5062	-2170	2.33	4617	2191	1666	795	2.10
Evansville, IN	608	5915	-4312	1.37	5192	2723	1888	1315	1.44
Fair Lawn , NJ	287	1889	-677	2.79	1373	764	606	254	2.39
Hartford, CT	669	7298	-4493	1.62	6325	3143	2324	1395	1.67
Highland Park, IL	248	1402	-351	3.99	1287	540	439	161	2.73
Mamaroneck, NY	376	2158	-1156	1.87	2112	995	674	453	1.49
Mansfield, OH	274	1392	-1017	1.37	1282	693	461	368	1.25
Mason , IO	166	725	-244	2.97	450	270	221	91	2.43
Medford, MA	515	3126	-2542	1.23	2844	1451	1011	725	1.39
Melrose, MA	239	955	-490	1.95	748	382	296	153	1.93
Michigan, IN	279	1200	-1228	0.98	1149	607	387	339	1.14
Moline, IL	351	2120	-1131	1.87	2153	967	733	382	1.92
Newport, RI	421	3682	-901	4.09	3330	1318	1093	369	2.96
Newton, MA	566	3983	-1545	2.58	3912	1740	1304	647	2.02
Norwood, MA	209	868	-274	3.17	655	333	281	107	2.63
Oak Park, IL	386	2479	-1079	2.30	2107	1129	822	450	1.83
Park Ridge, IL	191	917	-230	3.99	727	324	262	105	2.50
Pawtucket, RI	344	2012	-1564	1.29	1794	905	623	461	1.35
Peoria, IL	541	5498	-3715	1.48	4401	2383	1719	1099	1.56
Pittsfield, MA	259	1107	-796	1.39	1062	592	398	307	1.30
Racine, WI	500	4639	-5827	0.80	5336	2689	1629	1509	1.08
Ross, PA	374	2099	-960	2.19	1673	860	651	349	1.87
Royal Oak, MI	571	5131	-2057	2.49	4126	2007	1604	737	2.18
Salina, NY	230	1152	-593	1.94	1060	521	358	228	1.57
Skokie, IL	408	2249	-1172	1.92	2303	987	752	390	1.93
Somerville, MA	408	2249	-1172	1.92	2303	987	752	390	1.93
Springfield, MA	481	4362	-2829	1.54	3231	1903	1363	905	1.51
St Louis Park, MN	286	1361	-485	2.81	1162	540	419	192	2.18
Westfield , NJ	314	1903	-625	3.04	1414	673	555	221	2.51
Wilkes Barre, PA	334	1770	-916	1.93	1482	751	567	310	1.83
Wyandotte, MI	362	1676	-1468	1.14	1570	864	573	450	1.27

Appendix Table 4: Study Sample Sentiment Scores, Growing Cities

City	Sentiment Words	Positive Score	Negative Score	Pos. / Neg. Score Ratio	Total Tweets	Sentiment Tweets	Positive Tweets	Negative Tweets	Pos. / Neg. Tweet Ratio
Amherst , NY	647	7157	-3637	1.97	6088	3003	2231	1229	1.82
Beverly, MA	317	1552	-714	2.17	1194	602	486	214	2.27
Bloomfield, MI	413	3315	-1154	2.87	2578	1234	974	418	2.33
Bloomington, MN	485	3742	-1330	2.81	3312	1503	1170	530	2.21
Brick , NJ	553	8945	-2304	3.88	5438	2991	2527	810	3.12
Brighton, NY	676	7548	-2959	2.55	6626	3144	2360	1227	1.92
Brookline, MA	622	5067	-2077	2.44	4330	2040	1569	767	2.05
Calumet , IL	253	1336	-1063	1.26	1243	648	432	332	1.30
Chelsea, MA	235	1092	-556	1.96	1065	492	367	201	1.83
Cherry Hill , NJ	691	8509	-3723	2.29	6883	3464	2506	1469	1.71
Cranston, RI	523	3744	-1960	1.91	3250	1563	1148	677	1.70
Danbury, CT	492	3972	-2101	1.89	3423	1713	1273	684	1.86
Des Plaines, IL	387	2556	-1147	2.23	2127	1035	790	404	1.96
Elkhart, IN	370	2689	-1568	1.71	2181	1138	831	513	1.62
Elyria, OH	308	1777	-1129	1.57	1501	807	580	385	1.51
Ewing , NJ	212	876	-339	2.58	801	365	285	127	2.24
Farmington Hills, MI	528	3611	-2201	1.64	3638	1685	1207	734	1.64
Greece, NY	503	4099	-2551	1.61	3566	1825	1277	842	1.52
Hutchinson, KS	261	1267	-660	1.92	968	557	396	262	1.51
Janesville, WI	267	1002	-708	1.42	859	493	332	263	1.26
Kenosha, WI	438	3511	-1788	1.96	2812	1439	1118	552	2.03
Kokomo, IN	292	1748	-877	1.99	1324	746	558	311	1.79
Lancaster, OH	379	2423	-1662	1.46	1626	989	722	477	1.51
Lancaster , NY	264	1274	-737	1.73	1001	578	429	261	1.64
Leominster, MA	270	1227	-598	2.05	1125	577	399	267	1.49
Lexington, MA	160	430	-608	0.71	539	295	142	197	0.72
Livingston , NJ	216	1473	-445	3.31	1262	623	488	204	2.39
Long Beach, NY	218	1112	-392	2.84	1103	432	344	138	2.49
Lowell, MA	531	4510	-2539	1.78	3497	1867	1343	857	1.57
Mentor, OH	444	3819	-1962	1.95	2964	1583	1176	651	1.81
Middle, PA	379	2347	-845	2.78	1829	918	710	330	2.15
Middle, OH	229	901	-501	1.80	682	379	274	159	1.72
Minnetonka, MN	317	2068	-588	3.52	1481	767	645	234	2.76
Mishawaka, IN	370	3002	-1329	2.26	2018	1056	814	433	1.88
Newark, OH	254	1143	-492	2.32	798	453	360	164	2.20
Norwich, CT	343	1499	-1056	1.42	1277	710	484	351	1.38
Peabody, MA	291	1605	-718	2.24	1388	660	497	265	1.88
Pekin, IL	209	866	-461	1.88	699	406	286	197	1.45
Plainfield , NJ	342	2485	-949	2.62	1897	935	750	319	2.35
Poughkeepsie City, NY	250	1442	-1728	0.83	1168	598	500	290	1.72
Poughkeepsie Town, NY	348	2199	-1084	2.03	2058	923	684	366	1.87
Reading, PA	478	3402	-2949	1.15	3118	1681	1139	863	1.32
Roseville, MN	306	1577	-984	1.60	1460	716	521	304	1.71
Southfield, MI	529	3975	-3892	1.02	3977	2056	1355	1055	1.28
St Charles, MO	348	2451	-1001	2.45	1784	921	723	323	2.24
Taunton, MA	399	2310	-1792	1.29	1777	1002	717	493	1.45
Vineland , NJ	327	1598	-1173	1.36	1499	715	520	337	1.54
Wausau, WI	121	544	-185	2.94	440	247	186	108	1.72
West Orange , NJ	520	4532	-2501	1.81	4314	1940	1448	822	1.76
Wyoming, MI	498	3784	-3051	1.24	3837	1957	1264	966	1.31