Shrinking Cities and Subjective Well-Being: An Investigation of Resident Attitudes and Opinions via Micro-Blog Sentiment Analysis

A thesis submitted by

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In partial fulfillment of the requirements for the degree of

Master of Arts

in

Urban & Environmental Policy & Planning

Tufts University

May 2015

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Abstract

Shrinking cities have gained a generally negative image in the traditional media and popular consciousness, while at the same time the use of so-called Big Data for policy and planning purposes has exploded. This thesis explores the use of Big Data in the form of micro-blog sentiment analysis to determine if there are differences between shrinking and growing cities in terms of subjective well-being. Furthermore, it lays the groundwork for a deeper understanding of what type of subjective well-being a Twitter sentiment analysis is truly measuring, rather than relying on the assumption that happiness can be gauged with a single metric. My results demonstrate that there is some crossover between a traditional form of subjective well-being measurement and a tweet sentiment analysis. I also suggest that the traditional metric and micro-blog figures are each measuring one of the distinct forms of subjective well-being as described by the positive psychologists.

Acknowledgements

Huge thanks go to my adviser, Justin Hollander, for his continual support and insights throughout this process. Justin is a first-rate scholar who always knows the right questions to ask, keeps the thesis process moving forward at just the right pace, and has a compelling vision for the future use of Big Data. Great thanks also go to my reader, Henry Renski, a man of formidable mathematical and analytical talent who has a unique ability to see research questions from multiple angles with incredible nuance.

The Lincoln Institute of Land Policy deserves thanks for funding, and the entire Urban Attitudes Lab has been of immense help in terms of technical support and sharing of resources, including Dibyendu Das who created the program the UAL has been using to analyze tweets. Particular thanks go to Cara Foster-Karim whose work on her own thesis has truly led the way for future research at the UAL. It is hard to imagine how my thesis would have been completed without Cara having forged the path for the rest of us to follow.

Additional thanks to go my wife, Heidi Seekins, who has provided tremendous support throughout my time at Tufts, our two little ones who spent many hours climbing on me while I composed this thesis, and everyone at The Tam and Columbia River Brewing. Finally, much gratitude to Jeffrey W. Nichols at IBM for help in acquiring 2013 tweet data, Matthew B. Streeter at the US Census Bureau for municipal boundary GIS shapefiles, and Ryan Bailey for assistance in organizing American Housing Survey Data.

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Chapter 1: Introduction

Declining cities in North America and Europe have gained increasing attention over the last decade as municipal leaders, planners and researchers have grappled with how to confront decreasing population. At bottom, this represents a conflict between the traditional idea of urban growth as the be-all, end-all goal of a city on the one hand, with the stark reality that many cities may simply never approach their previous peak population on the other. Despite popular perception, including sensationalist stories in the media about cities like Detroit that have seen better days, initial research suggests that the link between negative population growth and a lower quality of life is not so clear cut as might be expected (Hollander, 2011; Delken, 2008), nor for that matter should it be taken for granted that residents of cities prefer population growth over stability or decline (Van Dalen & Henkens, 2011).

A second field of emerging literature is that which has gained the widespread moniker of "Big Data." In the past, when massive amounts of electronic information, including personally volunteered data, were not nearly as available, and when computing capabilities were comparatively small, that data was more of a static entity with specific and limited value; in contrast, Big Data is dynamic, continually relevant and additive (and added to), and provides unique insights and opportunities not previously available (Mayer-Schönberger & Cukier, 2013). This enables students like myself to test research questions that we would not have been able to investigate even

five years ago, at least not from the angles or with the input of millions of people that we can now. Researchers have begun exploring, for example, how they might determine the subjective well-being (SWB, the term used as a stand-in for happiness in psychological literature) of individuals based upon Facebook status updates (Kim & Lee, 2011), how "tweets" sent by users of Twitter might be used in assisting with emergency preparedness efforts for natural disasters, epidemics and social uprisings (Merchant, Elmer & Lurie, 2011), and how tweets provide valuable land use information for urban planners (Frias-Martinez & Frias-Martinez, 2014).

In utilizing the latter of these two emerging fields as a means of exploring the former, this thesis will examine, as regards cities with flat or declining population, the perceptions residents have of the places in which they live, testing the broad assumption that it is relatively unpleasant to live in cities that are not growing when compared with those that are. In particular, I will be investigating eight cities nationwide, determining the degree to which there is a correlation between having flat or declining population and having a lower level of reported or measured SWB in those cities. I accept that the sample size is less than ideal, but it is a starting point from which future work may proceed. Moreover, I was limited by the realities of the data available to me. The specific cities were chosen due to the existence of several million tweets gathered from those cities in 2013, as well as the US Census Bureau having conducted the American Housing Survey in those cities at some point between 2007 and 2011.

With all of the above in mind, I ask the following two research questions:

1. Are there differences in resident perceptions of neighborhood quality of life, as well as expressed positive and negative sentiment, when considering changes in population among cities between 1970 and 2010?
2. In computing differences among cities, is Twitter a reliable gauge of resident perceptions when compared with more traditional measures of well-being?

To answer these questions, two sets of data, briefly referred to above, will be employed for my analysis. The first is a series of tweets collected in two-week periods during December 2013 and March 2015. The tweets have been evaluated with proprietary sentiment analysis software developed at the Tufts Urban Attitudes Lab (UAL), using a dictionary created expressly for sentiment analyses of social media data sets (Nielsen, 2011). Sentiment analysis is a common methodology for determining the positive or negative attitudes and opinions being expressed within text, and social media has created a flood of academic work exploiting sentiment analyses, a literature review of which is found in Section 3.

The second set of data has been extracted from the American Housing Survey, a more extensive questionnaire than is presently used during the decennial census. One question in particular asks respondents to rate their neighborhood on a scale of 1 to 10, and responses have been averaged across

each city investigated in this thesis. Of importance in the analysis herein is my belief - so far not given attention in the literature - that sentiment analysis of text is measuring one particular aspect of SWB, while questions about neighborhood satisfaction, or other aspects of life satisfaction, are getting at an entirely different aspect of SWB. It should not be surprising, then, that in answering research question #2 I find little correlation between these two data sets, though this does not render sentiment analysis an illegitimate form of measurement. I began this process with little advance knowledge of different measures of human happiness, but have developed a greater understanding of SWB that leads me to the conclusion that both traditional surveys and sentiment analysis have valuable, separate roles to play in assisting with the determination of SWB across different populations.

The rest of the thesis will proceed as follows. Section 2 provides a discussion of the shrinking cities phenomenon, including the historical reasons for shrinkage, the dominant paradigm of growth, and a literature review of recent work in this topic. Section 3 will cover the burgeoning field of Big Data, and particularly how sentiment analyses are applied to microblogging data, as well as the use of Twitter as a data set in the formulation of urban policy and planning. Section 4 provides an introduction to the concept of SWB, different ways psychologists conceive of SWB, and where sentiment analyses fits in. Section 5 outlines the methods employed in my analysis, a presentation of my data sets, and covers the limitations inherent in this type of research. In Section 6 I put forward my findings,

while Section 7 offers concluding thoughts.

Chapter 2: Literature Review

Shrinking Cities

Cities that are losing population are often given the pejorative label of "declining" - a label that applies to more than mere population loss - in the popular imagination, the media and academic literature. Indeed, decreasing population is often linked with multiple negative phenomena, such as unemployment, dim economic prospects, increasing crime, and ultimately a lower quality of life. At the extreme, Forbes (2008) has come up with a list of "America's Fastest-Dying Cities" that combines measures of population loss, unemployment, and lackluster GDP to determine which metropolitan areas have the worst outlook for the future. Multiple other media outfits have jumped on the dying cities bandwagon (24/7 Wall St., 2010; AOL Real Estate, 2009; Newsweek 2011), and still others publish rankings of the "most miserable" cities in the country (Business Insider, 2014;[1] Forbes, 2013). A ubiquitous theme among all lists of "dying" or "miserable" cities is population loss.

While these lists might be relatively recent, the trend of major American cities losing population dates back to the post-World War II era, a time when: pent-up demand after a decade and a half of relative poverty and sacrifice; federal support for suburban housing development in the form of loan guarantees and tax write-offs for housing outside the city, while large sections of the center city itself were redlined; and the creation of the

[1] From work done by Gallup.

Interstate Highway System all contributed to the flight of middle-class, primarily white, citizens out of cities and into the suburbs (Teaford, 2006). To these forces can be added technological change that rendered large, older factories obsolete, the expansion of air travel, infrastructure provision in outlying areas (facilitated by improved capital markets), and the development of modern telecommunications systems (Rybczynski & Linneman, 1999).

Consequently, people and businesses moved out of large center cities in the north, often heading south, or in the case of manufacturing firms overseas (albeit with other causes, such as cheaper labor costs, added to the above). The results have become so entrenched in American culture that for decades, larger cities like Detroit, Cleveland and St. Louis, as well as smaller cities like Flint, MI and Youngstown, OH, among many others, have been referred to as being part of the so-called Rust Belt. Their names have effectively become bywords for a combination of population loss, safety concerns, urban blight and a lack of economic opportunity. Moreover, these cities readily contrast with their counterparts in the Sun Belt: southern cities like Houston, Phoenix and San Diego that have seen massive population gains paired with consistent economic growth. Even in those southern cities, however, the same forces pushed residents and businesses to the margins of urban centers, and population growth in the seven fastest growing major cities between 1950 and 1990 was significantly fueled by large land annexations to the tune of a more than doubling in land area in each of those

seven cities (Rybczynski & Linneman, 1999).

An examination of the 100 largest cities in American history, as measured by the peak populations of all cities nationwide at any point in time, shows that 27 cities had their population high point before the year 2000, with 14 having peaked in 1950, 6 having peaked in 1960, and 5 having peaked in 1970.[2] Two others peaked in 1930, while no cities had their peak in 1940, 1980, or 1990. These cities are enumerated in Table 1 below. It should be noted that some of these cities have seen a rebound from their population nadir, even as others have continued to lose residents.

Cities at their peak in…

1930	1940	1950	1960	1970	1980	1990
Jersey City	None	Baltimore	Akron	Atlanta	None	None
Newark		Boston	Birmingham	Kansas City, MO		
		Buffalo	Dayton	Norfolk		
		Chicago	Milwaukee	Richmond		
		Cincinnati	New Orleans	Toledo		
		Cleveland	St. Paul			
		Detroit				
		Minneapolis				
		Philadelphia				
		Pittsburgh				
		Rochester				
		St. Louis				
		Syracuse				
		Washington				

Table 1: Peak population year for cities among the 100 largest in US history.

Many of the cities in Table 1 can fairly be described as being "past their prime" as far as the wider public discourse is concerned, as the popular media articles noted above attest. Other cities in the table have managed a

[2] Author's calculations using US Census data from throughout the 20th Century.

comeback of sorts, in spite of their checkered past, while remaining well below their population high point (a la Pittsburgh), or have seen very modest population growth in the center city while the suburban population has exploded (a la Atlanta). The overarching pattern, however, is one in which growth, of any sort, is necessarily deemed to be positive, while decline is a sign of weakness and failure. As Beauregard (2003) observes, population loss is a stigma that stands in opposition to the ideal of expansion held by civic leaders. A small population loss indicates stagnation, while a large population loss is nothing short of traumatic, indicating serious flaws in a city's political economy (Beauregard, 2003).

This squares with one of the more influential conceptualizations of urban land use - the idea of the city as a "growth machine" in which a land-based elite, as well as the elite's allies in municipal government, pushes for ever-increasing intensification of land in pursuit of greater profit (Molotch, 1976). In this model, population, industrial and commercial growth are all wedded in the cycle of land use escalation. To be sure, since at least the mid-eighteenth century, American land use law has generally encouraged growth for economic reasons, with, for example, 47 states by 1885 having rejected the British common law idea that "uninterrupted enjoyment" of light and air provides an easement against development of adjoining property (Friedman, 2005).

On the other hand, adverse possession laws were readily adopted and strengthened in the United States, with western states taking the lead in

shortening the period of time required for an interloper to take possession of a piece of property that was not hers (Friedman, 2005). While it is certainly true that adverse possession has existed to clarify title, it is also a means of shifting land to more productive use (Fennell, 2006). And as Pallagst (2009) notes in her case studies of cities that are losing population, even the heralded "smart growth" movement in the United States, while embracing the idea of sustainable development, by definition includes growth at its core.

All of these strains of thought emphasize an idea of increasing population and continued development of land as part and parcel of what it means to be a successful city. Yet, as Hollander, Pallagst, Schwarz and Popper (2009) make clear, there is an emerging movement of planners, architects, activists and academics that challenges the notion that population (and land development) must increase in order to improve a municipality's chances of having a high quality of life. For the leaders of this movement, decline is re-envisioned as "shrinkage," and they do not take for granted that shrinking cities are necessarily places that are worse off as a result of having a lower population; indeed, initial research examining responses to the American Housing Survey suggests that there is great variation among cities, both growing and shrinking, in terms of resident perceptions of neighborhood quality (Hollander, 2011).

The origins of rigorous academic study of shrinking cities can be traced to literature from just after the turn of the 21st Century covering cities in the former East Germany following German reunification. Among the

studies of shrinking East German cities are Bontje's (2004) examination of the city of Leipzig as it developed a strategy to right-size the city's built environment and infrastructure in the face of likely permanent population loss, as well as Steinführer's and Haase's (2007) argument that shrinking cities in East Germany should not be considered solely within a post-socialist context, as they face similar forces as many cities across Western Europe. Glock and Häußermann (2004) explore responses at the federal level in Germany to confront the vast oversupply of housing stock in shrinking East German cities, while Franz (2004) finds a questionable relationship between population loss and economic decline in East German cities, as the majority of cities studied saw economic growth paired with both population decline and job losses, with possible differentiation in future economic outlook predicated upon the makeup of a city's industrial or commercial sectors.

Without a doubt, as previously discussed, there are many potential causes for a city to lose population, but population loss is typically regarded as a negative sign of a city's success as a place of employment and economic growth (Hollander and Nemeth, 2011; Downs, 1997). This connection is elucidated in a thorough analysis of urban decline by Friedrichs (1993), using both theory and empirical studies of American and German cities as a basis, which formulates a theory of population loss predicated upon an initial deterioration of a city's industrial base. Perhaps of great importance is the theory's inclusion of limited industrial diversity as being at the heart of virtually all cases of urban decline. Linking up to this idea, some researchers

focus on urban shrinkage as a direct result of the forces of neoliberal globalization, with declining cities being those that have lost out to global cities in the process of "creative destruction" (Martinez-Fernandez, Audirac, Fol & Cunningham-Sabot, 2012).

Echoing this linkage between economic milieu and city decline is a study of shrinking cities in Germany that finds residents are more concerned with unemployment and crime than residents of growing cities (Delken, 2008). However, the same study fascinatingly finds that residents of shrinking West German cities report a higher overall quality of life than residents of stable or growing West German cities, and that residents of shrinking East German cities report a higher overall quality of life than residents of growing East German cities (residents of stable East German cities reported the highest life satisfaction in that region). Similarly, a study of the Netherlands ascertaining the degree to which residents fear or favor population changes at the world, national and local levels shows that for all three levels residents preferred stability or decline over growth, with varied factors playing into residents' calculations of how population changes might impact their personal welfare (Van Dalen & Henkens, 2011).

Other studies of shrinking cities have focused on city leaders coming to terms with - and accepting - the reality that their city might grow *or* shrink, and switching to flexible strategies centered on robustness and resilience as opposed to rational planning of expected population changes (Wiechmann, 2008). Youngstown, Ohio was at the forefront of this

movement to accept shrinkage as a reality, creating the Youngstown 2010 plan between 2002 and 2004 with a focus on improving the city's quality of life instead of focusing on rekindling growth, with declining parts of the city reimagined as parks and green spaces (Pallagst, 2009).[3] Also pertinent are the sometimes neglected physical impacts of shrinkage, with one review noting that cheap housing is a primary characteristic, and that a combination of cheap, abundant housing and weak labor demand tends to attract individuals with low levels of human capital (Glaeser & Gyourko, 2005). A further study generates a metric, occupied-housing-unit density, for evaluating the physicality of depopulating neighborhoods, with the upshot being that changes to quality of life are not deterministically established in the wake of population loss (Hollander, 2010).

One appealing thread of study in the field of shrinking cities, echoing some of Youngstown's thinking, is to envision "rewilding" formerly urban neighborhoods, or to consider the implementation of parks and community gardens. Haase (2008) conceptualizes shrinking cities as the opposite of sprawl, and envisions managed shrinkage as an opportunity to enhance species habitats and engender a process that induces the ecological restoration of cities. Additional research investigates the plethora of ecosystem services, such as mitigation of air and water pollution, retention of stormwater, and recreation, that can be part of urban greening initiatives in shrinking cities (Schilling & Logan, 2008). Here again, Germany has led the

[3] Youngstown's 2010 plan and associated documents are available online: http://www.cityofyoungstownoh.com/about_youngstown/youngstown_2010/index.aspx

way, notably with the International Building Exhibition (IBA) at Emscher Park, a project undertaken in 1989 to create a 570-acre park amidst abandoned industrial sites in the Ruhr region (Dettmar, 2005). Meanwhile, Rosol (2005) suggested the creation of community gardens as a means of provisioning new green space in Berlin, meeting the government's guidelines for additional green space while addressing vacant land.

Finally, it is worth considering how the very idea of quality of life is measured, as it often comes with an emphasis on capital and capital's privileged position in determining value (Rogerson, 1999). There may be other, overlooked priorities that play a prominent role in subjective well-being, and as a result we may want to reconsider the degree to which metrics tied to capital are truly the metrics that residents would use in deciding how happy they are about where they live (Rogerson, 1999). In this vein, while a natural inclination may be to focus on the ways in which a city might respond to population loss, concentrating on proposed policies to address shrinkage, there are important questions of equity and social justice that must be addressed in the process of planning for a city's future and considering resident quality of life (Hollander & Nemeth, 2011).

Micro-Blogging Sentiment Analysis

Social media data sets, including data from micro-blogging platform Twitter, are part of what is know as "Big Data," a term first used by NASA in 1997 to describe quantities of data so large that they tax memory and hard disk capacity (Cox & Ellsworth, 1997). Since around 2008, the term has been

used to describe a veritable phenomenon in academia, government, business and the media in which data is no longer seen as an entity with limited value after an initial use; rather, it is an input to be continually used in innovation, service creation, and as a means of gleaning information not previously available (Mayer-Schönberger & Cukier, 2013).

As Twitter posts are the form of Big Data utilized in my analysis, this section will examine the ways in which sentiment analyses - a qualitative measurement of opinions and attitudes - of Twitter data have been used for a myriad of academic research purposes. Furthermore, I will discuss how Twitter data has been applied in a wide variety of urban planning contexts across the globe.

Sentiment analysis, sometimes referred to as opinion mining, is the analysis of expressed attitudes and opinions with the goal of determining the degree to which there are positive or negative sentiments therein (Liu, 2012). In this qualitative method, a score is assigned to each textual entity within a larger body of data based upon the strength of modifying words within that entity (Godbole, Srinivasaiah & Skiena, 2007). For example, a tweet containing the word "good" would be assigned a positive score, a tweet containing the words "very good" would be assigned an even higher positive score, a tweet with the word "bad" would be assigned a negative score, and so on.

As would be expected, there are beneficial and limiting features of micro-blogging sentiment analyses that must be kept in mind when doing

such research. On the beneficial side are its relative ease and low cost, with people who use Twitter (or Facebook, or Foursquare, or any number of other platforms) freely volunteering information on a virtually unlimited number of topics. Traditional surveys or polls are more time intensive, cost far more to conduct, and can cover only so many topics. On the other hand, micro-blogging applications have not been universally adopted, certainly skewing toward a younger demographic. There may be other demographic factors at play, such as socioeconomic status, meaning that a representative sample of the broader population is unlikely.

Nonetheless, there are multiple ways in which micro-blogging data may effectively influence or even create policies, programs and institutions. Particularly relevant to my work, multiple studies have been conducted investigating different measures of happiness as calculated from tweets. One analysis determined that among users of Twitter who are determined to be in the same social network, due to replying to one another's tweets, happiness is assortative, although the researchers did not attempt to distinguish between homophily and contagion (Bliss, Kloumann, Harris, Danforth & Dodds, 2012). These results were confirmed by an analogous study that found people with relatively higher or lower subjective well-being connecting with people who have a similar subjective well-being (Bollen, Gonçalves, Ruan & Mao, 2011).

Sentiment analysis of daily tweets over a five-month period in 2008, compared with newsworthy events occurring during that time, indicates that

social, political, cultural and economic events are correlated with significant changes in public mood as measured by the sentiment analysis (Bollen, Mao & Pepe, 2011). A lengthier study of nearly 4.6 billion tweets over 33 months also demonstrates a strong relationship between notable events in the news and the sentiments expressed about the participants in those events (Dodds, Harris, Kloumann, Bliss & Danforth, 2011).

A geographic analysis of tweets calculated the happiest and saddest cities and states, in addition to showing that various factors such as frequency of tweets, use of obscenities, and obesity rates have consistent correlations with places that show less happiness (Mitchell, Frank, Harris, Dodds & Danforth, 2013). An analysis of neighborhoods in London showed a strong link between sentiments expressed in tweets emanating from those neighborhoods and traditional measures of that community's socioeconomic well-being, such as income and crime (Quercia, Ellis, Capra & Crowcroft, 2012). These kinds of investigations on the relationship between particular places and the mood of tweets posted by Twitter users in those places has been applied to the 2012 London Olympic Games and 2013 Milan Design Week (Balduini et al., 2013), the city of Newcastle upon Tyne (Mearns et al., 2014), 15 museums in Yorkshire County, UK (Lovelace, Malleson, Harland & Birkin, 2014), and the whole of New York City (Bertrand, Bialik, Virdee, Gros & Bar-Yam, 2013).

An attention-grabbing utilization of Twitter analyses the degree to which the sentiments of tweets about certain topics can be used as a reliable

predictor of world events or trends within those topics. This includes a study asserting that a high level of emotion, positive or negative, in tweets on a given day correlates with decreases in stock market indexes the following day, while a low level of emotional tweeting correlates with an increase in stock market indexes the following day (Zhang, Fuehres & Gloor, 2011b). Likewise, the same authors analyze retweets in the United States that contain the words "hope," "fear, " or "worry," as well as certain economic keywords like "dollar," "gold," or "oil," finding that there are significant correlations between market movement and retweets for most, but not all, of the keywords (Zhang, Fuehres & Gloor, 2011a).

A particularly lively debate has centered on the ability of Twitter to predict elections. Tumasjan, Sprenger, Sandner and Welpe (2010) conducted a count of tweets (as well as a sentiment analysis) leading up to the German federal election of 2009, finding that the volume of tweets mentioning each political party corresponded exactly to the ranking of those parties in terms of vote share. The researchers express surprise at this result given Twitter's unrepresentative sample of the voting public, but note that Twitter users are more well-educated than the public as a whole, and influence pundits in the media who frame the political debate for a nationwide audience (Tumasjan, Sprenger, Sandner & Welpe, 2010). Jungherr, Jürgens and Schoen (2012) directly rebut those arguments by saying that Tumasjan, Sprenger, Sandner and Welpe (2010) neglected to include the Pirate Party, which had almost twice as many mentions in tweets leading up to the German federal election

in 2009 as the next closest party (the Christian Democrats, who actually received the most votes).

Gordon (2013) extended tweet geospatial analysis to the 2008 and 2012 US presidential elections at the state level, finding that the volume of tweets mentioning a particular party or candidate has a pro-Democratic Party bias (likely because of a liberal-skewing Twitter user base), and while accuracy improved significantly between 2008 and 2012 this may be due to the latter being a more closely contested election. This research also found that a sentiment analysis of tweets that assigned a 'vote' for Mitt Romney or Barack Obama to each Twitter user produced a more accurate picture of how each vote stated than a simple volume count of tweet mentions did, although there was still a pro-Obama bias (Gordon, 2013).

O'Connor, Balasubramanyan, Routledge and Smith (2010) likewise found an improvement over time in correlation between sentiments for tweets containing the words economy, job or jobs and traditional measures of consumer confidence, as well as seeing a stronger correlation between tweet sentiments about Obama and his job approval rating in 2009 than between tweet sentiments about Obama and his standing in public polling during 2008. On the other hand, the frequency of tweets was found to have a stronger correlation with polls than sentiment scores (O'Connor, Balasubramanyan, Routledge & Smith, 2010). Sang and Bos (2012) used counts of political parties mentioned in tweets to analyze results of the 2012 Dutch senate elections, finding that these counts would have accurately predicted the results for 52 out of 75 seats, a figure that was improved to 57 out of

75 seats when a sentiment analysis was introduced. Other researchers, however, have echoed the words of Jungherr, Jürgens and Schoen (2012), stating that no elections have actually been predicted, no common method of establishing Twitter 'votes' has been agreed upon, and there is no clear comparison between Tweets and other data sources like polls, election results, or party shares of seats (Metaxas & Mustafaraj, 2012; Gayo-Avello, 2012).

Micro-Blogging and Urban Planning

The use of Twitter and other micro-blogging data to enhance urban planning and related studies of place is a relatively new development due to the newness of the platform itself - Twitter was launched in the summer of 2006. Despite Twitter still being less than a decade old, numerous efforts have been made, both inside and outside of academia, to apply the corpus of tweets from particular locations to a variety of urban issues and planning endeavors.

On the practitioner side, planners in Brisbane, Australia used a system they called Discussions in Space (DIS) in which a large public screen was used to encourage residents to participate via Twitter in a planning process that the Brisbane City Council had created to envision what the city would look like in the year 2050 (Schroeter & Houghton, 2011). Residents were asked to send in their "bright ideas" for the future of Brisbane, either by texting to a specific number or by using an exclusive hashtag, with several tweets deemed to be relevant or interesting posted to the public screen. An additional study focusing on suburban areas of Brisbane asked participating

mothers to check-in via one of three mobile phone applications at every location where they brought their children for physical activity over a one-week period, with implications for improving public health (Ben-Harush, Carroll & Marsh, 2012).

Also as regards public health, a study by Eichstaedt et al. (2015) established that an analysis of language patterns of tweets, using pre-established dictionaries for positive and negative emotions, positive and negative social relationships, and engagement and disengagement, was a better predictor of heart disease mortality at the county level than a model of common demographic, socioeconomic and health risk factors such as smoking and diabetes. Another study of tweets at the local level provides conclusive evidence that transit agencies engaging more actively with other Twitter users, as opposed to simply blasting out information with no dialogue, experienced a significantly improved level of Twitter discourse surrounding public transit (Schweitzer, 2014).

As might be expected, many urban-focused uses of Twitter data involve mapping where tweets are coming from, and analyzing the content of those tweets. MacEachren et al. (2011) created a web-based application to query the Twitter API for tweets relevant to crisis management and disaster relief efforts, moving beyond geo-location of the tweets to including locations mentioned in tweet contents as well, while Sakaki, Okazaki and Matsuo (2010) established the ability of their tweet classifier to detect earthquakes and send out warning emails faster than the Japan Meteorological

Association's Broadcasts. Antonelli et al. (2014) created a program with a dashboard of information, including maps and timelines, displaying the location of tweets during citywide events, with an eye to ultimately including sentiment analysis as part of the dashboard's reports. A similar paper describes a dashboard of tweet location data coming from the 2012 London Olympic Games and 2013 Milan Design Week, including a sentiment analysis of the latter (Balduini et al., 2013).

Other city-level studies include the creation of clusters of Foursquare check-ins posted to Twitter in several neighborhoods of Pittsburgh, enabling maps of behavior patterns for clusters of residents that do not conform to traditional neighborhood boundaries (Cranshaw, Schwartz, Hong & Sadeh, 2012), as well as an investigation of public mood via sentiment analysis of tweets in New York City, showing how attitudes shift in relation to nearby landmarks or facilities such as Times Square, hospitals and jails (Bertrand, Bialik, Virdee, Gros & Bar-Yam, 2013). A smaller scale was adopted in a study examining flows of visitors to 15 museums in Yorkshire, UK from nearby residential areas (Lovelace, Malleson, Harland & Birkin, 2014).

Movement patterns were the primary focus of a look into aggregation and dispersion of people in different parts of Tokyo as determined by geo-located tweets (Fujisaka, Lee & Sumiya, 2010), while a paper on case studies of geo-located tweets in New York, London and Madrid shows how land use can be determined by changes in tweet volume throughout the day (Frias-Martinez, Soto, Hohwald & Frias-Martinez, 2013). Similarly, Wakamiya, Lee

and Sumiya (2011) classify Japanese municipalities into one of four categories - bedroom, office, nightlife and multifunctional - based upon number of tweets, number of Twitter users, and movement of Twitter users. Mobility patterns have also been demonstrated with social media applications that require users to 'check-in' to locations they visit (Cheng, Caverlee, Lee & Sui, 2011). Hollander, Graves and Leventhal (2014) compare geo-located tweets from New Bedford, Massachusetts with the text of public meeting minutes in the same city, finding remarkable similarity in terms of sentiment across a host of issues including education, parks and public health.

Subjective Well-Being and Sentiment Analysis

The study and description of happiness is at least as old as the Ancient Greeks, with Aristotle's defining of eudaimonia, often translated as happiness or welfare, typically seen in the literature as a foundational moment, and carrying through the Western philosophical cannon in the works of thinkers including Aquinas, Mill and Bentham (Ryff & Singer, 2008; Diener, Sapyta & Suh, 1998). More recently have come the humanist psychologists such as Maslow, Rogers and Fromm, and ultimately the positive psychologists who aim to change the very focus of psychology from one based solely upon the eradication of mental illness to a field encompassing the improvement of otherwise normal lives and the identification and nurturing of talent (Boniwell, 2008; Sheldon & Kasser, 2001).

In psychological literature, happiness is referred to as "subjective

well-being," which is the term I will use throughout this section and elsewhere in this thesis. Subjective well-being is commonly divided into two parts: 1) life satisfaction, and 2) affect, both pleasant and unpleasant (Diener, Suh, Lucas & Smith, 1999; Boniwell, 2008). Life satisfaction is an assessment an individual makes about his or her own life on the whole, with satisfaction being determined by the difference between what one pictures as the ideal life and distance, or lack thereof, from that ideal at the time of the assessment; affect, on the other hand, refers to positive and negative emotions and moods as a result of events occurring in our daily lives (Diener, Suh, Lucas & Smith, 1999; Boniwell, 2008).

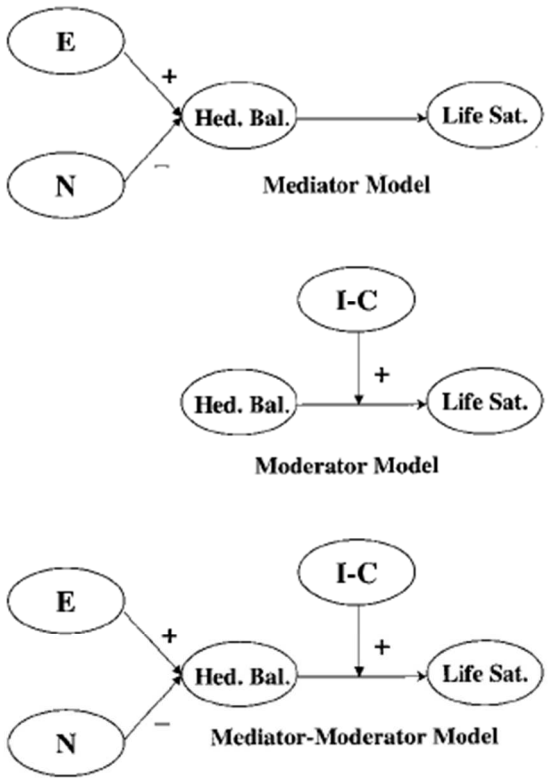
While much research remains to be done in teasing out the various components of both pieces of subjective well-being, psychologists have reached near-consensus on the so-called "Big Five Personality Traits" that describe individual personalities in a consistent and non-overlapping way (Soldz & Vaillant, 1999). These traits include: Neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness, and are referred to as NEO PI-R in the literature (n, e and o standing for the first three traits in this list, which were the first three discovered, and PI-R standing for personality inventory - revised), demonstrating remarkable replicability across ages and cultures (McCrae & Terracciano, 2005). A 45-year study of men graduating from Harvard College that followed them throughout their life found that neuroticism and extraversion demonstrated the most correlation with life course variables such as early adult

adjustment, maximum income, substance abuse and depression (Soldz & Vaillant, 1999).

In fact, the prevalence of these two traits in effecting one's subjective well-being, as revealed in personal surveys, reports of friends and acquaintances, studies of twins, daily diaries, online reports, and personality tests, has led researchers to state, "happiness is a thing called stable extraversion" (Schimmack, Radhakrishnan, Oishi, Dzokoto & Ahadi, 2002; quote from Francis, 1999). This form of happiness is most directly getting at the portion of subjective well-being described above as affect - that is, the difference between the pleasant moods and emotions one feels and the unpleasant moods and emotions one feels, although there is little doubt that affect is a significant contributor to the judgments one makes in rating one's life satisfaction (Davern, Cummins & Stokes, 2007).

In other words, while neuroticism and extraversion are key to affect, also known in the literature as "hedonic balance," other personality traits influence an individual's hedonic balance, and both environmental factors and hedonic balance play a significant role in determining one's overall subjective well-being. For example, chronically available sources of external information, such as one's academic or work performance, or one's romantic satisfaction, play a separate role determining life satisfaction that is uninfluenced by personality factors that create hedonic balance (Schimmack, Diener & Oishi, 2002). In addition, evidence strongly suggests personality traits predict hedonic balance almost uniformly across cultures, while culture

itself plays a moderating role between personality and life satisfaction as hedonic balance has a greater influence in determining life satisfaction in individualistic cultures than in collectivist cultures (Schimmack, Radhakrishnan, Oishi, Dzokoto & Ahadi, 2002). As shown in Figure 1 below, this is known as the mediator-moderator model, combining the mediation of personality traits and their effect on life satisfaction indirectly via hedonic balance with the moderating influence of culture.



Models of personality, culture, and subjective well-being. E = Extraversion; N = Neuroticism; Hed. Bal. = hedonic balance (pleasant affect − unpleasant affect); Life Sat. = life satisfaction; I–C = individualism–collectivism.

Figure 1: Models of personality, culture and subjective well-being. Source: Schimmack, Radhakrishnan, Oishi, Dzokoto and Ahadi, 2002.

The relationship between affect and life satisfaction is therefore an "intricate" one that does not lend itself to easy disambiguation (E. Diener, personal communication, March 16, 2015). However, a form of determining affect in particular, known as sentiment analysis (or opinion mining), has exploded in the 21st century as information technology has been set to the task of determining the positive and negative attitudes and opinions people express about products, services, political campaigns, and virtually anything else that can be described in words (Pang & Lee, 2008). This thesis relies on the sentiment analysis form of measuring subjective well-being, summing the collective sentiments of Twitter users at the municipal level to determine the relative subjective well-being of the residents of each municipality in terms of pleasant and unpleasant affect.

To perform the sentiment analysis, a body of text must be acquired, and there must be a way of evaluating the textual body to determine the sentiments thereof. For example, hundreds of online movie reviews have been compiled and combed for words expressing positive or negative sentiment (Pang, Lee & Vaithyanathan, 2002). This study used multiple machine learning methods in which the researchers attempted to train the analysis software to make it more accurate in classifying sentiments. Prabowo and Thelwall (2009) tested three different forms of sentiment analysis on movie reviews, product reviews and MySpace comments - rule-based classification, supervised learning and machine learning - concluding that a hybrid approach produced the best results. Each of these approaches

requires researchers to actively participate in creating rules and algorithms that are used in determining sentiment classification.

As these studies demonstrate, sentiment analyses can certainly become rather complex, involving multiple iterations of testing and improving a classification scheme. They may also involve the classification of single words, phrases, sentences or entire documents, depending on the objective of the study. Nasukawa and Yi (2003) used the subject(s) and object(s) of a sentence as the entities upon which sentiment is applied, finding this method to be far more accurate than classifying entire documents. A case in point is that a movie review may have multiple positive and negative statements, sometimes even within one sentence, and negative descriptions of a specific actor or the cinematography may contrast with an overall positive review of the film (Nasukawa & Yi, 2003). In these more complicated research cases, the objective of a sentiment analysis is to determine the "contextual polarity" of a given sentiment; that is, given the context of the content being analyzed, is the sentiment expressed positive or negative (Wilson, Wiebe & Hoffman, 2009)?

A simpler approach, one that does not make contextual distinctions on the fly - instead relying on the characteristic polarity of a word - is the lexicon-based approach. In this methodology, researchers utilize a dictionary containing thousands of sentiment-expressing words that have been determined to be either positive or negative, with rigorous testing of the dictionary to ensure validity being clearly preferable (Taboada, Brooke,

Tofiloski, Voll & Stede, 2011). The words within a given textual body may be summed into totals of positive and negative word uses, or may be given a score meant to capture the degree of sentiment for particular words, for instance on a range from -3 to +3. In this latter methodology, "good" might be given a score of +1, "bad" a score of -1, "great" a score of +2, and "amazing" a score of +3. My thesis uses the latter approach, multiplying each sentiment-containing word by its associated score, and then summing the total scores of positive and negative words across all tweets.

A primary limitation of this particular form of sentiment analyses is that a statement with an obviously negative sentiment to human eyes may not contain a specific keyword contained in the dictionary being used by the sentiment analysis software that would be classified as negative (Pang, Lee & Vaithyanathan, 2002). For instance, if I were to review the restaurant I ate lunch at today with the question, "Who could eat this stuff?" it would not generate a negative score in a sentiment classifier that simply looks for negative terms. Alternatively, a word that is typically classified as explicitly positive or negative may not actually be expressing a sentiment (Wilson, Wiebe & Hoffman, 2009). An example of this would be when talking about a land trust, with the word "trust" being classified as expressing a positive sentiment when it is in fact being used as a noun. Limitations will be further discussed in the Methods section of this thesis.

With sentiment analysis and opinion mining taking off as a form of research in the wake of "Web 2.0," it is no surprise that much of the

published literature in this field is deployed in the analysis of websites and social media. Mullen and Malouf (2006) scoured online political forums using a Naïve Bayes machine learning algorithm, attempting to make predictions about a user's political affiliation in terms of party or placement on the left-right spectrum, asserting sentiment analysis to be a more challenging task when analyzing political statements. Gruzd, Doiron and Mai (2011) gathered tweets posted during the 2010 Winter Olympic Games in Vancouver, and used the lexicon-based software SentiStrength in determining that there were three times as many positive tweets as negative posted by users talking about the games and that retweets of positive tweets outnumbered retweets of negative tweets by a ratio of 2.5:1. Interestingly, the authors additionally demonstrated that while users who post more positive tweets than negative generally have more followers, users who post more negative tweets are far more prolific in terms of tweet volume (Gruzd, Doiron & Mai, 2011).

A lexicon-based approach was also used by Kramer (2010) in analyzing the status updates of approximately 100 million Facebook users to calculate a basic metric of happiness for the United States that could be extended to other nations, while establishing both convergent and face validity of Facebook status updates as a means of doing so. Melville, Gryc and Lawrence (2009) refined the results of a lexicon-based sentiment analysis using a supervised machine learning classification. Other work has looked at improving tweet sentiment analysis methodology by examining the efficacy of focusing on emoticons, hashtags and the presence of intensifiers

(Kouloumpis, Wilson & Moore, 2011). Go, Bhayani and Huang (2009) focused solely on emoticons as training material for machine learning processes in providing sentiment to consumers and feedback to businesses about products and services.

Chapter 3: Methods

The approach utilized in this thesis is a lexicon-based sentiment analysis of tweets employing the AFINN dictionary, as well as a comparison of the sentiment analysis results with responses to the American Housing Survey (AHS) and multiple demographic variables. As described in the previous section, the tweets collected will be analyzed for words deemed to represent positive and negative sentiment, and the scores for all sentiment-containing words will be computed for each city being investigated into positive and negative totals. These cities have been chosen as a cross-section of cities in the United States with regard to population changes over the last half century, in addition to being present in at least one AHS in the last eight years.

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 "looooooove" as "love." It has been used in multiple research studies to date, including an analysis of tweets emanating from New Bedford, MA between 9 February and 3 April, 2014 (Hollander, Graves & 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 & Manasantivongs, 2013), and as part of a model predicting fluctuations in global currency markets (Jin et al., 2013).

Tweets were acquired in two multi-week periods, with the first being between 26 November, 2013 and 20 January, 2014, and the second being between 3 and 19 March, 2015. While the second batch is a much smaller data set, it nonetheless contains a sufficient number of tweets for comparison. All tweets were collected via a software program created at the Tufts Urban Attitudes Lab (UAL) that links up to the Twitter API "Decahose," a stream provided by Twitter that contains a 10% sample of all tweets. Figure 2 shows a small set of sample tweets as displayed within the UAL software, exported to Excel in .csv file format. Column A contains an anonymous identifying number for the user instead of his or her actual user name.

◇	A	B	C	D	E
1	162965776	I'm so tired	-84.388977	33.756307	2015-03-03 15:32:51
2	230573079	Aye man I need to go get my piercing today fr !	-84.441818	33.681245	2015-03-03 15:32:53
3	468611502	GOOD MORNING	-84.369766	33.745663	2015-03-03 15:33:06
4	13729242	Microsoft Will Offer a Peek at SharePoint 2016 at Ignite by @druadh20	-84.345716	33.734866	2015-03-03 15:33:08
5	154316034	@_ImBoldBitchhh They had more people. I didn't go but I heard	-84.412031	33.750896	2015-03-03 15:33:09
6	81472795	@_naptural_ @TheyCallMeEli__ Lmaoo ive never heard anything like it	-84.509793	33.843409	2015-03-03 15:33:17
7	468611502	My birthday tomorrow	-84.376104	33.744145	2015-03-03 15:34:33
8	2247244138	Why tf are we learning science in world history	-84.372097	33.780193	2015-03-03 15:34:47
9	235235379	21 st birthday I will be bringing the city out	-84.403843	33.708725	2015-03-03 15:35:21
10	139604119	Mmmmmm I do have a type	-84.403984	33.707372	2015-03-03 15:35:21
11	756673417	Niggas always make promises but break em	-84.489138	33.698938	2015-03-03 15:36:42
12	43463937	What what you mean you can't? Whay is wrong with these people	-84.442184	33.765766	2015-03-03 15:36:49

Figure 2: Sample tweets from Atlanta

Location of tweets was determined by geolocation, as Twitter has a setting that allows users to turn on or off the posting of one's latitude and longitude coordinates as part of each tweet. Although the UAL program is not able to directly connect latitude and longitude coordinates with the city in which those coordinates are located, I used ArcGIS to determine coordinates for the smallest rectangular box that could be drawn around each city using municipal boundary shapefiles from the US Census Bureau. The coordinates

of the northeast and southwest corners of each box are input into the UAL software to begin scraping tweets that fall within those coordinates.

Figure 3 shows a representative sample of one such box, including the reality that these boxes will always extract some tweets from just outside the city in question. Appendix A shows the images of each city's municipal boundaries and the boxes that fit around those boundaries, while Table 2 below enumerates the cities from which tweets were collected and their respective changes in population over a 40-year period.

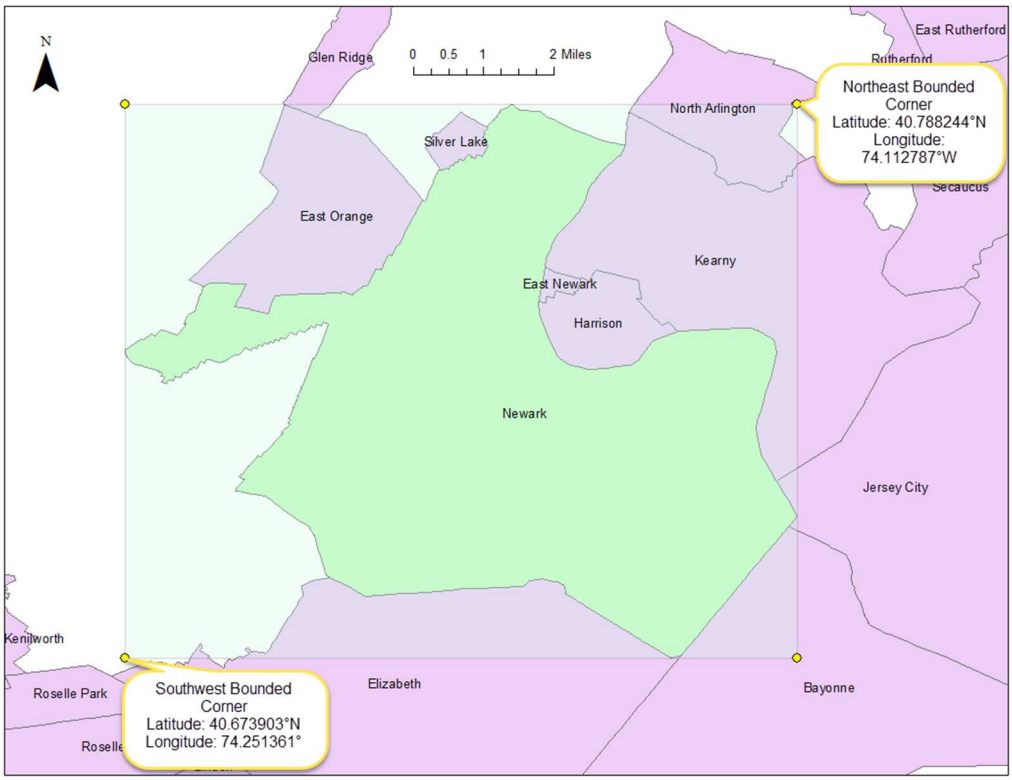


Figure 3: Newark city boundaries and coordinates

City	Population Change 1970 - 2010
Atlanta	-76,970
Houston	867,461
Indianapolis	75,821
New Orleans	-249,642
Newark	-104,790
Providence	-1,171
St. Louis	-302,942
Washington	-154,787

Table 2: Cities for which tweets were collected in 2013, 2014 and 2015

For simplicity's sake, I label the first batch of tweets, despite including data from January 2014, as "2013 tweets," and the second batch as "2015 tweets." After running each city's tweets through the sentiment analysis program, initial statistics were calculated for each city in terms of total positive and negative tweets, the percentages of tweets with positive or negative sentiment, and the average sentiment score per tweet. Average sentiment score per tweet is calculated by dividing the overall sentiment score for a city by the number of tweets from that city.

These statistics were chosen for providing different angles through which the data might be considered, although it turns out that there is no impact, at least for my data, between choosing the average sentiment score per tweet and the percentage of tweets with positive sentiment. In ordinal terms, the rankings of cities from 1 - 8 based on these statistics are virtually the same, and in interval terms they provide no statistically different correlations with any of my other variables. Additionally, t-tests were run to determine if there were significant differences between the two tweet data

sets from 2013 and 2015, both for average tweet scores and positive tweet percentages.

With regard to my other data set, the US Census Bureau conducts the AHS every two years in select metropolitan areas, with respondents grouped by geographic area within each metropolis. Of particular value for my purposes is that one of the groupings contains only responses from residents of the central city within a metropolitan area. One question in the survey asks respondents to rate their neighborhood on a 1 - 10 scale, and responses haven been averaged for all residents. Multiple demographic variables have also been gathered for these cities, and for each variable cities were ranked on an ordinal scale from 1 to 8 based upon decreasing values for the given variable.

An initial analysis attempted to discern if there were correlations between the eight cities for which both 1) tweets were gathered and 2) at least one AHS was undertaken in the city since 2007. With all data now in ordinal form, I used the Spearman's Rho statistical test to look for correlations between tweets, AHS results, and all demographic variables. The findings of these tests will be presented in the Results and Analysis section.

One problem to note prior to delving into the analysis, beyond the small sample size of cities, was that there was not a close-to-even split among the cities, with only two of the eight falling into the shrinking category. Of much greater import, however, was the realization that tweets and the AHS are getting at very different aspects of subjective well-being. The previous

section discussed how a sentiment analysis of tweets is primarily a measure of affect; the AHS, on the other hand, asks respondents to rate their neighborhood on a 1 - 10 scale, and an evaluation of the quality of one's neighborhood would be one piece of the puzzle in a broader evaluation of one's life satisfaction. Therefore, it was not especially surprising when no correlations were found across the eight cities in question in terms of those cities ranking relatively higher or lower in the AHS having a similar position in the tweet sentiment analysis. Nonetheless, some interesting parallels were uncovered.

Chapter 4: Results and Analysis

Initial statistics of tweets were calculated as shown in Tables 3 and 4 below, with Table 3 containing 2013 data and Table 4 containing 2015 data. The "average score per tweet" calculation was derived by dividing a city's overall score by that city's total number of tweets, and "% positive sentiment tweets" is the share of total tweets collected from each city that contained at least one word with positive sentiment. Appendix B includes additional data details.

City	Overall Score	Avg. Score Per Tweet	Sentiment Containing Tweets	Total Tweets	% Positive Sentiment Tweets
Atlanta	971,693	0.2108	2,526,884	4,608,671	37.66%
Houston	1,168,144	0.2005	3,101,918	5,827,597	35.96%
Indianapolis	567,103	0.3142	1,035,167	1,804,805	40.11%
New Orleans	243,410	0.0977	1,336,069	2,492,313	35.30%
Newark	680,821	0.2060	1,735,069	3,305,276	35.59%
Providence	105,352	0.1893	309,133	556,671	37.46%
St. Louis	318,451	0.2130	842,460	1,494,820	38.55%
Washington	435,869	0.1596	1,462,535	2,731,275	36.00%

Table 3: 2013 tweet sentiment analysis results

City	Overall Score	Avg. Score Per Tweet	Sentiment Containing Tweets	Total Tweets	% Positive Sentiment Tweets
Atlanta	18,702	0.1255	76,819	149,010	35.19%
Houston	28,572	0.0469	313,556	609,335	33.60%
Indianapolis	27,150	0.2355	63,268	115,311	37.60%
New Orleans	-13,514	-0.0738	89,875	183,195	31.26%
Newark	4,126	0.0687	31,007	60,035	34.00%
Providence	6,015	0.1807	17,132	33,288	34.71%
St. Louis	8,912	0.2281	20,356	39,078	35.96%
Washington	29,181	0.1228	120,351	237,626	33.99%

Table 4: 2015 tweet sentiment analysis results

As the tables demonstrate, all cities had a positive overall score in 2013, and only New Orleans had a negative score in 2015. Even in the case of New Orleans in 2015, there were more positive sentiment containing tweets (57,260) than negative sentiment containing tweets (48,903), but the negative words were more extreme on the polarity spectrum of the AFINN dictionary. In no case did any city have more tweets with negative sentiment than positive sentiment, although there is clearly a dip in sentiment across the board in 2015 from 2013. My analysis does not attempt to determine a reason for this, but as the literature on sentiment analysis of tweets has found, Twitter picks up shifts in global or national sentiment as a result of current events, and likewise captures affect related to more mundane happenings in the lives of users. As of yet, there has not been established a way with micro-blog sentiment analysis to ascertain intercity differences in life satisfaction.

T-tests were run to determine if there were significant differences between the 2013 and 2015 data sets when considering how the cities rank in comparison with one another from one year to the next, and the results were quite remarkable in that the two tweet data sets show a very high level of consistency. In comparing average tweet scores between the two data sets, a t-score of 2.043163 and a p-value of 0.060332 were returned, which is not significant at the 95% confidence level but is significant at the 90% confidence level. In comparing the percent of positive sentiment containing tweets between the two data sets, a t-score of 2.468886 and a p-value of

0.027042 were returned, which is significant at the 95% confidence level. Perhaps even more astonishing is that the correlations between 2013 average tweet scores and the 2015 percentage of tweets with positive sentiment, and vice versa, are even higher, as noted in Table 5. The results are clear confirmation of the reliability of tweets as a source for consistently determining the positive and negative affect of individuals on a geographic basis.

	2013 Avg. Tweet Score	**2013 % Positive Sentiment Tweets**
2015 Avg. Tweet Score	t = 2.043163; p = 0.060332*	t = 2.552087; p = 0.023024**
2015 % Positive Sentiment Tweets	t = 9.308373; p < 0.00001**	t = 2.468886; p = 0.027042**

Table 5: T-tests of 2013 and 2015 tweet data sets.
* = significant at 90% confidence; ** = significance at 95% confidence

For the AHS, Table 6 below lists my eight cities, the most recent year when the survey was conducted in those cities, and the averaged neighborhood ratings from those years. Averages were computed from the responses of all those who completed the AHS in each city, with every respondent rating his or her neighborhood on a scale of 1 to 10. The results are noteworthy in that all eight cities fall within a band of 0.769 points, and show that people generally have a positive feeling about their neighborhood.

CITY	State	Survey Year	Opinion
Atlanta	GA	2011	7.3366399
Houston	TX	2007	7.3757942
Indianapolis	IN	2011	7.3570151
New Orleans	LA	2011	7.7070155
Newark	NJ	2009	6.9993629
Providence	RI	2011	7.5216321
St. Louis	MO	2011	7.3990850
Washington	DC	2007	7.7681837

Table 6: AHS Survey Results. Source: US Census Bureau, averaged by Ryan Bailey.

To determine if there were significant correlations between my tweet and AHS data, and between each of those data sets and a series of demographic variables, I first ranked the cities 1 through 8 for each data set. This conversion to rankings follows from the data being ordinal in nature; that is, one person's rating of 5 for their neighborhood could carry very different meaning for that person than another individual's rating of 5 for the same neighborhood. Thus, the data cannot be treated as if there is robust quantitative value therein. The same concept applies to tweet data, as there is no inherent quantitative meaning to scoring the sentiment of a piece of text, and so the data must be treated as ordinal. In classifying data as ordinal, I am stating that there is directional difference between the data - a score of 8 is more positive than a score of 6 - but that the differences cannot be understood as necessarily being linear. Table 7 shows the ordinal rankings of cities for AHS and tweet results, as well as the several demographic characteristics I included in my statistical tests. Appendices B and C contain the actual figures from which ordinal rankings were determined.

For the sake of saving valuable space, and so as not to confuse the

reader with an overabundance of statistics, it should be noted that I did not include in this table a ranking of cities based upon the percentage of tweets that contained positive sentiment, instead focusing on how the cities lined up when considering the average sentiment per tweet. However, to ensure that using one metric as opposed to another would not throw off the results, statistical tests were completed for both metrics in comparison to all other variables, and the results were almost exactly the same. In no cases were there any statistically significant differences.

City	AHS Rank	Avg. Tweet Score 2013	Avg. Tweet Score 2015	Median Income	% Under 18	College Grad %
Atlanta	3	3	4	2	7	2
Houston	6	5	7	3	1	5
Indianapolis	1	1	1	4	3	7
New Orleans	5	8	8	6	5	3
Newark	8	4	6	8	2	8
Providence	2	6	3	5	4	6
St. Louis	7	2	2	7	6	4
Washington	4	7	5	1	8	1

City	Pop. Change 1970 - 2010	Foreign Born %	Mean Travel Time to Work	Median Value of Owned Homes	% Persons Below Poverty
Atlanta	4	6	4	3	5
Houston	1	2	3	6	6
Indianapolis	2	5	7	8	7
New Orleans	7	8	6	5	4
Newark	5	3	1	2	1
Providence	3	1	8	4	2
St. Louis	8	7	5	7	3
Washington	6	4	2	1	8

Table 7: Ordinal rankings of AHS, tweet and demographic data

I used a common statistical test known as Spearman's Rho, used for determining if there are significant relationships between sets of ordinal data, to carry out my analysis of the rankings in Table 7. Perhaps disappointingly, no significant relationships were found between my three data sets (AHS, 2013 tweets, and 2015 tweets) and any of the demographic variables at the 95% confidence level. A significant negative correlation was found, however, between AHS scores and mean travel time to work in minutes at the 90% confidence level. Unsurprisingly, a significant positive relationship was found between 2013 tweet rankings and 2015 tweet rankings at the 95% confidence level, with the r-score at 0.7381 and the p-value at 0.03655. Although no significant relationship was found between either tweet data set and AHS scores, it is clear that for some cities the average tweet score rankings and the AHS rankings matched up quite closely. For 2015 tweets and the AHS, the r-score is 0.5 with a p-value of 0.20703, while the r-score for 2013 tweets and the AHS comes in at 0.09524 with a corresponding p-value of 0.82251.

Notwithstanding the lack of correlation between the AHS and tweets, as seen in Table 7 both tweet data sets and the AHS found the same city, Indianapolis, as the highest-ranking city. Additionally, Atlanta was ranked third in the AHS, third for 2013 tweets and fourth for 2015 tweets, and Houston had similar results across the three data sets - sixth in the AHS, fifth for 2013 tweets and seventh for 2015 tweets. Thus, even though the Spearman's Rho found no statistical significance, it is evident that there is

some crossover between these data sets for specific cities, meaning that Twitter sentiment analyses, despite the potentially broad difference between daily affect and neighborhood satisfaction, are still able to pick up in some cases a relative ranking of happiness that mirrors other data sets. Appendix D presents a matrix of full statistical results for all variables with Spearman's Rho values and p-values.

Most importantly for this thesis, no significant relationship was found between any of my three data sets and the ranking among the cities in population change between 1970 and 2010, even at the 90% confidence level. This means that I find no evidence for a claim that living in a city with substantial population loss over the last several decades leads to a lower evaluation of one's life satisfaction as measured by neighborhood satisfaction in the AHS, or to a more negative daily attitude or emotional state as measured by a tweet sentiment analysis. It can certainly be pointed out that there are also no correlations when considering a multitude of demographic data, but this does not overturn my lack of finding in regard to shrinking cities and lower subjective well-being.

To further solidify these results, I performed a Pearson's r correlation analysis of all data not including the AHS figures. The reason for converting data to ordinal form for the above Spearman's analysis was to allow a comparison across subjective data sets; however, this eliminates a substantial quantity of valuable information. I retained the data in its original form as well, allowing for a correlation analysis between my two tweet data

sets and the myriad demographic data with no conversion to ordinal rankings. As noted above, the full demographic data is shown in Appendix C, and there is not space to replicate that table in full here.

For this Pearson's analysis, both average tweet scores and the percentage of tweets with positive sentiment were included. As with Spearman, no statistically significant correlations were found between any of the tweet figures and the demographic variables, although multiple correlations between the demographics themselves were surfaced. Moreover, all tweet statistics were significantly correlated at the 95% confidence level, as shown in Table 8 below. Appendix E contains the full results of the Pearson's r analysis.

	Avg. Tweet Score 2013	Avg. Tweet Score 2015	% Positive Sentiment Tweets 2013	% Positive Sentiment Tweets 2015
Avg. Tweet Score 2013	r = 1; p = N/A	**r = 0.8176; p = 0.013171 ** **	**r = 0.8237; p = 0.011952** **	**r = 0.9037; p = 0.002074 ** **
Avg. Tweet Score 2015	**r = 0.8176; p = 0.013171** **	r = 1; p = N/A	**r = 0.8706; p = 0.004905** **	**r = 0.9778; p < 0.0001** **
% Positive Sentiment Tweets 2013	**r = 0.8237; p = 0.011952** **	**r = 0.8706; p = 0.004905 ** **	r = 1; p = N/A	**r = 0.9199; p = 0.001209 ** **
% Positive Sentiment Tweets 2015	**r = 0.9037; p = 0.002074** **	**r = 0.9778; p < 0.0001** **	**r = 0.9199; p = 0.001209** **	r = 1; p = N/A

Table 8: Statistical correlations of tweets with Pearson's r analysis.
* * = Significant at 95% confidence

As a final point in this section, I would be remiss if I did not mention that a larger collection of tweets was gathered between March 23rd and April 10th, 2015 as a supplement to the 2015 tweet data set. With the 2015 data set used in this thesis being so much smaller than the 2013 data set, there was concern that the raw number of tweets would be insufficient for statistical analysis, and the additional tweet collection effectively increased by 50% the total number of tweets gathered in 2015 - an increase from 1.4 million to 2.1 million tweets.

However, the rankings of the cities stayed exactly the same, as shown in Table 9. All of the additional data thus did not yield any differences at all for the purposes of Spearman's rho statistical analysis of ordinal rankings. Moreover, a Pearson's r calculation looking for a correlation between the larger tweet data set's average tweet score and population changes between 1970 and 2010 remained woefully out of the range of statistical significance, with a p-value of 0.8152 for the original 2015 data set and 0.709 for the larger 2015 data set.

City	Avg. Score Per Tweet - Full Data Set	Avg. Score Per Tweet - Initial 2015 Data	% Positive Sentiment Tweets - Full Data Set	% Positive Sentiment Tweets - Initial 2015 Data
Atlanta	4	4	3	3
Houston	7	7	7	7
Indianapolis	1	1	1	1
New Orleans	8	8	8	8
Newark	6	6	5	5
Providence	3	3	4	4
St. Louis	2	2	2	2
Washington	5	5	6	6

City	Avg. Score Per Tweet - Full Data Set	Avg. Score Per Tweet - Initial 2015 Data
Atlanta	0.157	0.1255
Houston	0.048	0.0469
Indianapolis	0.216	0.2355
New Orleans	-0.076	-0.0738
Newark	0.075	0.0687
Providence	0.148	0.1807
St. Louis	0.232	0.2281
Washington	0.136	0.1228

Table 9: 2015 Full and initial data comparison

The similarity of the data sets, notwithstanding an increase in data quantity of 50%, strongly suggests that patterns of positive and negative affect become apparent in tweet data sets at least as small as seven figures, and perhaps even smaller. While larger data sets are ideal, it may not be necessary for researchers to spend several weeks or months gathering data, depending on what it is that is being researched. Furthermore, combined with the T-tests described above, this is further evidence that we can have confidence in the consistency of Twitter as a source of data regarding subjective well-being.

Chapter 5: Conclusions and Recommendations

This thesis has demonstrated that for eight major cities in the United States there exists no correlation between population gain or loss in that city from 1970 to 2010 and the subjective well-being of the residents of that city, as measured by the AHS and millions of total tweets. For my first research question, "Are there differences in resident perceptions of neighborhood quality of life, as well as expressed positive and negative sentiment, when accounting for changes in population among cities between 1970 and 2010?", the answer is "No," there is no difference between shrinking and growing cities as far as how those cities compare with one another in terms of SWB.

In answering my second research question, "In computing differences among cities, is Twitter a reliable gauge of resident perceptions when compared with more traditional measures of well-being?" I have come to the conclusion that the answer is "Yes," but I cannot point to significant statistical evidence beyond the literature to substantiate this statement. There was not found to be a statistically significant correlation between AHS results and tweet results, at least as far as ordinal ranking of cities is concerned, though I did find very similar rankings for three of my sample cities: Indianapolis, Atlanta and Houston. Future studies should, where possible, include a much larger cohort of municipalities to determine if a larger sample size can surface a statistical correlation.

Moreover, psychological literature suggests that the AHS and tweets are getting at two different pieces of subjective well-being, life satisfaction

and affect. AHS asks residents to rate their neighborhood from 1 to 10, and this rating is reflective of only a piece of how a respondent might answer the larger question of how he or she would rate his or her overall life satisfaction. Tweets instead are measuring the positive and negative affect that Twitter users demonstrate via the content of their posts. Although the literature certainly indicates that there is a relationship between life satisfaction and affect, they would not occupy the exact same space in a Venn Diagram of SWB, so the lack of statistically significant relationship between AHS and tweets is not proof that Twitter is without merit in determining at least one aspect of SWB.

In the coming years, theses at the UAL and elsewhere might consider utilizing multiple dictionaries for sentiment analysis, as well as incorporating other traditional measures of happiness. An in-depth study of one city, with manual scoring of a body of tweets, might provide additional insights. Should time and funding permit, short interviews with residents of cities from which tweets are being gathered could directly ask about overall life satisfaction rather than relying on AHS data that present an incomplete picture of this metric.

To that end, future research using microblogging data as a corpus for sentiment analysis should strongly engage with the psychological literature in thinking about what kind of happiness or SWB is being measured. A promising line of inquiry may involve interviews with positive psychologists to outline different forms of SWB in greater depth, with an objective of

determining how surveys, polls, text analysis and other bodies of data shine a light on particular forms. The first wave of sentiment analysis research has been completed, and now is the time to develop more a more rigorous understanding of what exactly sentiment analyses are telling us.

Finally, the ultimate purpose of even performing these analyses must be mentioned. A review of urban planning literature that includes microblogging data indicates that the uses of this data for planners is only at a very early stage. Sentiment analyses can inform public officials and employees about how residents are moving about their city, what they think of particular places in their city, and what service gaps there are for different populations. My research intimates that shrinking cities specifically are not places doomed to negativity and pessimism. Indeed, the many cities among my cohort that have lost large chunks of their population base over the last several decades demonstrate that quality of life can be retained and enhanced, and there may be a serendipitous relationship to be developed with positive psychologists who are capable not only of describing what different metrics of SWB are truly measuring, but how those metrics might be increased over the long-term.

Limitations and Future Research

Simply put, no sentiment analysis will be perfect, and they necessarily involve subjective judgments. So while sentiment analysis is a valid form of qualitative inquiry, it can always be improved, and this section will describe the limitations inherent in my thesis. Before moving on to the limitations that

come from the difficulty of analyzing language, it must be acknowledged that Twitter is not necessarily a representative sample of the population at large, and likely skews toward a younger user base (Gayo-Avello, 2011). Therefore, certain demographic groups may be under represented, and results of a sentiment analysis conducted on tweets should considered as one source of information augmenting other sources like traditional polling.

Among the language-based challenges is that of negation. For example, a tweet could describe something as "never good," which the UAL software, using the AFINN dictionary, would treat as a tweet containing a positive sentiment - good, with a value of +3. Clearly the intent of the writer, however, is to express a negative sentiment. There are many strategies employed to overcome the limitation of negation, of which Taboada, Brooke, Tofiloski, Voll and Stede (2011) provide an excellent overview. One strategy, partially employed by the AFINN dictionary, is recognizing the two words "don't like" as a negative sentiment. However, the dictionary does not yet contain a sufficient number of these terms. Moreover, there are sentences in which the negation is more than one word away from the modifier, which requires algorithms that determine the polarity of an entire sentence rather than simply looking for sentiment-containing words.

A similar limitation is the use of rhetorical devices, a la, "I was expecting to love it," which would be classified very positively based on the word "love," but is actually expressing something much less positive if not outright negative (Mullen & Malouf, 2006). The dictionary is also generally

incapable of recognizing sarcasm, does not analyze emoticons, and cannot hope to cover the full range of slang employed in tweets, though it does include some slang words and a wide variety of vulgarities. A potential line of future inquiry is generating manual counts of uses of sarcasm and other rhetorical devices, and determining the degree to which the sentiment score computed by the dictionary is inaccurate. It may turn out that such instances do not significantly impact the results of a sentiment analysis.

The sentiment analysis software itself is admittedly imperfect, and is still getting the kinks worked out. During the course of this thesis, as well as other work being done at the UAL, it was noticed that the software has a problem with contractions, considering the word "won't," for example, to be the word "won" followed by the letter "t." While this does not cause any difference as regard to the letter t, the word "won" is considered a positive sentiment, and thus incorrectly contributes to the positive total for that city. Given the size of these tweet files - in some cases containing over a million tweets for a single city - it is infeasible to manually make corrections to contraction problems, and is rather an issue for the UAL to work out in the future.

An additional limitation, most clearly demonstrated in the case of Houston with its multiple annexations of land along highway spurs leading into and out of the city, is that tweets are not restricted entirely to the central city in question. Some tweets in this analysis are certainly posted from outside the central city, although it is worth considering why this might or

might not be important. Are tweets posted from half a mile outside of Atlanta or St. Louis unrepresentative of the affect experienced by residents of those cities? Such tweets may, in fact, come from residents of those cities. How would a study be devised to exclude tweets from non-residents, including only tweets from residents of the central city? For instance, there is no guarantee that a tweet from downtown Atlanta belongs to a resident of Atlanta as opposed to a tourist.[4]

To address this latter problem, future researchers might include only those tweets coming from users who consistently post from the city being investigated, or, despite the potential unreliability of the location users volunteer on their Twitter profiles, by matching reported location with the lat/long coordinates of tweets. Also worth consideration is that even tweets from tourists in New Orleans might fairly represent the affect that is, for whatever reasons, created or generated by New Orleans for people that experience life in one way or another in that city. Researchers should give pause when formulating research questions, and give serious thought to what it is they are trying to measure or analyze.

For example, are we looking *only* into the affect experienced by residents of cities, regardless of the implications that shrinkage or growth might have on commuters, shoppers and tourists? What implications do shrinkage and growth have in terms of creating and sustaining affect or life satisfaction that in turn attract or repel non-residents? How might we

[4] Conversely, are only tweets from residents posted while those residents are in the city itself relevant to a sentiment analysis?

conceptualize cities in the context of their metropolitan statistical areas (MSAs) as determined by the US Census Bureau? Are there differences among growing or shrinking central cities when bearing in mind the growth or shrinkage of the suburbs and exurbs? Atlanta, a city that has technically shrunk since 1970 but that has seen incredible growth at the metro level, is a prime example. While these questions are beyond the work of this thesis, they are important considerations for future research.

Implications for Urban Planning and Policy

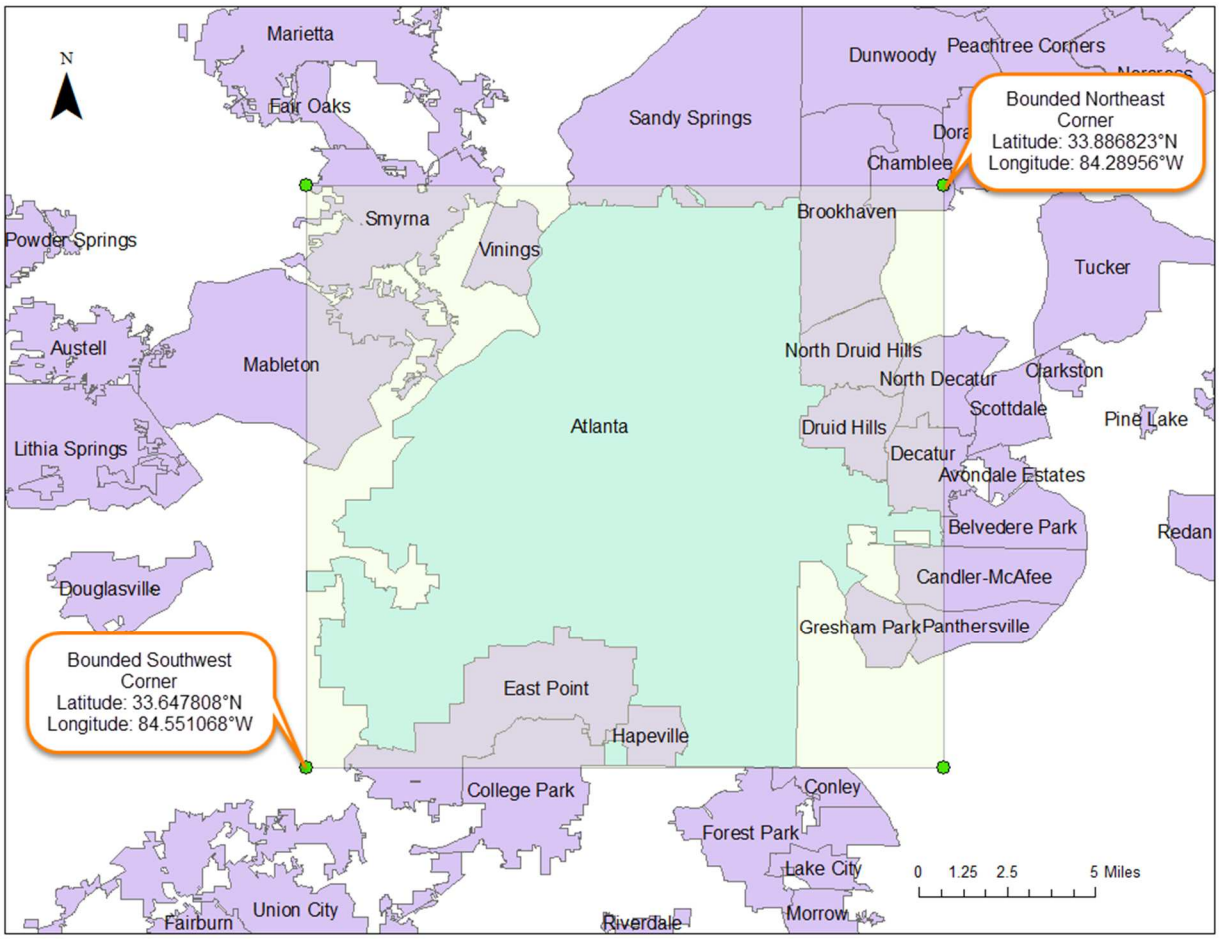
With respect to my first research question, my findings confirm previous work suggesting that the relationship between decreasing population and SWB are not nearly as clear-cut as would be expected given popular perceptions. As a result, shrinking cities should not be considered places that are doomed to a declining quality of life and therefore unworthy of investment. Indeed, a look back at the 20th century suggests undeniably that cities once thought to be beyond hope are quite capable of finding stability and resurgence. Strategies employed in cities that have already experienced a turnaround should be given a fair effort in shrinking cities, and in any case, stability should be seen as an objective worthy of pursuit in its own right. The work of the positive psychologists holds significant promise here for urban planners and policy makers, and their research should be strongly regarded as a bridge between the fields of psychology and planning.

As to my second research question, the implications of Twitter for the future of urban planning and policy are nuanced, but are affirmative in its

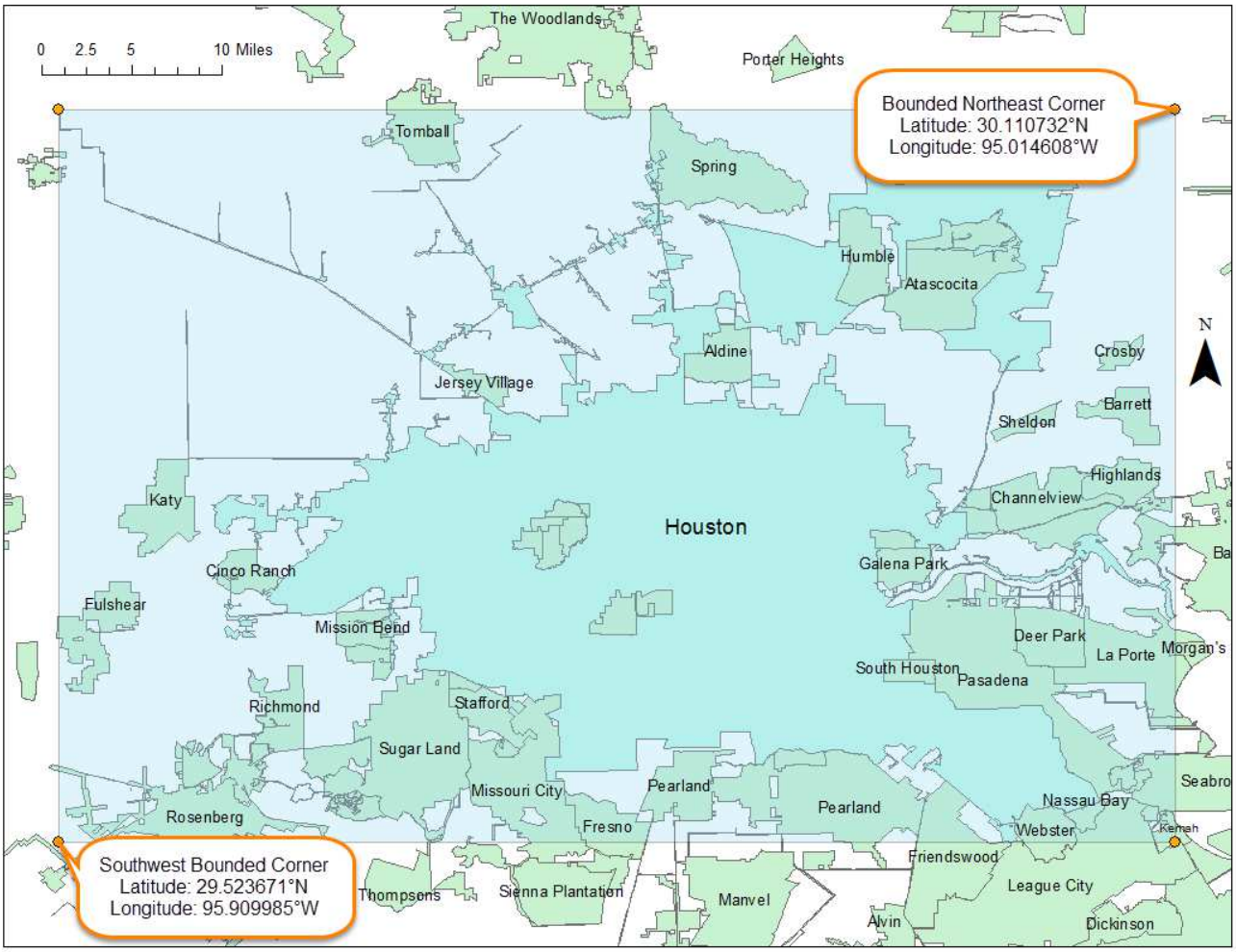
value. It is not sufficient for planners or policy makers to presume that a sentiment analysis, or for that matter a more traditional measure of SWB such as a poll or survey, will provide a complete picture of the happiness of residents or visitors. The specific form of SWB, and the ways in which different forms will interact with one another and with the larger culture, must be considered at the outset. Though sentiment analysis can now be done relatively cheaply and quickly, this should not lead to simplistic or reductionist approaches and assumptions.

This is particularly relevant when realizing that the different ways of measuring SWB will provide complementary information rather than serving as substitutes. Planners and policy makers concerned with SWB should determine in advance what they are trying to measure in light of the ultimate aims of how their metrics will be used, and ensure that the data they are gathering will truly speak to what is attempting to being measured. This task will be made easier in the future as research into Big Data continues to surface improved means of conducting sentiment analysis, new ways of overcoming limitations, and the ability to eliminate noise and hone in on the specific sentiments that are of particular relevance to the research, planning and policy making under consideration. As this process unfolds, the value of tweets and other social media datasets for planners and policy makers only stands to increase considerably.

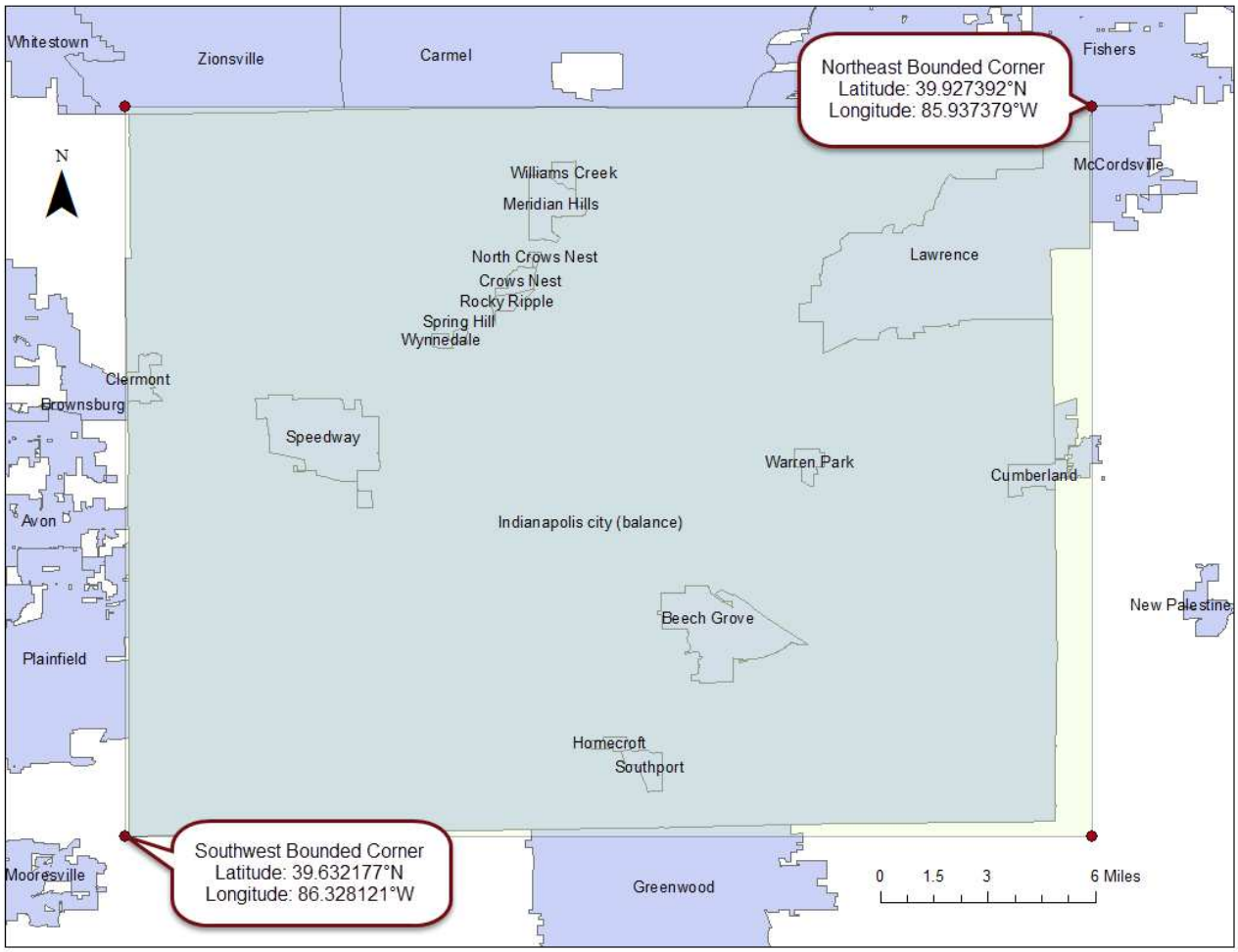
Appendix A



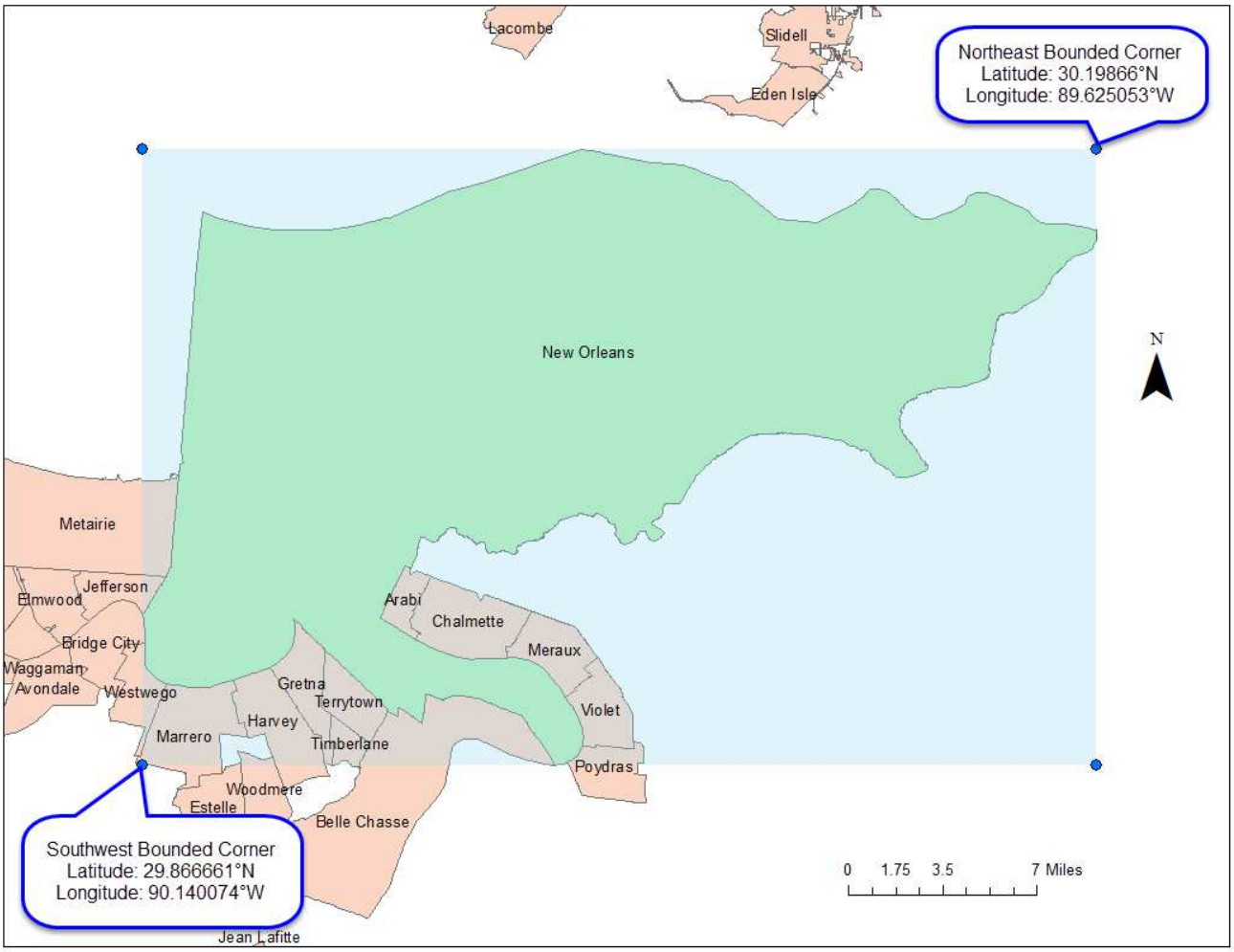
Atlanta with latitude/longitude coordinates



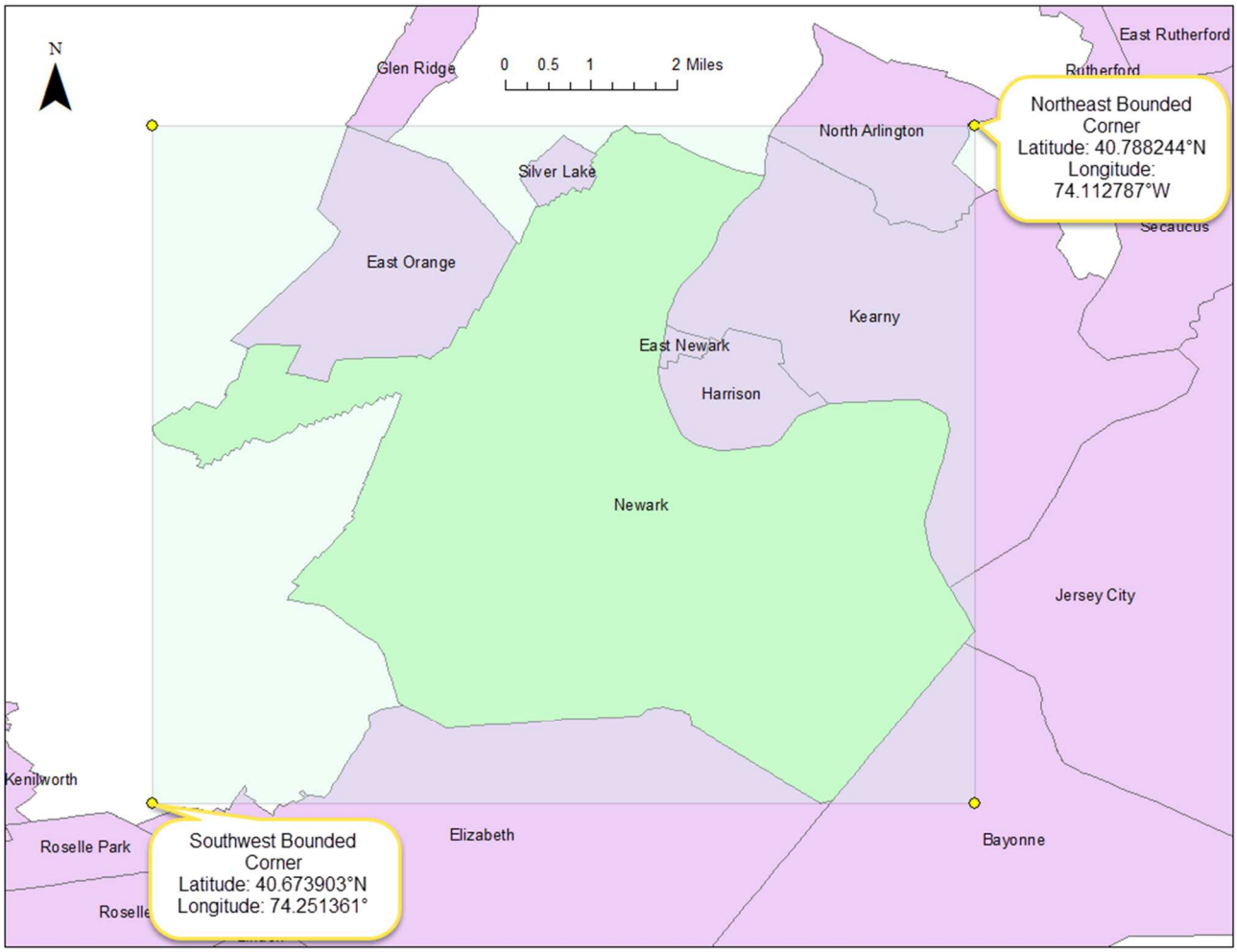
Houston with latitude/longitude coordinates



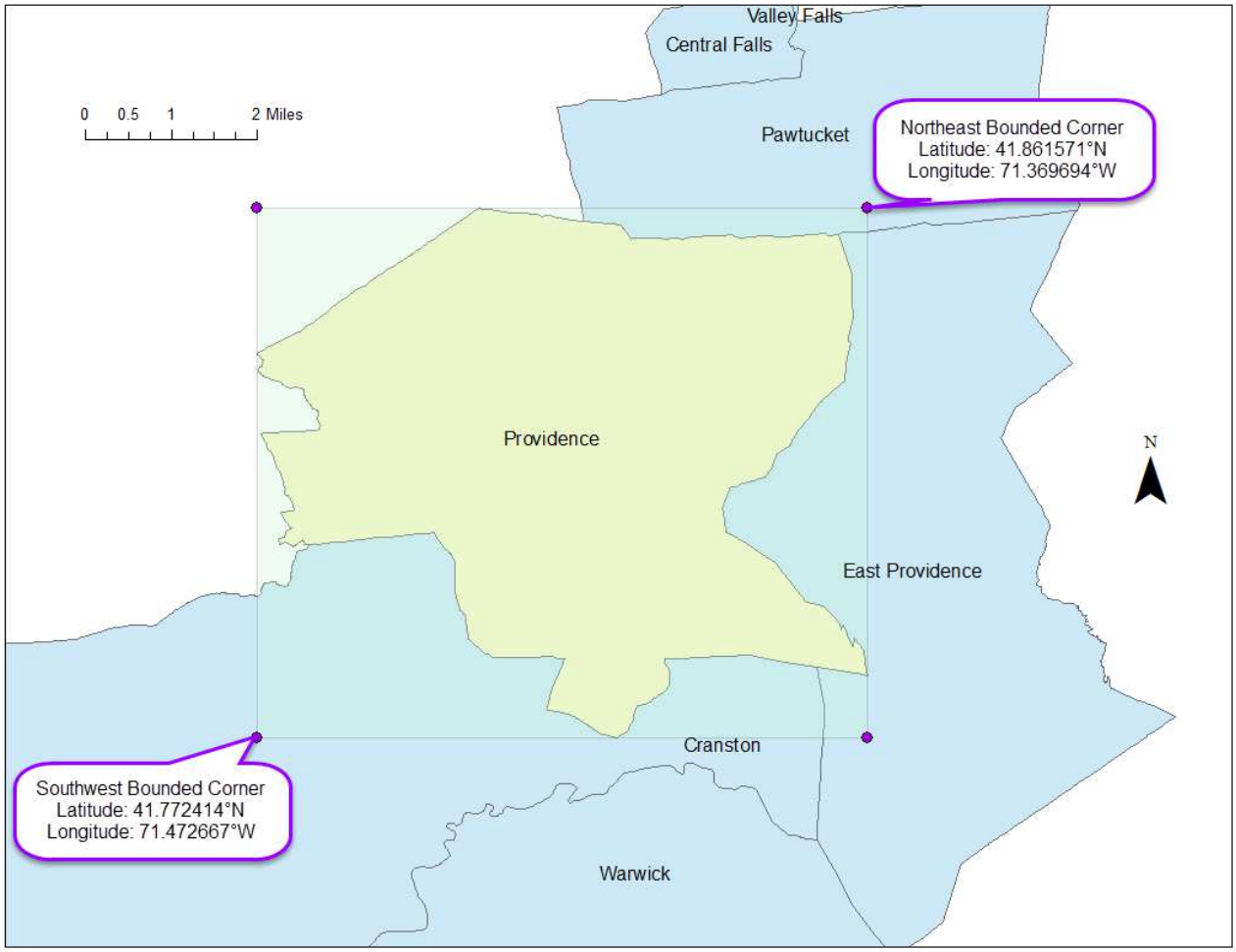
Indianapolis with latitude/longitude coordinates



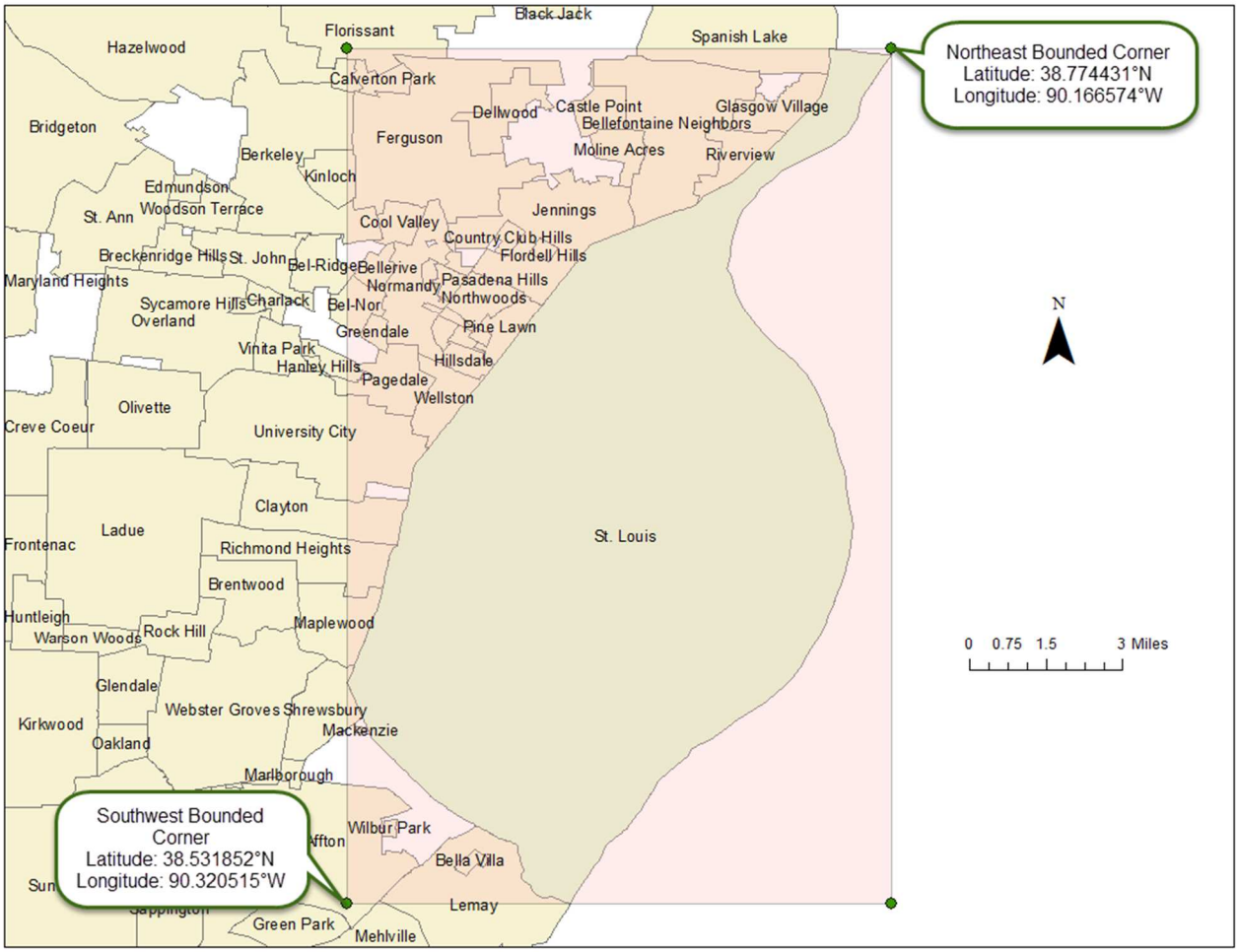
New Orleans with latitude/longitude coordinates



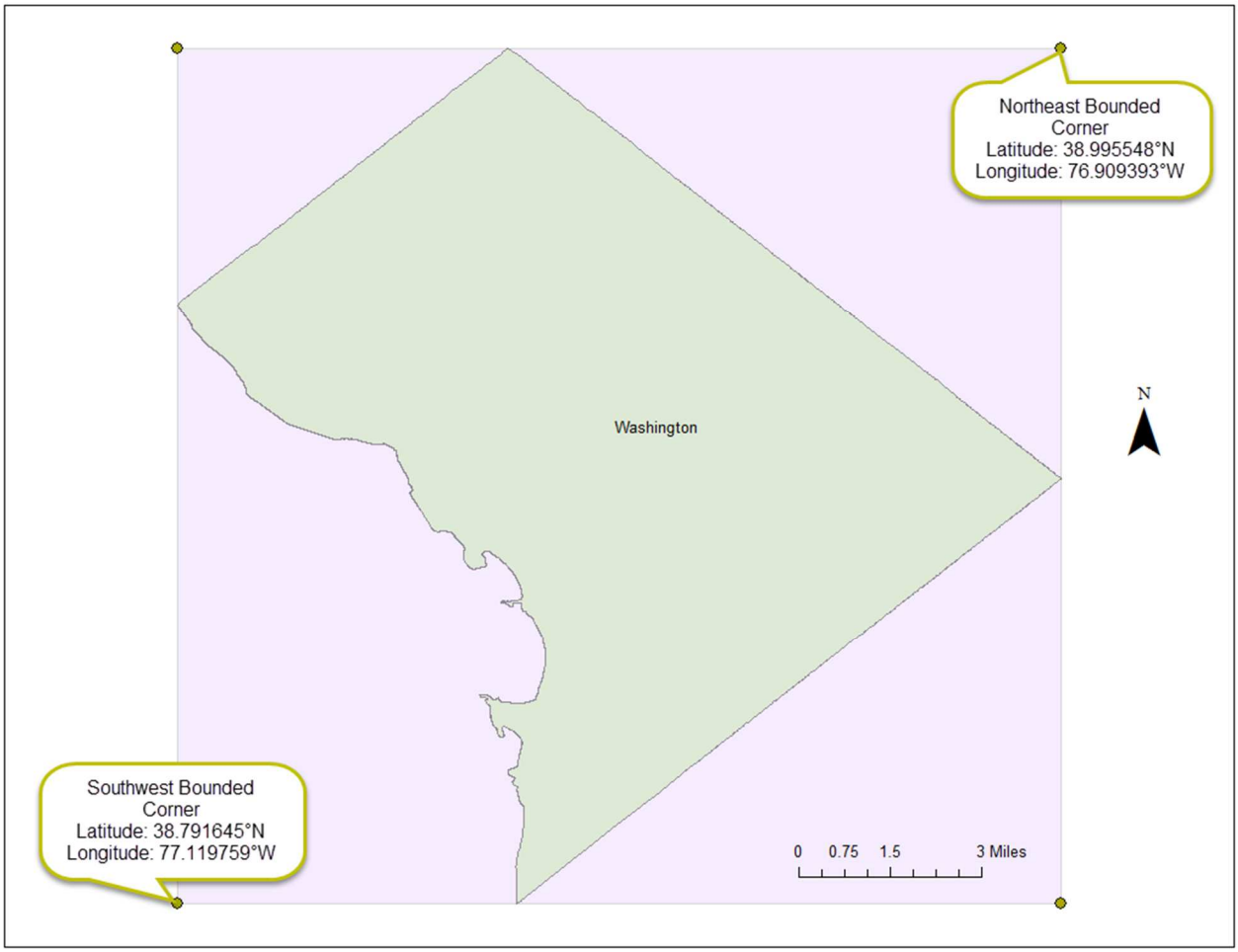
Newark with latitude/longitude coordinates



Providence with latitude/longitude coordinates



St. Louis with latitude/longitude coordinates



Washington, D.C. with latitude/longitude coordinates

Appendix B

2013 Tweet Data

City	Positive Score	Negative Score	Overall Score	Average Score Per Tweet	Sentiment Containing Tweets	Total Tweets
Atlanta	5,306,108	-4,334,415	971,693	0.211	2,526,884	4,608,671
Houston	6,383,987	-5,215,843	1,168,144	0.200	3,101,918	5,827,597
Indianapolis	2,221,306	-1,654,203	567,103	0.314	1,035,167	1,804,805
New Orleans	2,603,198	-2,359,788	243,410	0.098	1,336,069	2,492,313
Newark	3,626,840	-2,946,019	680,821	0.206	1,735,069	3,305,276
Providence	640,322	-534,970	105,352	0.189	309,133	556,671
St. Louis	1,744,355	-1,425,904	318,451	0.213	842,460	1,494,820
Washington	2,950,291	-2,514,422	435,869	0.160	1,462,535	2,731,275

City	Positive Sentiment Tweets	Negative Sentiment Tweets	% Tweets w/ Sentiment	% Positive Sentiment Tweets	% Negative Sentiment Tweets	Difference[5]
Atlanta	1,735,626	1,274,876	54.83%	37.66%	27.66%	10.00%
Houston	2,095,748	1,591,752	53.23%	35.96%	27.31%	8.65%
Indianapolis	723,960	514,026	57.36%	40.11%	28.48%	11.63%
New Orleans	879,760	704,040	53.61%	35.30%	28.25%	7.05%
Newark	1,176,198	885,125	52.49%	35.59%	26.78%	8.81%
Providence	208,508	160,536	55.53%	37.46%	28.84%	8.62%
St. Louis	576,301	429,502	56.36%	38.55%	28.73%	9.82%
Washington	983,297	751,414	53.55%	36.00%	27.51%	8.49%

[5] The difference is calculated by subtracting the percentage of tweets containing negative sentiment from the percentage of tweets containing positive sentiment.

2015 Tweet Data

City	Positive Score	Negative Score	Overall Score	Average Score Per Tweet	Sentiment Containing Tweets	Total Tweets
Atlanta	157,366	-138,664	18,702	0.126	76,819	149,010
Houston	612,865	-584,293	28,572	0.047	313,556	609,335
Indianapolis	133,556	-106,406	27,150	0.235	63,268	115,311
Manchester	18,840	-12,236	6,604	0.433	8,311	15,259
New Britain	8,654	-7,673	981	0.131	4,166	7,487
New Orleans	156,535	-170,049	-13,514	-0.074	89,875	183,195
Newark	61,741	-57,615	4,126	0.069	31,007	60,035
Providence	34,492	-28,477	6,015	0.181	17,132	33,288
St. Louis	43,255	-34,343	8,912	0.228	20,356	39,078
Stamford	10,796	-7,133	3,663	0.376	5,017	9,741
Washington	239,492	-210,311	29,181	0.123	120,351	237,626
Waterbury	17,660	-20,622	-2,962	-0.177	9,504	16,769

City	Positive Sentiment Tweets	Negative Sentiment Tweets	% Tweets w/ Sentiment	% Positive Sentiment Tweets	% Negative Sentiment Tweets	Difference
Atlanta	52,441	38,811	51.55%	35.19%	26.05%	9.15%
Houston	204,731	168,041	51.46%	33.60%	27.58%	6.02%
Indianapolis	43,360	31,883	54.87%	37.60%	27.65%	9.95%
Manchester	6,025	3,966	54.47%	39.48%	25.99%	13.49%
New Britain	2,821	2,199	55.64%	37.68%	29.37%	8.31%
New Orleans	57,260	48,903	49.06%	31.26%	26.69%	4.56%
Newark	20,409	16,758	51.65%	34.00%	27.91%	6.08%
Providence	11,554	8,873	51.47%	34.71%	26.66%	8.05%
St. Louis	14,053	10,227	52.09%	35.96%	26.17%	9.79%
Stamford	3,547	2,310	51.50%	36.41%	23.71%	12.70%
Washington	80,763	61,817	50.65%	33.99%	26.01%	7.97%
Waterbury	6,033	5,481	56.68%	35.98%	32.69%	3.29%

Appendix C

City	Median Income	% Under 18	College Graduation %	Pop. Change 1970 - 2010	Foreign Born %	Mean Travel Time to Work	Median Value of Owned Homes	% Persons Below Poverty
Atlanta	$46,631	19.4%	46.8%	-76,970	7.7%	25.1	$210,000	25.0%
Houston	$45,010	25.9%	29.2%	867,461	28.3%	25.9	$123,900	22.9%
Indianapolis	$41,962	25.0%	27.3%	75,821	8.7%	22.6	$118,000	20.9%
New Orleans	$37,146	21.3%	33.7%	-249,642	5.9%	23.0	$183,700	27.3%
Newark	$33,960	25.6%	12.7%	-104,790	27.2%	32.3	$243,200	29.1%
Providence	$37,632	23.4%	28.5%	-1,171	30.0%	21.4	$196,300	29.0%
St. Louis	$34,582	21.2%	29.6%	-302,942	6.7%	23.9	$119,200	27.4%
Washington	$65,830	17.2%	52.4%	-154,787	13.8%	29.7	$445,200	18.6%

Source: US Census Quick Facts

Atlanta: http://quickfacts.census.gov/qfd/states/13/1304000.html

Houston: http://quickfacts.census.gov/qfd/states/48/4835000.html

Indianapolis: http://quickfacts.census.gov/qfd/states/18/1836003.html

New Orleans: http://quickfacts.census.gov/qfd/states/22/2255000.html

Newark: http://quickfacts.census.gov/qfd/states/34/3451000.html

Providence: http://quickfacts.census.gov/qfd/states/44/4459000.html

St. Louis: http://quickfacts.census.gov/qfd/states/29/2965000.html

Washington: http://quickfacts.census.gov/qfd/states/11000.html

Appendix D

Note that "Avg. Tweet Score Rank," as described in the text, was calculated by dividing the total sentiment score for a city by the total number of tweets from that city. Including only those tweets that contained sentiment, rather than all tweets, produced no significant differences, and indeed the rankings were a virtual mirror image of one another in both cases.

	AHS Rank	**Avg. Tweet Score Rank 2013**	**Avg. Tweet Score Rank 2015**	**Median Income**	**% Under 18**	**College Graduation %**
AHS Rank	r = 1; p = N/A	r = 0.09524; p = 0.82251	r = 0.5; p = 0.20703	r = 0.54762; p = 0.16003	r = -0.21429; p = 0.61034	r = 0.09524; p = 0.82251
Avg. Tweet Score Rank 2013	r = 0.09524; p = 0.82251	r = 1; p = N/A	**r = 0.7381; p = 0.03655****	r = -0.14286; p = 0.73577	r = 0.16667; p = 0.69324	r = -0.40476; p = 0.31989
Avg. Tweet Score Rank 2015	r = 0.5; p = 0.20703	**r = 0.7381; p = 0.03655****	r = 1; p = N/A	r = 0.02381; p = 0.95537	r = -0.19048; p = 0.6514	r = -0.21429; p = 0.61034
Median Income	r = 0.54762; p = 0.16003	r = -0.14286; p = 0.73577	r = 0.02381; p = 0.95537	r = 1; p = N/A	r = -0.40476; p = 0.31989	r = 0.61905; p = 0.10173
% Under 18	r = -0.21429; p = 0.61034	r = 0.16667; p = 0.69324	r = -0.19048; p = 0.6514	r = -0.40476; p = 0.31989	r = 1; p = N/A	**r = -0.8333; p = 0.01018****
College Graduation %	r = 0.09524; p = 0.82251	r = -0.40476; p = 0.31989	r = -0.21429; p = 0.61034	r = 0.61905; p = 0.10173	**r = -0.8333; p = 0.01018****	r = 1; p = N/A
Pop. Change 1970 - 2010	r = 0.45238; p = 0.2604	r = 0.21429; p = 0.61034	r = 0.09524; p = 0.82251	r = 0.38095; p = 0.35181	r = 0.61905; p = 0.10173	r = -0.42857; p = 0.2894
Foreign Born %	r = 0.09524; p = 0.82251	r = -0.11905; p = 0.77889	r = 0; p = 1	r = 0.14286; p = 0.73577	r = 0.5; p = 0.20703	r = -0.45238; p = 0.2604
Mean Travel Time to Work	**r = -0.66667; p = 0.07099***	r = -0.09524; p = 0.82251	r = -0.47619; p = 0.23294	r = 0.09524; p = 0.82251	r = 0; p = 1	r = 0.14286; p = 0.73577
Median Value of Owned Homes	r = -0.16667; p = 0.69324	r = -0.52381; p = 0.18272	r = -0.40476; p = 0.31989	r = 0.2381; p = 0.57016	r = -0.38095; p = 0.35181	r = 0.33333; p = 0.41975
Persons Below Poverty	r = -0.45238; p = 0.2604	r = 0; p = 1	r = -0.07143; p = 0.86653	**r = -0.83333; p = 0.01018****	r = 0.28571; p = 0.49273	r = -0.5; p = 0.20703

	Pop. Change 1970 - 2010	**Foreign Born %**	**Mean Travel Time to Work**	**Median Value of Owned Homes**	**Persons Below Poverty**
AHS Rank	r = 0.45238; p = 0.2604	r = 0.09524; p = 0.82251	**r = -0.66667; p = 0.07099***	r = -0.16667; p = 0.69324	r = -0.45238; p = 0.2604
Avg. Tweet Score Rank 2013	r = 0.21429; p = 0.61034	r = -0.11905; p = 0.77889	r = -0.09524; p = 0.82251	r = -0.52381; p = 0.18272	r = 0; p = 1
Avg. Tweet Score Rank 2015	r = 0.09524; p = 0.82251	r = 0; p = 1	r = -0.47619; p = 0.23294	r = -0.40476; p = 0.31989	r = -0.07143; p = 0.86653
Median Income	r = 0.38095; p = 0.35181	r = 0.14286; p = 0.73577	r = 0.09524; p = 0.82251	r = 0.2381; p = 0.57016	**r = -0.83333; p = 0.01018****
% Under 18	r = 0.61905; p = 0.10173	r = 0.5; p = 0.20703	r = 0; p = 1	r = -0.38095; p = 0.35181	r = 0.28571; p = 0.49273
College Graduation %	r = -0.42857; p = 0.2894	r = -0.45238; p = 0.2604	r = 0.14286; p = 0.73577	r = 0.33333; p = 0.41975	r = -0.5; p = 0.20703
Pop. Change 1970 - 2010	r = 1; p = N/A	**r = 0.66667; p = 0.07099***	r = -0.14286; p = 0.73577	r = -0.21429; p = 0.61034	r = -0.2619; p = 0.53092
Foreign Born %	**r = 0.66667; p = 0.07099***	r = 1; p = N/A	r = 0.11905; p = 0.77889	r = 0.2619; p = 0.53092	r = 0.11905; p = 0.77889
Mean Travel Time to Work	r = -0.14286; p = 0.73577	r = 0.11905; p = 0.77889	r = 1; p = N/A	r = 0.59524; p = 0.11953	r = -0.07143; p = 0.86653
Median Value of Owned Homes	r = -0.21429; p = 0.61034	r = 0.2619; p = 0.53092	r = 0.59524; p = 0.11953	r = 1; p = N/A	r = 0.09524; p = 0.82251
Persons Below Poverty	r = -0.2619; p = 0.53092	r = 0.11905; p = 0.77889	r = -0.07143; p = 0.86653	r = 0.09524; p = 0.82251	r = 1; p = N/A

* = Statistically significant at 90% confidence level; ** = statistically significant at 95% confidence level.

Appendix E

	Avg. Tweet Score 2013	Avg. Tweet Score 2015	% Positive Sentiment Tweets 2013	% Positive Sentiment Tweets 2015	Median Income
Avg. Tweet Score 2013	r = 1; p = N/A	**r = 0.8176; p = 0.013171****	**r = 0.8237; p = 0.011952****	**r = 0.9037; p = 0.002074****	r = -0.116; p = 0.784443
Avg. Tweet Score 2015	**r = 0.8176; p = 0.013171****	r = 1; p = N/A	**r = 0.8706; p = 0.004905****	**r = 0.9778; p < 0.0001****	r = -0.0197; p = 0.963072
% Positive Sentiment Tweets 2013	**r = 0.8237; p = 0.011952****	**r = 0.8706; p = 0.004905****	r = 1; p = N/A	**r = 0.9199; p = 0.001209****	r = -0.1517; p = 0.719896
% Positive Sentiment Tweets 2015	**r = 0.9037; p = 0.002074****	**r = 0.9778; p < 0.0001****	**r = 0.9199; p = 0.001209****	r = 1; p = N/A	r = -0.0695; p = 0.870107
Median Income	r = -0.116; p = 0.784443	r = -0.0197; p = 0.963072	r = -0.1517; p = 0.719896	r = -0.0695; p = 0.870107	r = 1; p = N/A
% Under 18	r = 0.4381; p = 0.277617	r = 0.078; p = 0.854342	r = 0.0989; p = 0.815768	r = 0.1807; p = 0.668491	**r = -0.6271; p = 0.096082***
College Graduation %	r = -0.285; p = 0.493856	r = -0.0707; p = 0.867879	r = -0.0255; p = 0.952208	r = -0.1069; p = 0.801084	**r = 0.8095; p = 0.014908****
Pop. Change 1970 - 2010	r = 0.2278; p = 0.587421	r = -0.0992; p = 0.815217	r = -0.1074; p = 0.800168	r = 0.0178; p = 0.966632	r = 0.1053; p = 0.804017
Foreign Born %	r = 0.0004; p = 0.99925	r = -0.0392; p = 0.926575	r = -0.3649; p = 0.37412	r = -0.0647; p = 0.879026	r = -0.1128; p = 0.790287
Mean Travel Time to Work	r = -0.117; p = 0.782619	r = -0.2239; p = 0.594007	r = -0.5373; p = 0.169662	r = -0.2767; p = 0.50706	r = 0.319; p = 0.441213
Median Value of Owned Homes	r = -0.4003; p = 0.325763	r = -0.1785; p = 0.672354	r = -0.4575; p = 0.254369	r = -0.3133; p = 0.449871	**r = 0.7633; p = 0.027547****
% Persons Below Poverty	r = -0.2629; p = 0.529305	r = -0.1604; p = 0.704369	r = -0.1822; p = 0.66586	r = -0.186; p = 0.65921	**r = -0.8421; p = 0.008713****

	% Under 18	College Graduation %	Pop. Change 1970 - 2010	Foreign Born %
Avg. Tweet Score 2013	r = 0.4381; p = 0.277617	r = -0.285; p = 0.493856	r = 0.2278; p = 0.587421	r = 0.0004; p = 0.99925
Avg. Tweet Score 2015	r = 0.078; p = 0.854342	r = -0.0707; p = 0.867879	r = -0.0992; p = 0.815217	r = -0.0392; p = 0.926575
% Positive Sentiment Tweets 2013	r = 0.0989; p = 0.815768	r = -0.0255; p = 0.952208	r = -0.1074; p = 0.800168	r = -0.3649; p = 0.37412
% Positive Sentiment Tweets 2015	r = 0.1807; p = 0.668491	r = -0.1069; p = 0.801084	r = 0.0178; p = 0.966632	r = -0.0647; p = 0.879026
Median Income	**r = -0.6271; p = 0.096082***	**r = 0.8095; p = 0.014908****	r = 0.1053; p = 0.804017	r = -0.1128; p = 0.790287
% Under 18	r = 1; p = N/A	**r = -0.877; p = 0.004234****	r = 0.5641; p = 0.14527	r = 0.5685; p = 0.141463
College Graduation %	**r = -0.877; p = 0.004234****	r = 1; p = N/A	r = -0.1507; p = 0.721686	r = -0.4691; p = 0.240954
Pop. Change 1970 - 2010	r = 0.5641; p = 0.14527	r = -0.1507; p = 0.721686	r = 1; p = N/A	r = 0.5562; p = 0.152245
Foreign Born %	r = 0.5685; p = 0.141463	r = -0.4691; p = 0.240954	r = 0.5562; p = 0.152245	r = 1; p = N/A
Mean Travel Time to Work	r = -0.0541; p = 0.89876	r = -0.0775; p = 0.855268	r = -0.0094; p = 0.982376	r = 0.2841; p = 0.495282
Median Value of Owned Homes	**r = -0.6484; p = 0.082024***	r = 0.5477; p = 0.159951	r = -0.3134; p = 0.449719	r = 0.0483; p = 0.909578
% Persons Below Poverty	r = 0.3156; p = 0.446369	r = -0.5991; p = 0.116532	r = -0.2864; p = 0.491642	r = 0.2578; p = 0.537615

	Mean Travel Time to Work	**Median Value of Owned Homes**	**% Persons Below Poverty**
Avg. Tweet Score 2013	r = -0.117; p = 0.782619	r = -0.4003; p = 0.325763	r = -0.2629; p = 0.529305
Avg. Tweet Score 2015	r = -0.2239; p = 0.594007	r = -0.1785; p = 0.672354	r = -0.1604; p = 0.704369
% Positive Sentiment Tweets 2013	r = -0.5373; p = 0.169662	r = -0.4575; p = 0.254369	r = -0.1822; p = 0.66586
% Positive Sentiment Tweets 2015	r = -0.2767; p = 0.50706	r = -0.3133; p = 0.449871	r = -0.186; p = 0.65921
Median Income	r = 0.319; p = 0.441213	**r = 0.7633; p = 0.027547****	**r = -0.8421; p = 0.008713****
% Under 18	r = -0.0541; p = 0.89876	**r = -0.6484; p = 0.082024***	r = 0.3156; p = 0.446369
College Graduation %	r = -0.0775; p = 0.855268	r = 0.5477; p = 0.159951	r = -0.5991; p = 0.116532
Pop. Change 1970 - 2010	r = -0.0094; p = 0.982376	r = -0.3134; p = 0.449719	r = -0.2864; p = 0.491642
Foreign Born %	r = 0.2841; p = 0.495282	r = 0.0483; p = 0.909578	r = 0.2578; p = 0.537615
Mean Travel Time to Work	r = 1; p = N/A	r = 0.6064; p = 0.110984	r = -0.1366; p = 0.747043
Median Value of Owned Homes	r = 0.6064; p = 0.110984	r = 1; p = N/A	r = -0.3896; p = 0.340055
% Persons Below Poverty	r = -0.1366; p = 0.747043	r = -0.3896; p = 0.340055	r = 1; p = N/A

* = Statistically significant at 90% confidence level; ** = statistically significant at 95% confidence level.

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