## UNIVERSITY OF CALIFORNIA

## Santa Barbara

Cultural Amenities and the Consumer City Hypothesis

A Thesis submitted in partial satisfaction of the requirements for the degree Master of Arts in Geography

by

Bonnie Elizabeth Bounds

Committee in charge:

Professor Helen M. Couclelis, Chair

Professor Stuart H. Sweeney

Professor Daniel R. Montello

March 2015

The thesis of Bonnie Elizabeth Bounds is approved.

Stuart H. Sweeney	
Daniel R. Montello	
Helen M. Couclelis, Committee Chair	

March 2015

## ACKNOWLEDGEMENTS

I am eternally grateful to Dr. Helen M. Couclelis, Dr. Stuart H. Sweeney, and Dr. Daniel R. Montello for their patience and assistance through all of the stages of completing this thesis. I would also like to thank my family and friends for their moral support.

### **ABSTRACT**

## Cultural Amenities and the Consumer City Hypothesis

by

#### Bonnie Elizabeth Bounds

The rise of the modern service- and information-based economy has accompanied an increased concern for quality of life compared to earlier eras. The consumer city hypothesis argues that in a post-industrial society, people increasingly value the location-specific amenities a particular city has to offer when deciding where to live. This is in contrast to traditional wisdom, which holds that jobs are the sole or most important criterion in attracting people to a given place. While other studies have found an association between natural amenities and greater demand for places that have them, there is much less work focusing on whether cultural amenities have the same effect. This analysis aims to discover whether there is additional evidence to support the consumer city hypothesis by investigating the relationship between cultural amenity levels (as measured by employment in amenity-related fields) and demand for particular places (as measured by median home prices).

This study examines 357 Metropolitan Statistical Areas in the United States (including those in Alaska and Hawaii). Data from the American Community Survey and

the Bureau of Labor Statistics were used to measure amenity-related employment, median home prices, and other demographic variables. Four linear regressions were run to determine the relationship between these variables in the years 2012 and 2005, as well as to discover the predictive value of amenity-related employment for future median home prices and changes in median home prices over time.

The results indicate that higher levels of cultural amenity-related employment are indeed associated with higher median home prices, providing support for the consumer-city hypothesis. Furthermore, levels of amenity-related employment at one point in time can be strong predictors of median home prices several years later, although they proved less useful for predicting the percentage change in median home values over time. Amenity-related employment may therefore be a potentially useful indicator to consider when predicting median home values. These findings also open up avenues for future research into the applicability of the consumer-city hypothesis in other First World countries as well as the developing world.

## 1. Introduction

It has been argued that the post-industrial society values personal fulfillment and quality of life much more highly than earlier eras, when people might have been content to live anywhere that offered plenty of jobs and was relatively safe. In advanced economies, people who have a choice are increasingly opting to live in areas where they believe their lives outside of work (and perhaps even inside it) will be more enjoyable—and this is where amenities come into play. Traditional wisdom would suggest that cities with the most jobs to be filled would see the greatest growth; however, in developed countries, this fails to consider the impact that quality of life has on households' location decisions. Although economic opportunities are certainly important—particularly in the wake of the 2008 global recession—the amenities a particular urban area has to offer also serve as a pull factor.

This phenomenon does not affect all segments of the population equally: low-skilled, low-paid workers will still have to weigh job availability more heavily in their location decisions due to economic necessity. However, we can expect to see the effects of amenities on migration more strongly among educated, middle- to upper-middle class individuals, since these groups of people generally have a strong desire to live in amenity-rich areas as well as the economic ability to actually make this possible. As explained by Florida (2012) in his theory of the creative class, cities with more amenities appeal to these people because they offer more opportunities to nurture their creativity as compared to other areas, such as factory towns. Furthermore, since these "creative class" workers tend to have higher human capital, they may also have a greater financial ability to choose where they live, since higher human capital is often associated with higher earning potential.

In a paper entitled "Consumer city," Glaeser, Kolko, and Saiz (2001) introduced the idea of cities as goods that can be consumed. Their "consumer-city hypothesis" is that people's demand for cities is based in part on the amenities that particular cities have to offer. Glaeser et al. (2001) also introduced the distinction between physical and cultural amenities that has been adopted by subsequent writers on the subject, with the majority of studies focusing primarily or exclusively on physical amenities, which happen to be easier to quantify.

One marker of a consumer city is a higher presence of human capital—another concept of the post-industrial age - whereby talented people who are in a position to choose where they live tend to choose areas that offer them more in terms of consumption. We expect that this is especially true in the case of cultural amenities, which tend to appeal more strongly to educated people. This follows Florida's (2002b) argument that among other factors, amenities attract people with higher human capital to particular urban areas.

This study focuses primarily on cultural amenities for two main reasons. The first is that, as noted above, cultural amenities are not as widely studied in the literature as natural amenities are, so I hope to help rectify this imbalance. The second reason is that cultural amenities are not tied to physical locations in the way that natural amenities generally are, and this makes them more of an 'equal-opportunity' asset: that is, even cities that do not boast many natural amenities could still shine as cultural centers. In this analysis, I seek to determine whether cultural amenities are associated with higher demand for cities that have them, just as others have found that places with many natural amenities are more desirable. Specifically, I hypothesize that metropolitan areas with more cultural amenities will

experience greater demand to live in these areas. To address this hypothesis, I investigate two sub-hypotheses:

- 1) Higher levels of cultural amenities (as measured by amenity-related employment) in a given metropolitan area are associated with greater demand (as measured by higher median home prices) for that area, and
- 2) An area's employment at one point in time in fields related to cultural amenities can be used to predict median home values in that area at a later point in time.

To this end, I investigate the association between several indicators of high levels of cultural amenities on the one hand (as measured employment in amenity-related fields as a percentage of total employment), and median home prices (as a proxy for demand) on the other. The results indicate that higher levels of cultural amenities are indeed associated with higher median home prices. This of course cannot be interpreted as evidence for a causal link between cultural amenities and higher demand for a particular area; further research would be needed to disentangle correlation from causation. Still, the fact that a positive link exists between cultural amenities and median home prices does provide some additional support for the consumer-city hypothesis. Additionally, these results provide an argument for the inclusion of cultural amenity employment in any comprehensive amenity indices that researchers working on this topic might create in the future.

#### 2. Literature Review

2.1 The post-industrial society and quality of life

Even before the notion of the consumer city was formally developed, interest in amenities had been growing for some time, motivated by the greater concern for quality of life that arose as part of the societal changes brought about by the post-industrial transition. Bell (1973) makes the connection between the transition from a manufacturing-based economy to a service- and information-based economy on the one hand, and an increased demand for services and amenities rather than products, on the other. As Bell (1973) explains, "[i]f an industrial society is defined by the quantity of goods as marking a standard of living, the post-industrial society is defined by the quality of life as measured by the services and amenities—health, education, recreation, and the arts—which are now deemed desirable and possible for everyone" (p.127). As developed economies move most of their economic activity in the tertiary, quaternary, and even quinary sectors, workers become more concerned with seeking opportunities to improve or maintain their quality of life by "consuming" amenities and services. Cities that offer the highest concentrations of amenities should thus be seen as more desirable locations for living and working. Furthermore, since the tertiary and more advanced sectors are much less reliant on resources found in specific locations than the primary and secondary sectors, workers and companies are afforded considerably more flexibility in terms of where they locate, making it more likely that locations will be chosen in large part for the amenities on offer. Prior to this, the standard industrial-age assumption was that migration choices were driven almost exclusively by wherever the most jobs and/or the best pay could be found. This strongly supported assumption is at least as old as Ravenstein's (1889) seminal work on the laws of migration, where the author writes that upon asking migrants what led them to move, "[i[n] most

instances it will be found that they did so [migrate] in search of work of a more remunerative or attractive kind than that afforded by the places of their birth" (181).

## 2.2 Historical roots and recent work on the consumer city hypothesis

Tiebout (1956) developed the notion of people "voting with their feet" by choosing to live in municipalities where local expenditures match their own preferences and priorities, whether it be an excellent local school system or a municipal golf course. The continuing significance of this article is that it anticipated the current knowledge that jobs and other economic factors are not the only things that people consider when making location decisions: they also take into account their personal preferences. This idea was furthered by Graves and Linneman (1979), who argued that people may move not just for economic reasons, but also because they are drawn to particular location-specific amenities. Sjaastad (1962) argued that people decide to migrate when the net benefits of moving are greater than the net costs of doing so; his analysis only considers wages, but the principle would still hold if the amenities in a new place were considered part of the net benefits of moving there.

Clearly the utility of amenities - and the extent to which these may be counted among the net benefits of moving - can vary by age, sex, and other demographic characteristics. In their analysis of migration among white males, Clark and Hunter (1992) write that while older men are more attracted to areas with more amenities on offer, and younger men are more attracted to labor opportunities, younger men are also strongly attracted to central city areas. While this study does not reveal how much amenities contributed to this central-city attraction in the 1990s, similar findings today would appear

totally unremarkable. Firms too may consider amenities in their location decisions because it is much easier to attract skilled workers to high-amenity than to low-amenity areas (Gottlieb, 1995). Rogerson (1999) discusses in great detail the importance of quality of life indicators to both individuals and to the companies who seek to attract the most desirable workers. Greenwood and Hunt's (1989) argument that jobs are much more important than amenities in driving migration seems to be less true today than it was in 1989, unless primarily low-skilled, low-income workers are considered. Further, there is evidence to suggest that from a worker's perspective, living in a high-amenity area can serve as an additional type of compensation, and consequently may reduce the amount of pay a person would require to be convinced to live in that particular area (Clark & Hunter, 1992; Graves & Linneman, 1979; Deller, Lledo, & Marcouiller, 2008). These ideas of amenities as a benefits arise from Rosen's (1974) hedonic pricing model, which allows for the individual valuation of desirable environmental characteristics as part of a diverse bundle of goods offered by a place.

The notion of the "consumer city" has officially existed since the beginning of the 21<sup>st</sup> century, when Glaeser, Kolko, and Saiz (2001) introduced it in their paper of the same name. These authors posit that cities with more to offer in terms of amenities experience faster growth than cities with less to offer. Although the effect of amenities on migration, as well as the relatively recent trend of migration to central cities had been discussed separately in the literature before, Glaeser and his colleagues were among the first to put these two phenomena together in the context of US metropolitan areas to suggest that people might actually be basing their location decisions (either in full or in part) on the amenities

particular cities have to offer. Their article discusses several small thought experiments, the most intriguing one being a simple regression of log median income on log median home values. The authors call the residuals the "amenity index," arguing that the unexplained difference between home values and income indicates some sort of extra desirability (or lack thereof, depending on whether the residual is positive or negative). This sets a precedent for using home prices as a measure of a place's attraction, since it is unlikely that people would be willing to pay more to live in undesirable places.

Although cities are the focus of the consumer-city hypothesis, some particularly illustrative examples of amenities driving migration and growth are also found in suburban and rural areas. There is evidence to show that at least in the western US, rural areas that offer more amenities experience higher in-migration as well as higher incomes, though in these cases the focus tends to be on natural amenities rather than cultural ones (Shumway & Otterstrom, 2010).

## 2.3 What are "amenities" in an urban context?

In discussing amenity-driven growth, it is crucial to delineate what constitutes an amenity and what does not. There is plenty of scholarly work discussing the effect amenities can have on migration and location choice, but there is no good, consistent definition of an amenity (Deller et al., 2008). As mentioned earlier, there is a consensus that amenities fall into two categories: (a) natural or physical amenities, which include a pleasant climate, proximity to bodies of water, outdoor recreation opportunities, and public parks; and (b) cultural amenities, which include features such as art galleries, coffee shops, sports

stadiums, and festivals. Of these two types, natural amenities are typically more tangible and better defined. As far as cultural amenities go, the lines are more blurred, since people's preferences vary. There are also fewer quantifiable variables comparable to, say, annual precipitation, hours of winter sunlight, annual number of days of sunshine, or other such data that are used to measure natural amenities; additionally, data that tabulates the number of coffee shops, galleries, or other related businesses in an area may become obsolete quickly due to the fact that businesses can close or relocate. This can make cultural amenities harder to measure, and may also contribute to the fact that many studies of amenity-driven growth neglect them in favor of looking more at natural amenities.

Thus, very generally, it is understood that amenities can be related to either particular physical characteristics of a place (such as a coastal location or a temperate climate) or to its cultural and entertainment-related characteristics (e.g., a notable art scene or a vibrant downtown area), and usually to both. Older work had shown that physical amenities, particularly climate, have more robust positive effects on a place's desirability than cultural ones (Clark & Hunter, 1992; Graves, 1980), although there was also evidence to suggest that cultural and recreational amenities can add to the appeal (Clark & Kahn, 1988). More recent research however has clearly indicated that cultural amenities could be particularly important for attracting migrants with higher human capital (Florida, 2002b). Indeed, anybody can enjoy a view of the ocean or a temperate climate, but art museums and opera houses tend to attract a more highly skilled and educated population. Conversely, cities with greater human capital see less outmigration (Whisler, Waldorf, Mulligan, & Plane, 2008). However, despite the intuitive appeal (and evidence for) the arguments linking cultural

amenities and populations with high human capital, it is not clear that cultural amenities on their own are enough to significantly affect property values (and by proxy, housing demand): for example, Boualam (2014) finds that while cultural amenities may increase the livability of areas, they do not have a significant impact on median rents.

Studies that do discuss cultural amenities usually include them alongside natural amenities. This is useful in the sense that it is often a combination of natural and cultural amenities that attracts people to a place, but the drawback is that the impact of cultural amenities on their own is not fully explored in the general case (an exception is Boualam, 2014: see above). For example, in their paper on amenities in selected Colorado communities, Ganning and Flint (2010) attempt to create an amenity index that reflects the value of both natural and cultural amenities. Since their area of interest is home to several skiing communities, they include physical variables such as forest cover and proximity to water, as well as economic and cultural variables such as percentage of seasonal housing and employment in arts, entertainment, and recreation. The focus on a relatively small and fairly homogenous study area makes considerable detail possible, but the approach does not distinguish the effect of cultural versus physical amenities, nor does it easily scale to larger regional and national levels. Despite the associated data challenges, it is important to consider cultural amenities in any study of amenity-driven growth. Besides direct measures of amenities such as tallying up specific types of businesses, it is also possible to use indirect measures, such as employment in the appropriate industries (Markusen, Wassall, DeNatale, & Cohen, 2008). Although this may not necessarily provide the most accurate representation of amenity levels in a particular area (depending on what aspects one is trying

to measure), the advantage of this approach is that it is easier and quicker for preliminary investigations, and if the results prove interesting enough to merit closer inspection, more direct forms of measurement may be used.

It should be noted that cultural amenities are particularly interesting from a local policy standpoint since they are controllable to some extent, and could therefore potentially be manipulated to increase a place's attractiveness: a city might not be able to do anything about its chronically wet and miserable weather, for example, but it could in principle invest in a new music center, arts fair, or sports stadium. Whisler et al. (2008) argue that young, college-educated people value recreation and cultural amenities highly and tend to leave areas with low human capital. These authors suggest that in the case of metro areas that are struggling to build a strong human capital base, "investments in cultural activities and recreational opportunities could possibly payoff [sic] by reducing the loss of the young college-educated residents" (90). This modern emphasis on the importance of cultural amenities also has interesting theoretical implications.

## 2.4 Implications for classical location theory

Part of what makes the consumer-city hypothesis so interesting is that it turns much of classical location theory on its head. A first obvious challenge is to the basic/non-basic distinction. Basic industry normally refers to manufacturing and other types of production intended for export, and non-basic industry refers to businesses like grocery stores and doctors' offices, which provide goods and services intended for local consumption. Historically, the idea had been that basic industry was what attracted valuable workers to a

city and led to economic and population growth, and thus had to be up and running successfully before non-basic industry could develop. However, the consumer city hypothesis implies that the non-basic industries can develop in the absence of basic industries and moreover, also attract the most valuable workers. In fact, they can even become a sort of basic industry in their own right: instead of exporting goods, they can 'export' high-level services and lifestyles by serving as a location-specific attraction that brings outsiders in to experience it. An example might be a particularly reputable doctor whose patients come from all over the globe, or famous restaurants like Chez Panisse in Berkeley or Alinea in Chicago, which attract 'foodies' from near and far.

Another element of classical location theory that the consumer-city hypothesis defies is Christaller's central place theory (1933), which lays out the idea that human settlements develop in a hierarchy based on the dual effects of range, which refers to the distance a person is willing to travel for a particular good or service, and threshold, which refers to the minimum number of customers within the range of a particular good or service needed to support that particular good or service. This theory explains why it is typically much easier to find a gas station or a place to buy milk than it is to find a luxury car dealership: milk and gas have much shorter ranges and lower thresholds than luxury vehicles. What the consumer-city hypothesis argues, though, is that the threshold for certain amenities traditionally ranked as "medium level" such as good restaurants or a great local art scene is actually lower, and their range greater than one would expect based on central place theory. In effect, what this says is that smaller cities can actually support more of these types of amenities than one would think.

Further, the consumer-city hypothesis contradicts the work of Alonso (1964), which extends von Thünen's (1826) model of agricultural land use to urban land use by introducing the notion that each land use is characterized by its own utility-based bid-rent function. One of the implications of the theory is that poorer households end up on more expensive land near the city center, since they have a greater need to be near their jobs and cannot afford the transportation necessary to live farther away, whereas wealthier households end up living farther out on larger parcels of land. In contrast, the consumer-city hypothesis predicts that city centers should become more desirable places to live due to the greater access to urban amenities that they provide, resulting in wealthier people increasingly living in central city areas. As Ehrenhalt (2012) explains, the urban cores of some American cities are already seeing an influx of affluent households, which shows that the consumer-city conception of urban land use may already be taking hold.

### 3. Methods and data

Based on the literature described above, I expect that cities with more cultural amenities will have higher median home prices than those with fewer cultural amenities to offer. To investigate this assumption, the analysis seeks to determine whether 1) greater amenity-related employment is associated with higher median home prices and 2) whether amenity-related employment can be used to predict future median home prices. In order to examine the relationship between cultural amenities and demand for US cities that have them, this study employed statistical analysis techniques. The analysis was performed on 357 Metropolitan Statistical Areas (MSAs) in the United States, including those in Alaska

and Hawaii. Median home prices were used as a proxy for demand, and several demographic and geographic variables (described below) were included to account for different characteristics that might affect demand for particular places. Ultimately, four linear regressions were run using the R statistical software to investigate the model's ability to account for demand in different metropolitan areas.

#### 3.1 Data sources

All of the data were obtained from the U.S. Census Bureau's American Community Survey (ACS) 3-year estimates for 2012 and 2005, with the exception of education data (obtained from the 2011 ACS 3-year estimates) and the employment data (obtained from the Bureau of Labor Statistics for 2012 and 2005). Three-year-estimates were chosen over one-and five-year estimates since they offered a compromise between recency and precision, respectively. ACS data were chosen over decennial census data since they are released on a more frequent basis, and compared to other potential data sources, they have the advantage of being easy to obtain, fairly comprehensive, and available free of charge.

MSAs were chosen as the unit of analysis, as in the original Glaeser et al. (2001) study and others (Florida, 2002a, 2002b; Whisler et al., 2008). Besides having some precedent in the literature, MSAs also reflect the fact that many (if not most) metropolitan areas in the United States stretch over county lines, so using them as the unit of analysis is an efficient way to include all counties that are associated with a particular urban area. The analysis included 357 MSAs in the United States (excluding Puerto Rico), since this was the

total number of MSAs included in the 2005 data. In order to facilitate comparisons over time, eight MSAs that were added between 2005 and 2012 were excluded from the study.

The years 2012 and 2005 were chosen as the years of analysis with some reservations, as they were only seven years apart, which may not necessarily provide a clear picture of change over time. However, these particular years were chosen because 1) 2012 was the latest year for which reliable data was available at the time most of this work was done and 2) the ACS datasets used only went back as far as 2005, so it was not possible to look at any earlier years. An additional complication, addressed further in the Discussion, is that the 2008 recession hit in the middle of this time period, disrupting longer-term trends. With different data sources it might have been possible to look at longer and more typical time periods.

#### 3.2 Variable definitions

The variables for log median home value and log median income were chosen as in the original Glaeser et al. (2001) study. However, instead of using an index value such as the Freddie Mac House Price Index to measure home value, I used raw price data from the ACS; using index values skewed results too heavily towards areas with rapid growth (such as oil towns) and did not adequately reflect demand based on other characteristics.

Unfortunately, using price data does not account for varying sizes of homes and other attributes that may influence prices aside from demand. That is, an amenity-poor area with larger homes may have a median price comparable to that of an amenity-rich area with smaller homes. Nevertheless, median home prices are still a reasonable measure of demand

because it is difficult to imagine people paying large sums of money to live somewhere if there is no actual demand to drive prices up.

Education levels were measured as a percentage of the population aged 25 years and up with a bachelor's degree or higher, and this variable was chosen because education is a known measure of human capital. Furthermore, it seems likely that a more educated population might also be associated with a higher demand for cultural amenities, particularly since (as noted above) people with more education may be more likely to have jobs that allow some leisure time than their less-educated peers. In the case of the 2012 data, the 2011 3-year ACS estimates were chosen for this variable rather than the 2012 3-year estimates because the 2012 estimates were missing values for some MSAs and it seemed unlikely that the percentages would change drastically over a year's time.

The employment proportion was constructed by dividing each MSA's employment in selected industries (arts, design, entertainment, sports, and media) by the total employment in that MSA. Although it might have been beneficial to include other industries (such as research and development or food service), the categorization of industries by the BLS was such that particular segment was the only segment that included occupations we wanted and did not include occupations that would be unhelpful for this study. This segment also does a fairly good job of capturing most of what might be called "amenity" workers. The decision to measure amenities by occupation was based on the assumption that a larger number of workers in that field would indicate a greater offering of amenities in the area, and it also proved simpler than attempting to count up numbers of restaurants, museums, etc. in an area, for example. There is also some precedent for using

amenity employment as a metric for amenity levels (Markusen et al., 2008), though it is not commonly used as a predictor of demand as it is here.

Population was included to account for the fact that areas with larger populations are by default more likely to have more amenities per capita on offer simply by virtue of their size (see Christaller's central place theory).

Median age was also included in the model, as older populations would generally have had more years in the workforce than younger ones. With more time in the workforce, older people would be more likely to have accumulated the necessary capital to purchase a more expensive home.

To account for unmeasured features of MSAs that are unique to regions, the eight BEA-defined regions were included as fixed effects. Although dividing the country into regions is never a precise process—for example, who is to say that Texas belongs in the southwest and not in the southeast?—the BEA divisions did not seem unreasonable. The BEA regions are split along state lines, so in the case of MSAs covering multiple states, each MSA was assigned to the state having the highest proportion of households in that particular MSA. The only exception to BEA categorization was in the case of Washington, D.C., which fell into the Southeast because most of its population resides in Virginia. Dummy variables were assigned to each region except the "Far West" region (containing Alaska, California, Hawaii, Nevada, Oregon, and Washington), which served as the control.

#### 4. Results

4.1 Initial model – 2012 data

Initially, a regression model was run for 357 MSAs using data from 2012 (with the exception of education levels, for which 2011 data was used) to examine the predictive power of the variables described above. Log median income, education levels, employment proportion, log population, median age, and 7 regional indicator variables were regressed onto log median home values. Log transformations for median home values, median income, and population were used to account for these variables being one-sided (that is, able to reach positive infinity but not below 0).

Table 1

Variable Name	Explanation	
logMedHouseValue	Log median house value	
logMedIncome	Log median income	
pctBachPlus	Percentage of population 25 and up with	
	bachelor's degree or higher	
emplRatio	Amenity employment as a percentage of total	
	employment	
logPop	Log population	
medAge	Median age	
neng	New England (Connecticut, Maine,	
	Massachusetts, New Hampshire, Rhode	
	Island, Vermont)	
mest	Mideast (Delaware, Maryland, New York,	
	New Jersey, Pennsylvania)	
glak	Great Lakes (Illinois, Indiana, Michigan,	
	Ohio, Wisconsin)	
plns	Plains (Iowa, Kansas, Minnesota, Missouri,	
	Nebraska, North Dakota, South Dakota)	
sest	Southeast (Alabama, Arkansas, Florida,	
	Georgia, Kentucky, Louisiana, Mississippi,	
	North Carolina, South Carolina, Tennessee,	
	Virginia [including Washington, D.C.], West	
	Virginia)	
swst	Southwest (Arizona, New Mexico,	
	Oklahoma, Texas)	
rkmt	Rocky Mountain (Colorado, Idaho, Montana,	
	Utah, Wyoming)	

fwst (not included in	Far West (Alaska, California, Hawaii,
regressions)	Nevada, Oregon, Washington)

The model itself is as follows:

## log Med House Value 2012

```
= logMedIncome2012\beta_1 + pctBachPlus2012\beta_2 + emplRatio2012\beta_3 \\ + logPop2012\beta_4 + medAge2012\beta_5 + neng12\beta_6 + mest12\beta_7 \\ + glak12\beta_8 + plns12\beta_9 + sest12\beta_{10} + swst12\beta_{11} + rkmt12\beta_{12}
```

The adjusted R-squared of this model was 0.81, which showed that the model was a good fit. Additionally, all but one of the variables were significant at the 95% level or higher; the only variable that was not significant was log population (see table 2). Of particular interest was the fact that the proportion of amenity employment to total employment was significant at the p < 0.05 level and had the largest coefficient by far, which suggests that amenity employment is a very strong predictor of home prices. Median income and education levels were also strong predictors with positive coefficients. Median age proved to be significant as well, though its effects were quite small. The regional variation dummies all showed small but significant negative coefficients, indicating that in comparison to the default Far West region, all other regions were associated with slight decreases in median home values, possibly due to higher home values in California and Hawaii driving the average Far West home values up. As the results from the model

provided some confirmatory evidence for a link between amenities and higher median home prices, I decided that further investigation was justified.

## 4.2 Regression with 2005 data

To examine change over time, the model was re-run to include data from 2005. logMedHouseValue2005

 $= logMedIncome2005\beta_1 + pctBachPlus2005\beta_2 + emplRatio2005\beta_3$   $+ logPop2005\beta_4 + medAge2005\beta_5 + neng05\beta_6 + mest05\beta_7$   $+ glak05\beta_8 + plns05\beta_9 + sest05\beta_{10} + swst05\beta_{11} + rkmt05\beta_{12}$ 

The 2005 data yielded somewhat different results, but was nonetheless a fairly good fit with an adjusted R-squared of 0.76. Again, all variables but one were significant at the 0.05 level or better, but in this case, the employment proportion was the only variable that was not significant (see table 3). However, it did have a very high coefficient compared to the other variables. As in the previous iteration of the model, median income and education levels were also significant, although this time median income was much more significant than education levels. Median age was significant again, but with a similarly small effect. As before, the regional dummy variables were all highly significant and all had small negative coefficients. These results, while not as encouraging as the ones from 2012, still justified further investigation. They also suggest some variability in the usefulness of amenities as indicators of demand.

## 4.3 Predicting 2012 median house values with 2005 data

As the model fit the data from both 2012 and 2005 fairly well, it was decided to regress 2012 median home values against 2005 regressors. This regression had an adjusted R-squared of nearly 0.8 (see table 4), which showed it to be an even better fit than the previous regression (using 2005 data) and almost as good as the initial regression (using 2012 data). In this case, the employment proportion was found to be statistically significant at the 0.05 level with a coefficient much higher than those of the rest of the variables, which suggests that it functions as a very good predictor of median house prices. As in the previous regressions, median income and education levels were also very significant, though they had a less dramatic impact than that of the employment proportion. Median age continued to be significant with a slightly larger effect than in the previous regressions, suggesting that its impact became somewhat stronger. Overall, these results indicate a significant link between higher amenity levels in 2005 and higher demand in 2012.

#### 4.4 Percentage change

Lastly, I decided to examine the effect of the variables using 2005 data to predict the percentage change in median home prices from 2005 to 2012 as a means of exploring a possible causal link between amenity employment and increases in median home prices. In this case, the dependent variable was changed to the percentage change in home prices between 2005 and 2012.

$$\begin{split} \textit{PctChange} &= \textit{logMedIncome} 2005\beta_1 + \textit{pctBachPlus} 2005\beta_2 + \textit{emplRatio} 2005\beta_3 \\ &+ \textit{logPop} 2005\beta_4 + \textit{medAge} 2005\beta_5 + \textit{neng} 05\beta_6 + \textit{mest} 05\beta_7 \\ &+ \textit{glak} 05\beta_8 + \textit{plns} 05\beta_9 + \textit{sest} 05\beta_{10} + \textit{swst} 05\beta_{11} + \textit{rkmt} 05\beta_{12} \end{split}$$

However, this exercise proved to be less fruitful. With an adjusted R-squared of 0.37, the model was not an ideal fit (see table 5). Although the employment proportion still had a much higher effect than the other variables, it did not prove to be statistically significant. Median income and population, however, did turn out to be statistically significant, though with slightly negative effects. Based on these results, it would appear that cultural amenities are not a useful predictor of percentage change in home values (and demand) over time.

About 77% of the MSAs studied experienced increases in median home prices between 2005 and 2012, with the remaining 23% experiencing decreases or no change. Among metro areas that saw the greatest decreases in home prices, California cities were disproportionately represented, which may indicate that California homes were greatly overvalued in the real estate bubble leading up to the 2008 recession and consequently lost more value when the bubble collapsed. On the other hand, metro areas that saw the greatest increases tended to be oil towns (for example, Midland, Texas; Odessa, Texas; and Lafayette, Louisiana) or otherwise located in Sunbelt states, which may point to larger economic trends or other geographic factors (such as warm climates or newer, less dense urban areas) as key drivers of home price increases. It appears that amenity employment is not a good predictor of later changes in home prices, so further inquiry into the connections between amenity employment and percentage change in home prices was dropped.

#### 5. Discussion

## 5.1 Results and implications

The major finding of this study is that there is a positive association between cultural amenities and higher home prices, which provides support for the consumer-city hypothesis in that cities that are presumably the most in demand also tend to have greater employment in cultural amenity-related fields. The greater cultural amenity employment in more desirable cities suggests that residents of these cities tend to "consume" more cultural amenities than their counterparts in less desirable areas. Furthermore, this also shows that amenity-related employment can be used as a predictor of home values at a later point in time. Since cities with higher amenity employment in 2005 saw higher home prices in 2012, it is possible that amenities contribute to an area's resilience in the face of a global economic crisis, or at least are indicators of a place's underlying resilience. Although employment in cultural amenity-related fields is not directly associated with increases in median home prices over time, its association with higher median home prices in general shows that areas with more amenities do see higher demand.

There is also a strong correlation between education levels and cultural amenity employment [0.63], which shows that more highly-educated populations are associated with greater amenity employment. Though this does not mean that highly educated people tend to work in amenity-related fields or to consume those amenities, this does support the notion of a "creative class" that may be choosing to live in cities with higher home prices due to the greater presence of cultural amenities. Unsurprisingly, education levels also serve as a

predictor of higher home values, so it seems that there is some interplay between greater amenity employment and educated populations that makes some cities generally more desirable than others, or it could be that desirable areas tend to attract more educated people who enjoy consuming cultural amenities.

It must be acknowledged that the model does a better job of predicting home values for some places than for others. For example, in comparing the residuals for each MSA among the 2012, 2005, and combined 2005-2012 regressions, some MSAs consistently have high positive residuals, which indicates that their median home values were higher than the model predicted they should be (see Table 6). Consequently, it seems reasonable that the MSAs for places like Honolulu and New York City consistently have high positive residuals, as these are generally considered desirable for reasons well beyond their cultural amenities. However, each set of residuals also contains surprises. Salinas, California, has a high positive residual in the 2012, 2005, and combined regressions; meanwhile, in the 2012 regression, the relatively unknown Valdosta, Georgia, has a higher positive residual than Napa or San Diego. In the 2005 regression, Sandusky, Ohio, has a higher positive residual than Orlando, Florida, or Los Angeles, and in the combined regression, Sacramento beats out both Napa and Los Angeles, among other cities. On the other hand, cities that are known for being creative-class hotbeds such as Portland, Oregon, and Durham/Chapel Hill, North Carolina, sometimes end up with more negative residuals than lesser-known cities like Dalton, Georgia (a mill town), and Saginaw, Michigan, suggesting that the home prices of some areas are not keeping pace with their cultural offerings. In general, the MSAs that are furthest off the mark with the greatest positive residuals tend to be located in California or in

Sunbelt states, which may indicate that a good climate or other geographic factors tend to drive home prices up. There is no obvious pattern amongst MSAs with the greatest negative residuals, suggesting that a variety of factors may cause home prices to be lower than amenity levels would predict (see table 6). This seems to confirm that cultural amenities are just one of several factors that people consider when choosing where to live, and they may not even be among the most important ones.

While the results from this model leave plenty of gaps to be filled in—for example, a more in-depth look at potential causal relationships between amenity-based employment and higher home prices would be helpful--the fact that there is a significant positive partial correlation between cultural amenity employment and home prices for some of the models tested is in line with the key ideas of the consumer-city hypothesis. Although the model may not be as useful as one would like in its predictions for individual cities, it does point to more of a macro-scale relationship between cultural amenities and desirability in metro areas.

Practical implications of these findings suggest that fostering cultural amenities could potentially be a useful part of a larger strategy for cities looking to maintain or increase their appeal to potential residents with high human capital. Increasing cultural amenities is clearly not a panacea for ailing cities--as described above, and as noted by Boualam (2014), higher amenity employment is not directly linked to increases in home prices over time. It would be foolish for a community to prioritize amenity growth over other areas of civic improvement unless several other favorable conditions are also present. However, it seems reasonable to suggest that because higher amenity levels are associated

with greater attraction to areas that have them, promoting cultural amenity growth (or at least failing to discourage it) would contribute to an area's overall appeal.

## 5.2 Limitations of the study

Due to a variety of constraints, it was not always possible to use the best approach in carrying out this study; a number of things could have been done differently if circumstances had allowed. Most of the major problems or possible criticisms of this study can be sorted under four different headings.

## 5.2.1 Methods, data, and levels of analysis

First and foremost, the metropolitan statistical area (MSA) may not be the ideal unit of analysis for this type of work, since MSAs vary widely in the types and extent of areas they cover. Because MSAs are composed of counties and do not consider city limits or other relevant boundaries, each individual MSA also contains a different mix of urban, suburban, and/or rural areas, depending on the makeup of its constituent counties. For example, by design an MSA combines one or more cities with their suburban peripheries. This means that several areas with very different characteristics are lumped together and counted as one statistical unit, which may hide some important trends as well as significant differences in urban quality from one part of an MSA to another. However, there are precedents in the literature for using this level of spatial analysis (Glaeser et al., 2001; Florida, 2002; Whisler et al., 2008). Additionally, data were much more readily available at

this scale than at some other scales: in particular, BLS data were available at the MSA, state and national levels, but not at lower levels like counties or cities.

Another problem lies with the BEA regions used to categorize MSAs. While many of the categorizations seem obvious (for example, few would argue that the state of Georgia belongs in any region other than the Southeast), others are more complicated. The Far West region includes both cold, sparsely populated Alaska and sunny, populous California, and having such a heterogeneous set of states grouped together likely contributes to inaccuracy in predictions for the region. Depending on the specific area of interest, alternative categorizations could result in more accurate predictions.

#### 5.2.2 Real estate and the recession

The 2008 global financial crisis hit in the middle of the study period, causing worldwide economic upheaval. Consequently, the U.S. economy in 2005 and in 2012 were two fundamentally different creatures, and this complicates my analysis in a number of ways. The variables most affected by the recession are probably median home value and median income. Especially since the burst of the U.S. real estate bubble in 2006 was at the heart of the crisis, this poses real problems for the analysis of home values over time. The upside of this situation is that it provided an opportunity to investigate whether amenities contribute to a metro area's resilience in the wake of the recession.

Another problem is that because of demographic and lifestyle changes, many young professionals may prefer to rent their homes instead of buying, so using the value of owner-occupied housing as a metric for demand may not accurately reflect the desirability of places

with high concentrations of young renters. According to the U.S. Census Bureau, although homeowners outnumber renters in all but one of the MSAs in the U.S., owner-occupied housing units make up only about 65% of all occupied housing units, which means that 35% of occupied housing units are not well-represented by the ACS data used in this analysis. However, conflating median rent and median home values would be problematic because not all renters are renters by choice: people who might prefer to own their home but cannot afford a mortgage may be forced to rent instead. Rent-control is also an issue because it may lead to discrepancies between rent paid and what the home is actually worth. As a result, owner-occupied home prices remain an appropriate metric to use for this analysis.

## 5.2.3 Amenity employment

This study also uses the proportion of employment in certain amenity-related fields to total employment in a given MSA as a proxy for (mostly) cultural amenities. In general, it makes sense to expect that metro areas with more cultural amenities should have higher employment in the appropriate amenity-related fields, though one could argue that the characterization of amenity-related fields used in this study is somewhat arbitrary. First, as mentioned earlier, the BLS category used does not include employment in restaurants and certain other facilities normally associated with cultural amenities – though of course restaurants are not only used by the high-human capital people that also enjoy art museums and concert halls. Second, that category also includes employment in sports, some of which may be more associated with natural rather than cultural amenities. Additionally, cultural

amenities and related employment may be unevenly distributed throughout MSAs, whereas natural amenities such as climate tend to be more uniformly distributed at this scale.

## 5.2.4 Correlation, causality, and multicollinearity

This analysis examines the correlation between higher amenity employment and higher home prices, and while correlation does not equal causation, it does provide some evidence for amenities as an attracting factor in location decisions. However, this also creates a chicken-and-egg situation: it is possible that the reason metro areas with more cultural amenity employment in 2005 saw higher home prices in 2012 is that those areas were already fairly resilient to begin with, and as a result were able to support more amenities (as opposed to a struggling city). This study does not investigate causality, and consequently is unable to shine any light on whether amenities lead to higher home prices or vice-versa.

Multicollinearity is also a problem with this model, as several of the variables (specifically, median income and education levels) are likely strongly correlated with each other. While this does not compromise the integrity of the model as a whole, it does mean that the prediction abilities of individual variables are probably not represented as accurately as one would like. Since the amenity employment proportion is the variable of most interest in this situation, the worst-case scenario would be that its predictive power was grossly over-or underestimated, but this risk did not justify removing other variables to account for this possibility.

#### 6. Conclusion

The consumer city hypothesis may be part of a broader search for new urban growth and land use theories formulated for the demographic, socio-economic, and cultural changes of the post-industrial age. The results of this study support the consumer-city hypothesis in that they reveal a link between higher cultural amenity levels and higher home prices.

Furthermore, they also show a connection between higher cultural amenity levels and higher home prices at a later point in time, which provides evidence for the consumer-city phenomenon as a process that is continuing over time. Although it will take much more time and careful study to determine whether the consumer-city hypothesis reflects an isolated phenomenon or a key new understanding of how cities work in the post-industrial age, the findings of this analysis indicate that real-world processes are already showing some of the tendencies it describes.

In addition to providing support for the consumer-city hypothesis, this analysis also opens up a number of opportunities for future research. For example, much more investigation of possible causality between amenities and home prices will be needed in order to provide a more conclusive argument in favor of the consumer-city hypothesis. Furthermore, it could be useful to repeat the analysis used in this study at a later point in time to see if the same effects are found over a greater period of time, or perhaps the analysis could be done at different spatial scales to see if evidence to support the consumercity phenomenon exists over larger or smaller geographic areas. It would also be worthwhile to examine other metrics for demand aside from home prices: while it makes sense that people are willing to pay more to live in more desirable areas, this does not reflect

all demand for those areas. For example, it excludes young "creatives" who may prefer to rent a home in an amenity-rich city than to own one in a less well-endowed area. Future studies might consider renter-occupied housing or a combination of owner-occupied and renter-occupied housing to see if patterns from this analysis also appear with other housing types.

Another important avenue for future work would be to examine the applicability of the consumer-city hypothesis in more First World countries aside from the US. European countries could provide a particularly interesting setting for future inquiry, given that Europeans have traditionally shown a preference for multifamily housing in central city areas, whereas Americans have only recently begun to shift away from the quintessential 'American Dream' of a single-family home in the suburbs. Developing countries might also yield intriguing possibilities: while this phenomenon currently focuses on First World cities in countries with mostly service- and information-based economies, it could also be useful in predicting and understanding future growth patterns in countries with less-developed economies. It may also be the case that some developing-world cities are already beginning to display some of the characteristics described by the consumer-city hypothesis. As the world continues to urbanize, understanding cities and their processes will become more and more important. By investigating the consumer-city hypothesis from a somewhat different perspective than in previous work, this research provides fragments towards an urban location theory for the post-industrial age.

#### References

- Alonso, W. (1964). *Location and land use; toward a general theory of land rent*. Cambridge, MA: Harvard University Press.
- Bell, D. (1999). *The Coming of Post-Industrial Society: A Venture in Social Forecasting* (Reissue edition). New York, NY: Basic Books. (Original work published 1973)
- Boualam, B. (2014). Does culture affect local productivity and urban amenities? *Regional Science and Urban Economics*, 46, 12–17. http://doi.org/10.1016/j.regsciurbeco.2014.01.008
- Christaller, W. (1957). A critique and translation of Die zentralen Orte in Süddeutschland. (C. W. Baskin, Trans.). Charlottesville, VA. (Original version published 1933)
- Clark, D. E., & Hunter, W. J. (1992). The Impact of Economic Opportunity, Amenities and Fiscal Factors on Age-Specific Migration Rates. *Journal of Regional Science*, *32*(3), 349–365. http://doi.org/10.1111/j.1467-9787.1992.tb00191.x
- Clark, D. E., & Kahn, J. R. (1988). The Social Benefits of Urban Cultural Amenities. *Journal of Regional Science*, 28(3), 363–377. http://doi.org/10.1111/j.1467-9787.1988.tb01088.x
- Deller, S. C., Lledo, V., & Marcouiller, D. W. (2008). Modeling Regional Economic Growth with a Focus on Amenities. *Review of Urban & Regional Development Studies*, 20(1), 1–21. http://doi.org/10.1111/j.1467-940X.2008.00139.x
- Ehrenhalt, A. (2012). *The Great Inversion and the Future of the American City* [Kindle edition]. Vintage. Retrieved from Amazon.com.
- Ewers, M. C. (2007). Migrants, markets and multinationals: competition among world cities for the highly skilled. *GeoJournal*, 68(2/3), 119–130.
- Florida, R. (2002a). Bohemia and economic geography. *Journal of Economic Geography*, 2(1), 55–71. http://doi.org/10.1093/jeg/2.1.55
- Florida, R. (2002b). The Economic Geography of Talent. *Annals of the Association of American Geographers*, 92(4), 743–755. http://doi.org/10.1111/1467-8306.00314
- Florida, R. (2012). *The Rise of the Creative Class, Revisited* (Revised edition). New York, NY: Basic Books. (Original work published 2002)
- Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, *1*(1), 27–50. http://doi.org/10.1093/jeg/1.1.27
- Gottlieb, P. D. (1995). Residential Amenities, Firm Location and Economic Development. *Urban Studies*, 32(9), 1413–1436. http://doi.org/10.1080/00420989550012320
- Graves, P. E. (1980). Migration and Climate. *Journal of Regional Science*, 20(2), 227–237. http://doi.org/10.1111/j.1467-9787.1980.tb00641.x
- Graves, P. E., & Linneman, P. D. (1979). Household migration: Theoretical and empirical results. *Journal of Urban Economics*, 6(3), 383–404. http://doi.org/10.1016/0094-1190(79)90038-X
- Greenwood, M. J., & Hunt, G. L. (1989). Jobs versus amenities in the analysis of metropolitan migration. *Journal of Urban Economics*, 25(1), 1–16. http://doi.org/10.1016/0094-1190(89)90040-5

- Markusen, A., Wassall, G. H., DeNatale, D., & Cohen, R. (2008). Defining the Creative Economy: Industry and Occupational Approaches. *Economic Development Quarterly*, 22(1), 24–45. http://doi.org/10.1177/0891242407311862
- Ravenstein, E. G. (1885). The Laws of Migration. *Journal of the Statistical Society of London*, 48(2), 167–235. http://doi.org/10.2307/2979181
- Rogerson, R. J. (1999). Quality of Life and City Competitiveness. *Urban Studies*, *36*(5-6), 969–985. http://doi.org/10.1080/0042098993303
- Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82(1), 34–55.
- Shumway, J. M., & Otterstrom, S. M. (2001). Spatial Patterns of Migration and Income Change in the Mountain West: The Dominance of Service-Based, Amenity-Rich Counties. *The Professional Geographer*, 53(4), 492–502. http://doi.org/10.1111/0033-0124.00299
- Sjaastad, L. A. (1962). The Costs and Returns of Human Migration. *Journal of Political Economy*, 70(5), 80–93.
- Tiebout, C. M. (1956). A Pure Theory of Local Expenditures. *Journal of Political Economy*, 64(5), 416–424. http://doi.org/10.2307/1826343
- U.S. Census Bureau. (2011, October). *Housing Characteristics: 2010*. Retrieved March 17, 2015, from http://www.census.gov/prod/cen2010/briefs/c2010br-07.pdf.
- Von Thünen, J. H. (1966). *Isolated state; an English edition of Der isolierte Staat*. (C. M. Wartenberg, Trans., P. Hall, Ed.) (1st ed.). Oxford, New York: Pergamon Press. (Original work published 1826)
- Whisler, R. L., Waldorf, B. S., Mulligan, G. F., & Plane, D. A. (2008). Quality of Life and the Migration of the College-Educated: A Life-Course Approach. *Growth and Change*, *39*(1), 58–94. http://doi.org/10.1111/j.1468-2257.2007.00405.x

# Appendix A - Tables

**Table 2: 2012 Regression Results** 

	Dependent variable:
	Log Median House Value 2012
Intercept	2.224***
	(0.774)
Log Median Income 2012	0.872***
	(0.076)
Percentage of Population 25 and Up with a Bachelor's Degree or Higher 2011	0.015***
	(0.002)
Employment Ratio 2012	8.467**
	(3.365)
Log Population 2012	-0.001
	(0.010)
Median Age 2012	0.007***
	(0.002)
New England	-0.219***
	(0.050)
Mideast	-0.397***
	(0.037)
Great Lakes	-0.561***
	(0.032)
Plains	-0.595***
	(0.040)
Southeast	-0.374***
	(0.032)
Southwest	-0.474***
	(0.037)
Rocky Mountains	-0.277***
	(0.043)
Observations	357
$\mathbb{R}^2$	0.818
Adjusted R <sup>2</sup>	0.811
Residual Std. Error	0.161 (df = 344)
F Statistic	$128.459^{***}$ (df = 12; 344)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*\*p<0.01 Coefficients are the first value shown for each variable; standard error is given in parentheses

**Table 3: 2005 Regression Results** 

	Dependent variable:
	Log Median House Value 2005
Intercept	-2.330 <sup>*</sup>
-	(1.314)
Log Median Income 2005	1.245***
	(0.131)
Percentage of Population 25 and Up with a Bachelor's Degree or Higher 2005	0.006**
	(0.003)
Employment Ratio 2005	4.396
	(5.350)
Log Population 2005	0.059***
	(0.014)
Median Age 2005	$0.009^{**}$
_	(0.004)
New England	-0.462***
-	(0.075)
Mideast	-0.731***
	(0.056)
Great Lakes	-0.796***
	(0.047)
Plains	-0.849***
	(0.058)
Southeast	-0.657***
	(0.047)
Southwest	-0.715***
	(0.057)
Rocky Mountains	-0.455***
	(0.062)
Observations	357
$\mathbb{R}^2$	0.764
Adjusted R <sup>2</sup>	0.756
Residual Std. Error	0.236 (df = 344)
F Statistic	$92.753^{***}$ (df = 12; 344)

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01 Coefficients are the first value shown for each variable; standard error is given in parentheses

Note:

Table 4: Predicting 2012 Median Home Prices with 2005 Data

	Dependent variable:
<del></del>	Log Median House Value 2012
Intercept	0.741
•	(0.934)
Log Median Income 2005	1.025***
	(0.093)
Percentage of Population 25 and Up with a	0.009***
Bachelor's Degree or Higher 2005	
	(0.002)
Employment Ratio 2005	9.082**
	(3.805)
Log Population 2005	0.005
	(0.010)
Median Age 2005	0.002
	(0.003)
New England	-0.226***
	(0.053)
Mideast	-0.377***
	(0.040)
Great Lakes	-0.622***
	(0.033)
Plains	-0.588***
	(0.041)
Southeast	-0.387***
	(0.034)
Southwest	-0.406***
	(0.041)
Rocky Mountains	-0.220***
Rocky Mountains	(0.044)
Observations	357
$R^2$	0.801
Adjusted R <sup>2</sup>	0.794
Residual Std. Error	0.168 (df = 344)
F Statistic	115.573*** (df = 12; 344)

\*p<0.1; \*\*p<0.05; \*\*\*\*p<0.01 Coefficients are the first value shown for each variable; standard error is given in parentheses

Note:

 Table 5: Predicting Percentage Change in Median House Value, 2005-2012

	Dependent variable:
	Percentage Change in Median House Value, 2005-2012
Intercept	2.948***
	(0.895)
Log Median Income 2005	-0.193**
	(0.089)
Percentage of Population 25 and Up with a Bachelor's Degree or Higher 2005	0.002
	(0.002)
Employment Ratio 2005	5.068
	(3.646)
Log Population 2005	-0.056***
	(0.010)
Median Age 2005	-0.009***
	(0.003)
New England	0.203***
	(0.051)
Mideast	0.329***
	(0.038)
Great Lakes	0.129***
	(0.032)
Plains	0.230***
	(0.039)
Southeast	0.248***
	(0.032)
Southwest	0.297***
	(0.039)
Rocky Mountains	0.209***
•	(0.042)
Observations	357
$\mathbb{R}^2$	0.395
Adjusted R <sup>2</sup>	0.373
Residual Std. Error	0.161 (df = 344)
F Statistic	$18.684^{***}$ (df = 12; 344)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01 Coefficients are the first value shown for each variable; standard error is given in parentheses

Greatest Positive Residuals - 2012 Regression	Table 6: MSAs with 10 Greatest Positive	e and Ne	egative Residuals (excluding Percentage C	Change)
New York-Northern New Jersey-Long Island, NY-NJ-PA         0.496         Kennewick-Pasco-Richland, WA         -0.426           Honolulu, HI         0.470         Rochester, NY         -0.375           Flagstaff, AZ         0.464         Las Vegas-Paradise, NV         -0.350           Santa Cruz-Watsonville, CA         0.451         Syracuse, NY         -0.350           Sant Luis Obispo - Paso Robles, CA         0.373         Binghamton, NY         -0.341           Salinas, CA         0.359         Johnstown, NY         -0.332           Santa Ere, NM         0.352         Pittsburgh, PA         -0.332           Kankakee-Bradley, IL         0.330         Spokane, WA         -0.320           Greatest Positive Residuals - 2005 Regression           Greatest Positive Residuals - 2005 Regression           Salinas, CA         0.756         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.649           Santa Fe, NM         0.684         Anchorage, AK         -0.652           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.462           Sunta Barbara-Santa Maria-Goleta, CA         0.510         Seattle-Tacoma-Bellevue, WA         -0			Greatest Negative Residuals – 2012 Reg	gression
Honolulu, HI	Ocean City, NJ	0.540	Elmira, NY	-0.457
Plagstaff, AZ	New York-Northern New Jersey-Long Island, NY-NJ-PA	0.496	Kennewick-Pasco-Richland, WA	-0.426
Santa Cruz-Watsonville, CA         0.451         Syracuse, NY         -0.350           San Luis Obispo – Paso Robles, CA         0.373         Binghamton, NY         -0.341           Salinas, CA         0.359         Johnstown, NY         -0.339           Santa Fe, NM         0.352         Pittsburgh, PA         -0.332           Atlantic City-Hammonton, NJ         0.335         Fairbanks, AK         -0.331           Kankakee-Bradley, IL         0.330         Spokane, WA         -0.326           Greatest Positive Residuals - 2005 Regression           Greatest Positive Residuals - 2005 Regression           Greatest Negative Residuals - 2005 Regression           Salinas, CA         0.766         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.6647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.655           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545 <td>Honolulu, HI</td> <td>0.470</td> <td>Rochester, NY</td> <td>-0.375</td>	Honolulu, HI	0.470	Rochester, NY	-0.375
San Luis Obispo – Paso Robles, CA         0.373         Binghamnon, NY         -0.341           Salinas, CA         0.359         Johnstown, NY         -0.339           Santa Fe, NM         0.352         Pitisburgh, PA         -0.331           Atlantic City-Hammonton, NJ         0.335         Fairbanks, AK         -0.331           Kankakee-Bradley, IL         0.300         Spokane, WA         -0.226           Greatest Positive Residuals – 2005 Regression             Greatest Negative Residuals – 2005 Regression               Greatest Positive Residuals – 2005 Regression               Salinas, CA             0.766             Spokane, WA             -0.669               Naples-Marco Island, FL             0.753             Kennewick-Pasco-Richland, WA             -0.647               Ocean City, NJ             0.734             Fairbanks, AK             -0.628               Santa Fe, NM             0.684             Anchorage, AK             -0.628               Santa Barbara-Santa Maria-Goleta, CA             0.615             Portland-Vancouver-Beaverton, OR-WA             -0.462               New York-Northern New Jersey-Long Island, NY-NJ-PA             0.540             Seattle-Tacoma-Bellevue, WA             -0.430               Prescott, AZ             0.540 <td>Flagstaff, AZ</td> <td>0.464</td> <td>Las Vegas-Paradise, NV</td> <td>-0.363</td>	Flagstaff, AZ	0.464	Las Vegas-Paradise, NV	-0.363
Salinas, CA         0.359         Johnstown, NY         -0.339           Santa Fe, NM         0.352         Pittsburgh, PA         -0.332           Atlantic City-Hammonton, NJ         0.335         Fairbanks, AK         -0.331           Kankake-Bradley, IL         0.330         Spokane, WA         -0.326           Greatest Positive Residuals - 2005 Regression           Salinas, CA         0.766         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.433           Merced, CA         0.540         Yakima, WA         -0.410           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals - Prediction Regression         Greatest Negative Residuals - Prediction Regression <td>Santa Cruz-Watsonville, CA</td> <td>0.451</td> <td>Syracuse, NY</td> <td>-0.350</td>	Santa Cruz-Watsonville, CA	0.451	Syracuse, NY	-0.350
Santa Fe, NM         0.352         Pittsburgh, PA         -0.332           Atlantic City-Hammonton, NJ         0.335         Fairbanks, AK         -0.331           Kankakee-Bradley, IL         0.330         Spokane, WA         -0.326           Greatest Positive Residuals - 2005 Regression           Greatest Negative Residuals - 2005 Regression           Greatest Negative Residuals - 2005 Regression           Salinas, CA         0.766           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.655           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.540         Seattle-Tacoma-Bellevue, WA         -0.410           Greatest Positive Residuals - Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435	San Luis Obispo – Paso Robles, CA	0.373	Binghamton, NY	-0.341
Atlantic City-Hammonton, NJ         0.335         Fairbanks, AK         40.331           Kankakee-Bradley, IL         0.330         Spokane, WA         40.326           Greatest Positive Residuals – 2005 Regression           Salinas, CA         0.766         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.565           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.433           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.540         Yakima, WA         -0.410           Greatest Positive Residuals – Prediction Regression         Greatest Negative Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rocheste	Salinas, CA	0.359	Johnstown, NY	-0.339
Kankakee-Bradley, IL         0.330         Spokane, WA         -0.326           Greatest Positive Residuals - 2005 Regression           Salinas, CA         0.766         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.410           Prescott, AZ         0.504         Yakima, WA         -0.410           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression         Greatest Negative Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY	Santa Fe, NM	0.352	Pittsburgh, PA	-0.332
Greatest Positive Residuals – 2005 Regression           Salinas, CA         0.766         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.411           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355	Atlantic City-Hammonton, NJ	0.335	Fairbanks, AK	-0.331
Salinas, CA         0.766         Spokane, WA         -0.669           Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.411           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355	Kankakee-Bradley, IL	0.330	Spokane, WA	-0.326
Naples-Marco Island, FL         0.753         Kennewick-Pasco-Richland, WA         -0.647           Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.411           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK	Greatest Positive Residuals – 2005 Regression		Greatest Negative Residuals – 2005 Reg	gression
Ocean City, NJ         0.734         Fairbanks, AK         -0.628           Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.504         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.410           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression         Greatest Negative Residuals – Prediction Regression         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.335           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.355           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.325	Salinas, CA	0.766	Spokane, WA	-0.669
Santa Fe, NM         0.684         Anchorage, AK         -0.565           Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.440           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.414           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression         Greatest Negative Residuals – Prediction Regression         O.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.330           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.322           Las Cruces, NM         0.386         Ithaca, NY	Naples-Marco Island, FL	0.753	Kennewick-Pasco-Richland, WA	-0.647
Flagstaff, AZ         0.627         Corvallis, OR         -0.562           Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.504         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.411           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.332           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.3	Ocean City, NJ	0.734	Fairbanks, AK	-0.628
Santa Barbara-Santa Maria-Goleta, CA         0.615         Portland-Vancouver-Beaverton, OR-WA         -0.464           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.414           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.355           Farmington, NM         0.412         Fairbanks, AK         -0.330           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.326           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pa	Santa Fe, NM	0.684	Anchorage, AK	-0.565
New York-Northern New Jersey-Long Island, NY-NJ-PA         0.545         Olympia, WA         -0.453           Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.414           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.355           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Flagstaff, AZ	0.627	Corvallis, OR	-0.562
Merced, CA         0.540         Seattle-Tacoma-Bellevue, WA         -0.440           Prescott, AZ         0.504         Yakima, WA         -0.414           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.355           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.325           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Santa Barbara-Santa Maria-Goleta, CA	0.615	Portland-Vancouver-Beaverton, OR-WA	-0.464
Prescott, AZ         0.504         Yakima, WA         -0.414           Port St. Lucie-Fort Pierce, FL         0.493         Pittsburgh, PA         -0.410           Greatest Positive Residuals – Prediction Regression         Greatest Negative Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.325           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	New York-Northern New Jersey-Long Island, NY-NJ-PA	0.545	Olympia, WA	-0.453
Port St. Lucie-Fort Pierce, FL0.493Pittsburgh, PA-0.410Greatest Positive Residuals – Prediction RegressionOcean City, NJ0.582Las Vegas-Paradise, NV-0.435New York-Northern New Jersey-Long Island, NY-NJ-PA0.511Rochester, NY-0.370Honolulu, HI0.502Wichita Falls, TX-0.355Santa Fe, NM0.487Reno-Sparks, NV-0.352Farmington, NM0.412Fairbanks, AK-0.350San Luis Obispo-Paso Robles, CA0.393Elmira, NY-0.322Las Cruces, NM0.386Ithaca, NY-0.325Flagstaff, AZ0.373Johnstown, PA-0.323Santa Barbara-Santa Maria-Goleta, CA0.355Kennewick-Pasco-Richland, WA-0.316	Merced, CA	0.540	Seattle-Tacoma-Bellevue, WA	-0.440
Greatest Positive Residuals – Prediction Regression         Greatest Negative Residuals – Prediction Regression           Ocean City, NJ         0.582         Las Vegas-Paradise, NV         -0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.322           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Prescott, AZ	0.504	Yakima, WA	-0.414
Ocean City, NJ         0.582         Las Vegas-Paradise, NV         .0.435           New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Port St. Lucie-Fort Pierce, FL	0.493	Pittsburgh, PA	-0.410
New York-Northern New Jersey-Long Island, NY-NJ-PA         0.511         Rochester, NY         -0.370           Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Greatest Positive Residuals – Prediction Regression	n	Greatest Negative Residuals – Prediction F	Regression
Honolulu, HI         0.502         Wichita Falls, TX         -0.355           Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Ocean City, NJ	0.582	Las Vegas-Paradise, NV	-0.435
Santa Fe, NM         0.487         Reno-Sparks, NV         -0.352           Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	New York-Northern New Jersey-Long Island, NY-NJ-PA	0.511	Rochester, NY	-0.370
Farmington, NM         0.412         Fairbanks, AK         -0.350           San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Honolulu, HI	0.502	Wichita Falls, TX	-0.355
San Luis Obispo-Paso Robles, CA         0.393         Elmira, NY         -0.332           Las Cruces, NM         0.386         Ithaca, NY         -0.325           Flagstaff, AZ         0.373         Johnstown, PA         -0.323           Santa Barbara-Santa Maria-Goleta, CA         0.355         Kennewick-Pasco-Richland, WA         -0.316	Santa Fe, NM	0.487	Reno-Sparks, NV	-0.352
Las Cruces, NM0.386Ithaca, NY-0.325Flagstaff, AZ0.373Johnstown, PA-0.323Santa Barbara-Santa Maria-Goleta, CA0.355Kennewick-Pasco-Richland, WA-0.316	Farmington, NM	0.412	Fairbanks, AK	-0.350
Flagstaff, AZ 0.373 Johnstown, PA -0.323 Santa Barbara-Santa Maria-Goleta, CA 0.355 Kennewick-Pasco-Richland, WA -0.316	San Luis Obispo-Paso Robles, CA	0.393	Elmira, NY	-0.332
Santa Barbara-Santa Maria-Goleta, CA 0.355 Kennewick-Pasco-Richland, WA -0.316	Las Cruces, NM	0.386	Ithaca, NY	-0.325
Santa Barbara-Santa Maria-Goleta, CA 0.355 Kennewick-Pasco-Richland, WA -0.316	Flagstaff, AZ	0.373	Johnstown, PA	-0.323
Santa Cruz-Watsonville, CA 0.335 Buffalo-Niagara Falls, NY -0.315	Santa Barbara-Santa Maria-Goleta, CA	0.355	Kennewick-Pasco-Richland, WA	-0.316
	Santa Cruz-Watsonville, CA	0.335	Buffalo-Niagara Falls, NY	-0.315

## Appendix B – Plots

Figure 1

#### Observed vs. Predicted Median Home Values - 2012

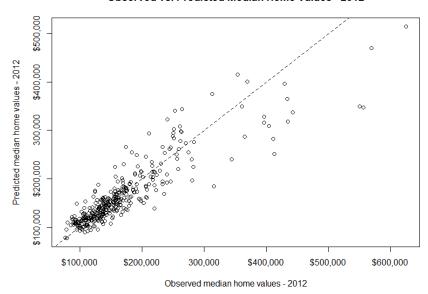


Figure 2

#### Observed vs. Predicted Median Home Values - 2005

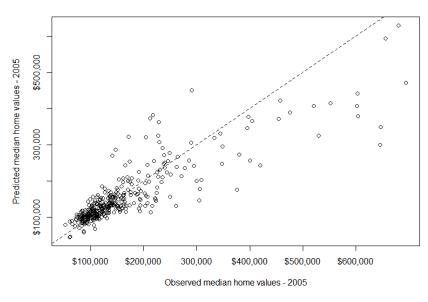


Figure 3

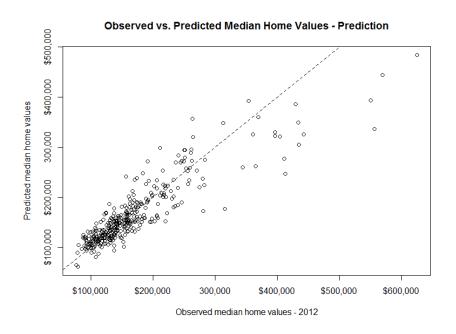


Figure 4

