THE SPATIAL AND GENTRYFING EFFECTS OF TRAFFIC CONGESTION

by

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(Under the Direction of Richard W. Martin)

ABSTRACT

Urban economic theory suggests that rising levels of traffic congestion will lead to smaller, more compact cities with residents living closer to the central business district (CBD). If the value of time lost commuting increases with income then high-income households should experience a stronger pull to the CBD than low-income households. These essays use data on traffic congestion in U.S. cities between 1980 and 2000 to test whether the extent to which high-income households' location within the central cities of U.S. metropolitan areas was affected by traffic congestion levels. Then test the extent to which high-income households are moving into gentrifiable neighborhoods as they disburse throughout the city center due to increases in traffic congestion levels. Independent metropolitan level measures of traffic congestion find statistical significance with respect to the location of high-income households with this effect increasing with median household income. With respect to gentrification, the findings demonstrate that traffic congestion is significant with respect to income gains in both central cities overall and the gentrifiable neighborhoods within central cities, but that the gentrifiable neighborhoods of these central cities experience 26% greater income gains with respect to all central city neighborhoods given the same levels of traffic congestion.

INDEX WORDS: Urban Economics, Spatial Analysis, Gentrification, Real Estate

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THE SPATIAL EFFECTS OF TRAFFIC CONGESTION

INTRODUCTION

Traffic congestion has become an ever increasing problem within American cities since 1980 and has been intensifying since 1990. Although it has experienced a recent decline beginning in 2008, there is no reason to expect traffic congestion to continue this trend given the last three decades of data. It costs individuals and corporations billions of dollars every year by wasting massive amounts of fuel, time, and money.

Traffic congestion is vitally relevant to city and county governments because around 70% of their respective budgets are derived from revenue generated by property taxes. If increasing traffic congestion is one of the factors causing high-income households to be more centralized in CBDs, it could significantly affect the tax basis of cities by driving up property values. This paper answers the question “Are high-income households more centralized in metropolitan areas with higher levels of traffic congestion?” The answer to this question is that traffic congestion is in fact a statistically significant contributor to the spatial patterns of high-income households within MSAs.

The hypothesis in this paper is that the more traffic congestion there is within a metropolitan statistical area (MSA), the greater the percentage of a city’s high-income households there are living in the city center since the usual positive association between income and distance from the city center may be weakened or reversed. This hypothesis is based on the urban spatial model developed by Alonso (1964), Muth (1967), and Mills (1969) along with the work of Baum-Snow (2007) which demonstrated that in the average city, for each exogenously assigned highway not constructed, the population decline in the central city was cut by more than half between 1950 and 1990.

To test this hypothesis, the paper presents a model which demonstrates how traffic congestion impacts high-income households more so than low-income households. The paper does so by estimating a series of regressions in which the change in the central city's share of high-income households is regressed on a set of explanatory variables that includes the change in metropolitan traffic congestion. The definitions of household income levels are based on the definitions of the Department of Housing and Urban Development (HUD). The factors controlled for include city size, location of amenities, housing age, public transportation usage, overall population location, and job location while the data set includes 91 MSAs over two time periods accounting for 182 observations.

Here, traffic congestion is accounted for by using two different MSA level measures; a travel time index and a measure for annual hours lost per commuter due to traffic congestion.[1] Both were taken from the Texas Transportation Institute's Urban Mobility Reports which compares peak period travel speeds to non-peak period travel speeds, isolating the traffic congestion portion of an MSA's travel times. The first measure accounts for the severity of an MSA's traffic congestion when it occurs while the second measure includes the how frequently the roads are congested in an MSA. These measures allow the model to truly measure whether or not a greater percentage of high-income households live closer to (further from) the city center in metropolitan areas with more (less) traffic congestion within an MSA.

The model predicts that for every 1% increase in peak travel period travel times with respect to non-peak period travel, the percentage of high-income (households with 120% of

[1] The F-test for statistical significance between the variances of the two traffic congestion measures is significant and the correlation of the two measures is 0.387.

median household income for an MSA or more) and very high-income (households with 200% of median household income for an MSA or more) households in the central city will increase by .82% and 1.64% over the given ten year time periods, respectively. These results also demonstrate that the effect is more dramatic for very high-income households than it is for high-income households given that the coefficient for very high-income households is twice that of the high-income households. There are similar results using the annual number of hours lost per commuter to proxy for traffic congestion where for every 1% increase in traffic congestion, the percentage of high-income and very high-income households in the central city will increase by .024% and .035%, respectively, over the given ten year time periods. Lastly, the paper demonstrates that traffic congestion is not statistically significant with respect to the location of both low-income (households with 80% of median household income for an MSA or less) and very low-income (households with 50% of median household income for an MSA or less) households.

The paper proceeds as follows. Section II provides a discussion of the relevant literature in spatial patterns by income groups. Section III provides a theoretical model which demonstrates how increased traffic congestion more adversely impacts high-income households driving them back towards the city center. Section IV contains the details of the regressions and the variables used in them. Section V provides the descriptive statistics for the data set as well as the variables used in the regressions. Section VI discusses the regression estimation results. Lastly, Section VII concludes the paper.

LITERATURE REVIEW

The foundation of this paper is the well known urban spatial model developed by Alonso (1964), Muth (1967), and Mills (1969). In this monocentric model the rich live further from the city center than the poor if and only if the income elasticity of housing demand exceeds the income elasticity of marginal commuting costs. The model predicts that as commuting costs rise within a metropolitan area, the city decreases spatially with prices per square foot and densities closer to the city center increasing. Within the model, there is a pull between two opposing forces in high income households. Suburbs satisfy high housing demand with low prices per square foot and the city center satisfies time-cost based demand for short commute times. Wheaton (1977) argues that these two forces are equal in size while Glaeser, Kahn, and Rappaport (2008) argue that the time-cost force is stronger and high-income households will live closer to the city center. Given these mixed results, others have searched outside of the basic model for a feasible explanation.

Prior literature provides three explanations for this pattern; the attractiveness of amenities, access to public transit, and the age of housing stock within an MSA. Brueckner, Thisse, and Zenon (1999) argue that historical amenities in the city center might attract the rich more than the poor and lead households to stratify by income in a manner similar to what would be found in Paris, France. Nechyba and Walsh (2004) argue that fiscal amenities in homogeneous suburbs allow high income households to avoid redistributive central city taxation while improving the quality of public goods. Leroy and Sonstelie (1983) provide a model where transportation mode choice can help to explain location patterns by income. They state that when a new, faster, initially expensive mode of transportation is adopted by the rich, the weakened time-cost force may cause them to move to the suburbs. Then, as the fixed and variable costs of this mode of transportation decrease, the comparative advantage of the rich taking on high material costs diminishes. Given that both income groups now use the same transportation mode, poor commuters become high bidders for suburban housing. The rich then begin competing more effectively where they have a comparative advantage, the CBD, and become the dominant bidders in this area. Glaeser et al. (2008) argued that since city centers have high population densities and therefore support pubic transit services better than suburban locations; they attract more poor who rely on less expensive public transportation. While these arguments help to explain location of high and low income households, the majority of these models are static and do not allow for neighborhood evolution over time.

Brueckner and Rosenthal (2009) present a dynamic model where dwelling age plays a deterministic role with respect to location patterns. They propose that the rich will occupy the suburbs when young dwellings are only found there, but when central city redevelopment occurs and a second generation of housing stock is built, the rich will move to this new housing stock creating central city gentrification.

The research agenda outlined in this paper is based on the belief that incorporating traffic congestion can provide further explanatory power for the spatial patterns observed in U.S. cities. Baum-Snow (2006) and (2007) present a version of the monocentric city model, similar to that of Anas and Moses (1979), which incorporates heterogeneous commuting speeds via the introduction of radial commuting highways. He argues that each additional highway ray causes commute times to reduce city center population at a decreasing rate, housing prices to decline, land consumption to increase, and central city density to decline providing evidence that highways account for about one-third of the urban population decentralization between 1950 and 1990. This has a basis in the analysis conducted by LeRoy and Sonstelie (1983). However, one short-coming of their transportation mode choice model is that only a few large cities have public transit usage levels high enough for it to be considered a valid alternative to the automobile. For example, New York City is the only one of the ten largest U.S. cities where at least twenty percent of its population uses public transportation for their work commute. Baum-Snow's approach has several advantages over symmetric or one-dimensional space models; the equilibrium land use structures exhibit heterogeneity in residential density conditional on distance to the city center, the analytical implications apply very generally across preference specification and city structures, and the model generates simulation results that are quantitatively robust to a variety of metropolitan area structures. Baum-Snow's base model assumes that transportation is not congestible, but he later incorporates it. This addition means that the results are no longer insensitive to the metropolitan area population and the effect on city center density from adding a new ray is lessened.

The primary contribution of this paper to the literature is that this will be the first paper to truly separate out and measure the impact of traffic congestion on location patterns by income using the Alonso-Muth-Mills models' definition of commute costs.

THEORETICAL MODEL

The purpose of the monocentric model outlined in this section is to show the links between the locations of different income groups to the levels of traffic congestion in MSAs. The key assumption needed to develop this analysis is that the marginal valuation of one's time rises sharply with income. The paper will first present the Alonso-Muth-Mills model to show that it does not account for location patterns by income. Then it adds traffic congestion to the model and obtains the same results. Next it present a modified version of the Alonso-Muth-Mills model with two income groups, high-income households and low-income households, but without congestion to demonstrate the classical U.S. location by income pattern where the low-income households live in the city center and the high-income households live in the suburbs. The paper will then assume that the high-income households have a higher opportunity cost of commute time and that there is traffic congestion to demonstrate how this pattern can be reversed and the high-income households will now occupy the city center while the low-income households occupy the suburbs. This theoretical model will provide evidence that a greater percentage of an MSA's high-income households will live in the city center in an MSA with higher congestion levels.

In this formal model, let x denote distance to the CBD. Housing consumption is represented by q and consumption of a composite non-housing good is represented by c with a strictly quasi-concave utility function given as $v(c, q)$. Also the price per unit of housing is p. The model assumes that all individuals have identical tastes and live within the city limits 0 to *x-bar*. The CBD is located at one end, $x = 0$, and the suburbs are located at the other end $x =$ *x-bar*. All employment is located in the CBD and workers commute to the CBD in a straight-line. The first portion of this model will contain a single income group, y, and commuting cost per mile is denoted by t; therefore, disposable income at distance x is $y - tx$ and the budget constraint is $c + pq = y - tx$.

Maximizing utility takes the form of $\text{Max}_q\, v(y - tx - pq, q) = u$ and the first order conditions are as follows:

$$\frac{v_2(y - tx - pq, q)}{v_1(y - tx - pq, q)} = p \tag{1a}$$

$$v(y - tx - pq, q) = u \tag{1b}$$

Eq. (1a) states that individuals will choose the optimal *q* conditional of *p* and Eq. (1b) states that an individual's consumption bundle must afford utility, *u*. Accounting for these two conditions will yield solutions for *p* and *q* based on *x*, *y*, *t*, and *u*. The derivation with respect to *t* (below) states that as commuting costs, *t*, increase in direct proportion to housing prices per square foot, *p*.[2]

$$\partial p/\partial t = (1/u^{*1/\beta})(\alpha/\beta)^{\alpha/\beta}(\alpha/\beta+1) \left[\frac{y - tx}{1 + \alpha/\beta}\right]^{\alpha/\beta} [-x/(1+ \alpha/\beta)] < 0 \qquad (2g)$$

An increase in *t* causes a clockwise rotation of the house price, *p*, contour which can be viewed in Figure 1. This is due to an increase in housing demand inside of the central city (left of *x-hat*) which increases land rent and consequently prices per square foot for housing. The end result is that the population within the central city lives in smaller dwellings with higher population density levels. At the same time, the opposite effect occurs in the suburbs (right of *x-hat*). The model also demonstrates that the city should decrease spatially ($x\text{-}bar_1$ to $x\text{-}bar_2$) which can be seen in Figure 1 below. Overall, the utility level of the city's population decreases as stated in Mills (1987).

If traffic congestion is added to the model, then commute costs per round trip mile with congestion are greater than commute costs per round trip mile without congestion, $t_c > t$. This simply results in a further decline in housing prices per square foot in the suburbs and a further increase in housing prices per square foot in the central city, but the model does not determine who moves into the central city to drive the price increases since it only contains one income group. While the Alonso-Muth-Mills model predicts that the overall population will move closer to the city center with increasing commute costs per round trip mile, *t*, our model demonstrates that the percentage of high-income households retained in the central city will be greater than

[2] The derivation of this equation can be found in Appendix A.

both the percentage of the overall population and the percentage of low-income households retained in the central city due to an increase in *t*.

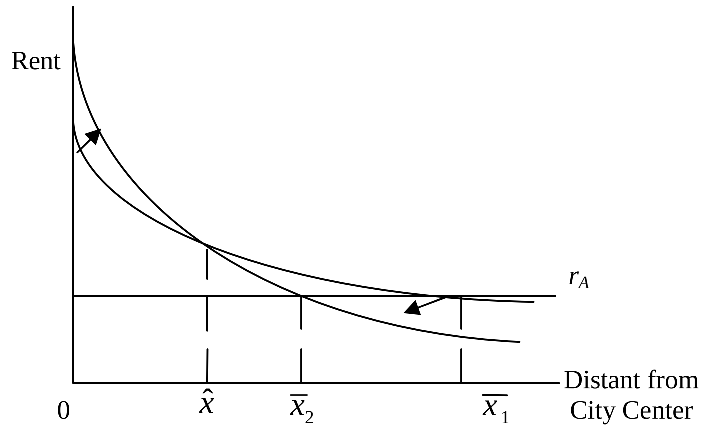

Figure 1.
Increased Commuting Costs In the Alonso-Muth-Mills Model

Alonso left his model of location by income indeterminate because he stated that he had no priori basis for establishing the tastes of urban residents for commuting. He also did not attempt to establish an income elasticity for land. Muth removed commuting from the utility function and assigned a time cost component to it instead, he was able to show that the total marginal cost of commuting would be inelastic with respect to wage income given certain assumptions. Both Alonso and Muth assumed that the marginal costs of commuting would be inelastic with respect to income. Meanwhile, the time value literature that had appeared since Alonso stated that the marginal cost of time had been related to the wage rate and thus would rise proportionally with wage income under certain assumptions. If so, the sum of the two types of costs would have an income elasticity of less than one. Around this time, Muth estimated an income elasticity for housing of greater than or equal to one. This appeared to make the location model determinant since it seemed that the savings from cheaper land would increase more rapidly with income than would the value of additional access, but Muth (1969) assumed that commuting was neither enjoyable nor troublesome. This would suggest that the value of time spent commuting should be nearly the after-tax wage rate and leads back to the indeterminacy of

Alonso's formulation since how the value of this consumption component varies with income is unknown.

The critical difference between the Alonso model and the Muth model is that Alonso puts commuting time in the utility function while Muth does not. In the standard theory of urban residential location, the relationship between a household's wage rate and its residential location depends on the relative magnitudes of the elasticity of marginal commuting costs (*MC,w*) and the elasticity of housing demand (*q,w*). Muth argued that the elasticity of housing demand is greater than the elasticity of marginal commuting costs because the elasticity of housing demand is greater than one while the elasticity of marginal commuting costs is between one and zero. This implies that income rises with distance from the CBD. Currently, the consensus is the elasticity of housing demand is less than one, implying a theoretically ambiguous result. Moreover, Wheaton (1977) found the elasticities to be identical; therefore, these models do not definitively explain the spatial distribution of households by income.

Now the model will incorporate two sets of workers into the model; high-income and low-income households. High-income households and their incomes will be represented by N_h and y_h respectively while low-income households and their incomes will be represented by N_l and y_l. For both income groups, every household inelastically supplies one unit of labor to the market and $y_h > y_l$. The first assumption in this portion of the model is that land consumption is fixed for both types of households with high-income households consuming one unit of land and low-income households consume θ unit of land while $1 > \theta$ since $y_h > y_l$. The second assumption is that both high- and low-income households have an equal per-unit cost of commuting, $t_h = t_l$. Also, the amount of land that is needed to house an MSA's population is $N_h + \theta N_l \equiv$ *x-bar* and lot sizes do not change in this model while they are allowed to vary in the Alonso-Muth-Mills model.

If $r(x)$ denotes the bid-rent curves for both income groups, one can derive $r(x)$ via their budget constraints. The high-income household budget constraint is $y_h - t_h x = r_h(x) + c_h$ and solving for the high-income household bid-rent curve yields $r_h(x) = y_h - t_h x - c_h$. Similarly, the low-income household budget constraint is $y_l - t_l x = r_l(x) + c_l$ and solving for the low-income household bid-rent curve yields $r_l(x) = y_l - t_l x - c_l$. Both bid-rent curves are straight lines in x and high- and low-income households have slopes of $-t_h$ and $-t_l/\theta$ with respect to x. The low-income household bid-rent curve is steeper than the high-income household bid-rent curve since $\theta < 1$ and the bid-rent curves of both income groups are equal at θN_l. Low-income households have a steeper slope because they have to spread their housing costs over fewer units; therefore, they need a greater change in rents to compensate them for their commuting costs. In this monocentric model, low-income households occupy the CBD (from $x = 0$ to $x = \theta N_l$) and high-income households occupy the suburbs (from $x = \theta N_l$ to $x = x\text{-}bar$) as is demonstrated in Figure 2.

In equilibrium, all households within an income group must have equal utility levels and since incomes do not vary within them, households living further from the CBD must be exactly compensated for their increased commuting costs via lower land prices. Accounting for the fact that c is the same at all locations for a given income group, the bid-rent curve for a particular income group demonstrates the land rent at each location that exactly compensates a household for the additional commuting costs at more distant locations.

Now let us assume that instead of both high- and low-income households having an equal per-unit cost of commuting, $t_h = t_l$, high-income households have higher opportunity costs for time spent commuting since they have higher wages, $t_h > t_l$. Therefore, high-income households are expected to have a higher per-unit cost of commuting. This will steepen the slope of high-income households' bid-rent curve (from $r_h^1(x)$ to $r_h^2(x)$)with respect to low-income households, since land consumption remains constant and commuting costs for the high-income households have increased compared to low-income households, $t_h > t_l$. Now, θN_l^1 shifts inward closer to the city center to θN_l^2 and some high-income households outbid the lower-income households moving into the CBD as is demonstrated in Figure 2.

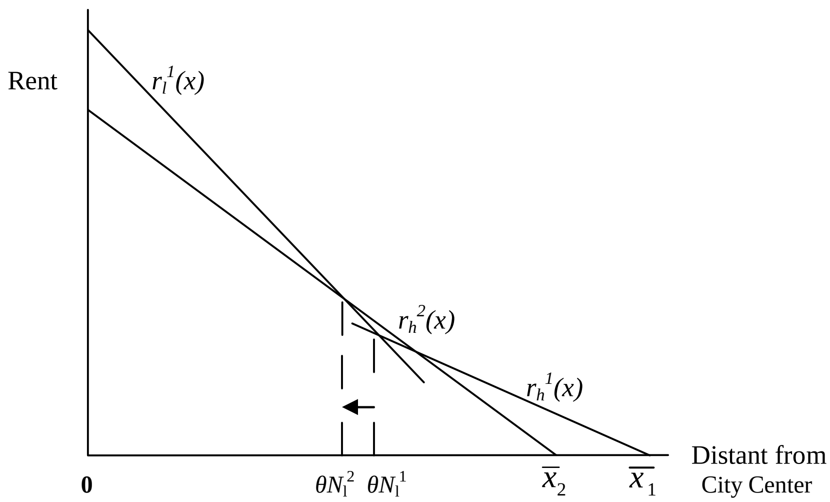

Figure 2.
The Monocentric City with $t_h = t_l$, then $t_h > t_l$

Lastly, traffic congestion is added to the model so that even though high-income households consume more land than low-income households ($1 > \theta$), they face higher commute time opportunity costs ($t_h > t_l$) and congestion increases t for both income groups ($t^c > t$); therefore, if $t_h^c > t_h$, $t_l^c > t_l$, *and* $t_h > t_l$, then $t_h^c > t_l^c$. Bid-rent curves for both income groups steepen, but high-income households are more adversely affected by congestion due to their higher opportunity cost of time spent commuting. The slope of high-income households' ($r_h^2(x)$ to $r_h^3(x)$) bid-rent curves will steepen even further with respect to low-income households ($r_l^2(x)$ to $r_l^3(x)$). Now, θN_l^2 shifts inward even closer to the city center to θN_l^3 and even more high-income households should outbid low-income households continuing their move into the CBD as is demonstrated in Figure 3.

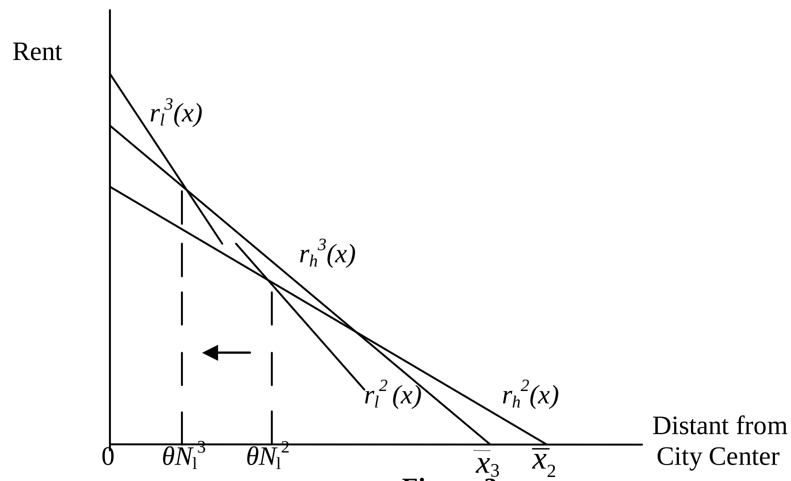

Figure 3.
The Monocentric City without Congestion, then with Congestion

In conclusion, an MSA with higher levels of traffic congestion should experience a greater percentage of its high-income households dwelling in the CBD and a greater percentage of its low-income households dwelling in the suburbs than an MSA with lower levels of traffic congestion.

ECONOMETRIC MODEL

The initial sample set collected included 101 metropolitan areas with highly detailed traffic congestion data. Anchorage, Alaska was excluded do to the fact that the NCDB qualifies 100% of every census tract as central city. Nine other were excluded form the dataset due to a lack of reliable amenity data. The final sample set includes 91 MSAs.

The regressions will test the central hypothesis by accounting for MSA traffic congestion via a travel time index and annual hours lost per commuter due to traffic congestion. The percentage change in high-income households living in the city center over a given ten year period is regressed on traffic congestion as well as other factor which can contribute to location by income:

$$\Delta HICC = \alpha + \beta_1(\Delta Cong) + \beta_2(\Delta Perpopcc) + \beta_3(\Delta Perjobscc) + \beta_4(\Delta Pubtrans) + \beta_5(\Delta Hsgage) + \beta_6(\Delta Histamen) + \beta_7(\Delta Natamen) + \beta_8(\Delta Cultamen) + \beta_9(\Delta Teams) + \beta_{10}(Year) + \beta_{11}(Medium) + \beta_{12}(Large) + \beta_{13}(Vlarge) + e_i \quad (3)$$

These will be linear, pooled, cross-sectional regressions using 1980, 1990 and 2000 MSA level data which will be run using two ten year time periods; 1980 to 1990 and 1990 to 2000.[3] The two ten year periods are pooled together for the regressions. The $\Delta HICC$ dependent variable will be calculated as the change over the given ten year period in the number of high-income households in the city center divided by the total number of high-income households in an MSA. A household will be defined as a high-income household if its income is greater than 120% of the MSA median household income which is the definition used by the U.S. Department of Housing and Urban Development (HUD). Regressions are also run using 200% of the MSA median household income as the definition for a very high-income household. The Neighborhood Change Database (NCDB) to was used to obtain the population weighted median incomes for each MSA using the census tracts within it. The NCDB not only distinguishes whether or not a census tract lies within the CBD, but gives the proportion of a census tract that lies within the CBD if it lies partially in the CBD and partially in the suburbs. This will allow us to obtain the total number of high-income households living in the CBD as well as the total number of high-income households in the MSA. The NCDB's 2000 definition of the CBD are used. The CBD is defined as the area within the city center of an MSA. Everything else within an MSA will be considered suburbs. This measure remains constant throughout time.

[3] The years are pooled because 7 out of the 8 specifications have insignificant coefficients for the YEAR variable at the 5% level and the average t-stat for the YEAR variable is 1.51.

Regressions using the percentage change in low-income households within the central city, Δ*LICC*, as the dependent variable are also run. This is done because theory suggests that the impact of traffic congestion should be smaller for low-income households. These are calculated as the change over the given ten year period in the number of low-income households in the city center divided by the total number of low-income households in an MSA. A household will be defined as a low-income household if its income is less than 80% of the MSA median household income which is the definition used by the U.S. Department of Housing and Urban Development (HUD). Then we run regressions using 50% of the MSA median household income as the definition for a very low-income household.

A description of the independent variables follows. The Δ*Cong* variable accounts for the change in an MSA level travel time index measure over the given ten year period and is taken from the Texas Transportation Institute's Urban Mobility Reports which compares peak period travel time to non-peak period travel time. It divides average MSA peak congestion travel time by average MSA free-flow travel time. This measure includes both recurring and incident conditions and can be used to compare trip length during peak congestion time to trip length during free-flow travel time. Therefore, it both isolates the congestion portion of travel time and accounts for MSA's that are more spread out and have inherently longer travel times because of travel distance. For example, if this index is 1.2 for a given MSA, a 30 minute trip during free-flow travel time should take 36 minutes during peak congestion travel time. A given MSA should experience a greater percentage of its high-income households living in the CBD, the higher the travel time index is for that MSA. The commute speed information will come from the INRIX dataset used by the Texas Transportation Institute. The INRIX dataset anonymously collects traffic speed data in these areas from personal trips, commercial delivery vehicle fleets, and a range of other agencies and companies. The speed data incorporates conditions for every day of the year and every hour of the day including the effects of weather problems, traffic crashes, special events, holidays, work zones, and other congestion-causing elements for almost every major roadway in the U.S.

The second measure used to account for Δ*Cong* is the number of annual hours lost per commuter due to traffic congestion within each MSA and is also taken from the Texas Transportation Institute's Urban Mobility Reports. This variable is substituted for the travel time index in the second set of regressions. It is calculated using the daily delay in hours multiplied by the number of days in a 50 work week year and 1.25 persons per vehicle. The daily delay in hours is calculated by subtracting the ratio of daily vehicle miles traveled to non-peak period speeds from the ratio of daily vehicle miles traveled to peak period speeds. Traffic congestion delay is assigned to commuters during the peak times and to the entire MSA population during non-peak hours. All calculations are made at the individual roadway section level for each hour of the week.

The Δ*Perpopcc* and Δ*Perjobscc* variables account for the change in the percentage of the entire MSA population living in and the percentage of jobs within the central city limits, respectively, over a given ten year period. The calculation were made in a fashion similar to the Δ*HICC* variable by totaling the population and number of jobs within the central city limits and the total population and number of jobs in each census tract for the entire MSA. The data for these two variables was also obtained from the NCDB.

The Δ*Pubtrans* variable accounts for the change in the percentage of households in a given MSA that use public transit over the given ten year period. This variable will account for the fact that low-income households are more likely to use public transportation as well as live closer to it. The Δ*Hsgage* variable represents the change in the central city housing age index over the given ten year period, which is a ratio dividing the median dwelling age in the central city by the median dwelling age in the suburbs of an MSA. This measure was constructed based on the findings of Brueckner and Rosenthal (2009) which states that high-income households will be more competitive for a younger housing stock than low-income households. The lower this ratio is, the more likely the rich will live in the city center since the rich are willing to outbid the poor to live in newer dwellings. The data for these two variables was also obtained from the NCDB.

The Δ*Histamen*, Δ*Natamen* and Δ*Cultamen* variables were constructed based on the work of Brueckner et. al. (1999) where they demonstrated that more high-income households will live in central cities that have higher levels of local amenities located within their respective central cities. These variables measure the changes in unobserved amenity effects that may be correlated with the regressors. Three variables are used to account for these effects; Δ*Histamen* will account for an MSA's historical amenities, Δ*Natamen* will account for and MSA's natural amenities, and Δ*Cultamen* will account for an MSA's cultural amenities.

The Δ*Histamen* variable will account for the change in number of historical places documented by the National Register of Historical Places within an MSA's central city limits per 1000 residents. The per 1000 residents measure is calculated using the entire MSA population. Using a per capita measure will account for the fact that older, larger cities will inherently have more historical monuments. The data is available by county; therefore, it is necessary to account for the percentage of each of the MSAs' counties that are in the central city using the NCDB's 2000 definitions of the MSAs' city centers. The greater the change in the Δ*Histamen* variable over the given ten year period, the greater the expected increase in the percentage of high-income households residing in the central city over the same ten year period.

The Δ*Natamen* variable accounts for the change in number acres of interior water within the central city limits per 1000 residents in an MSA and is calculated in the same fashion as the Δ*Histamen* variable. Brueckner et. al. (1999) discussed the importance of this measure with respect to the location of high-income households in an MSA. The greater the change in the Δ*Natamen* variable over a given ten year period, the greater the expected increase in the percentage of high-income households residing in the central city over the same ten year period. The data was collected from the U.S. Geological Survey's National Water Information System database.

The Δ*Cultamen* accounts for the change in number of professional operas, theatre groups, orchestras, ballets and museums within an MSA's central city limits per 1000 residents and is calculated using the same methodology as the Δ*Histamen* and Δ*Natamen* variables. The data was original collected using the *Places Rated Almanac*, then each cultural amenity's location and date of existence was verified via either the internet or phone call.

The Δ*Teams* variable accounts for the change in the number of National Football League (NFL), National Basketball Association (NBA), Major League Baseball (MLB) and National Hockey League (NHL) teams located within the central city limits of each MSA per 1000 residents living in the MSA. The paper excludeds college and women's professional sports teams because cities do not generally build stadiums to attract and maintain these types of teams. Professional sports stadiums can potential drive high-income households out of the central city due to increases in taxes and other factors.

The *Medium*, *Large*, and *Vlarge* variables control for city size with medium being defined as MSAs with populations between 500,000 and 1,000,000, large as MSAs with populations between 1,000,000 and 3,000,000, and very large as MSAs populations over 3,000,000. MSAs with populations less than 500,000 are defined as small. The definition used for city size comes from the 2000 Texas Transportation Institute's Urban Mobility Report definition of MSA sizes. The paper uses this definition so as to be the most inclusive definition of MSA size and to keep it constant avoiding potential endogeneity, similar to the rational for using the Neighbohood Change Database when obtaining data in expanding MSAs over time.[4]

DESCRIPTIVE STATISTICS

Table 1, below, provides the summary statistics for the entire data set broken up into two, ten-year time periods; 1980 to 1990 and 1990 to 2000. There are several trends between the two time periods. First, the percentage of overall populations and jobs in the central cities declined over both periods, but at a decreasing rate. The number of cultural and historical amenities in the central cities per capita more than doubled on average between 1980 and 1990 while interior water acres per capita fell by almost 25%. The number of professional sports within central cities increased on average, but slightly declined per capita over the same time period. Traffic congestion increased by nearly 5% when measured via the travel time index and nearly 125% when measured via the annual hours lost per commuter due to traffic congestion measure between 1980 and 1990 while public transportation usage declined by more than 25% over the same time period. On average, housing age in the central city versus the suburbs slightly increased between 1980 and 1990.

[4] Letting the city size variables vary between years does not affect the results.

Between 1990 and 2000, the number of cultural and natural amenities in the central cities per capita increased by 25% on average while historical amenities fell by more than 25%. The number of professional sports within central cities increased on average, but only slightly increased per capita over the same time period. Traffic congestion increased by nearly 5% when measured via the travel time index and nearly 100% when measured via the annual hours lost per commuter due to traffic congestion measure between 1990 and 2000 while public transportation usage declined by more than 7% over the same time period. On average, housing age in the central city versus the suburbs slightly declined between 1990 and 2000.

Table 1. Summary Statistics - All MSA's

	1980-1990				1990-2000			
Variable	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev
TTI	0.00%	17.59%	4.30%	3.66%	-1.71%	15.93%	4.81%	3.28%
HOURSLOST	0.00%	400.00%	121.85%	80.73%	-5.00%	500.00%	100.84%	87.62%
PERPOPCC	-36.79%	5.55%	-7.96%	7.13%	-23.36%	4.50%	-7.54%	5.07%
PERJOBSCC	-31.40%	35.68%	-4.79%	8.24%	-24.19%	398.32%	-3.52%	43.12%
PUBTRANS	-69.64%	167.01%	-25.93%	27.78%	-50.20%	101.19%	-7.61%	25.68%
HSGAGE	-34.40%	419.43%	3.33%	48.96%	-37.80%	48.36%	-1.08%	11.31%
CULTAMEN	-69.53%	885.94%	167.13%	176.48%	-58.80%	1757.35%	26.93%	189.47%
NATAMEN	-55.91%	6.50%	-23.01%	13.02%	-37.18%	895.77%	24.17%	108.66%
HISTAMEN	-23.55%	902.76%	91.57%	106.80%	-72.40%	65.51%	-28.10%	22.51%
TEAMS	-54.40%	89.17%	-2.59%	18.53%	-100.00%	158.93%	2.80%	30.16%

This table reports the summary statistics of the independent variables for the high- and low-income household regressions during two different time periods; *1980 to 1990* and *1990 to 2000*. The *Minimum Value*, *Maximum Value*, *Mean* and *Standard Deviation* are listed for each of the independent variables during both time periods.

RESULTS

High-Income Households

In this section, regression estimates for two different high-income and two different very high-income household specifications are presented. The regression in farthest left column of Table 2, below, consists of the base regression where were the Texas Transportation Institute 2000 Urban Mobility Report's definitions of MSA size, the definition for a high-income household is 120% median household income of the MSA, and the Texas Transportation Institute's travel time index are used. In the second column, a more stringent definition of a very high-income household is used, 200% median income of the MSA or higher. The third and fourth columns are the same regressions as the first and second columns, respectively, except that the Texas transportation Institute's annual hours lost per commuter due to traffic congestion measure is used to account for traffic congestion. While the coefficients are slightly different, they all share the same sign despite the different specifications. Also, the same variables which are statistically significant for the original specification in the first column remain statistically significant in all columns with the exception of housing age ratio which is significant at in both high-income household measures, but not the very high-income household measures.

As expected the percentage change in overall population located in the central city is positively correlated with the percentage of high-income households located in the central city and is statistically significant. The coefficients among the various specifications demonstrate that for every 1% increase in overall population moving into the central cities over the given ten year time periods, there is an increase between .99% and 1.04% in high-income households moving into the central city over the same time period.

Theory expects the percentage of high-income households in the central city to decrease with increases in the housing age ratio and the coefficients provide evidence that this is true. For every 1% increase in the housing age index, the percentage of high-income households living in the central city decreased between .050% and .056% over the given ten year time period, but was statistically significant for both high-income household measures and neither of the very high-income household measures.

The spatial model presented in Brueckner et. al. (1999) predicts that high-income households will live closer to central city, such as in Paris, France, if there are more amenities near the city center than in the suburbs. The change in the number acres of interior water within the central city limits per 1000 residents in an MSA is negative and statistically significant. The findings demonstrate high-income and very high-income households leaving the central city at a rate of .026% to .031%, respectively, with every 1% increase in the number acres of interior water within the central city limits per 1000 residents in an MSA. We do not feel as though this is result is definitive evidence that natural amenities do not attract high-income households to the central city. In fact, we feel as though a more in depth study of amenities needs to be conducted.

Table 2. Percent High-Income in the Central City Regression Coefficients

	Specification			
	Travel Time Index		Annual Hours Lost	
Variable	HICC 120%	HICC 200%	HICC 120%	HICC 200%
TTI	0.821***	1.638***	-	-
	(2.99)	(4.42)	-	-
HOURSLOST	-	-	0.024**	0.035**
	-	-	(2.30)	(2.40)
PERPOPCC	1.005***	1.040***	0.991***	1.01***
	(6.92)	(5.31)	(6.75)	(4.97)
PERJOBSCC	0.026	0.012	0.026	0.011
	(0.94)	(0.33)	(0.91)	(0.29)
PUBTRANS	-0.022	-0.012	-0.002	-0.022
	(-0.70)	(-0.28)	(-0.05)	(-0.49)
HSGAGE	-0.050**	-0.054	-0.053**	-0.056
	(-1.98)	(-1.58)	(-2.04)	(-1.58)
CULTAMEN	<0.001	<0.001	<0.001	<0.001
	(1.55)	(0.78)	(1.59)	(0.81)
NATAMEN	-0.027**	-0.030**	-0.026**	-0.031**
	(-2.64)	(-2.06)	(-2.42)	(-2.04)
HISTAMEN	0.010	0.010	0.010	0.010
	(1.06)	(0.81)	(1.07)	(0.74)
TEAMS	-0.091***	-0.093***	-0.092***	-0.100***
	(-2.67)	(-2.02)	(-2.64)	(-2.05)
Observations	182	182	182	182
Adjusted R^2	.29	.23	.27	.17

This table reports the regression coefficients with their corresponding t-stats below them in parentheses for four different high-income and very high-income household traffic congestion specifications. These specifications are from left to right; the *120% and 200% of Median Household Income* definitions for a high-income and very high-income households, respectively, using the *Texas Transportation Institute's Travel Time Index* as a measure for traffic congestion and the *120% and 200% of Median Household Income* definitions for a high-income and very high-income households, respectively, using the *Texas Transportation Institute's Annual Hours Lost per Commuter Due to Traffic Congestion* as a measure for traffic congestion. Statistical significance is designated by *** at the 1% level, ** at the 5% level, and * at the 10% level.[5]

An increase in the number of professional sports teams within the central city of an MSA per 1000 residents can drive high-income households out of the area where the stadiums are located due to the potential negative externalities such as tax increases that follow a professional sports team's introduction into an area. The paper finds this to be true with high-income and very

[5] The F-test for statistical significance between the variances of the 120% and 200% median household income measures is significant.

high-income households leaving the central city at a rate of .091% to .100%, respectively, with every 1% increase in the number of professional sports teams within the central city of an MSA per 100 residents.

The most important implication of the results in this paper has to do with the traffic congestion coefficients. In all four specifications, traffic congestion is found to be statistically significant in the direction that the theoretical model predicts. As traffic congestion increases within an MSA, high-income households are more adversely affected than low-income households due the fact that their time is more valuable and high-income households are, therefore, more likely to move into the central city. The model predicts that for every 1% increase in peak congestion period travel time over free-flow travel time, the percentage of high-income households in the central city will increase by .82% and 1.64% over the given ten year time period for high-income and very high-income households, respectively. It also demonstrates that effect increases with median household income given that the coefficient for very high-income households is 1.64 while the coefficient for high-income households is 0.82. Similar results are found using the annual number of hours lost per commute measure to measure traffic congestion where for every 1% increase in traffic congestion, the percentage of high-income and very high-income households in the central city will increase by .024% and .035%, respectively, over the given ten year time period. Both measures are statistically significant.

Low-Income Households

In this section, regression estimates for two different low-income and very low-income household specifications are presented. The regression in farthest left column of Table 3, below, consists of the base regression where low-income household ss 80% median household income of the MSA or lower, and used the Texas Transportation Institute’s travel time index. In the second column, the more stringent definition of a very low-income household, 50% median income of the MSA or lower, is used. The third and fourth columns are the same regressions as the first and second columns, respectively, except that the Texas transportation Institute's annual hours lost per commuter due to traffic congestion measure to account for traffic congestion is used.

As expected the percentage change in overall population located in the central city is positively correlated with the percentage of low-income households located in the central city and is statistically significant. The coefficients among the various specifications demonstrate that for every 1% increase in overall population moving into the central cities over the given ten year time periods, there are increases of .763% and .795% in low-income households moving into the central city over the same time period, respectively, meaning that the ratio of low-income to overall population should remain steady as individuals move into the central city.

Table 3. Percent Low-Income in the Central City Regression Coefficients				
	Specification			
	Travel Time Index		Annual Hours Lost	
Variable	LICC 80%	LICC 50%	LICC 80%	LICC 50%
TTI	0.658	-0.024	-	-
	(0.89)	(-0.11)	-	-
HOURSLOST	-	-	-0.001	-0.004
	-	-	(-0.05)	(-0.48)
PERPOPCC	0.773***	0.795***	0.763***	0.795***
	(6.67)	(6.98)	(6.40)	(6.99)
PERJOBSCC	0.011	<0.001	0.010	<0.001
	(0.47)	(0.06)	(0.43)	(0.05)
PUBTRANS	-0.008	0.021	-0.002	0.018
	(-0.31)	(0.82)	(-0.07)	(0.72)
HSGAGE	-0.018	0.042**	-0.020	0.042**
	(-0.87)	(2.09)	(-0.94)	(2.12)
CULTAMEN	<-.001	<-.001	<-.001	<-.001
	(-0.61)	(-1.94)	(-0.59)	(-1.95)
NATAMEN	0.006	0.006	0.004	0.005
	(0.70)	(0.65)	(0.05)	(0.62)
HISTAMEN	<0.001	0.007	<-.001	0.007
	(0.06)	(1.04)	(-0.11)	(1.00)
TEAMS	0.011	0.017	0.003	0.016
	(0.39)	(0.63)	(0.12)	(0.59)
Observations	182	182	182	182
Adjusted R^2	.23	.29	.28	.29

This table reports the regression coefficients with their corresponding t-stats below them in parentheses for four different low-income and very low-income household traffic congestion specifications. These specifications are from left to right; the *80% and 50% of Median Household Income* definitions for a low-income and very low-income households using the *Texas Transportation Institute's Travel Time Index* as a measure for traffic congestion and the 8*0% and 50% of Median Household Income* definitions for a low-income and very low-income households using the *Texas Transportation Institute's Annual Hours Lost per Commuter Due to Traffic Congestion* as a measure for traffic congestion. Statistical significance is designated by *** at the 1% level, ** at the 5% level, and * at the 10% level.[6]

Prior research states that the percentage of very low-income households in the central city to decrease as the ratio of median housing age in the central city divided by median housing age in the suburbs declined and the coefficients provide evidence that this is true. For every 1% increase in the housing age ratio, the percentage of very low-income households living in the

[6] The F-test for statistical significance between the variances of the 80% and 120% median household income measures is significant.

central city increased by .042% over the given ten year time period. Therefore, as the housing stock in the suburbs increases in age when compared to that of the central city, the very low-income households move to the older housing stock.

The most important implication of the results in this paper has to do with the traffic congestion coefficients. In all four specifications, traffic congestion is found to be both statistically insignificant with respect to low-income and very low-income households just as the theoretical model predicts. As traffic congestion increases within an MSA, high-income households are more adversely affected than low-income households due the fact that their time is more valuable.

CONCLUSION

Increases in MSA traffic congestion levels hold significant explanatory power when determining why high-income households live closer to the city center. Traffic congestion and other factors which influence high-income households’ decision to live within the central city limits of an MSA have always been important to the budgets of these cities since on average about 70% of local government revenue comes from property taxes which are directly linked to housing prices. Since the dramatic decline in housing prices across the country, these factors have taken on even great importance as local governments struggle to meet their budgets.

This paper measures traffic congestion using two MSA level measures; a travel time index taken and annual hours lost per commuter due to traffic congestion. Both were taken from the Texas Transportation Institute Urban Mobility Reports which compares peak congestion period travel times to free-flow travel times, isolating the traffic congestion portion of an MSA’s travel times.

This proposal makes three primary contributions to the literature. First, it includes a theoretical model that uses the Alonso-Muth-Mills model as a base, but is able to explain location patterns of high- and low-income households while their model is ambiguous with regards to this matter. Second, the model demonstrates traffic congestion's economic relevance within an MSA. Third, this research is the first to truly separate out and measure the impact of traffic congestion on location patterns by income using the Alonso-Muth-Mills models' definition of commute time, *t*.

The model predicts that that for every 1% increase in peak period travel time over non-peak period travel time, the percentage of high-income and very high-income households in the central city will increase by .82% and 1.64%, respectively, over the given ten year time period using HUD's definitions. It also demonstrates that effect increase with median household income level. Significant results are also found using the annual number of hours lost per commute measure to measure traffic congestion. Lastly, the paper finds that traffic congestion is not statistically significant with respect to the location of low-income and very low-income households using HUD's definitions.

CHAPTER 2

IS THERE A LINK BEWEEN TRAFFIC CONGESTION AND GREATER GENTRIFICATION PRESSURE

INTRODUCTION

Increasing traffic congestion levels has become a topic of great relevance within American cities since the early 1980s. It wastes massive amounts of fuel, time, and money costing individuals and corporations billions of dollars every year. This paper answers the question "Has increased traffic congestion contributed to gentrification pressure in metropolitan areas between 1980 and 2000?" This issue is vitally relevant to city and county governments because around 70% of their respective budgets are derived from revenue generated by property taxes. If increasing traffic congestion is one of the factors causing gentrifiable neighborhoods to be revitalized within metropolitan statistical areas' (MSAs) central business districts (CBDs), it could significantly affect the tax basis of cities by driving up property values.

In other words, since prior research has demonstrated that high-income households remain more centralized in the city centers of metropolitan statistical areas (MSAs) with increasing levels of traffic congestion, this paper attempts to determine whether they are moving into gentrifiable neighborhoods as they disburse throughout the city center.

To test this hypothesis, the paper presents a model which demonstrates how traffic congestion impacts the income growth of both the central cities of MSAs and their gentrifiable neighborhoods. The paper does so by first estimating a regression in which the change in the median household income growth in MSAs' central cities is regressed on a set of explanatory variables that includes the change in metropolitan traffic congestion levels. Next, the change in the median household income growth in central cities' gentrifiable census tracts is regressed on a set of explanatory variables that includes the change in metropolitan traffic congestion levels and central city income growth. Lastly, the coefficients of the two sets of regressions are compared to see if the gentrifiable census tracts experience an added income growth effect greater than that already experienced by all central city census tracts.

Here, the definition of a gentrifiable census tract is one which has a median household income between 50% and 80% of its respective MSA's median household income. These percentages represent the Department of Housing and Urban Development's (HUD) definitions of very low-income and low-income households, respectively.

This paper uses two independent, MSA level measures of traffic congestion, annual hours lost per commuter due to traffic congestion and a travel time index, which were taken from the Texas Transportation Institute's Urban Mobility Reports. The congestion measures compare peak travel period travel times to non-peak period travel times isolating the traffic congestion portion of an MSA's travel times and speeds. The other factors controlled for include MSA density, location of amenities, housing age, public transportation usage, overall population location, and job location while the data set includes 91 MSAs over two time periods accounting for 182 observations.

The model predicts that for every 1% increase in the number of annual hours lost per commuter due to traffic congestion, an MSA's central city and gentrifiable census tracts will experience a significant .031% and .039% increase in median household income, respectively, over a given ten year period. These results are verified by using the travel time index as a specification check. Using this measure to proxy for traffic congestion the model finds that a 1%

increase in the index results in significant .725% and .910% increases in median household income of an MSA's central city and gentrifiable census tracts, respectively. Most importantly, taffic congestion's effect is nearly 26% greater when accounting for just the gentrifiable census tracts within an MSA's central city rather than all central city census tracts.

The paper proceeds as follows. Section II provides a discussion of the relevant gentrification literature. Section III contains details of the regressions and the variables. Section IV provides descriptive statistics for both all central city neighborhoods' and just the gentrifiable neighborhoods' data sets. Section V discusses and compares the regression estimation results of the two data sets. Lastly, Section VI concludes the paper.

LITERATURE REVIEW

Since the 1950's, the phenomena of suburbanization has seen high-income households moving out of the central city along with both low-income households and overall MSA populations. However, over the past thirty years, CBD neighborhoods in many cities have experienced gentrification pressure, meaning that the housing stock has been renovated and high-income households have moved in resulting in an increase in the median household income of these neighborhoods over time. Gentrification refers to this upgrading of CBD neighborhoods, especially ones that have lower than average median household income when compared to their respective MSA's. It is also often accompanied by increases in the number of households, a growing housing stock, and changes in neighborhood demographic composition.

Gentrification has become a very controversial topic. The increase in property values benefits the low-income property owners and increases city budgets, but the low-income renters are sometimes forced out of their neighborhoods due to increasing rents. This has caused some unrest between gentrifiers and long-term renters. These factors have made gentrification a topic of interest for developers, activists, and local government officials seeking re-election.

Previous studies have demonstrated that gentrification is more likely to occur in census tracts that are closer to the city center, have older housing stock, and greater levels of amenities. According to Kolko (2008), U.S. regions vary in how well their cities fit the general pattern of gentrification. Gentrification first occurred in the Northeast between 1980 and 1990. Cities in the South and Midwest soon followed, exhibiting characteristics of gentrification between 1990 and 2000. There are also MSAs that have experienced gentrification multiple times. This has occurred in some of the oldest cities in the U.S. such as Washington D.C. and is referred to as re-gentrification. This paper will refer to all changes that are consistent with gentrification such as re-gentrification as gentrification.

Some papers such as McKinnish et. al. (2007) have applied a quantitative definition to gentrification. They define gentrification as the bottom quintile of census tracts with respect to median household income. There study takes place between 1990 and 2000 with an average household income below $30,079 at the beginning of their sample period. The growth rate was around 33% over the ten year period. By comparison, the average household income in 1990 for the data set used in this paper is a very similar $23,399 with a growth rate of 31% between 1990 and 2000.

Gentrification is the antithesis of traditional urban spatial patterns where high-income households live farther from the CBD than low-income households. The foundation of these theories is the well known urban spatial model developed by Alonso (1964), Muth (1967), and Mills (1969). The model demonstrates that as commuting costs rise within a metropolitan area, the city decreases spatially with prices per square foot and densities closer to the city center increasing. This model has historically met with great success explaining spatial patterns of both land use and real estate prices within U.S. cities, but it has met with less success predicting current location patterns by income. Within the model, there is a pull between two opposing forces in high-income households. Suburbs satisfy high housing demand with low prices per square foot and the city center satisfies time-cost based demand for short commute times. In extensions of this monocentric model the rich live further from the city center than the poor if and only if the income elasticity of housing demand exceeds the income elasticity of marginal commuting costs. Wheaton (1977) argues that these two forces are equal in size while Glaeser, Kahn, and Rappaport (2008) later argue that the time-cost force is stronger and high-income households will live closer to the city center. Given these mixed results and the fact that this is contrary to the general U.S. pattern, others have searched outside of the basic model for a feasible explanation.

Prior literature provides four explanations for this pattern; demographics, access to public transit, the age of the housing stock, and the attractiveness of amenities within a given MSA. Demographic characteristics are the first factor discussed which contributes to residential patterns and neighborhood change. Education, race, levels of homeownership, and crime rates are all discussed in prior literature, which theorizes that the household location decisions of different income groups depend on the characteristics and behaviors of others in the neighborhood. Some studies include these factors as controls, but Rosenthal (2007) makes them the focus of his analysis while Martin (1997) demonstrates that preferences for particular neighbors including racial prejudice can drive neighborhood dynamics as well.

The second factor is access to public transportation. Leroy and Sonstelie (1983) provide a model where transportation mode choice helps to explain location patterns by income. They state that when a new, faster, initially expensive mode of transportation is adopted by the rich, the weakened time-cost force may cause them to move to the suburbs. Later, as there is a decline in the costs of this mode of transportation, the comparative advantage of the rich using it diminishes. Now that both income groups are using the same transportation mode, poor commuters will become high bidders for suburban housing. The rich then begin to use their comparative advantage in the CBD and become the dominant bidders in this area. Glaeser et al. (2008) argued that city centers attract more poor since they rely on less expensive public transportation and have high population densities resulting in them better supporting pubic transit services than suburban locations.

Housing stock characteristics are a third factor contributing to residential income patterns and neighborhood change. Muth (1973) demonstrated that housing deteriorates with age and is occupied by successively lower-income households while experiencing lower housing demand. He then showed that new housing is constructed at the edge of the city where cheap land is available. This implies that a neighborhood's median household income should decline everywhere except at the city's edge. Bond and Coulson (1989) provide an extension of the filtering model that suggests rehabilitation of deteriorated housing stock can contribute to reverse filtering. Due to the fact that there is some fixed cost associated with rehabilitation, housing deteriorates until it is sufficient to warrant the cost of rehabilitation. The older and more downtrodden a housing unit, the smaller the flow of housing services; therefore, the benefit of rehabilitation or redevelopment is greater a long with the likelihood of gentrification. This predicts that gentrification should occur in neighborhoods where the housing is the oldest, most deteriorated, or abandoned. Brueckner and Rosenthal (2009) use age of the housing stock as the typical measure used to predict gentrification. They present a dynamic model where dwelling age plays a deterministic role with location patterns and propose that the rich will occupy the suburbs when young dwellings are only found there, but when central city redevelopment occurs and a second generation of housing stock is built, the rich will move to this new housing stock creating central city gentrification.

The location of amenities is the fourth factor contributing to residential income patterns and neighborhood change. Brueckner, Thisse, and Zenon (1999) argue that historical amenities in the CBD can lead households to stratify by income in a manner similar to what would be found in Paris, France due to the fact that these amenities attract high-income households more than low-income households. Nechyba and Walsh (2004) argue that high-income households are able to avoid redistributive central city taxation while improving the quality of public goods in homogeneous suburbs due to fiscal amenities.

More recently, Baum-Snow (2006) and (2007) incorporate heterogeneous commuting speeds via the introduction of radial commuting highways into a version of the monocentric city model. His argument is that each additional highway ray causes commute times to reduce city center population at a decreasing rate resulting in house price decreases followed by increases in land consumption and a decline in central city density. He provides evidence that highways account for about one-third of the urban population decentralization between 1950 and 1990.

The contribution of this paper to the vast gentrification literature universe is that it truly isolates the effects of traffic congestion on income growth in both all central city census tracts and just the gentrifiable census tracts within central cities over the period 1980 to 2000. The majority of studies dealing with this issue use commute to work times as a measure for congestion. This paper will make use of two independent, MSA level measures, annual hours lost per commuter due to traffic congestion and a travel time index, taken from the Texas

Transportation Institute's Urban Mobility Reports which compares peak congestion period travel time to free-flow travel time isolating traffic congestion effects on the median household income of an MSA's central city gentrifiable census tracts.

ECONOMETRIC MODELS

The initial sample set collected included 101 metropolitan areas with highly detailed traffic congestion data. Anchorage, Alaska was excluded do to the fact that the Geolytics Neighborhood Change Database (NCDB) qualifies 100% of every census tract as central city. Nine other were excluded from the dataset due to a lack of reliable amenity data. The final sample set includes 91 MSAs.

Since the primary hypothesis is that increasing traffic congestion within an MSA will contribute to gentrification pressure in cities over time due to the fact that the usual positive association between household income and distance from the city center may be weakened or reversed, it is necessary to define gentrifiable census tracts. They are defined as census tracts which have a median household income between 50% and 80% of their MSA's median household income which are the Department of Housing and Urban Development's definitions of very low-income and low-income households respectively.[7] Then, the hypothesis is tested by studying the changes in median household income for these census tracts over time based on the effects of increases and decreases in traffic congestion levels within the given MSAs over the same time frame. The paper does so because, by definition, gentrification refers to the housing stock of a central business district (CBD) being renovated and high-income households moving

[7] The F-test for statistical significance between the variances of MSAs' gentrifiable and non-gentrifiable census tracts' median household income is statistically significant.

into areas mostly occupied by lower-income households, resulting in an increase in the median household income of these neighborhoods over time.

The regressions in this paper test the central hypothesis by accounting for MSA level traffic congestion via annual hours lost per commuter due to traffic congestion measure and a travel time index which will be substituted for the prior measure in a separate set of regressions as a specification check. The city center is defined as the area within the city limits of an MSA and will be defined using 2000 definitions of the CBDs taken from the NCDB. Everything else within an MSA will be considered suburbs. Gentrification pressure will be measured by the change in median household income over a given ten year period for an MSA's gentrifiable census tracts. This change will be regressed on changes in traffic congestion as well as changes in the other factors which can contribute to location by income and the percentage change in the central city's median household income. This will help to determine whether or not the independent variables are statistically significant with respect to gentrification pressure at the MSA level. These will be linear, pooled, cross-sectional regressions using 1980, 1990, and 2000 MSA level data which will be run using two ten year time periods; 1980 to 1990 and 1990 to 2000. The regression can be viewed below:

$$\begin{aligned} \Delta MHIGT = {} & \alpha + \beta_1(\Delta Cong) + \beta_2(\Delta Mhicc) + \beta_3(\Delta Perpopgt) + \beta_4(\Delta Perjobsgt) + \\ & \beta_5(\Delta Pubtransgt) + \beta_6(\Delta Hsgagegt) + \beta_7(\Delta Histamengt) + \beta_8(\Delta Natamengt) + \\ & \beta_9(\Delta Cultamengt) + \beta_{10}(\Delta Teamsgt) + \beta_{11}(Year) + \beta_{12}(Medium) + \\ & \beta_{13}(Large) + \beta_{14}(Vlarge) + e_i \end{aligned} \tag{1}$$

The $\Delta MHIGT$ dependent variable will be calculated as the change over the given ten year period in the median household income of an MSA's gentrifiable census tracts. The NCDB is used to obtain the population weighted median household incomes for each MSA's gentrifiable census tracts. The NCDB not only distinguishes whether or not a census tract lies within the CBD, but gives the proportion of a census tract that lies within the CBD if it lies partially in the

CBD.[8] This along with median household income measures will allow us to identify gentrifiable census tracts since, by definition; they are within the central city.

A description of the independent variables follows. The Δ*Cong* variable is the annual hours lost per commuter due to traffic congestion within each MSA. It is taken from the Texas Transportation Institute's Urban Mobility Reports and is calculated using the daily delay in hours multiplied by the number of days in the 50 work week year and 1.25 persons per vehicle. The daily delay in hours is calculated by subtracting the ratio of daily vehicle miles traveled by non-peak period speeds from the ratio of daily vehicle miles traveled by peak period speeds. Traffic congestion delay is assigned to commuters during the peak times and to the entire MSA population during non-peak hours. All calculations are made at the individual roadway section level for each hour of the week. The measure includes both recurring and incident conditions and can be used to compare trip length during peak travel time to trip length during free-flow travel time. Therefore, it both isolates the congestion portion of travel time and accounts for MSA's that are more spread out and have inherently longer travel times because of travel distance not only accounting for the severity of congestion when it occurs, but the frequency with which it occurs.

The second measure used as a proxy for the Δ*Cong* variable accounts for the change in an MSA level travel time index measure over the given ten year period and is taken from the Texas Transportation Institute's Urban Mobility Reports which compares peak period travel time to non-peak period travel time. It divides average MSA peak congestion travel time by average MSA free-flow travel time. This measure includes both recurring and incident conditions and can be used to compare trip length during peak congestion time to trip length during free-flow travel time. Therefore, it both isolates the congestion portion of travel time and accounts for MSA's

[8] None of the gentrifiable census tracts were partially in the CBD and partially in the suburbs.

that are more spread out and have inherently longer travel times because of travel distance. For example, if this index is 1.2 for a given MSA, a 30 minute trip during free-flow travel time should take 36 minutes during peak congestion travel time. A given MSA should experience a greater percentage of its high-income households living in the CBD, the higher the travel time index is for that MSA. The commute speed information will come from the INRIX dataset used by the Texas Transportation Institute. The INRIX dataset anonymously collects traffic speed data in these areas from personal trips, commercial delivery vehicle fleets, and a range of other agencies and companies. The speed data incorporates conditions for every day of the year and every hour of the day including the effects of weather problems, traffic crashes, special events, holidays, work zones, and other congestion-causing elements for almost every major roadway in the U.S. This variable accounts for the intensity of congestion when it occurs. This measure is used as a specification check due to the fact that unlike the annual hours lost per commuter due to traffic congestion measure which accounts for not only the severity of congestion when it occurs, but the frequency with which it occurs, the travel time index only account for the severity of congestion when it occurs.

The Δ*Mihcc* variable controls for the change in median household income over a given ten year period for all census tracts within the central city limits and is expected to be highly correlated with the dependent variable. The Δ*Perpopgt* and Δ*Perjobsgt* variables account for the change in the percentage of the entire MSA population living in and the percentage of an MSA’s total jobs within gentrifiable census tracts, respectively, over a given ten year period. They will be calculated by totaling the population and number of jobs within the gentrifiable census tracts of an MSA and dividing by the total population and number of jobs in each census tract for the entire MSA, respectively. The data for these two variables was obtained from the NCDB.

The Δ*Pubtransgt* variable accounts for the change over a given ten year period in the percentage of households in the gentrifiable census tracts within an MSA that use public transit. This variable will account for any influence that the quality of a metropolitan area's public transportation system may have on residential income patterns. The data for this variable was also obtained from the NCDB.

The Δ*Hsgagegt* variable represents the change over a given ten year period in the median dwelling age in the gentrifiable census tracts within an MSA. This measure was constructed using theory from Brueckner and Rosenthal (2009) which states that high-income households will be more competitive for a younger housing stock than low-income households. The lower the median housing age is in the gentrifiable census tracts, the more likely the rich will live there since the rich are willing to outbid the poor to live in newer dwellings. The data for this variable was also obtained from the NCDB.

The Δ*Histamengt*, Δ*Natamengt*, and Δ*Cultamengt* variables were constructed based on the work of Brueckner et. al. (1999) where they demonstrated that more high-income households will live in census tracts that have higher levels of local amenities located within them. These variables measure the unobserved amenity effects that may be correlated with the regressors. Three variables will be used to account for these effects; Δ*Histamengt* will account for an MSA's historical amenities, Δ*Natamengt* will account for an MSA's natural amenities, and Δ*Cultamengt* will account for an MSA's cultural amenities.

The Δ*Histamengt* variable will account for the change over a given ten year period in the number of historical places documented by the National Register of Historical Places within an MSA's gentrifiable census tracts per 1000 residents. The per 1000 residents measure is calculated using an MSA's gentrifiable census tract population. Using a per capita measure will account for the fact that older, larger cities will inherently have more historical monuments. The data contains physical addresses of the sites; therefore, it was possible to identify the census tract for each historical place. The greater the increase in the Δ*Histamengt* variable over the given ten year period, the greater the expected increase in gentrifiable census tracts' median incomes over the same ten year period.

The Δ*Natamengt* variable accounts for the change over the given ten year period in the number of acres of interior water within the central city limits per 1000 residents in an MSA's gentrifiable census tracts and is calculated in the same fashion as the Δ*Histamengt* variable. Brueckner et. al. (1999) discussed the importance of this measure with respect to the location of high-income households in an MSA. The greater the increase in the Δ*Natamengt* variable over the given ten year period, the greater the expected increase in gentrifiable census tracts' median incomes over the same ten year period. This data was collected from the U.S. Geological Survey's National Water Information System database.

The Δ*Cultamengt* variable accounts for the change over the given ten year period in the number of professional operas, theatre groups, orchestras, ballets, and museums within an MSA's gentrifiable census tracts per 1000 residents and is calculated using the same methodology as the Δ*Histamengt* and Δ*Natamengt* variables. The data was originally collected using the *Places Rated Almanac*, then each cultural amenity's location and date of existence was verified via the internet or phone call. It is expected to interact with the dependent variable in the same fashion as both Δ*Histamengt* and Δ*Natamengt*.

The Δ*Teamsgt* variable accounts for the change over the given ten year period in the number of National Football League (NFL), National Basketball Association (NBA), Major League Baseball (MLB), and National Hockey League (NHL) teams located within an MSA's gentrifiable census tracts per 1000 residents living in these census tracts. College and women's professional sports teams were excluded since cities do not generally build stadiums to attract and maintain these types of teams. Professional sports stadium can potential drive high-income households out of the central city due to increases in taxes and other factors.

The *Medium*, *Large*, and *Vlarge* variables control for MSA population densities with medium being defined as MSAs with populations per square mile between 300 and 500, large as MSAs with populations per square mile between 500 and 1,000, and very large as MSAs populations per square mile of over 1,000. MSAs with populations per square mile less than 300 are defined as small. The average population density in the United States was around 80 people per square mile according to the 2000 Census. The paper uses this definition so as to be the most inclusive definition of MSA size and to keep it constant avoiding potential endogeneity, similar to the rational for using the Neighbohood Change Database when obtaining data in expanding MSAs over time.[9]

Before measuring the effects of traffic congestion on the income growth of the gentrifiable census tracts within the central cities of MSAs, it is important understand the relationship between traffic congestion and the income growth of all census tracts in the central cities of MSAs. Therefore, we also run the following regression which can be viewed below:

$$\begin{aligned}\Delta MHICC = {} & \alpha + \beta_1(\Delta Cong) + \beta_2(\Delta Perpopcc) + \beta_3(\Delta Perjobscc) + \beta_4(\Delta Pubtranscc) + \\ & \beta_5(\Delta Hsgagecc) + \beta_6(\Delta Histamencc) + \beta_7(\Delta Natamencc) + \beta_8(\Delta Cultamencc) + \\ & \beta_9(\Delta Teamscc) + \beta_{10}(Year) + \beta_{11}(Medium) + \beta_{12}(Large) + \beta_{13}(Vlarge) + e_i \end{aligned} \tag{2}$$

The structure will be the exact same except the $\Delta MHICC$ dependent variable will be calculated as the change over the given ten year period in the median household income of an MSA's central city. This is the same variable controlled for as an independent variable in Eq. (1). Also, the independent variables are calculated in the same manner as those in Eq. (1), but include

[9] Letting the city size variables vary between years does not affect the results.

data from all census tracts within the MSAs' central city limits instead of just the getrifiable census tracts.

DESCRIPTIVE STATISTICS

Central Cities

Table 1, below, provides the summary statistics for the central city data set broken up into two, ten-year time periods; 1980 to 1990 and 1990 to 2000. The dependent variable, the change in median household income for all central city census tracts, increases at a decreasing rate.

Table 4. Summary Statistics – Central City Data Set

	1980-1990				1990-2000			
Variable	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev
MHICC	39.70%	93.90%	64.39%	12.19%	8.33%	50.70%	24.01%	8.74%
HOURS LOST	0.00%	400.00%	121.85%	80.73%	-5.00%	500.00%	100.84%	87.62%
TTI	0.00%	17.59%	4.30%	3.66%	-1.71%	15.93%	4.81%	3.28%
PERPOPCC	-36.79%	5.55%	-7.96%	7.13%	-23.36%	4.50%	-7.54%	5.07%
PERJOBSCC	-31.40%	35.68%	-4.79%	8.24%	-24.19%	98.32%	-3.52%	33.12%
PUBTRANS CC	-69.64%	167.01%	-25.93%	27.78%	-50.20%	101.19%	-7.61%	25.68%
HSGAGECC	-9.66%	58.26%	13.79%	10.83%	-3.30%	45.39%	19.54%	9.60%
CULTAMEN CC	-69.53%	885.94%	167.13%	176.48%	-58.80%	1757.35%	26.93%	189.47%
NATAMEN CC	-55.91%	6.50%	-23.01%	13.02%	-37.18%	895.77%	24.17%	108.66%
HISTAMEN CC	-23.55%	902.76%	91.57%	106.80%	-72.40%	65.51%	-28.10%	22.51%
TEAMSCC	-54.40%	89.17%	-2.59%	18.53%	-100.00%	158.93%	2.80%	30.16%

This table reports the summary statistics of the variables for the central city regressions for two different time periods; *1980 to 1990* and *1990 to 2000*. The *Minimum Value, Maximum Value, Mean* and *Standard Deviation* are listed for each of the variables during both time periods.

The percentage of overall populations and jobs in the central cities decreased over both periods, but at a decreasing rate. Public transportation usage also decreased over both periods, but at a decreasing rate, while housing age increased at an increasing rate. Cultural and historical amenities increased dramatically between 1980 and 1990 while cultural and natural amenities experienced significant increases between 1990 and 2000. Most importantly, both traffic congestion measures increased steadily over the two time periods.

Gentrifiable Census Tracts

Table 2, below, provides the summary statistics for the gentrifiable census tract data set broken up into two, ten-year time periods; 1980 to 1990 and 1990 to 2000. There are several trends between the two time periods. The dependent variables for the two separate regressions, the median household incomes for all census tracts (Table 1) and gentrifiable census tracts within central cities (Table 2), are both increasing at a decreasing rate. More importantly, the median household income gains for the gentrifiable census tracts are 10.9% and 21.9% greater than the gains for all central city census tracts for the periods 1980 to 1990 and 1990 to 2000, respectively.

The percentage of overall populations and jobs in the gentrifiable census tracts increased over both periods while they decrease on average for all central city census tracts. Public transportation usage decreased in the gentrifiable census tracts over both periods, but at a slower rate than all central city census tracts. Housing age in the gentrifiable census tracts decreased slightly over the two time periods while housing age in the overall central city increased around 20% for each of the time periods. Cultural amenities increased steadily at around 15% over the two time periods. Natural amenities experienced about a 15% decline between 1980 and 1990, but rebounded with about a 36% increase between 1990 and 2000. Historical amenities declined at a decreasing rate over the two time periods while teams decreased at an increasing rate over the two time periods. Most importantly, both traffic congestion measures increased steadily over the two time periods.

Table 5. Summary Statistics – Gentrifiable Census Tracts

	1980-1990				1990-2000			
Variable	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev
MHIGT	3.19%	194.45%	71.39%	34.92%	-7.86%	173.49%	30.35%	27.23%
TTI	0.00%	17.59%	4.30%	3.66%	-1.71%	15.93%	4.81%	3.28%
HOURSLOST	0.00%	400.00%	121.85%	80.73%	-5.00%	500.00%	100.84%	87.62%
PERPOPGT	-96.53%	419.45%	23.12%	93.87%	-28.14%	87.36%	10.79%	16.81%
PERJOBSGT	-100.00%	472.09%	29.84%	52.16%	-31.84%	77.10%	22.86%	17.18%
PUBTRANSGT	-69.25%	242.01%	-10.69%	35.93%	-45.04%	113.47%	-0.04%	24.48%
HSGAGEGT	-38.66%	58.26%	-3.79%	17.83%	-35.50%	45.36%	-2.37%	10.60%
CULTAMENGT	3.04%	39.43%	14.99%	7.07%	-8.58%	60.76%	14.93%	11.42%
NATAMENGT	-134.45%	270.88%	-14.37%	60.59%	-10.10%	222.95%	36.37%	34.99%
HISTAMENGT	-109.21%	-0.89%	-77.12%	16.19%	-70.10%	162.95%	-23.63%	34.99%
TEAMSGT	-74.04%	72.18%	-6.46%	24.28%	-100.00%	100.00%	-10.62%	75.07%

This table reports the summary statistics of the variables for the Gentrifiable Census Tracts (those with a Median Household Income between 50% and 80% of their respective MSA's Median Household Incomes) regressions for two different time periods; *1980 to 1990* and *1990 to 2000*. The *Minimum Value, Maximum Value, Mean* and *Standard Deviation* are listed for each of the variables during both time periods.

RESULTS

Central Cities

The regression estimates of the independent variables for the all central city census tracts are presented in Table 3 below. The most important implication of the results in this paper has to do with the traffic congestion coefficients. Which are found to be statistically significant using both measures. The model predicts that for every 1% increase in the number of annual hours lost per commuter due to traffic congestion within an MSA, the median household income of an MSA’s central city will increase by .031% over the given ten year time period. When using the travel time index to proxy for traffic congestion, the model predicts that for every 1% increase, the median household income of an MSA's central city will increase by .725% over the same ten year time period.

Central city income is expected to decrease with increases in the housing age and the coefficients provide evidence that this is true. For every 1% increase in housing age, the median household income of the central city decreased between .298% and .333% over the given ten year time period. Also, for every 1% increase in public transportation usage within the central city limits, the median household income of the central city decreased by .065% over the given ten year time period using the travel time index.

Table 6. Central City Income Growth Regression Coefficients

	Specification			
	Annual Hours Lost		Travel Time Index	
Variable	Coefficient	T-Stat	Coefficient	T-Stat
TTI	-	-	0.725**	2.38
HOURSLOST	0.031**	2.420	-	-
PERPOPCC	0.014	1.410	0.016	1.58
PERJOBSCC	0.002	0.18	<-.001	-0.07
PUBTRANSCC	-0.046	-1.40	-0.065**	-2.00
HSGAGECC	-0.298***	-2.97	-0.333***	-3.47
CULTAMENCC	0.651***	5.67	0.714***	6.24
NATAMENCC	0.064*	1.80	0.057	1.62
HISTAMENCC	-0.433***	-8.24	-0.425***	-8.18
TEAMSCC	0.003	0.16	0.022	1.14
Observations	182		182	
Adjusted R^2	0.55		0.56	

This table reports the regression coefficients with their corresponding t-stats beside them in for the Central City Income Growth specifications using the Texas Transportation Institute's *Annual Hours Lost per Commuter Due to Traffic Congestion* (Left) and *Travel Time Index* (Right) as a measures for traffic congestion. Statistical significance is designated by *** at the 1% level, ** at the 5% level, and * at the 10% level.

The spatial model presented in Brueckner et. al. (1999) predicts that high-income households will live closer to central city, such as in Paris, France, if there are more amenities near the city center than in the suburbs. The change in the number of historical and cultural amenities residents living are both statistically significant. Median household income increases at a rate between .651% and .714% with every 1% increase in the number of cultural amenities per 1000 living within the central city of an MSA. The paper also finds that median household income decreases at a rate between .425% and .433% with every 1% increase in the number historical amenities within the central city limits per 1000 residents living in the central city of an MSA. Central city income growth is expected to increase by .064% for every 1% increase in the number historical amenities within the central city limits per 1000 residents living in the central city of an MSA when using annual hours lost per commuter to proxy for traffic congestion.

Gentrifiable Census Tracts

The regression estimates of the independent variables for the gentrifiable census tracts within the MSA's central cities are presented in Table 4, below. Again, the most important implication of the results in this paper has to do with the traffic congestion coefficients which are statistically significant using both measures. The model predicts that for every 1% increase in the number of annual hours lost per commuter due to traffic congestion within an MSA, the median household income of an MSA's gentrifiable census tracts will increase by a significant .039% over the given ten year time period. When using the travel time index to proxy for traffic congestion, the model predicts that for every 1% increase, the median household income of an MSA's central city will increase by .910% over the same ten year time period. These coefficient is around 26% greater than that found in the entire central city regressions demonstrating that traffic congestion's effect on median household income is greater for an MSA's gentrifiable census tracts than all census tracts within the central city. Also, the gentrifiable census tracts experience between a significant 1.54% and 1.58% increase in median household income for every 1% in central city income over a given ten year period.

Central city income is expected to decrease with increases in the housing age and the coefficients provide evidence that this is true. For every 1% increase in housing age, the median household income of the central city decreased between a significant .284% and .339% over the given ten year time period. Also, for every 1% increase in public transportation usage within the gentrifiable census tracts within the central city limits of an MSA, median household income in the tracts decreases between .112% and .127%.

The changes in the number of historical and cultural amenities are statistically significant. Median household income increases at a rate between 1.033% and 1.036% with every 1% increase in the number of cultural amenities per 1000 living within the gentrifiable census tracts of an MSA. This coefficient is around 50% greater than that found in the entire central city regressions demonstrating that the median household income in a central city's gentrifiable census tracts are more positively affected by increases in cultural amenities. The paper also finds similar results for historical amenities where median household income increases at a rate between .394% and .438% with every 1% increase in the number historical amenities per 1000 residents living in the gentrifiable census tracts of an MSA. This measure was significant and negative in the central city regressions (Table 3).

Table 7. Gentrifiable Census Tracts Income Growth Regression Coefficients

	Specification			
	Annual Hours Lost		Travel Time Index	
Variable	Coefficient	T-Stat	Coefficient	T-Stat
TTI	-	-	0.910**	2.17
HOURSLOST	0.039*	1.79	-	-
CCINCCHNG	1.539***	12.12	1.583***	12.32
PERPOPGT	0.008	0.46	0.010	0.57
PERJOBSGT	-0.010	-0.45	-0.009	-0.44
PUBTRANSGT	-0.127**	-2.30	-0.112**	-2.04
HSGAGEGT	-0.284*	-1.70	-0.339**	-2.04
CULTAMENGT	1.036***	4.93	1.033***	4.87
NATAMENGT	-0.054	-0.92	-0.070	-1.18
HISTAMENGT	0.394***	3.86	0.438***	4.27
TEAMSGT	0.015	0.46	0.025	0.76
Observations	182		182	
Adjusted R^2	0.55		0.56	

This table reports the regression coefficients with their corresponding t-stats beside them in for the Gentrifiable Census Tracts Income Growth specifications using the Texas Transportation Institute's *Annual Hours Lost per Commuter Due to Traffic Congestion* (Left) and *Travel Time Index* (Right) as a measures for traffic congestion. Statistical significance is designated by *** at the 1% level, ** at the 5% level, and * at the 10% level.

CONCLUSION

Increases in MSA traffic congestion levels hold significant explanatory power when determining why neighborhoods gentrify. Since the dramatic decline in housing prices across the country, the topic of gentrification has taken on even greater importance as local governments struggle to meet their budgets. On one hand, the increase in property values benefits the low-income property owners and increases city budgets, but the low-income renters are sometimes forced out of their neighborhoods due to increasing rents. These factors have made gentrification a topic of interest for developers, activists, and local government officials seeking re-election.

The contribution of this paper to the vast gentrification literature universe is that this paper truly isolates the congestion portion of commute speeds and times and measures their impact on both all central city census tracts and just the gentrifiable census tracts within central cities over the period 1980 to 2000. The majority of studies dealing with this issue use commute to work times as a measure for congestion. This paper makes use of two independent, MSA level measures, annual hours lost per commuter due to traffic congestion and a travel timeindex, taken from the Texas Transportation Institute's Urban Mobility Reports which compares peak congestion period travel time to free-flow travel time isolating traffic congestion effects on the median household income of an MSA's gentrifiable census tracts.

The model predicts that for every 1% increase in the number of annual hours lost per commuter due to traffic congestion, an MSA's central city and gentrifiable census tracts will experience between .031% and .039% significant increases, in median household income, respectively, over a given ten year period. These results are verified using the travel time index as a specification check findings that an MSA's central city and gentrifiable census tracts will experience between .725% and .910% significant increases, in median household income, respectively, over a given ten year period. Most importantly, traffic congestion's effect is nearly 26% greater when accounting for just the gentrifiable census tracts within an MSA's central city rather than all central city census tracts.

REFERENCES

Alonso, William, *Location and Land Use* (Cambridge, MA: Harvard University Press, 1964).

Anas, A., and L. Moses. “Mode Choice, Transport Structure and Urban Land Use,” *Journal of Urban Economics* 6 (1979), 228-246.

Baum-Snow, Nathaniel, “Suburbanization and Transportation in the Monocentric Model,” *Journal of Urban Economics* 62 (2007), 405-423.

Baum-Snow, Nathaniel, “Did Highways Cause Suburbanization?” *Quarterly Journal of Economics* 122 (2007), 775-805.

Boyer, Richard and David Savageau. *Places Rated Almanac* (1981). New York, New York: Rand McNally and Company.

Boyer, Richard and David Savageau. *Places Rated Almanac* (1989). New York, New York: Prentice Hall Travel.

Bond, Eric W., and N. Edward Coulson, “Externalities, Filtering, and Neighborhood Change,” *Journal of Urban Economics* 26 (1989), 231-249.

Brueckner, Jan K., Jacques-Francois Thisse, and Yves Zenon, “Why Is Central Paris Rich and Downtown Detroit Poor?” AN Amenity Based Theory,” *European Economic Review* 43 (1999) 91-107.

Brueckner, Jan K., and Stuart S. Rosenthal., “Gentrification and Neighborhood Housing Cycles: Will America’s Future Downtowns be Rich?” *The Review of Economics and Statistics* 91 (2009), 725-743.

Glaeser, Edward L., Matthew E. Kahn, and Jordan Rappaport, “Why Do the Poor Live in Cities?” *Journal of Urban Economics* 63 (2008), 1-24.

Kolko, Jed, “The Determinants of Gentrification,” (2007).

Leroy, Stephen F., and John Sonstelie, “Paradise Lost and Regained: transportation Innovation, Income, and Residential Location,” *Journal of Urban Economics* 13 (1983), 67-89.

Martin, Richard W. “"Job Decentralization with Suburban Housing Discrimination: An Urban Equilibrium Model of Spatial Mismatch," *Journal of Housing Economics*, 6 (1997), 293-317.

McKinnish, Terra, Randall Walsh and T. Kirk White, “Who Gentrifies Low Income Neighborhoods?” U.S. Census Bureau Studies Paper No. CES-08-02 (2008).

Mills, Edwin S., “An Aggregative Model of Resource Allocation in a Metropolitan Area,” *American Economic Review* 57 (1967), 197-210.

Muth, Richard F., *Cities and Housing* (Chicago: University of Chicago Press, 1969).

Muth, Richard F., “A Vintage Model of the Housing Stock,” *Papers of the Regional Science Association* 30 (1973),141-156.

National Register of Historic Places (National Register Information System, National Park Service, 2012).

Nechyba, Thomas J. and Randall Walsh, “Urban Sprawl,” *Journal of Economic Perspectives* 18 (2004), 177-200.

Neighborhood Change Database, 1980 – 2000 (GeoLytics in association with the Urban Institute, 2012).

Rosenthal, Stuart, “Where Poor Renters Live in Our Cities,” Harvard Joint Center for Housing Studies working paper RR07-2.

Savageau, David. *Places Rated Almanac* (2000). Foster City, California: IDG Books Worldwide, Inc.

Savageau, David. *Places Rated Almanac* (2007). Washington, DC: Places Rated Books.

Urban Mobility Reports, 1982 – 2011 (Texas A&M Transportation Institute, University Transportation Center for Mobility, 2012).

U.S. Geological Survey’s National Water Information System Database, (U.S. Department of the Interior, U.S. Geological Survey, 2012).

Wheaton, William, “A Bid Rent Approach to Urban Housing Demand,” *Journal of Urban Economics* 2 (1977), 15-32.

APPENDIX

Appendix A.

To understand the effects of an increase of *t* on *q*, we must first derive *c* and *q*, solve for *p*, then take the derivative of *p* with respect to *t*. The calculations follow:

Derivation of housing demand (q):

$$£ = c^{\alpha}q^{\beta} + \lambda(y - c - pq - tx)$$

$$\partial£/\partial c = \alpha c^{\alpha-1}q^{\beta} - \lambda = 0 \quad (2a)$$

$$\partial£/\partial q = \beta c^{\alpha}q^{\beta-1} - \lambda p = 0 \quad (2b)$$

$$\partial£/\partial\lambda = y - c - pq - tx = 0 \quad (2c)$$

Set Eq. (2a) equal to Eq. (2b):

$$\alpha c^{\alpha-1}q^{\beta} = (\beta/p)c^{\alpha}q^{\beta-1}$$

Rearrange Eq. (2d) to solve for the composite non-housing good (c):

$$c = (\alpha/\beta)pq \quad (2d)$$

Rearrange Eq. (2c) to solve for housing consumption (q):

$$q = 1/p\ (y - c - tx) \quad (2e)$$

Substitute Eq. (2e) into Eq. (2d):

$$c^* = (\alpha/\beta)p(1/p)(y - c - tx)$$
$$= \alpha/\beta(y - c^* - tx)$$
$$= \alpha/\beta(y - tx) - \alpha/\beta(c^*)$$
$$\Rightarrow c^* + \alpha/\beta(c^*) = \alpha/\beta(y - tx)$$

Therefore, $c^* = \dfrac{\alpha/\beta(y - tx)}{1 + \alpha/\beta}$ (2f)

Rearranging Eq. (2d) to solve for the composite housing good, (q):

$$q = (\beta/\alpha)c(1/p) \quad (2g)$$

Substitute Eq. (2f) into Eq. (2g):

$$q^* = (\beta/\alpha)(1/p)\left[\frac{\alpha/\beta(y - tx)}{1 + \alpha/\beta}\right]$$

Therefore, $q^* = 1/p\left[\dfrac{(y - tx)}{1 + \alpha/\beta}\right]$ (2h)

Derivation the price per square foot (p):

$$u(c^*,q^*) = u^* = c^{*\alpha}q^{*\beta}$$

Therefore, $u^* = \left[\dfrac{\alpha/\beta(y - tx)}{1 + \alpha/\beta}\right]^{\alpha}\left[1/p\ \dfrac{(y - tx)}{1 + \alpha/\beta}\right]^{\beta}$

$$= (\alpha/\beta)^{\alpha}\left[\frac{(y - tx)}{1 + \alpha/\beta}\right]^{\alpha+\beta}(1/p)^{\beta}$$

$$\Rightarrow p^{\beta} = (1/u^{*})(\alpha/\beta)^{\alpha} \left[\frac{y - tx}{1 + \alpha/\beta}\right]^{\alpha+\beta}$$

$$= p = \quad (1/u^{*1/\beta})(\alpha/\beta)^{\alpha/\beta} \left[\frac{y - tx}{1 + \alpha/\beta}\right]^{\alpha/\beta+1}$$

Lastly, take the derivative of p with respect to t:

$$\boldsymbol{\partial p/\partial t = \quad (1/u^{*1/\beta})(\alpha/\beta)^{\alpha/\beta}(\alpha/\beta+1) \left[\frac{y - tx}{1 + \alpha/\beta}\right]^{\alpha/\beta} [-x/(1+ \alpha/\beta)] \ < 0} \qquad (2g)$$