

**POSITIONAL COMPETITION:
FROM LOW-NUMBER LICENSE PLATES
TO McMANSIONS**

by

Boyang Liu

A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Master of Science in Agricultural and Resource Economics

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by

Boyang Liu

Approved: _____
John Mackenzie, Ph.D.
Associate Professor in charge of thesis on behalf of the Advisory Committee

Approved: _____
Titus O. Awokuse, Ph.D.
Chairperson of the Department of Applied Economics and Statistics

Approved: _____
Mark Rieger, Ph.D.
Dean of the College of Agriculture and Natural Resources

Approved: _____
James G. Richards, Ph.D.
Vice Provost for Graduate and Professional Education

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ABSTRACT

Over a century ago, Thorstein Veblen explored “conspicuous consumption” to signal social status. Building on Veblen, Fred Hirsch (1976) defined a “positional good” as a good that derives its value from a social consensus regarding its desirability relative to other goods in its category.

My thesis examines two positional goods: Delaware low-number license plates, and luxury houses, sometimes referred to as “McMansions.” First, because car-owners in Delaware actually own their license plate numbers, the state has an active secondary market in low-number tags. These are perfect positional goods: they have no functional value beyond that of an ordinary license plate, and they have explicit rank order. I used sale-price and asking-price data to estimate an empirical pricing model and the total economic surplus embodied in this small market.

Next, I analyze evidence of positional competition in the US housing market, using Decennial Census and American Community Survey data to show that (1) higher concentrations of wealth in a county induce high-income households to spend proportionally more of their incomes on housing, and (2) higher levels of local income inequality appear to augment this effect. My analysis also demonstrates how choice of residential location involves a trade-off between housing costs and commuting costs.

In the housing analysis, the primary dependent variable (the percent of high-income households that spend more than 30 percent of monthly income on housing) is truncated at zero, which biases the OLS estimator. Therefore I estimate Tobit models of

the positionality effect and test them for heteroscedasticity and normality; I compare these with CLAD models (Powell) which are robust with respect to non-normality and heteroscedasticity.

Chapter 1

INTRODUCTION

This thesis analyzes demands for positional goods. The value of any particular positional good depends on a social consensus regarding its rank relative to other goods in its class, rather than on any particular functional value it may have. For example, a Rolex watch is a positional good: it doesn't necessarily keep better time than a cheap Timex, but it signals the wearer's economic status to others who recognize and appreciate Rolex watches.

1.1 Low-Number Delaware License Plates

The first section analyzes what I consider to be a perfect positional good: low-number Delaware license plates. Unlike most states, Delaware's Division of Motor Vehicles assigns actual ownership of vehicle tag numbers to vehicle owners, and permits owners to transfer their numbers to other cars or owners. This has led to the creation of a secondary market for low numbers.

This market allocates the rights to use low numbers on vehicle tags; it is minimally concerned with the physical tags, which are typically replicas of worn-out original black-and-white porcelain tags. An original two- or three-digit antique tag that does not include the right to display the number on a vehicle can be bought for \$10 or \$20. The right to use the number on a vehicle may sell for more than \$100,000.

DMV regulations allow owners of tag numbers below 87000 to use the old-style “DEL.” black-and-white porcelain tags on their cars, and several firms make replicas of such plates to order. A low number on an old-style tag signals the vehicle owner is wealthy and/or politically well-connected and/or has old family ties in Delaware. (A second class of low numbers, from 87000 to 200000, can use original or replica stainless steel black-and-white “DELAWARE” tags, but I am not analyzing this market.)

Fred Hirsch (1976) theorized that positional goods are likely to become speculative goods, which means the buyer of a positional good can justify it as an “investment” rather than just a vanity purchase. Until about 2008, low-number Delaware tags increased significantly faster than the CPI. For example, tag number 9 sold for \$185,000 in July, 1993, and tag number 6 sold for \$675,000 at auction in February, 2008, which suggests an implicit annual rate of return of about nine percent. A *Wilmington News-Journal* account of the 2008 auction included comments by the buyer regarding the high implicit rate of return. However, since 2008, the speculative value of low-number tags appears to have fallen.

I estimate a simple econometric pricing model for low-number tags, estimate the aggregate capitalized value of the 87,000 tags in this market, and conclude with a brief discussion about extending property taxation to them.

1.2 McMansions

The second section of this thesis discusses the US market for “McMansions,” i.e. very large newly-constructed single-family houses. Like the overall housing market, the

market for McMansions is driven by land prices, mortgage rates, quality of local amenities and commuting costs. But I hypothesize that the demand for McMansions also reflects a degree of positional competition. The speculative bubble in the US housing market prior to 2007, driven by easy credit and preferential tax treatment of mortgage interest and capital gains roll-overs, actually made this positional competition highly profitable for a decade or more as high-income households could realize highly-leveraged capital gains by “flipping” large houses for even larger houses.

My main analysis tests for evidence of positional competition in county-level housing cost data extracted from the 2000 US Census of Population and Housing, and two kinds of data extracted from the 2012 American Community Survey (ACS). There are several likely indicators of positional competition in county-level housing market.

The principal signal of likely positional competition would be a positive correlation between the relative percentage of high-income households in a county and the budget share that the typical high-income household spends on housing. My analysis tests a plausible positionality hypothesis: a higher concentration of wealthy households induces those households to compete for status by spending relatively more on housing. Preliminary XY scatterplots of the Census data for 1999 and 2012 appear to confirm this effect, and suggest that it grew stronger over time.

I also test the effect of income inequality, measured as Gini coefficients calculated from Census income distribution data for 1999 and 2012, on the housing expenditures of high-income households. My underlying hypothesis here is that positional competition is likely to be more pronounced in counties with higher income

inequality. If so, the typical budget share allocated to housing by high-income households will be positively correlated with the local Gini coefficient. Again, preliminary XY scatterplots of these data appear to confirm this hypothesis.

These scatterplots also suggest that positional competition affects some housing markets but not others. A number of counties have few or no high-income households that spend over 30% of their incomes on housing, so the distribution of these data is effectively censored at zero. So a formal econometric analysis of large budget shares allocated to housing necessitates use of limited-dependent-variable estimation methods, e.g., Heckman or Tobit.

Chapter 2

LITERATURE REVIEW

2.1 Background

Conventional demand theory assumes consumers' utility functions are autonomous, and the goods each individual consumes directly determine his or her absolute satisfaction. But in *The Theory of the Leisure Class* (1899) Thorstein Veblen suggests that our utilities are interdependent, and determined by our social status *relative to others*. This motivates competition for social status via “conspicuous consumption” of goods that signal the owner's status to others.

At best, this is a zero-sum game since one person's higher social position necessarily implies another's lower position. In fact, with diminishing marginal utility of status, positional competition may in fact be negative-sum game: my consumption increases my utility by reducing your utility. I don't necessarily have to enjoy my consumption directly; I enjoy that we both know I outrank you by consuming more than you. I enjoy imagining your envy. It doesn't matter that my actual psychic benefit may be small relative to your psychic cost.

Some forms of positional competition generate market distortions and waste physical resources. The traditional potlatches of some Pacific Northwest Indian tribes involved the ritual giving-away or outright destruction of a chief's possessions as proof

of his wealth and power. These rituals were outlawed in parts of the U.S. and Canada in the late 19th century.

The demand for large SUV's is partly driven by positional competition for highway safety. SUV's have lower fuel economy than passenger cars, but in collisions between large SUV's and passenger cars, the fatality rate in passenger cars is four times higher than in SUV's (National Highway Traffic Safety Administration). If anything, this safety advantage encourages riskier driving behavior among SUV owners, and a higher overall accident rate for SUV's than for passenger cars. A high gasoline tax would be an obvious corrective, functioning as an efficient proxy for taxes on vehicle weight, engine inefficiency, road miles driven, etc.

Positional consumption expenditures represent the scarcity rent of social status. Robert Frank (2008) and others have proposed capturing this rent and curbing wasteful consumption via consumption taxes. 150 years ago John Stuart Mill argued:

“Luxury taxes have some properties which strongly recommend them...they operate in some cases as... the only useful kind of sumptuary law. ... A great portion of the expenses of the higher and middle classes in most countries [is motivated by] regard to opinion, and an idea that certain expenses are expected from them, as an appendage of station; and I cannot but think that expenditure of this sort is a most desirable subject of taxation. If taxation discourages it, some good is done, and if not, no harm; for in so far as taxes are levied on things which are desired and possessed from motives of this description, nobody is the worse for them.

“When a thing is bought not for its use but for its costliness, cheapness is no recommendation. ...The consequence of cheapening articles of vanity, is not that less is expended on such things, but that the buyers substitute for the cheapened article some other which is more costly, or a more elaborate quality of the same thing; and as the inferior quality answered the purpose of vanity equally well when it was equally expensive, a tax on the article is really paid by nobody: it is a creation of public revenue by which nobody loses.”

But economists are by no means unanimous in calling for taxation of positional goods, particularly where their externality costs are not demonstrably negative. Envy may be at the root of the profit incentive, motivating people to work harder and more efficiently.

2.2 Theory and Literature Review

Veblen described (or satirized) conspicuous leisure, consumption and waste as universal behaviors observed in both primitive and advanced human societies. These behaviors originated in the social divisions of labor that might follow a tribal conquest, in which the winners would put the losers to work at low-status jobs such as farming, fetching firewood and cooking, and reserve the part-time high-status jobs such as religion, hunting and warfare—all with identifying accoutrements—for themselves. These high-status jobs also afforded them leisure time, which itself came to signal high social status.

Veblen viewed the modern economy as a two-tier social system in which the working class has evolved into “engineers” who are continually improving the efficiency with which they produce goods and services, while the leisure class evolved into predatory “businessmen” try to disrupt efficient market processes in order to extract profits for themselves.

Veblen summarized his theory: “The basis on which good repute in any highly organized industrial community ultimately rests is pecuniary strength; and the means of showing pecuniary strength, and so of gaining or retaining a good name, are leisure and a conspicuous consumption of goods”

An ordinary market demand schedule is the horizontal summation of individual consumers' demands. The conventional assumption is that individual demands are derived from autonomous individual utility functions, where no individual's utility is affected by any other individual's consumption behavior. This assumption implies a straightforward additivity of individual demands to obtain the market demand.

Leibenstein (1950) explains three violations of this additivity principle, where... (1) demand reflects the external effects of one person's consumption on another's utility; (2) demand reflects speculative motives; and (3) demand that reflects irrational whims, erroneous beliefs, etc. Most of his analysis is focused on the first type. He defines three demand effects resulting from interdependencies of consumers' utility functions:

(1a). The "bandwagon" effect is imitative: imitators will buy a good simply because other people are buying it. Anticipated bandwagon behaviors may stimulate early speculative buying, while late speculative buying may itself be bandwagon behavior. The bandwagon effect makes individual demands *more than* additive, and increases market demand volatility as popular tastes change.

(1b). The "snob" effect is exclusive: snobs will *avoid* a good because too many others are buying it and/or too much is being bought. The snob effect makes individual demands *less than* additive, and reduces market demand volatility as popular tastes change.

(1c). The "Veblen" effect is motivated by price directly. Price may signal unobservable quality attributes of a good, or the good may simply signal its price as

visible evidence of the wealth or social status of the person who possesses it.

Leibenstein's article explores some theoretical distinctions between these effects.

Formally, a "Veblen good" or "status good" is any luxury good for which demand *increases* as its price is increased. Its theoretical twin is the extreme-inferior Giffen good, which behaves the same way. When the price of a Giffen good falls, the effect of its negative income elasticity dominates the positive substitution effect. A Giffen good is readily substitutable for a higher-priced alternative good, and it commands a large share of the low-income household budget, so that its price decline boosts the effective purchasing power of the budget enough to make the preferred substitute affordable, so the household buys the preferred substitute instead. Similarly, when the price of a Veblen good falls, the snob effect dominates the bandwagon effect, so the quantity demanded falls.

Various researchers have experimented with surveys to gauge degrees of positionality in demand for various goods. In a typical study, survey respondents might be asked to indicate their preferences between paired alternative scenarios, e.g., "you live in a 3,000 square-foot house in a neighborhood where the average house size is 4,500 square feet" (scenario A) versus "you live in a 2,500 square-foot house in a neighborhood where the average house size is 2,200 square feet" (scenario B). Although scenario A gives respondents the bigger house, its inferior size relative to surrounding houses typically reduces its desirability relative to the smaller house in scenario B, so some respondents may choose B.

Solnick and Hemenway (2005) used such survey methods to demonstrate varying degrees of positionality across a spectrum of public and private goods and bads. People are more positional with regard to their incomes than their leisure time; more positional with regard to their children getting low grades in school than with longer commute times for themselves; and more positional with regard to national defense than national life expectancy.

Carlsson, Johansson-Stenman and Martinsson (2007) first applied a choice experiment using random samples in Sweden to measure people's perceptions of the degree to which position matters. Their results show that relative income and cars are highly positional, leisure and car safety comparatively are not.

Grolleau, Mzoughi and Said (2012) designed two types of survey using respectively convenient sample and random sample to capture the positional concerns in France. They show that two types of samples yield similar results, "position matters in French society and varies across domains". Moreover, people tend to think others are more positional than themselves.

Fred Hirsch's book *Social Limits to Growth* (1976) argues that rising affluence simply intensifies positional competition, so the average person is *relatively* no better off. This is consistent with Easterlin's (1974) finding that in any country wealthy people are likelier to report being happier than poor people, but across countries, absolute wealth is *not* correlated with happiness.

Positional goods are often luxury-speculative goods: as incomes rise and people spend larger budget shares on the fixed supply, their prices rise faster than the CPI, and

they acquire speculative value. Thus positional competition tends to be self-reinforcing, and may lead to speculative boom and bust cycles in positional goods markets.

Rising incomes increase individuals' abilities to bid for a fixed supply of a positional good. Hirsch views competition in the positional sector "as a general filtering device through which excessive demand has to be matched to available supply. This aspect at best yields no net benefit and usually involves additional resource costs, so that positional competition itself is liable to be a negative-sum game."

Chapter 3

LOW-NUMBER AUTOMOBILE TAGS IN DELWARE

3.1 Introduction

The State of Delaware began issuing license plates with the old postal abbreviation “DEL.” above the number to Delaware motorists in 1909. After varying tag colors in the earliest years, the state adopted a standard white-on-black porcelain tag style in the 1930’s with slots to hold registration renewal decals. In 1947, after the Department of Transportation had issued about 87,000 of these tags, it switched to stainless steel black-and-white tags with “DELAWARE” spelled out above the number. In 1959, it switched to the current aluminum blue and gold tags with stick-on renewal decals.

The white-on-black low-number “DEL.” porcelain tags are still legal to use, and have gradually acquired value as status goods. They suggest that the owner is a long-time Delawarean, or politically or socially influential, or just rich. By law, only standard numbers below 87,000, or limited numbers in special vehicle categories, may be displayed on porcelain “DEL” tags. The special categories PC (public conveyance, formerly issued for “station wagons”), T (truck), F (farm), C (commercial) are no longer restricted to these specific types of vehicle.

Delaware’s Division of Motor Vehicles allows a vehicle owner to transfer the tag along with the vehicle, so Delaware now has a private market for low tag numbers.

While most of the sales between private parties are not publicized, a few auction sales

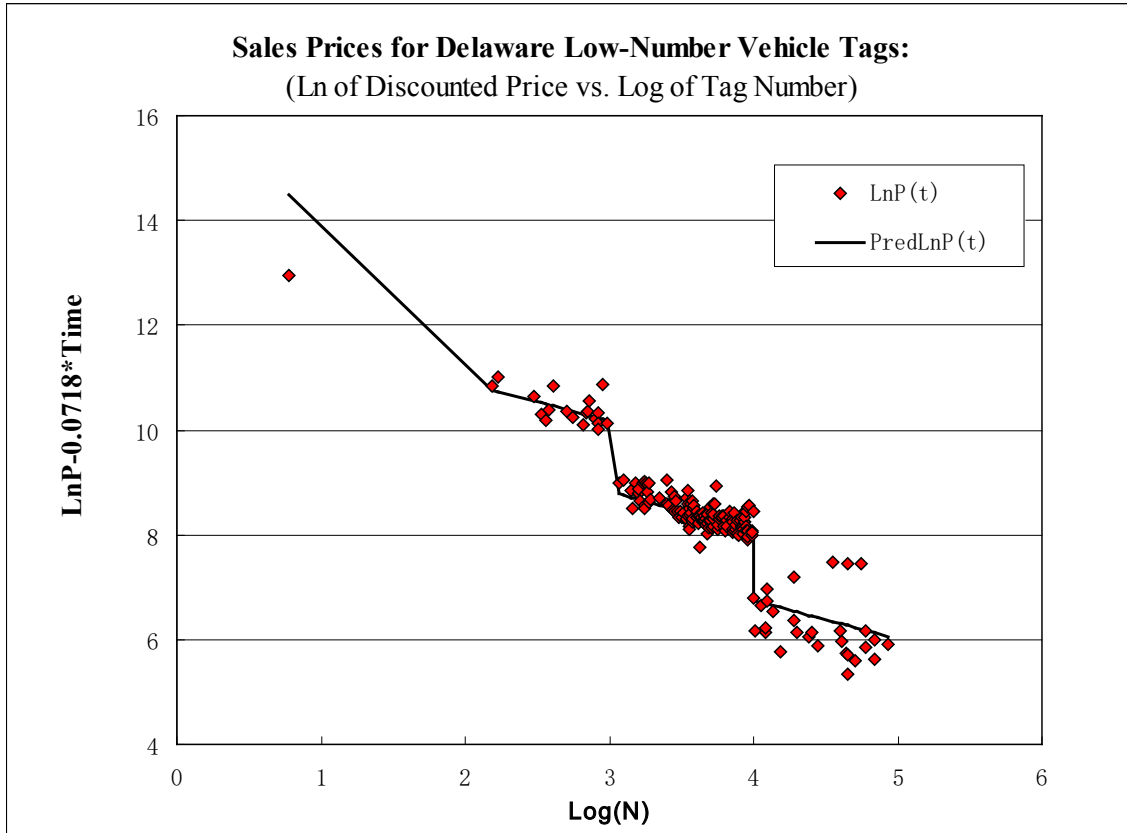
indicate the size and volatility of this market. Number 900 sold for \$85,000 in January, 2008; number 152 sold for \$58,000 in October, 2012; and number 6 sold for \$675,000 in February, 2008.

It is the *right to display* a specific low number on a Delaware-registered automobile that is valuable. The value of the physical plate is relatively trivial; if the original plate is lost or damaged, there are several local companies that specialize in manufacturing replica plates, and antique plates without usage rights are bought and sold on eBay for under \$30.

3.2 Analysis Using Sales Price Data

I obtained sales data from local news articles and various websites operated by tag dealers (Figure 3.1), and estimated a simple logarithmic pricing model for low-number (number only) Delaware tags. This dataset included the tag number N , the price paid, and the month and year of the sale. Since the sales data span 10 years (2005 through 2014), it is necessary to incorporate a time-discounting factor into the model.

Figure 3.1



3.2.1 Sales Price Model

Using continuous discounting, and allowing for discrete steps in value for different numbers of digits, my valuation model is:

$$\ln(e^{rt}P) = \beta_0 + \beta_1[\text{INT}(\log N)+1] + \beta_2 \text{FR}(\log N)$$

where P is the reported sale price paid, t is the time since the sale date, r is the discount rate, $\text{INT}(\log N)+1$ is the number of digits in tag N , and $\text{FR}(\log N)$ is the fractional remainder $\log N - (\text{INT}(\log N)+1)$. Rearranged to permit estimation of r , the model specification is:

$$\ln P = \beta_0 + \beta_1[\text{INT}(\log N)+1] + \beta_2 \text{FR}(\log N) - rt$$

3.2.2 Results

Table 3.1 Regression Results for Sales Price Model

	<i>Coefficients</i>	<i>Std Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	16.4099	0.1769	92.7694	0.0000
FR(logN)	-0.7287	0.0948	-7.6883	0.0000
INT(logN)+1	-2.0789	0.0437	-47.5552	0.0000
Time	-0.0718	0.0087	8.2105	0.0000

(N = 181; R² = 0.9304)

The predicted prices from this model, discounted by coefficient estimate -0.0718, are represented in the stepped trendline in Figure 3.1. The negative coefficient on the time variable implies these tags depreciated an average of 7.18 percent each year over the last decade. These tags have not been justified as “investments” over the past decade: their value is purely positional.

Figure 3.2

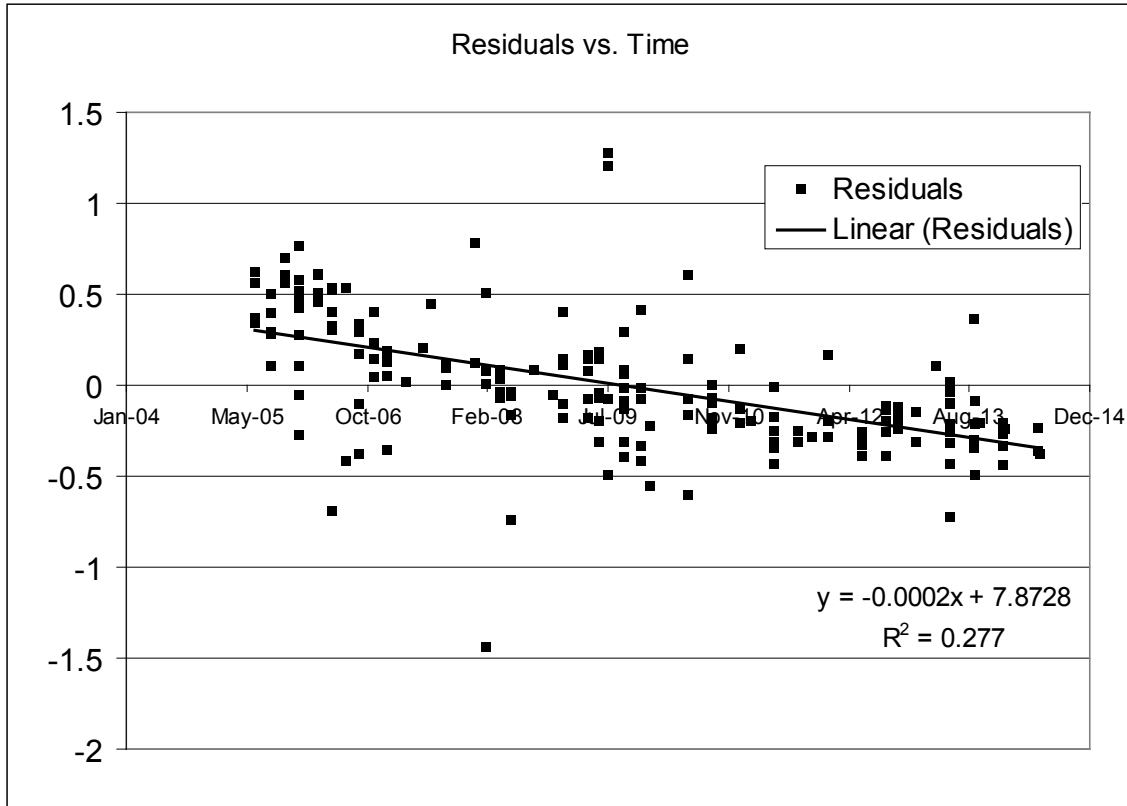
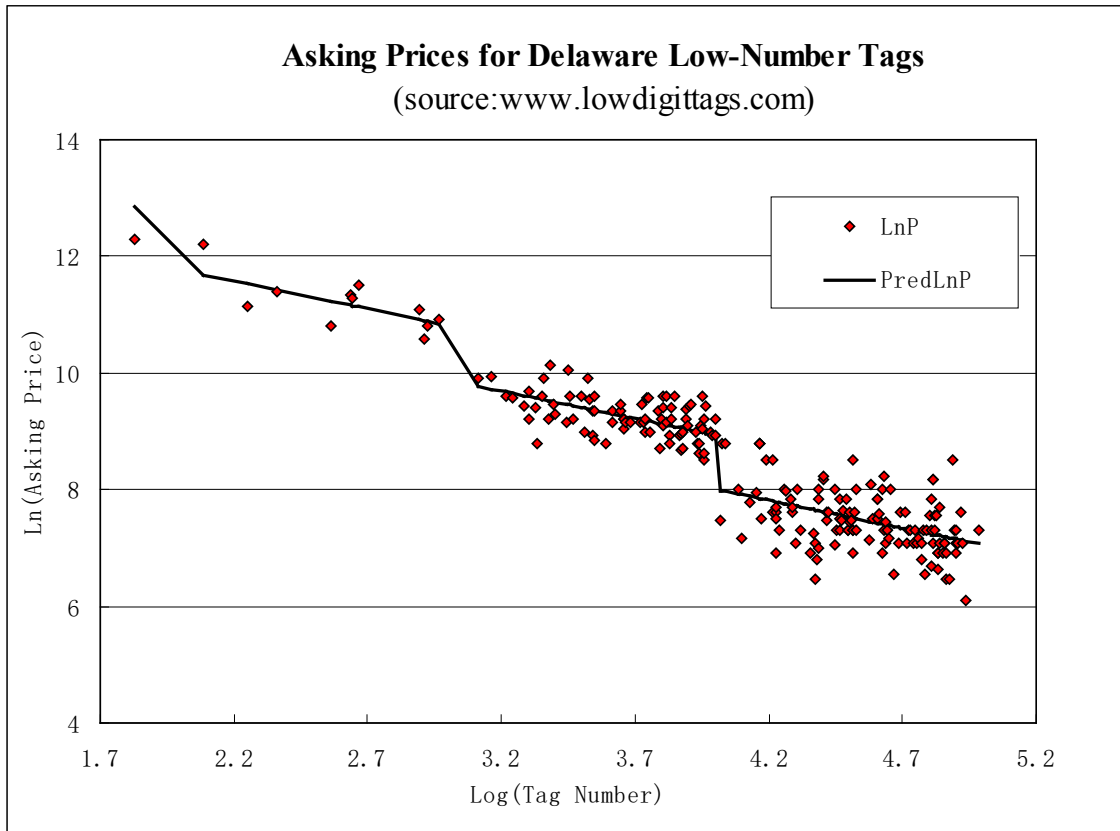


Figure 3.2 shows a clear linear relationship between residuals (calculated from the equation in table 3.1 without the time variable) and the time variable.

3.3 Analysis Using Asking Price Data

I also obtained current asking prices for low-number tags from www.lowdigittags.com, one of the largest dealers in Delaware tags. The current listings did not include any offers of one- or two-digit tags; these would typically be sold at auction. These data are shown in Figure 3.3.

Figure 3.3



I used these data to estimate a simpler asking price model that yielded the following results:

Table 3.2 Regression Results for Asking Price Model

	<i>Coefficients</i>	<i>Std Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	16.4523	0.2017	81.5599	0.0000
FR(logN)	-0.9455	0.1104	-8.5607	0.0000
INT(logN)+1	-1.8792	0.0453	-41.4964	0.0000

(source: www.lowdigittags.com; N=222; R² = 0.8872)

The sale price and asking price models are very similar, with high t -statistics for the independent variables. The implicit annual rate of depreciation estimated from the sale-price data is 7.18 percent. The inverse correlation between prices and tag numbers is strongly significant.

3.4 Conclusions

The integrals of these price functions, bounded 1 to 86,999 for N , yield rough estimates of the aggregate market value for all of Delaware's low-number tags. The integral of the sales price model is \$156 million, and the integral of the asking price model is \$359 million. Since the negative annual rate of return does not justify an investment motive, the total economic surplus represented in these tags is pure positional value.

This analysis could be extended to the parallel markets for low-number Delaware PC, T, F, FT, C and MC tag markets as well. Observed prices for these tags suggest that capitalized values in each of these smaller markets would be at least an order of magnitude smaller than the capitalized value in the digits-only market.

I contend that low-number Delaware tags are perfect positional goods: the supply is perfectly inelastic; the rank hierarchy is explicit in the number itself; the tags have no functional value beyond what an ordinary tag provides, and the tags have not yielded any speculative return over the last decade. The only elements of tag value not accounted for in these simple pricing models are patterns or sequences of digits that have some

aesthetic appeal, symbolic meaning, or personal significance to the buyer. I have not found another example of a perfect positional good in the economic literature.

In theory, low-number tags would be an ideal taxable commodity, but Delaware does not consider low-number tags to be taxable property, and does not charge any premium for transferring registrations of low-number tags. Because the supply of low-number tags is perfectly inelastic, a tiered transfer tax, sales tax or annual property tax on these tags could generate revenues for the State of Delaware without causing any market distortion or economic deadweight loss. Its incidence would fall entirely on the seller or owner. A tax on the scarcity rent of social status would be analogous to Henry George's theoretically efficient tax on land rents.

The only caution against heavy taxation of positional goods is that their exemption from taxation may be part of their appeal. As billionaire tax-cheat Leona Helmsley reportedly said, "*We don't pay taxes. Only the little people pay taxes.*"

(http://en.wikipedia.org/wiki/Leona_Helmsley)

Many positional goods are lightly taxed or tax-exempt, affording wealthy people some degree of tax-shelter. Since Delaware does not even have a sales tax, low-number vehicle tags are completely untaxed. Similarly, the demand for McMansions is stimulated by the deductibility of mortgage interest payments and very favorable tax treatment of long-term capital gains from housing. If taxes are for "the little people," then it is better for positional goods to signal tax avoidance rather than tax liability. Taxation of a positional good would eliminate its tax-avoidance signal and weaken any speculative investment demand as well.

The State of Delaware could pursue an alternative revenue strategy by defining an elite sub-class of low-number tags, and charging eligible number-owners a fee to join this elite. For example, the DMV could auction a limited number of rights to display four-digit or lower numbers on even older 1930's-style yellow tags (originals or replicas).

Chapter 4

EVIDENCE OF POSITIONAL DEMAND FOR McMANSIONS

4.1 Introduction

The bubble in the US housing market that burst in 2007 was caused by a number of factors: low mortgage interest rates supported by low inflation and increasingly efficient secondary markets in mortgage securities that recycled loanable funds back to mortgage originators; federal income tax deductions for home mortgage interest payments, preferential tax treatment of capital gains on homes; and steadily rising household incomes through the 1990's. While stock market indices and household income growth languished after 2000, housing prices continued to rise until late 2007, and then fell precipitously.

Much of the strong demand for housing was ordinary speculation, driven by rising prices and low mortgage rates that allowed speculators to realize highly leveraged capital gains. For example, a yuppie with a six-figure salary could buy a \$1,000,000 McMansion for \$50,000 down and a 3% “teaser” interest rate on a 3-year balloon mortgage. The payments on the \$950,000 mortgage for a nominal 30-year term would be only \$4,005 per month for the first 36 months—probably less than the house would cost to rent. If local house prices rose 15% over this time period, the yuppie could flip the

McMansion for \$1,150,000 before the balloon payment came due, and pay off the remaining \$890,449 balance on the mortgage for a net total return of \$259,551 on his \$50,000 down payment. He would get up to \$82,858 in mortgage interest deductions as well.

Assuming housing prices would continue to rise, he could roll \$200,000 of his gain over as a 5 percent down-payment on a \$4 million McMansion with another 3-year balloon mortgage with a 3% teaser rate. His initial monthly payments on the \$3,800,000 mortgage would be an onerous \$16,021 per month. But if house prices rose another 15% over 3 years, he could flip this house for \$4,600,000 and pay off the \$3,554,678 mortgage balance, and walk away with the difference. In summary, beginning with a \$50,000 down-payment, he would spend a total of \$720,943 over six years on mortgage payments, receive up to \$414,290 in income tax deductions, live in palatial houses, and finish up with \$1,045,321 in cash. In effect, he would have *earned* at least \$54,000 per year by living in McMansions.

On the other hand, if local house prices *fell* 15% before he got out of his second McMansion, he would only realize \$3,400,000 on a sale, his equity would be wiped out and he would be unable to pay off the mortgage balance. Being more than \$160,000 “underwater,” his best strategy might be to simply default on the mortgage and force the bank into a short sale or repossession. He could remain in the house for months or even years before the bank actually got possession of it. As a squatter, he would have no incentive to maintain its condition or value, so the house might be badly devalued by the time he was evicted.

It only took a small number of such defaults to trigger a cascade of financial contractions starting in late 2007. Mortgage processors would not forward scheduled interest and principal payments to the financial portfolios holding various strips (portions of interest or principal) of these mortgage bundles. Falling auction prices for these securities would cause leveraged fluctuations in derivative markets (e.g., put and call options on secondary market prices for these securities). The interrupted payments would trigger costly payoffs on credit default swaps, bankrupting some insurers behind those swaps. This credit contraction triggered a hard recession.

This section of my thesis analyzes the apparent role of positional competition in driving the speculative bubble in housing prices in the US. I test the hypothesis that a larger concentration of high-income households in a county induces the typical high-income household to commit a larger budget share to housing.

A strong market for McMansions may generate pecuniary externalities that make housing more expensive for all households at all income levels. On the downside, McMansions use more land per housing unit and increase the scarcity of buildable land. On the upside, high-income communities tend to demand high-quality local amenities (schools, parks, etc.) that get factored into all local home prices.

I use 2000 US Census of Population and Housing data and the Census Bureau's 2012 American Community Survey data on housing expenditures to answer the question: *Does an increased concentration of high-income households stimulate the typical high-income household to commit a larger budget share to housing?* The psychological

motivations of home-buyers are not discernible, but the market manifestations of positional behavior are.

The distributions of high-income households' housing budget shares vary widely across counties. In some counties there are no reported high-income households that spent more than 30% of their monthly incomes on housing in any of these years; in other counties, the percentage of high-income households that spent 30% or more of their monthly incomes on housing grew dramatically between 2000 and 2012. Figure 4.1 shows the geographic clustering of high-income households by county. These high-income counties are typically metropolitan. (Data for Miami-Dade were unavailable).

Figure 4.2 shows the percentages of high-income households that spent 30 percent or more of their monthly incomes on housing—my primary indicator of positional competition in local housing markets. A visual comparison of these maps suggests some regional differences in positional competitiveness in housing. The concentrations of wealth in California, Florida, the eastern Rockies counties of Colorado and the Pacific Northwest apparently stimulated more spending by wealthy households on housing than the concentration of wealth in the Northeast corridor.

Figure 4.3 shows the long-term run-up in US housing prices between 1990 and mid-2007, with sustained annual increases of five percent or more. This run-up, and the bubble that developed at the end of it, was facilitated by rapid expansion of mortgage credit to an aggregate of over \$14 trillion (Figure 4.4). The Case-Shiller housing price indices based on sale-resale data (Figures 4.4-4.7) show how housing prices declined by more than one-third after the bubble burst in late 2007.

Figure 4.1

**Percentage of Owner-Occupied Households that had
Incomes greater than \$100,000 in 1999, by County**

Source: 2000 Census of Population (SF3)

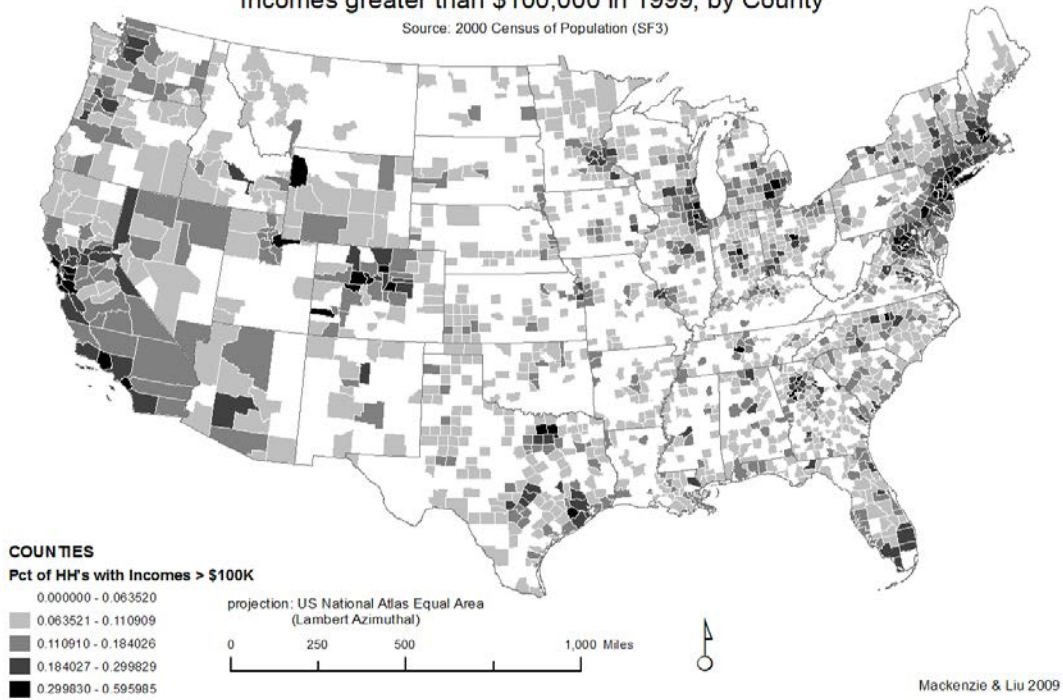


Figure 4.2

**Percentage of Households with 1999 Incomes > \$100,000
That Spend Over 30% of Monthly Income on Housing, by County**

Source: 2000 Census of Population (SF3)

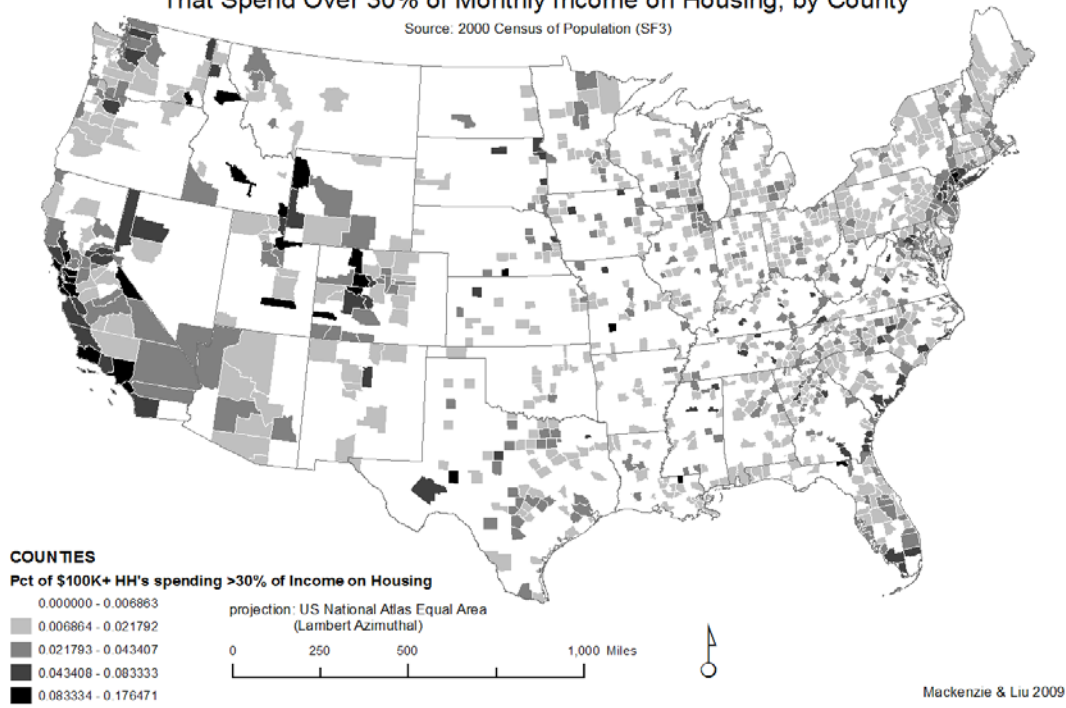


Figure 4.3

Quarterly Index of US Housing Prices, 1975-2014 (1980=100)
source: Federal Reserve Economic Data

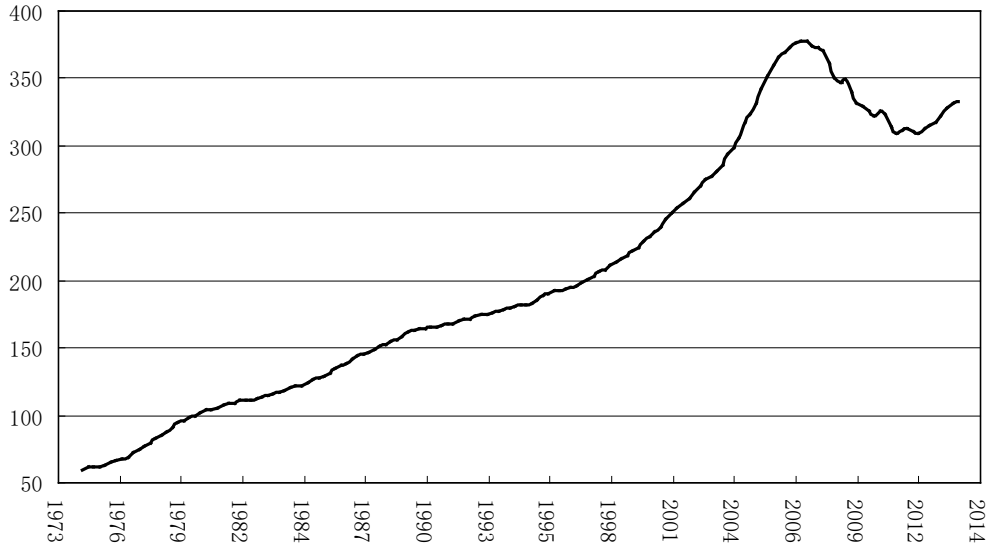


Figure 4.4

Total US Mortgage Debt and Family Household Mortgage Debt, 1954-2012
source: Economic Report of the President 2013

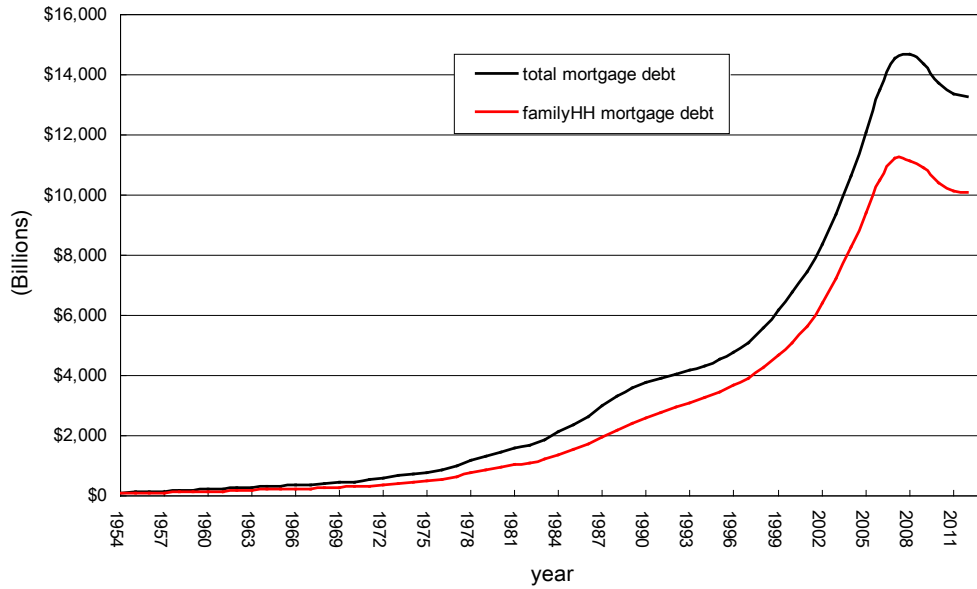


Figure 4.5



Figure 4.5 shows the Standard & Poor's Case-Shiller Home Price Index for the Los Angeles market (Los Angeles and Orange counties). Like the overall data, it peaked in 2006, then fell further due to the glut of unsold new housing, then recovered more following the collapse in new home construction.

Figure 4.6

Case-Shiller Home Price Index for Washington Metropolitan Area, 1987-2014

Source: Federal Reserve Economic Data

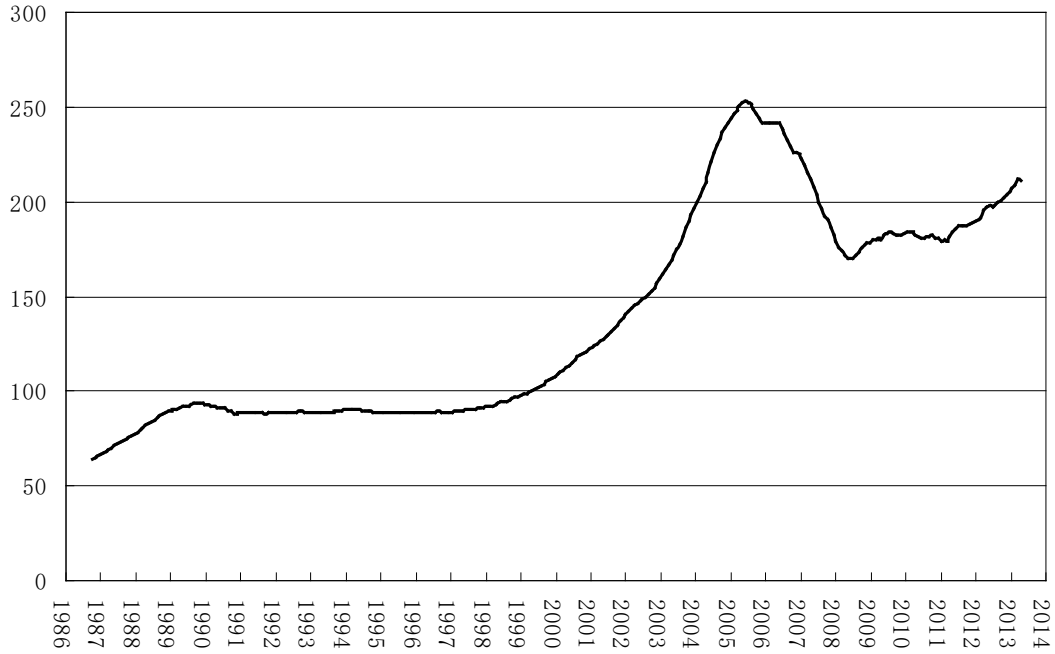


Figure 4.6 shows the somewhat smaller downturn and steadier subsequent recovery experienced in the Washington, D.C., Metropolitan Area housing market.

Figure 4.7

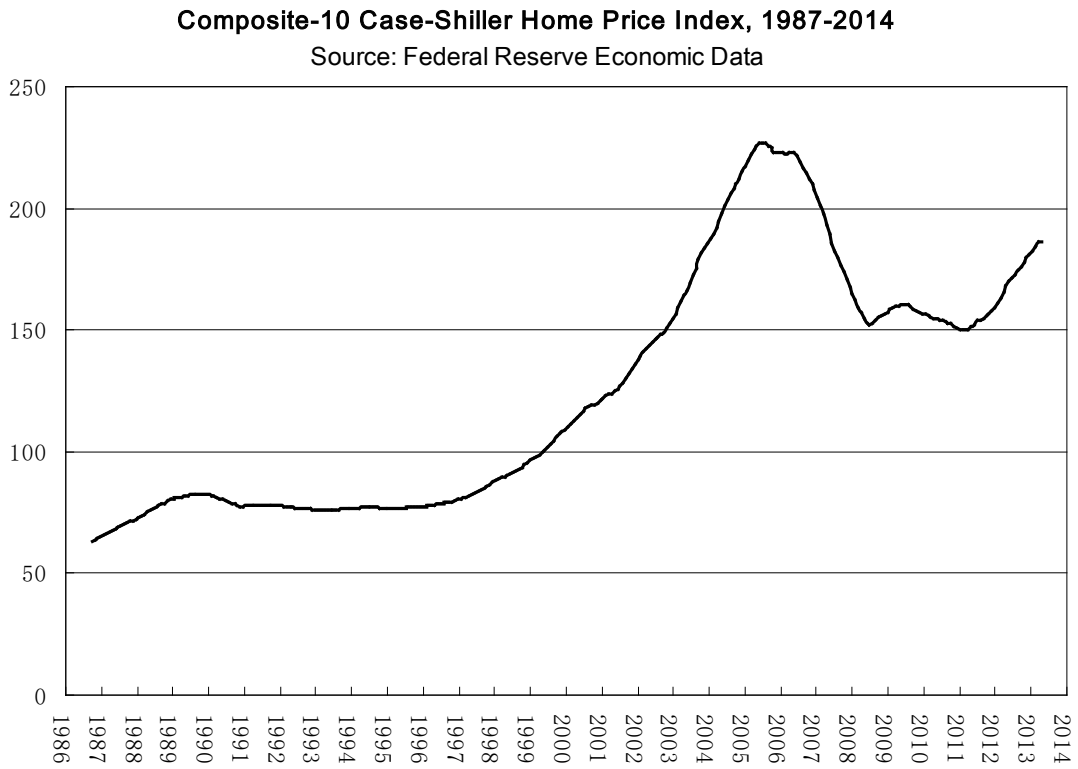


Figure 4.7 shows the Composite-10 Standard & Poor’s Case-Shiller Home Price Index for all 10 major Metropolitan Statistical Areas (Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco and Washington, DC.) in the United States.

Figure 4.8

Average Square Feet of Floor Area in New Single-Family Houses, 1973-2013

Source: United States Census Bureau



Figure 4.8 shows how the size (square footage of floor space) of the average new single-family house in the United States increased from 1,720 square feet in 1981 to 2,075 square feet in 1991; to 2,324 square feet in 2001; and to 2,480 square feet in 2011, a three-decade increase of over 44 percent. Several factors contributed to this:

1. Reduced construction costs. Engineering technologies have cut construction costs dramatically. For example, superior framing techniques like optimum-value engineering reduce building materials while maintaining the structural integrity, saving on construction labor as well as yielding more energy-efficient structures. Standardized construction processes, more available competitive contractors, better home design and

planning, these modern accessible choices combined reduce construction costs for home builders.

2. Housing is a luxury good, so housing expenditures rose more than proportionately as US incomes increased. US per-capita disposable personal income (in current dollars) grew from \$9,353 in Jan. 1981 to \$36,824 in Jan. 2011, a 294% increase (U.S. Department of Commerce: Bureau of Economic Analysis).

3. Lower real property taxes. Across the US, property taxes have generally failed to keep pace with income taxes. According to Federal Reserve Economic Data (FRED), state & local government property taxes grew from 77.1 in Jan. 1981 to 439.8 in Jan. 2011 (billions of dollars), a 470% increase; In the same period, personal income taxes grew from 47.9 to 291.2 (billions of dollars), a 508% increase.

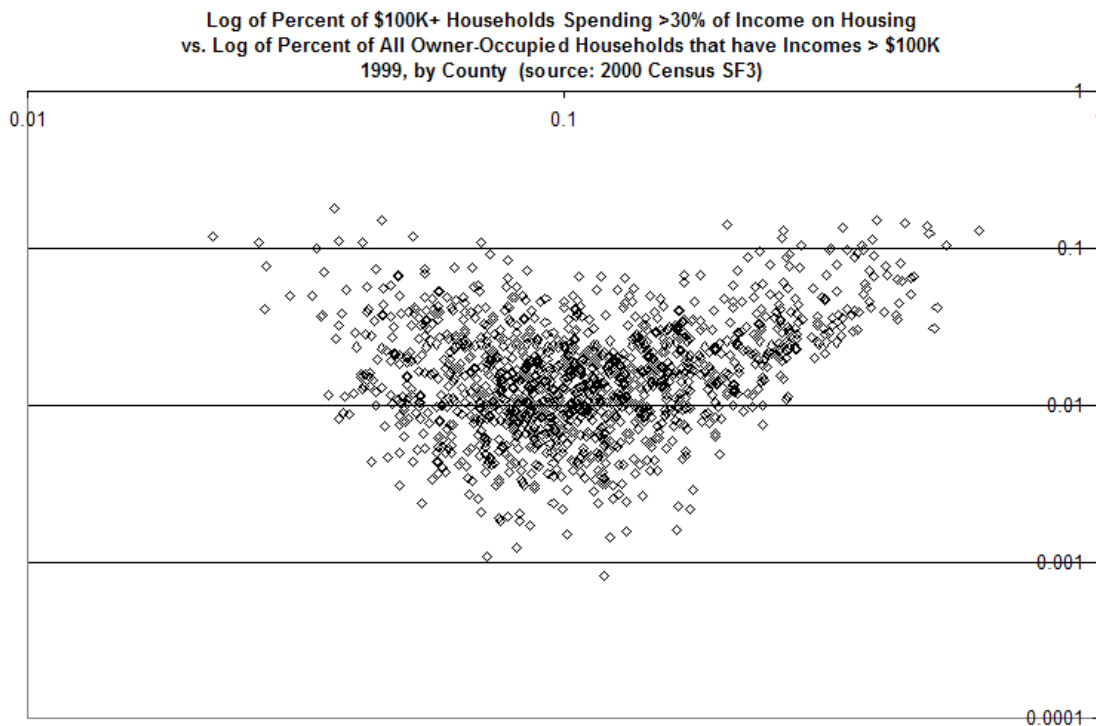
4. Commuting efficiency. Real gasoline prices were flat or decreasing for 20 years since 1981 and have only recently regained the real 1981 levels. Low real gasoline prices combined with increased Corporate Average Fuel Economy (CAFE) standards facilitated longer commutes that allowed people to buy bigger house lots and build bigger houses.

Figure 4.9 is a log-log scatter-plot of US counties where the percentage of households in each county with 1999 incomes of \$100,000 or more (horizontal axis) is plotted against the percentage of these high-income household that spent 30 percent or more of monthly incomes on housing (vertical axis). The right side (richer counties) exhibit a clear upward trend, and appear to support my positional competition hypothesis:

the higher the concentration of wealthy households, the more likely they are to compete on housing expenditures.

The U-shape of the overall plot suggests a threshold effect, and a secondary hypothesis: positional competition is not likely to occur until there is a sufficient concentration of wealthy households to trigger it.

Figure 4.9



The percentage of high-income households that spend 30 percent or more of their monthly incomes on housing is a 0-1 bounded variable, although the data are all clustered near the lower bound. The bounded nature of this variable indicates that some limited dependent variable estimation procedure should be used in econometric modeling of it.

4.2 Analytical Models

In empirical analysis, researchers often encounter dependent variable with censoring or truncated values, only observed in a certain range, like household expenditures on durable goods such as cars (left censored at zero), NFL ticket sales (right censored), and exchange rates (censored at both sides when the government intervenes). In such cases, the dependent variable is not a continuous random variable, but a hybrid of discrete and continuous domains. By failing to distinguish these, the OLS regression model yields biased results.

The econometrics literature offers several limited dependent variable (LDV) estimators that address these cases. For parametric estimation, there are Tobit model (Tobin 1958), the Hurdle model (Cragg 1971), Heckman's two-step model (Heckman 1976) and so on. In cases where the distribution of the disturbance is undetected, there are several semi-parametric methods: a Censored Least Absolute Deviation (CLAD) Estimator (Powell 1984), Powell's Symmetrically Censored Least Squares (SCLS) estimator (Powell 1986), Horowitz's Semi-parametric Generalized Least Squares Estimator (SGLS) model (Horowitz 1986) and so on. In testing hypothesized positionality in housing in high-income markets, I estimate and compare the Tobit, Multiplicative Heteroscedasticity Tobit and CLAD models.

4.2.1 Tobit (Censored Regression) Models

4.2.1.1 The Tobit Model

James Tobin first proposed the Tobit model (aka Tobin's Probit), using ML estimation. Amemiya (1984) divided it into five categories; the type I use in the thesis is the classic Tobit type I. The original model (Tobin 1958) is shown as follows:

W is the limited dependent variable, with a lower limit of L. Y is a variable with linear combination of explanatory variables (X_1, X_2, \dots, X_m), to which W is by hypothesis related.

$$(1) Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m$$

$$(2) W = L \quad (Y - \varepsilon < L),$$

$$W = Y - \varepsilon \quad (Y - \varepsilon \geq L).$$

$$(3) \Pr(W = L \mid Y, L) = \Pr(\varepsilon > Y - L) = Q\{(Y - L)/\sigma\}.$$

$$(4) \Pr(W > x \geq L \mid Y) = \Pr(Y - \varepsilon > x) = \Pr(\varepsilon < Y - x) = P\{(Y - x)/\sigma\}.$$

The cumulative distribution function for W given Y and L is:

$$(5) F(x; Y, L) = 0 \quad (x < L),$$

$$F(L; Y, L) = Q\{(Y - L)/\sigma\},$$

$$F(x; Y, L) = Q\{(Y - x)/\sigma\} \quad (x > L).$$

The probability density function is :

$$(6) f(x; Y, L) = \frac{1}{\sigma} Z\{(Y - x)/\sigma\} \quad (x > L).$$

The expected value of W given values of Y and L is:

$$(7) E(W; Y, L) = LQ\{(Y - L)/\sigma\} + YP\{(Y - L)/\sigma\} + \sigma Z\{(Y - L)/\sigma\}.$$

The likelihood of a sample is (derivation process omitted):

$$(8) \quad \varphi(a_0, a_1, \dots, a_m, a) = \prod_{i=1}^q \mathcal{Q}(\mathbf{I}_i' - a \mathbf{W}_i') \cdot \prod_{j=1}^r a Z(\mathbf{I}_j - a \mathbf{W}_j).$$

However in practical analysis, the formulation of Tobit model is usually given in terms of an index function (Greene, 2003), which is the approach I use in this thesis, given observations of independent variable left censored at zero:

$$(9) \quad \begin{cases} y_i^* = x_i' \beta + \varepsilon \\ y_i = 0 & \text{if } y_i^* \leq 0, \\ y_i = y_i^* & \text{if } y_i^* > 0. \end{cases}$$

The expected value in the normal term accordingly will be:

$$(10) \quad E[y_i | x_i] = \Phi\left(\frac{x_i' \beta}{\sigma}\right) (x_i' \beta + \sigma \lambda_i)$$

$$\text{Where } \lambda_i = \frac{\phi[(0 - x_i' \beta) / \sigma]}{1 - \Phi[(0 - x_i' \beta) / \sigma]} = \frac{\phi(x_i' \beta / \sigma)}{\Phi(x_i' \beta / \sigma)}$$

The log-likelihood for limited dependent variable is (Greene 2003):

$$(11) \quad \ln L = \sum_{y_i > 0} -\frac{1}{2} [\log(2\pi) + \ln \sigma^2 + \frac{(y_i - x_i' \beta)^2}{\sigma^2}] + \sum_{y_i = 0} \ln[1 - \Phi(\frac{x_i' \beta}{\sigma})]$$

The marginal effects are shown in two parts:

For the latent variable,

$$(12) \quad \frac{\partial E[y_i^* | x_i]}{\partial x_i} = \beta$$

For the marginal effect in the censored regression model, where a and b represent the lower and upper bounds of y (Greene 2003),

$$(13) \frac{\partial E[y | x]}{\partial x} = (F_b - F_a)\beta = \beta * \Pr[a < y_i^* < b]$$

When y is censored at zero and disturbances are normally distributed, we have

$$(14) \frac{\partial E[y | x]}{\partial x} = \beta \Phi\left(\frac{\beta'x}{\sigma}\right)$$

I used Stata's Tobit procedure to estimate the empirical Tobit models.

4.2.1.2 Assumptions and corrections for the Tobit model:

[1]. Normality. Amemiya (1973) proved the Tobit MLE to be consistent and asymptotically normal under normality assumptions, while violations of this assumption would lead to biased results. This assumption may be problematic when the disturbance variance is unknown; moreover, the severity of bias hinges on the degree of censored (truncated) sample observations (Arabmazar and Schmidt 1982). One possible solution is to assume other distributions like lognormal, exponential or Weibull in SAS's LIFEREG procedure or LIMDEP. In recent years, several semi-parametric estimators have also been proposed to deal with non-normal disturbances in censored regression models. Pagan and Ullah (1999) divided them into two categories, density-based estimators like censored least absolute deviations estimator (CLAD), symmetrically censored least squares estimator (SCLS) and non-density-based estimators like partially adaptive estimators.

[2]. Homoscedasticity. Violation of this assumption can lead to biased results (Maddala and Nelson, 1975), as we know the OLS model is still consistent but not efficient under heteroscedasticity. The bias increases with the severity of the heteroscedasticity and the extent of sample truncation (Arabmazar and Schmidt 1981). Possible solutions could be transformations of variables, doing estimation by substituting σ as σ_i (e.g., $\sigma = \sigma_i \exp(\mathbf{z}_i \gamma)$) in the equation, or looking for an alternative estimator which performs well under heteroscedasticity conditions (e.g. CLAD).

[3]. The standard Tobit assumes the mechanism determining the censoring is the same as the one determining the outcome (Kennedy 2008). When the assumption seems inappropriate, the Hurdle model (Cragg 1971) or Heckman sample selection model (Heckman 1976) are feasible alternatives, with separate equations determining the discrete and continuous regimes.

4.2.1.3 Assumption Tests for the Tobit Model

1. The conditional moment (CM) test to examine error terms distribution was first suggested by Newey (1985) and Tauchen (1985), using the outer product of gradient (OPG) regression. Pagan and Vella (1989) extended this approach to Tobit and discrete choice models.

The Tobit sample moment restrictions for normality test are (Drukker 2002):

$$m_i(\hat{\theta}) = \left\{ \begin{array}{l} \mathbf{I}_i \hat{\mu}_i^3 - (1 - \mathbf{I}_i)(\hat{z}_i^2 + 2)\hat{\sigma}^3 \hat{\lambda}_i \\ \mathbf{I}_i(\hat{\mu}_i^4 - 3\hat{\sigma}^4) + (1 - \mathbf{I}_i)(\hat{z}_i^2 + 3)\hat{\sigma}^4 \hat{\lambda}_i \hat{z}_i \end{array} \right\}$$

The chi-squared CM statistic is calculated as follows:

$$\tau = N - \text{RSS}$$

N and RSS are separately the number of sample observations and the sum of squared residuals of a particular artificial regression, which is “unity on a set of ‘regressors’ that comprise the observational contributions to the test indicator under consideration and those of the first derivative (score) of the log-likelihood” (Orme 1995).

Skeels and Vella (1999) pointed out that when using critical values from the asymptotic distribution, the CM test above tends to have actual size greater than its nominal size. Drukker (2002) developed a parametric bootstrap procedure to deal with the oversize problem, creating alternative critical values via Monte Carlo simulation.

2. Homoscedasticity is examined using likelihood ratio test:

$$\text{LR} = -2(LL_{null} - LL_{alternative})$$

LL_{null} is the log-likelihood of the null model, which is Tobit; $LL_{alternative}$ is the log-likelihood of the alternative model, which is the Multiplicative Heteroscedasticity Tobit (MHT) Model. In my case, the probability distribution of the LR statistic approximates a chi-squared distribution with two degrees of freedom.

4.2.2 The Multiplicative Heteroscedasticity Tobit (MHT) Model

For testing and comparison purpose, MHT is also applied given an adjusted error variance:

$$\sigma^2 = \sigma_i^2 \exp(\mathbf{z}_i \boldsymbol{\gamma})$$

Stata's user-developed module *tobithetm* does the estimation work easily. Since this model only treats the heteroscedasticity, leaving the normality assumption issues unsolved, I did not include the results of this model in the analysis below.

4.2.3 The Censored Least Absolute Deviations Estimator Model

CLAD (Censored Least Absolute Deviations) is a semi-parametric estimator, consistent and robust to conditional heteroscedasticity and distributional misspecification of the disturbances under rather general conditions. The original estimator proposed by Powell (1984) is written as:

$$\hat{\beta}_{CLAD} = \arg \min_{\beta} \sum_{i=1}^n |y_i - \max\{x' \beta, 0\}|$$

The CLAD estimator minimizes the sum of absolute residuals, which is “a generalization of the sample median to the regression context just as least squares is a generalization of the sample mean to the linear model” (Chay and Powell 2001), under the condition that the median of the error term is zero.

Also, to obtain consistent estimation results, there must be a substantial proportion of the observations in which the regression function $x' \beta$ has non-negative values (Powell 1984).

When $x' \beta \leq 0$, the function form $\sum_{i=1}^n |y_i - \max\{x' \beta, 0\}|$ is unrelated to β ; in other words, those observations are not informative. Therefore the CLAD estimator is

minimized using only the observations when $x'\beta > 0$. The user-contributed command *clad* in Stata calculates the results using Buchinsky's iterative linear programming algorithm (ILPA). When there are no negative predicted values in two consecutive iterations, convergence occurs to obtain a local minimum (Jolliffe, Krushelnytskyy and Semykina 2001).

The point estimate of CLAD can be directly interpreted as the median marginal effect of the explanatory variable, as CLAD marginal effect is equal to the point estimate for observations with positive predicted values and zero for observations with negative predicted values.

4.3 Data and Variables

In my preliminary analyses I used a single-bound Tobit procedure that accounts for the hypothesized threshold effect. The zero values of the dependent variable indicate counties where the count of high-income households spending 30 percent or more of their incomes on housing was truly zero, or less than the Census Bureau's minimum reportable count. (The Census Bureau routinely suppresses small count numbers to insure the confidentiality of individual respondents.)

4.3.1 Data Collection

I collected housing expenditure data on 3,141 counties from the 2000 Census of Population and Housing (excluding Alaska and Puerto Rico), and more recent data from

1- and 5-year 2012 American Community Survey (ACS) datasets. The ACS datasets yielded separately a total of 785 and 2,942 counties that had complete housing expenditure data for all two periods. My primary analysis focuses on the 1-year ACS dataset, which recorded the data for metropolitan areas with populations of 65,000 and over. For comparison purpose, estimations results using 5-year ACS datasets are also offered. I expected to see the strongest evidence of positional competition in the 1-year ACS dataset.

4.3.2 Variables for Analysis

Table 4.1 Definitions of Variables for Analysis

Variable	Explanation
Pctrich99pay30	Percent of wealthy households spending $\geq 30\%$ of income on housing in 1999
Pctrich99	Percent of wealthy households with incomes $\geq \$100,000$ in 1999
Gini99	Gini coefficients in 1999
Commute00	Average travel time to work per person in hours in 2000
Ratiopercapinc99	Ratio of county per capita income to mean per capita income of all counties in 1999
Owneroccupate99	Occupancy rate of owner-occupied housing units in 1999
Pctrich12pay30	Percent of wealthy households spending $\geq 30\%$ of income on housing in 2012
Pctrich12	Percent of wealthy households with incomes $\geq \$100,000$ in 2012
Gini12	Gini coefficients in 2012
Commute12	Average travel time to work per person in hours in 2012
Ratiopercapinc12	Ratio of county per capita income to mean per capita income of all counties in 2012
Owneroccupate12	Occupancy rate of the owner-occupied housing units in 2012

I specified and tested similar models for each of the two time periods. In each case the dependent variable is the proportion of wealthy households that spend more than 30 percent of their monthly incomes on housing (pctrich99pay30 and pctrich12pay30). In

the 2000 Census data and the 2012 ACS data I defined “high-income” as having earned more than \$100,000 in the previous year.

The independent variables include the percentage of owner-occupied households in the county that are “high-income,” the Gini index of income inequality in the county, average commute time to work, the ratio between per capita income and the mean per capita income and the occupancy rate of the owner-occupied housing units. To complement my primary hypothesis that higher concentrations of wealth incite more positional competition, I also hypothesize that more income inequality will stimulate positional competition: as high-income households are more clearly distinguished from other households, “keeping up with the Joneses” becomes more important.

I included average commute time as an explanatory variable to test two contradictory hypotheses. On the one hand, there is likely to be a substitution effect between housing expenditures and commuting expenditures: *ceteris paribus*, a household should be willing to pay more for a location with a shorter commute. On the other hand, a McMansion may provide psychic compensation for a long commute, and the long-distance commuter who spends less for a remote house lot can spend more for the house constructed on it. The ratio of per capita income represents the wealth level of each county and the occupancy rate of the owner-occupied housing units is also included to test how occupancy status may effect people’s decisions on positional competition.

4.3.3 Estimation Procedures

I used the Stata Tobit procedure to estimate preliminary single-bound Tobit models, Stata's *tobithetm* procedure to estimate Multiplicative Heteroscedasticity Tobit (MHT) models, and Stata's *clad* procedure to estimate Powell's censored least absolute deviations (CLAD) semi-parametric estimator models for each of the three time periods. The estimation results are summarized below:

4.4 Estimation Results

4.4.1 Estimation Results Using ACS 1-Year Dataset:

Table 4.2 Estimation Results for the 2000 Census Data Using ACS 1-Year Dataset

Parameter	CLAD Estimates	Tobit Estimates	MHT Estimates	MHT-HETERO Estimates
pctrich99	0.0808***	0.1222***	0.0768***	5.0955***
gini99	0.0938***	0.1059***	0.0940***	3.2721***
commute00	0.0526***	0.0264	0.0398***	0.4040
ratiopercapinc99	0.0140**	0.0155***	0.0069	-0.4829
owneroccurate99	-0.0142**	-0.0232***	-0.0147**	-1.9936***
intercept	-0.0514***	-0.0519***	-0.0389***	-0.0058
N	784	785		785
Log likelihood	-	2109.2957		2335.9262

* significant at 0.10, ** significant at 0.05, *** significant at 0.01

In the analysis of the 2000 Census data, *pctrich99pay30* is the dependent variable representing the percentage of owner-occupied households with 1999 incomes of

\$100,000 or more that spent more than 30 percent of their incomes on housing. *Pctrich99* is the percentage all owner-occupied households that had 1999 incomes of \$100,000 more. The estimations results from the 2000 Census data yield support for the positional competition hypotheses, which are higher concentrations of wealth and income inequalities incite more severe positional competition. The positive coefficient on *commute00* also supports the compensatory spending hypothesis. Bigger houses offer people psychic compensations for a longer commute. Moreover, positional competition seems to be more severe in a more wealthy area.

The hetero-corrected model yields higher-significance coefficients for the *pctrich99*, *gini99* and *owneroccurate99* variables, all these three explanatory variables are significant after correction, which implies they all contributed to the model heteroscedasticity. The coefficient for the *ratiopercainc99* variable switched to negative.

Table 4.3 Post Estimation Tests of the Tobit Model (2000 Census Data) Using ACS 1-Year Dataset

			Critical values		
			%10	%5	%1
Normality	CM	87.96	6.91	12.20	19.64
Homoscedasticity	LR	435.26	4.61	5.99	9.21

Given the high values of the statistics, both the normality and homoscedasticity assumptions are violated, so the basic Tobit model is biased.

Table 4.4 Estimation Results for the 2012 ACS 1-Year Dataset

Parameter	CLAD Estimates	Tobit Estimates	MHT Estimates	MHT-HETERO Estimates
pctrich12	0.1164***	0.1583***	0.0690***	1.6673***
gini12	-0.0798*	-0.0651	-0.0057***	-2.0592***
commute12	0.1644***	0.1818***	0.1428***	1.4092
ratiopercapinc12	0.0394***	0.0374***	0.0226	0.7067
owneroccurate12	-0.1660***	-0.1931***	-0.1109**	-3.7938***
intercept	0.0665***	-0.0694**	0.0415***	-0.1517
N	736	785		785
Log likelihood	-	1355.9470		1540.7206

* significant at 0.10, ** significant at 0.05, *** significant at 0.01

In the analysis of the 2012 American Community Survey 1-Year data, pctrich12pay30 represents the percentage of households with 2012 incomes of \$100,000 or more that spent more than 30 percent of their incomes on housing. Pctrich12 is the percentage of all households that had 2012 incomes of \$100,000 or higher. Gini12 is the Gini coefficient calculated from the distribution of 2012 household incomes. Commute12 is the average commute time in 2012. Rationpercapinc12 is the ratio between per capita income and the mean per capita income in 2012. Owneoccurate12 is the occupancy rate of the owner-occupied housing units in the whole housing units in 2012.

The positive coefficient on pctrich12 in the CLAD model supports the positional competition hypothesis, and the positive coefficient of the commute12 variable supports the compensatory spending hypothesis. Noticeably, the coefficient on gini12 switched to negative and became less significant.

According to MHT model results, *ptrich12*, *gini12* and *owneroccurate12* all contribute heteroscedasticity. Their coefficient values are significantly larger extent after correction.

The estimation results both support my positional competition hypotheses. The coefficients on *ptrich99* and *ptrich12* are 0.0808 and 0.1164 respectively, suggesting an increase in the positional competition effect between 2000 and 2012. It is clear that higher concentrations of wealth induce wealthy households to spend proportionately more of their incomes on housing.

Table 4.5 Post Estimation Tests of the Tobit Model (2012 ACS 1-Year Dataset)

			Critical values		
			%10	%5	%1
Normality	CM	60.82	6.96	9.97	14.19
Homoscedasticity	LR	369.55	4.61	5.99	9.21

The conditional moment test rejects null hypothesis of normally distributed error terms, The Likelihood ratio test rejects the null hypothesis of homoscedasticity. Non-normality and heteroscedasticity are still severe problems leading to inconsistent Tobit estimation results.

4.4.2 Estimation Results Using ACS 5-Year Dataset:

Table 4.6 Estimation Results for the 2000 Census Data Using ACS 5-Year Dataset

Parameter	CLAD Estimates	Tobit Estimates	MHT Estimates	MHT-HETERO Estimates
pctrich99	0.1115***	0.1806***	0.0349***	2.8512***
gini99	0.0422***	0.0096	0.0819***	1.2489***
commute00	0.0151	0.0062	0.0102	-2.0531***
ratiopercainc99	0.0213***	0.0274***	-0.0065	-0.2613*
owneroccurate99	-0.0261***	-0.0424***	-0.0250***	-1.5607***
intercept	-0.0325***	-0.0254***	0.0051	-0.0338***
N	1340	2942		2942
Log likelihood	-	2269.9264		3283.0565

* significant at 0.10, ** significant at 0.05, *** significant at 0.01

In the MHT results, the coefficients of all the explanatory variables except *ratiopercainc99* are all significant in the 95% confidence level after correction, causing heteroscedasticity issues.

The CLAD estimations results from the 2000 Census data yield similar support for the positional competition hypotheses. The positive coefficient on *commute00* also supports the compensatory spending hypothesis (its coefficient in the MHT models was negative after correction).

Table 4.7 Post Estimation Tests of the Tobit Model (2000 Census Data) Using ACS 5-Year Dataset

			Critical values		
			%10	%5	%1
Normality	CM	139.90	5.47	8.12	17.83
Homoscedasticity	LR	2026.26	4.61	5.99	9.21

Both assumptions of normal distribution and homoscedasticity are violated, so the Tobit model yields biased estimation coefficients.

Table 4.8 Estimation Results for the 2012 ACS 5-Year Dataset

Parameter	CLAD Estimates	Tobit Estimates	MHT Estimates	MHT-HETERO Estimates
pctrich12	0.2143***	0.2849***	0.0732***	2.9409***
gini12	-0.0540***	-0.0581**	-0.0094	-0.9174*
commute12	0.2025***	0.1901***	0.1041***	1.8715***
ratiopercapinc12	0.0159***	0.0085	0.0177***	0.0069
owneroccurate12	-0.1163***	-0.1410***	-0.1132***	-2.8132***
intercept	0.0257**	0.0408***	0.0611***	-0.0854***
N	2285	2942		2942
Log likelihood	-	3504.5009		4565.6643

* significant at 0.10, ** significant at 0.05, *** significant at 0.01

Pctrich12, commute12 and owneroccurate12 are the variables which cause heteroscedasticity. Compared to the results of the ACS 1-year dataset, counter-intuitively the coefficient on pctrich12 increases even bigger.

Pctrich12pay30 represents the percentage of households with incomes of \$100,000 or more that spent more than 30 percent of their incomes on housing in the 2008-2012 ACS 5-year recording period. Pctrich12 is the percentage of all households that had incomes of \$100,000 or higher; Gini12 is the Gini coefficient calculated from the distribution of household incomes, and commute12 is the average commute time in this 5-year period.

These estimation results also support the positional competition hypotheses. Comparing models from different time periods, the coefficients on pctrich99 and pctrich12 are 0.1115 and 0.2143 respectively, suggesting an increase in positionality between 2000 and 2012.

Table 4.9 Post Estimation Tests of the Tobit Model (2012 ACS 5-Year Dataset)

			Critical values		
			%10	%5	%1
Normality	CM	110.74	6.44	9.63	16.88
Homoscedasticity	LR	2122.33	4.61	5.99	9.21

The conditional moment test rejects the null hypothesis of normally distributed error terms, and the likelihood ratio test rejects null hypothesis of homoscedasticity. Non-normality and heteroscedasticity are still severe problems leading to inconsistent Tobit estimation results.

Chapter 5

SUMMARY AND CONCLUSIONS; FURTHER RESEARCH

5.1 Summary and Conclusions

While positional competition is understood intuitively by lay people, it is problematic for economists because it implies interdependence of consumers' utility functions. Classical demand theory assumes preferences are autonomous and exogenously determined.

Positional competition creates a sort of congestion externality, where each person's pursuit of higher social status in a given social frame increases the cost of status for all status-seekers in that frame. Robert Frank has argued that positional competition in the US housing market, manifested in land-intensive suburban housing developments, has contributed to inefficient land-use patterns with increased commuting costs for everyone. While it is tempting to conclude that positional competition is economically wasteful, I have avoided that conclusion. In fact, positional competition in the high-income sector of the US housing market has clearly motivated more construction and created more jobs in the US economy.

My thesis has researched two cases of positional competition: a very small market for low-number license plates in Delaware, and the large market for luxury housing in the US. The magnitude of the aggregate economic surplus in Delaware's low-number license plate market is surprising: even in recession, in a state with only 900,000 people,

it exceeds \$150 million. In summary, Delaware's low-number license plates are perfect positional goods. A black-and-white tag has no practical function beyond an ordinary license plate; its position is explicitly enumerated, and its price is determined by that position.

In contrast, luxury houses commingle function and social position, which is why I did not attempt to estimate the aggregate economic surplus in the US luxury housing market created by positional competition. Estimating the aggregate price premium in the US luxury housing market created by positional competition would be a good topic for further research.

My empirical analyses of Census and ACS data show a consistent positive relationship between the proportion of high-income households in a county and the monthly housing costs (as a percentage of income) that these high-income households incur. This effect is more pronounced in counties with higher income inequality. These results are consistent with positional competition in metropolitan housing markets. I have not found any alternative economic explanation for these empirical results.

I compared Tobit and CLAD models of this effect. Assumptions of normality and homoscedasticity are both violated in the Tobit model. After correcting for heteroscedasticity non-normality was still a problem. The alternative CLAD estimator (Powell) is more robust to departures from homoscedasticity and normal distribution, and the estimation results from the CLAD models reinforce those of the Tobit models.

5.2 Further Studies

There are many possible avenues for further research. Counties typically contain diverse housing markets, and the county-level data I used cannot show localized spillover effects of McMansions on adjacent housing. Possible spillover effects could be tested with very micro-level geographic analysis.

Another avenue of research might be hedonic analysis of the surpluses in various luxury housing markets created by positional competition.

Third, while I tested and compared a series of Tobit and CLAD models, there are a number of other limited dependent variable methods that I did not try. Wilhelm (2008) has developed a bootstrapped Hausman test of the validity of the Tobit model. Melenberg and Van Soest (1996) have developed alternative semi-parametric estimators like weighted CLAD for analysis.

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