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Three Essays on the Housing Market

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THREE ESSAYS ON THE HOUSING MARKET

BY

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ACCEPTANCE

This dissertation was prepared under the direction of Patrick Smith's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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Essay 1: Institutional Investment, Asset Illiquidity, and Post-Crash Housing Market Dynamics

Abstract: I demonstrate that housing's mildly segmented market structure adds an additional measure of asset illiquidity risk for owner-occupiers and their lenders by examining the effect of a house's conversion from the owner-occupied market to the rental market. From 2012 to 2014, I find that owner-occupied houses that were purchased by institutional investors and converted to rentals after the real estate crisis sold for approximately 5% less than similar houses that sold to owner-occupiers. The large discount was in addition to REO, foreclosure, short sale, and cash purchase discounts which, when combined, highlight the low liquidation value for owner-occupied housing.

Essay 2: Homeownership: An examination of its effect on house prices

Abstract: Subsidizing homeownership is only justifiable if it increases homeownership attainment and creates external benefits that outweigh their costs. Using parcel-level panel data I isolate and examine the effect of homeownership on surrounding house prices. Homeownership has a causal effect on house prices, but substantial variation exists across quantiles. Changes in homeownership have a lesser (greater) effect on house prices in the upper (lower) deciles of the conditional house price distribution - despite the fact that households in the upper deciles are the primary beneficiaries of the federal tax subsidies for homeownership.

Essay 3: School Quality, Latent Demand, and Bidding Wars for Houses

Abstract: I examine the recent rise of bidding wars and their effectiveness relative to traditional listing strategies. A simple theoretical model predicts that underpricing a house to incite a bidding war will be most effective in housing markets with high levels of latent demand. I use school quality as a proxy for latent demand as households with children naturally want their kids to go to the best school possible. I posit that the limited supply of housing within high quality school districts creates latent demand for housing within those districts. Evidence from Atlanta supports the model - I find that underpricing a house to incite a bidding war is more effective in markets with latent demand. However, underpricing does not outperform traditional listing strategies.

Institutional Investment, Asset Illiquidity, and Post-Crash Housing Market Dynamics

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Abstract

I demonstrate that housing's mildly segmented market structure adds an additional measure of asset illiquidity risk for owner-occupiers and their lenders by examining the effect of a house's conversion from the owner-occupied market to the rental market. From 2012 to 2014, I find that owner-occupied houses that were purchased by institutional investors and converted to rentals after the real estate crisis sold for approximately 5% less than similar houses that sold to owner-occupiers. The large discount was in addition to REO, foreclosure, short sale, and cash purchase discounts which, when combined, highlight the low liquidation value for owner-occupied housing.

1. Introduction

In the United States, there are two housing markets: owner-occupied and rental housing. Owner-occupied housing, by definition, must be a household's primary residence to qualify for preferential tax treatment.[1] Thus, owner-occupied housing is not only a consumption good but an investment as well. In contrast, rental housing is not purchased for personal consumption; it is viewed solely as an investment. The two housing markets are similar, in that, they provide housing services. However, comparisons of the two are difficult because of housing's mildly segmented market structure.

Liu, Grissom and Hartzell (1990) show that single-family housing has a mildly segmented market structure.[2] Housing is a mildly segmented market because while individuals can invest in both owner-occupied and rental housing, institutional investors can only invest in rental housing.[3] For individuals, the segmented demand results in an additional measure of risk and hence a higher return for owner-occupied housing.[4] Until recently, institutional investors have not invested in single-family houses arising in part from high transaction costs, lack of economies of scale (e.g. buying houses in bulk at a discount and property management issues), and perceived political implications.[5] Adverse political implications include, but are not limited to, fear of government regulation and negative publicity regarding bidding wars with potential homeowners given the political focus on subsidizing homeownership. Additionally, buying too

[1] Homeowners can deduct property tax and mortgage interest payments for their primary residence and a second home. However, the overwhelming majority (greater than 90%) of homeowners in the United States only own one personal residence. A detailed overview of owner-occupied and rental housing's taxation is provided in Section 3.

[2] Liu, Grissom and Hartzell (1990) examine the impact of a mildly segmented housing market in a CAPM context. The authors segment the housing market into owner-occupied housing and income-producing real estate, but do not consider taxes in an effort to reduce their model's complexity.

[3] Technically institutional investors can invest in owner-occupied housing in several ways. They can purchase owner-occupied houses and hold them as dealer (or investment) properties – in which case they cannot depreciate the asset over time and do not benefit from owner-occupied housing's preferential tax treatment, so their return is tied directly to the house's capital appreciation. Institutional investors can also purchase owner-occupied houses and convert them rentals – in which case they are no longer owner-occupied housing. Historically, institutional investors have not invested in the equity of owner-occupied housing and instead chose to lend equity to owner-occupiers. I discuss the mildly segmented housing market and its impact on institutional investment in owner-occupied housing in greater detail in Section 2.

[4] Stein (1995) shows that an exogenous negative shock to owner-occupied house prices coupled with the market's down-payment requirements can have self-reinforcing effects. I show that these self-reinforcing effects coupled with owner-occupied housing's preferential tax treatment, high transaction costs, and mildly segmented market structure can result in low liquidation values.

[5] Previous research on institutional trading focuses primarily on stock markets (see, for example, Lakonishok, Shleifer, and Vishny, 1992; Chan and Lakonishok, 1993). Institutional investors' trading behavior is important because they often take large positions and their continued presence on one side of the market can significantly affect pricing dynamics (Keim and Madhavan, 1995).

many houses in a neighborhood could change quality of life dynamics. However, the financial crisis created a potential arbitrage opportunity for institutional investors to enter the single-family housing market. House price declines, to levels which were significantly below their pre-crisis levels, together with large scale delinquencies and defaults, an increase in demand for single-family rental homes arising from these foreclosures, and the tightening of the mortgage market created a large supply of available owner-occupied housing which made economies of scale possible.

The purpose of this paper is to empirically examine the nature of the mildly segmented housing market given the recent entry by institutional investors. Ex-ante, as the single-family housing market becomes more integrated, the price of single-family homes should be bid up and returns should fall until no abnormal returns exist if the single-family housing market becomes fully integrated. However, segmentation might still exist due to, among other things, the preferential tax treatment associated with owner-occupied housing. As such, I explore how the entry of institutional investors influenced house prices by comparing the pre- versus post-crisis period using characteristic and propensity score matched samples in a difference in difference framework. The price differential I find provides an estimate of the asset illiquidity risk inherent in the owner-occupied housing market that is a byproduct of the mildly segmented market structure and the preferential tax treatment for owner-occupied housing. I also find that although institutional investors entrance in the post-crisis period increased prices thereby reducing returns and lessening the degree of housing market segmentation and asset illiquidity risk, the premium associated with owner-occupied housing persists.

This study focuses on institutional investment in the Atlanta, Georgia metropolitan housing market. Atlanta is the ideal setting for this study as it was one of the markets heavily targeted by institutional investors (Federal Reserve Bank of Atlanta 2013; Mills, Milloy, and Zarutskie 2015). I identify eleven institutional investors that were active in Atlanta from 2012 to 2014 – six of which were private equity firms and five of which were publicly traded companies.[6] The institutional investors that I identify are large "informed" financial entities that entered the Atlanta housing market, purchased single-family detached houses, and converted the houses to rentals during the post-crisis period. The institutional investors' large cash reserves and access to capital give them an advantage over investors that require mortgage financing in the

[6] A detailed overview of the eleven institutional investors is available in Appendix A.

housing market – especially during times of economy-wide distress. In my model, institutional investors substitute their investments in rental housing with investments in owner-occupied housing. However, when institutional investors purchase owner-occupied housing they convert it to rental housing for the short-term, as they cannot consume its services and can only invest in income-producing real estate. Although housing stock is generally considered perfectly inelastic to downward demand shocks, I show that the housing market's mildly segmented market structure allows owner-occupied housing to be redeployed as rental housing. In doing so, I illustrate the impact the mildly segmented market structure has on owner-occupied housing's asset illiquidity and the two housing markets' risk-return equilibrium condition.

The next section of this paper details housing's mildly segmented market structure. Section 3 provides an overview of owner-occupied housing's preferential tax treatment. Section 4 applies Shleifer and Vishny's (1992) asset liquidity framework to the owner-occupied housing market. Section 5 presents a model of post-crash housing market dynamics, Section 6 provides an overview of the data, Section 7 presents the empirical methodology and results, and Section 8 concludes.

2. Mildly Segmented Market Structure

There are several factors that contribute to housing's mildly segmented market structure including its (1) preferential tax treatment of owner-occupied housing, (2) dual role as a consumption and investment good, (3) heterogeneous housing stock, (4) differing economies of scale, and (5) illiquidity.

The United States government heavily subsidizes and promotes homeownership by providing preferential tax treatment for owner-occupied housing. Owner-occupiers benefit from the tax exemption of their implicit rental income and the exclusion of capital gains from the sale of their house. They can also deduct their mortgage interest, mortgage insurance premium, and property tax payments when filing their federal income taxes. The preferential tax treatment promotes homeownership, increases owner-occupier's consumption demand, and results in higher house prices. In essence, preferential tax treatment for owner-occupied housing increases owner-occupied house prices to a level that is prohibitively high for institutional investors, thereby restricting them from entering the market.[7]

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[7] This is similar to the notion of restricted marketability presented in Errunza and Losq's (1985) International Pricing Model under Mild Segmentation. Errunza and Losq argue that U.S. investors trade primarily in domestic

Housing has a dual role as both a consumption and investment good. The majority of owner-occupiers satisfy their consumption and investment demand for housing by owning only their primary residence without relying on the rental market to disentangle the two. Several studies show that owner-occupier's optimal level of housing as a consumption good often differs from its optimal level as an investment good (Henderson and Ioannides 1983; Brueckner 1997; Flavin and Yamashita 2002). As a result, owner-occupied housing is often "overdetermined" in homeowner's portfolios. The extent to which it is overdetermined is likely exacerbated by its preferential tax treatment.

Preferential tax treatment coupled with owner-occupied housing's dual role as a consumption good results in a heterogeneous housing stock. Housing's heterogeneous stock adds to the two markets' degree of segmentation as owner-occupiers and institutional investors' property type and size preferences differ according to their prevailing motives (consumption versus investment). The housing market's stock can be split into three property types: single-family detached, single-family attached, and multi-family housing. In theory, one could argue that the property types are interchangeable and perfect substitutes, as single-family attached and multi-family units are adaptive and can be redeployed (i.e. apartment buildings can be converted into condos and vice-versa), and owner-occupied single-family detached units can easily be converted into rentals. However, in reality, the motives of the housing market's participants (consumption versus investment) result in different property type preferences that are not perfect substitutes. For example, single-family detached units are usually owner-occupied, while rental housing is more likely to be a part of a multi-family building.

Previous research on conversion activity in housing markets has focused on condo conversions. An increase in condo conversions - from rental housing to owner-occupied housing - has been tied to an increase in the number of households without children (Sternlieb and Hughes 1975), rent controls (Sternlieb and Hughes 1975; Werczberger 1988), barriers to ownership in the single-family market (Sternlieb and Hughes 1975), tax considerations (Whinihan 1984), reduced profitability in the rental market relative to the "for sale" market (Diskin and Tashchian 1984; Crone 1988; Benjamin et al. 2008; Wiley 2009), low interest rates

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stocks because the cost of investing abroad is prohibitively high. I argue that institutional investors trade primarily in rental housing because, among other things, the cost of owner-occupied housing is prohibitively high due to its preferential tax treatment. Section 3 compares the tax code for owner-occupied and rental housing and examines its impact on house prices.

(Benjamin et al. 2008; Wiley 2009), and a growing demand for homeownership (Lea and Wasylenko 1983). The studies show that multi-family properties are valued differently in rental and owner-occupied housing markets over time and that the property owners maximized their return by converting rental housing to owner-occupied housing during boom periods. This study is similar, in that, I examine housing unit conversions. However, this study focuses on heterogeneous single-family detached houses that were converted from owner-occupied to rentals during the recent real estate crisis.

Rental housing is more likely to be part of a multi-family building from an institutional investors' perspective because they look to create economies of scale. Multi-family housing offers several advantages over single-family detached housing in this regard. Multi-family housing, by definition, includes multiple separate housing units within one building or several buildings in a single complex. Thus, institutional investors can purchase a large number of units in a single transaction. Multi-family housing units are also spatially concentrated, making them easier and cost-effective to manage, and typically have similar layouts and components, which helps minimize repair and replacement costs as parts can be purchased in bulk. Single-family detached housing units, in contrast, are generally not available for bulk purchase at a cost effective price point, making it difficult for investors to accumulate a large portfolio of houses in a short amount of time (i.e. the market has historically lacked economies of scale).[8] Single-family detached housing units are also spatially dispersed and more likely to have dissimilar layouts and components.

In addition to the differences between owner-occupiers and institutional investors highlighted above, clientele effects exist *within* the two groups. For example, when looking to purchase a house, local school quality is one of the primary considerations for owner-occupiers with children. Whereas, owner-occupiers who do not have school age children may not be as concerned with school quality. The size of the household plays a major role in the type of

[8] Block trades (i.e. bulk purchases) by institutional investors have been thoroughly examined in the general finance literature (see, for example: Kraus and Stoll 1972; Holthausen, Leftwich, and Mayers 1987; Saar 2001). The studies find that block trades by institutional investors impact the efficiency of the stock market and that block purchases have a longer permanent impact than block sales. We examine block trades by institutional investors in owner-occupied housing and note that there are several key differences between the two markets (heterogeneous versus homogeneous assets, passive versus active investments, and high versus low transaction costs - to name a few). In addition, institutional investors may shy away from block trades of single-family detached housing if they are targeting houses with specific characteristics in a limited number of concentrated geographical areas.

property owner-occupiers purchase. Single-family detached housing generally offers more living area and bedrooms, so it attracts large households.

Real estate is notoriously illiquid. In this paper I consider two types of illiquidity in owner-occupied housing markets: market illiquidity and asset illiquidity. I define market illiquidity as the inability to sell an owner-occupied house quickly at its full market value. Market illiquidity in housing, similar to most real estate, is a product of the market's high transaction costs, search costs, and down-payment requirements. Grossman and Laroque (1990) illustrate the impact of transaction costs on the liquidity of durable goods. In their model, households continuously consider whether to reoptimize their level of housing consumption in relation to changes in their wealth. They find that small transaction costs can make consumption changes occur very infrequently.[9] Stein (1995) develops a model which illustrates the self-reinforcing effect of down-payment requirements on falling house prices. He shows that a decrease in house price reduces homeowner's equity; thereby reducing the amount of money the homeowner has for a down-payment should they sell their current house. [10] A reduction in down-payment reserves reduces household mobility and the demand for owner-occupied housing. The reduced demand reinforces the decrease in house prices and explains housing's illiquidity in down markets.

Housing's degree of illiquidity varies across housing submarkets and property types, as only the capital appreciation component of housing, and not the income producing component, is subject to the illiquid nature of the market. The illiquid nature of owner-occupied housing has historically made rental housing's income-producing component more attractive to institutional investors. Additionally, although institutional investors can lend the equity for owner-occupied housing, they cannot directly invest in owner-occupied housing which provides income in the form of rental opportunity costs (Liu, Grissom and Hartzell 1990). Thus, market illiquidity reinforces the mildly segmented market structure.

Shleifer and Vishny (1992) define asset illiquidity as the difference between an asset's value in best use and its liquidation value. They argue that when firms are in financial distress their industry peers are likely in a similar situation, which leads to asset sales below their value in best use. When the housing market is in equilibrium, the best use for owner-occupied housing

[9] Using a transaction cost of five percent, Grossman and Laroque estimate the average time between house purchases is 20 to 30 years. Five percent is a conservative estimate of transaction costs in housing markets as real estate broker's commissions usually exceed five percent on their own.

[10] Stein (1995) does not include the rental housing market in his primary model.

is owner-occupancy and institutional investors, who value housing services based on their rental value, are constrained from investing in owner-occupied housing. The reduced demand results in an additional measure of risk for owner-occupied housing (Liu, Grissom and Hartzell 1990). In this paper, I define the additional risk from housing's mildly segmented market structure as its asset illiquidity risk.[11]

3. Taxation of Housing

In the United States, both owner-occupied and rental housing receive preferential tax treatment. However, the tax code differs for the two types of housing. The dissimilar tax code creates an environment in which the same house is valued differently by owner-occupiers and institutional investors. Using the break-even rental rate and user cost of housing approaches I examine the impact of the dissimilar tax treatment for owner-occupied and rental housing on housing values across the two markets.

3.1 Break-even Rental Rate

The break-even rental rate calculates the rate necessary to set the net present value of an investment opportunity equal to zero. In doing so, it allows us to evaluate the impact of the dissimilar tax code on house values across the two housing markets. Using a standard present value approach one can estimate the break-even rental rate β in housing market *y* as:

$$\text{PV} = [-V_0(1\text{-}l_0)] + [\textstyle\sum_{t=1}^{T} \frac{\beta^y V_{t-1} - E_t - X_t^y}{(1+r)^t}] + [\frac{(V_T - V_0(l_T) - G_T^y)}{(1+r)^T}] \tag{1}$$

$$X_t^y = \begin{cases} \left[-\tau_t^i \left((m * V_0 * l_{t-1}) + (\text{þ}_t V_{t-1})\right)\right], & if\ y = owner-occupied \\ \tau_t^i \left[\beta V_{t-1} - (m * V_0 * l_{t-1}) - C_t - (\text{þ}_t V_{t-1}) - dV_0\right], & if\ y = rental \end{cases} \tag{2}$$

$$G_T^y = \begin{cases} \max[0,\ \tau_T^g (V_T - V_0 - A_T)], & if\ y = owner-occupied \\ [\tau_T^g (V_T - V_0) + \tau_T^d (T * dV_0)], & if\ y = rental \end{cases} \tag{3}$$

Where:

V_t is the value of the house at time *t*

l_t is the loan-to-value ratio at time *t*

β^y is a constant break-even rental rate for housing market *y*

[11] I discuss owner-occupied housing's asset illiquidity risk in greater detail in Section 4.

T is the final time period in which the property is sold

E_t is the mortgage payment and operating expenses at time *t*

r is the discount rate

X_t^y is the mortgage interest and property tax deduction in the owner-occupied market OR the income tax on net rental income in the rental market

G_T^y is the capital gains tax paid in housing market *y*

τ_t is the income (τ_t^i), capital gains (τ_T^g), or depreciation recapture (τ_T^d) tax rate at time *t*

S_t is the standard tax deduction at time *t*

N_t is the non-housing itemized deductions at time *t*

m is the mortgage interest rate

C_t is the operating costs paid during time period *t*

$þ_t$ is the property tax rate at time *t*

A_T is the capital gains exemption allowance for owner-occupiers at time T

d is the rate of accounting depreciation expressed as a fraction of the purchase price

The present value calculation in Equation 1 contains three components that I separate in brackets. The first component represents the initial down payment that I assume is the same in the owner-occupied and rental housing markets. The second component represents the sum of the discounted explicit (implicit) after-tax rental income payments for rental (owner-occupied) housing. The second component includes a subcomponent (X_n^y) that varies based on the property's form of tenure. The third component, which also contains a subcomponent (G_n^y) that varies based on the property's form of tenure, represents the discounted after-tax capital appreciation.[12]

The two subcomponents highlight the key differences between owner-occupied and rental housing in the tax code. In Equation 2 owner-occupied housing is not taxed on its implicit rental income and mortgage interest and property tax payments can be deducted.[13] Whereas, rental

[12] For the sake of brevity I assume that purchasing and selling costs are zero.

[13] Homeowners can deduct their property taxes on any number of houses. However, homeowners can only deduct interest on the first $1,000,000 in acquisition debt and first $100,000 in home equity debt that is secured by their primary residence and second home. If a homeowner has a second home and they rent it out for part of the year, they must use the second home more than 14 days or more than 10% of the number of days during the year that the home

housing is taxed on its explicit rental income, but mortgage interest, property taxes, operating costs, and depreciation can be deducted.[14] Thus, the true benefit of the deductions for owner-occupiers is derived, in a large part, from the way the tax code treats their imputed rental income.[15]

The tax benefit for rental housing in Equation 2 depends on the investor's ability to claim passive activity losses. Investors who do not actively participate in their rental property's operations can only use the passive activity losses from the rental property to offset gains on other passive income.[16] Investors who actively participate in the operations of the rental property, and are not real estate professionals, benefit from a special allowance where they can use up to $25,000 of rental losses to offset their active income.[17] These tax benefits are not applicable to institutional investors. Equation 3 highlights the capital gain tax benefit afforded to owner-occupied housing. Single (married) owner-occupiers are not taxed on the first $250,000 ($500,000) in capital gains, A_T, from the sale of their primary residence.[18] Whereas, investors have to pay capital gain and depreciation recapture taxes when they sell their rental property.[19]

Using Equations 1-3 one could simultaneously determine the break-even rental rate that (1) an investor would explicitly need to charge to equal their opportunity cost of capital and (2) an owner-occupier would implicitly need to charge to cover its net costs and opportunity cost of

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is rented at a fair market rental rate, whichever is longer. If they do not meet these requirements, the property is considered a rental and not a second home (IRS Publication 936).

[14] The amount of property tax and mortgage interest that an investor can deduct is not capped because they are expenses that offset the rental income investors are taxed on. Investors use the Modified Accelerated Cost Recovery System (MACRS) to depreciate their residential rental property. The MACRS allows investor to depreciate the basis of their rental house (excluding land) using a straight-line method of 27.5 years (IRS Publication 527). The rate of depreciation often exceeds the actual decline in value of the house and allows the investor to defer income taxes until they sell the property when they have to pay a depreciation recapture tax.

[15] Equation 2 assumes that owner-occupiers do not claim the standard deduction. In reality, they only benefit from the mortgage interest and property tax deductions if they itemized their tax returns. Homeowners would decide whether to claim the standard deduction based on the following formula: $\max\left[S_t,\ -\tau_t^i\left((m * V_0 * l_{t-1}) + (\text{þ}_t V_{t-1}) + N_t\right)\right]$

[16] If the investor's passive losses exceed their passive gains that year they can carry them forward.

[17] The special allowance of $25,000 is subject to a phaseout rule in which it is reduced by 50% of the amount of the investor's modified adjusted gross income that is more than $100,000. If the investor's modified adjusted gross income is $150,000 or more, they generally cannot use the special allowance (IRS Publication 925).

[18] Homeowners are not taxed on the sale of their primary residence as long as they lived in the property an aggregate of two of the last five years and have not claimed the exemption within the past 24 months. Partial exemptions are possible for less than two years ownership and occupancy (IRS Publication 936).

[19] Investors can defer the capital gain and depreciation recapture taxes if they invest in a like-kind exchange. However, the basis from the rental property the investor sold is transferred to the rental property the investor purchased plus any additional investment they made in the new rental property.

capital. In a competitive market, the break-even rental rate for an investor is the market rental rate and households decide whether to become owner-occupiers by comparing their break-even rental rates to the market rental rates.

3.2 User Cost of Housing

Another approach to examining the impact of taxes on housing values is the user cost of housing. The user cost of housing approach focuses on the return to capital and relies on two conditions. The first condition is that households must be indifferent between owner-occupied and rental housing. One can evaluate a household's housing tenure choice by estimating its annual user cost of housing as an owner-occupier and renter. If the annual cost of housing is the same for an owner-occupier as a renter, then the household should be indifferent between the two. Following Poterba (1984) the annual cost of homeownership is:

$$O_t = [(1-\tau_t)(\text{þ}_t + m_t) + \phi_O]P_t - (P_{t+1} - P_t) \quad (4)$$

In Equation 4, there are five components in the annual cost of owner-occupied housing. The first component is the cost of forgone interest that the owner-occupier would have earned if they did not purchase a house. The forgone interest is calculated by multiplying the current market interest rate m_t by the house price P_t. The second component is the annual property taxes incurred by the owner-occupier, calculated as the property tax rate þ_t times the house price P_t. The third component is the tax deductibility of mortgage interest and property taxes, calculated as the owner-occupier's effective tax income rate τ_t times their mortgage and property tax payments ($\text{þ}_t + m_t$). The fourth component is the unobserved maintenance costs of owner-occupied housing, calculated as a fraction ϕ_O of the house's price P_t. The final component in Equation 4 is the capital gain (loss) for the year, calculated as the house price one year from today P_{t+1} minus the house price today P_t .

If an owner-occupier is indifferent between renting and homeownership, then the cost of renting R_t should equal the cost of owning ($O_t = R_t$). Substituting R_t into Equation 4:

$$R_t = [(1-\tau_t)(\text{þ}_t + m_t) + \phi_O]P_t - \mathrm{E}[P_{t+1} - P_t] \quad (5)$$

Where E[P_{t+1}- P_t] is the expected capital gain on the single-family house at time *t*. Deriving the transversality condition for owner-occupied house prices P_t in Equation 5:

$$P_t = \sum_{n=0}^{\infty} \frac{R_{t+n}}{(1+ (1-\tau_t)(þ_t+m_t)+\phi_O)^{n+1}} \tag{6}$$

The price of a house today P_t is the present value of expected future rents. Since future rents are unobservable, Equation 6 is simplified by assuming that future rents will increase at a constant rate of α which results in the following expression:

$$P_t = \frac{R_t}{(1-\tau_t)(þ_t+m_t)+\phi_O-\alpha} \tag{7}$$

The second condition is that investors must be indifferent between investing in owner-occupied housing and other assets. Thus, the net present value of the investment equals zero:

$$R_t - (þ_t+m_t+\phi_I)P_t + \mathrm{E}[P_{t+1} - P_t] = 0 \tag{8}$$

Where the property taxes $þ_t$ are the same as an owner-occupier, the investor can borrow money at market interest rate m_t, and the investor's unobserved costs of being a landlord are $\phi_I P_t$. Iterating Equation 8 one can derive the following transversality condition for investor house prices as:

$$P_t = \sum_{n=0}^{\infty} \frac{R_{t+n}}{(1+þ_t+m_t+\phi_I)^{n+1}} \tag{9}$$

Assuming a constant rate of rental growth, similar to Equation 7, then:

$$P_t = \frac{R_t}{þ_t+m_t+\phi_I-\alpha} \tag{10}$$

If the unobserved costs of investors and owner-occupiers are equal ($\phi_O = \phi_I$), then the rent-price ratio for owner-occupiers and investors are as follows:

$$RP_H = (1-\tau_t)(þ_t + m_t) + \phi_O - \alpha \tag{11}$$

$$RP_I = þ_t + m_t + \phi_I - \alpha \tag{12}$$

If owner-occupiers do not deduct interest and taxes, then $RP_H = RP_I$. If owner-occupiers do deduct interest and taxes, they should be willing to pay more than an investor.

3.3 Preferential Tax Treatment of Owner-occupied Housing

Previous studies that utilize the break-even rental rate and user cost of housing approach find that owner-occupiers should be willing to pay between 5% to 45% more than investors, depending on their income and corresponding tax bracket, due to the preferential treatment that owner-occupied housing is afforded in the tax code. Ozanne (2012) finds that the preferential tax treatment of owner-occupied housing results in a 5.6% savings for households in the 15% tax bracket using an approach similar to the one presented in Section 3.1. Households in higher tax brackets fare even better.[20] Ozanne estimates that households in the 25% (35%) tax bracket save approximately 16.3% (26.5%).[21] Studies that use the user cost of housing approach estimate that owner-occupiers should be willing to pay up to 45% more than an investor based on their ability to deduct interest and tax payments (Himmelberg, Mayer, and Sinai 2005; Glaeser and Gyourko 2010).[22]

The preferential tax treatment of owner-occupied housing discourages institutional investors from entering owner-occupier's favored housing markets, increases the degree of segmentation between the two housing markets, and adds an additional measure of asset illiquidity risk for owner-occupied housing. Lenders should be particularly concerned because owner-occupied housing's preferential tax treatment can raise house prices to a point in which a 20 percent down payment does not cover the price decrease were the owner-occupied house to be valued in its absence. Thus, when the housing market is in equilibrium, a newly purchased owner-occupied house may have negative equity when valued as rental housing.

In the next section, I apply Shleifer and Vishny's (1992) asset liquidity framework to the owner-occupied housing market to illustrate how preferential tax treatment exacerbates the housing market's mildly segmented market structure and adds to its asset illiquidity risk.

4. Owner-Occupied Housing's Asset Illiquidity

When an indebted owner-occupier has trouble making their mortgage payments and their creditor is unwilling to renegotiate the terms of their loan, they have limited options. The owner-occupier can attempt to quickly sell their house if they have enough equity or strategically default if they are underwater. Either way, the owner-occupied house is liquidated. If the shock

[20] Litzenberger and Sosin (1978) show that a progressive income tax promotes homeownership among middle and high income households. High income households also purchase rental properties which they rent to low income households.
[21] Not all households benefit from the preferential tax treatment of owner-occupied housing. Households in lower tax brackets may be better off financially if they rent and claim a standard tax deduction. The standard tax deduction in 2014 for single (married) taxpayers was $6,200 ($12,400).
[22] The two studies estimate the 45% premium based on a marginal tax rate of 25%, property tax rate of 1.5%, interest rate of 5.5%, unobserved costs of 2.5%, and a constant rate of rental growth of 3.8%.

that caused the owner-occupier's distress is market- or economy-wide, other households are likely experiencing the same distress when the house is put up for sale. Households that can potentially become owner-occupiers (i.e. put the house to its best use) likely have difficulty securing a loan or don't have enough money for a down-payment.

The situation is compounded by the fact that owner-occupiers can only own two owner-occupied houses.[23] If owner-occupiers purchase a third owner-occupied house they do not receive preferential tax treatment, even if they personally consume its housing services. Thus, owner-occupied housing can only be put to its best use if it's purchased by a household that does not already own two owner-occupied houses. I assume that the overwhelming majority of households that want to be owner-occupiers have already become owner-occupiers and in times of market-wide distress they are unable to trade up or down, which adds illiquidity to the market.

Current owner-occupiers are not restricted from purchasing the liquidated owner-occupied house. However, if they purchase the house I assume they convert it to rental housing, thereby becoming a landlord. Rental housing is not eligible for the same preferential tax treatment as owner-occupied housing, so the owner-occupied house would be revalued. Owner-occupiers can pay substantially more for housing services they consume due to their preferential tax treatment, so the conversion of an owner-occupied house to rental housing results in a large decrease in value. Landlords have the advantage of knowing the local neighborhood, housing quality, and being able to manage the property themselves. Therefore, landlords have several advantages over institutional investors. Competition among landlords would likely result in the second highest valuation of the owner-occupied house being liquidated. Unfortunately, an economy-wide distress will make it difficult for landlords attempting to secure a loan. Thus, owner-occupied housing has a significant amount of asset illiquidity risk as it may not be able to be put to its second best use.

When the housing market is in equilibrium, institutional investors are restricted to rental housing. However, when would-be owner-occupiers and landlords are credit constrained and the housing market is in disequilibrium, owner-occupied housing has to be sold to institutional investors as they, by definition, have deep pockets and do not require financing to complete the

[23] Although the majority of homeowners only own one owner-occupied house, previous research finds that housing is already "overdetermined" in their portfolios (Flavin and Yamashita 2002).

purchase. Institutional investors incur an extra set of costs when purchasing owner-occupied housing due to its lack of spatial concentration (i.e. it is labor intensive) and heterogeneous housing stock (i.e. lack of economies of scale). To manage their new portfolio of properties institutional investors have to invest in new technology and hire (train) a specialized local property management team. Thus, institutional investors incur higher upfront costs and take on additional risk relative to landlords. As a result, institutional investors demand a higher return and pay a lower price for owner-occupied housing compared to what a landlord or owner-occupier would pay if they were not credit constrained.

This was the case during the recent real estate crisis when a rash of foreclosures, strategic defaults, and the tightening of the mortgage market created a large supply of available owner-occupied houses. Figure 1 shows that homeownership rates peaked at 69.2 percent in the fourth quarter of 2004 and then steadily decreased to 64 percent in the fourth quarter of 2014 (U.S. Census 2014). The steady decline is significant because a one percent drop in homeownership represents a change in living situations for approximately 1.1 million households and up to an additional 1.1 million owner-occupied houses available for sale.

[Insert Figure 1]

An overview of the United States housing market is provided in Table 1 using data from the 2006 to 2013 American Community Surveys (ACS). Table 1 illustrates the steady decline in homeownership and rise of rental occupancy. The total number of occupied units increased by almost 4.7 million between 2006 and 2013. Occupied rentals outpaced the increase in occupied units with an increase of over 5.9 million units, which represented a 16.2% increase. Whereas, the number of owner-occupied units decreased by 1.2 million units, or 1.1%, despite the overall increase in occupied units. The bottom section of Table 1 breaks down the occupied rental market by property type and clearly illustrates that single-family units were the primary gainers in rental occupancy. Single-family housing was the only property type that increased its market share from 2006 (31%) to 2013 (35.1%). Separating single-family housing into attached and detached units shows that conversions of single-family detached houses into rental properties had the largest impact. The number of occupied single-family detached rental properties increased by over 1.27 million units, representing a 13.8% increase over the seven year period.

[Insert Table 1]

5. Post-Crash Housing Market Dynamics

The recent real estate boom and subsequent crash was the product of overly optimistic future price expectations for owner-occupied housing (Glaeser et al. 2008; Piazzesi and Schneider 2009). Liu, Nowak and Rosenthal (2014) show that house price increases during the real estate boom of the mid-2000s were not justified by fundamentals and incentivized speculative developers to expand the existing single-family housing stock. When supply exceeds demand in housing markets, vacancies increase and prices fall (Wheaton 1990). Thus, oversupplying the housing market during a boom can result in significant economic and social welfare losses (Glaeser et al. 2008). In my model, I show that large-scale investment and conversions of owner-occupied housing into rental housing reduces the available owner-occupied housing stock, decreases vacancies, and increases prices.

Figure 2 presents the market equilibrium *E*, boom *B*, and post-crash *C* price dynamics in the owner-occupied housing market. I assume that pre-boom prices in 2001 were based solely on the underlying fundamentals of supply and demand. Thus, prices were in equilibrium in Figure 2 at P^E. Liu et al. (2014) show that house price increases from 2004-2006 were not justified by fundamentals, and that in response speculative developers expanded the housing stock (from H^E to H^B). The housing bubble burst in 2007 and the anticipated demand never materialized, so prices must eventually fall to P^C on the demand curve for the market to clear (Glaeser et al. 2008; Liu et al. 2014). The downward price correction is magnified if lending standards are tightened or unemployment increases as a result of the bubble bursting (Haughwout et al. 2012).

In Figure 2, I also present a model of post-crash housing market dynamics. Unlike previous research I do not assume that the supply of housing is fixed. Thus, the shift from H^B back towards H^E represents the reduction in available owner-occupied housing stock. The cost to convert a property from owner-occupied to a rental is negligible, so institutional investors can easily convert a house to a rental property, and vice-versa when the market rebounds. However, when institutional investors purchase and convert houses to rentals they pay cash and no longer benefit from owner-occupied housing's preferential tax treatment. As such, institutional investors pay lower prices relative to homeowners for owner-occupied housing. The difference in price represents owner-occupied housing's asset illiquidity risk.

[Insert Figure 2]

As institutional investors purchase owner-occupied houses and convert them to rental housing they reduce the available owner-occupied housing stock and push the market back towards equilibrium. In my model, institutional investors target owner-occupied housing with the highest anticipated yields based on (1) expectations of mean reversion in prices and (2) rental income.[24] In doing so, institutional investors impose a disciplining effect by reducing the available housing stock. As the housing stock shifts inward to $H^{\#}$, prices move up the demand curve from C towards $C^{\#}$, thereby reducing the relative price divergence.[25] Thus, the model supports institutional investors' expectations of mean reverting prices.

If the market's population continues to grow and the single-family housing market begins to recover, the model predicts that demand will gradually increase. As demand increases, prices will move up the supply curve from $C^{\#}$ to $E^{\#}$. As prices increase and demand grows, some institutional investors will convert their properties back to owner-occupied housing by listing them for sale instead of renting them out. As institutional investors reintroduce the converted houses back to the owner-occupied housing market they gradually shift the available housing stock back towards H^{B}. As institutional investors convert and sell their rental properties to owner-occupiers prices will move up the demand curve from $E^{\#}$ to B.

6. Data

The analysis in this paper focuses on single-family detached homes in the Atlanta, GA metropolitan area.[26] Atlanta is the ideal setting for this study as it attracted considerable institutional investment after the real estate crash. In their examination of large "buy-to-rent" investors, Mills, Molloy and Zarutskie (2015) find that Atlanta had the second highest buy-to-rent market share in 2012 – only Phoenix, AZ (6.5%) had a higher market share than Atlanta's

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[24] I examine institutional investors' expected returns in Section 6.

[25] If lending standards are tightened or unemployment increases, the demand for housing will decrease and the demand curve will shift inwards resulting in lower prices (Haughwout et al. 2012). Regardless, owner-occupied houses redeployed as rental housing will reduce the available owner-occupied housing stock and prices will increase up the 'reduced' demand curve.

[26] I focus on single-family detached housing for several reasons. First, single-family detached housing is the largest property type in the United States, representing 63.1% of the occupied housing stock (ACS 2006). Second, single-family detached housing is synonymous with owner-occupied housing as 86.9% of its stock was owner-occupied prior to the real estate crisis (ACS 2006). Third, single-family detached housing gained the largest market share after the real estate crash.

6.4%. In 2013, Atlanta (11.6%) had the second highest market share again - Winston-Salem, NC (12.2%) had the highest market share. In 2014, Atlanta (5.0%) had the fourth highest buy-to-rent market share - only Charlotte, NC (6.6%), Jacksonville, FL (6.6%), and Memphis, TN (5.1%) outpaced Atlanta (Mills et. al 2015).[27]

Atlanta's housing market is also very similar to the United States market as a whole. As displayed in Table 2, 36.5% of occupied housing units were rentals in both Atlanta and the United States in 2013. In addition, prior to the real estate crash single-family detached housing's market share in Atlanta and the United States were nearly identical (25.4% in Atlanta versus 25.9% in the United States in 2007). In 2013, single-family detached rental properties accounted for 31.7% of the Atlanta rental market after experiencing a 25.2% increase in the number of rental units between 2007 and 2013. Single-family detached rental housing also grew across the United States, albeit at a slower pace of 11.2% over the same time period, accounting for 28.8% of the rental market in 2013.

[Insert Table 2]

The data for this study comes from several sources. The first two sources are datasets compiled by CoreLogic. The first CoreLogic dataset contains county tax assessor records. The tax assessor dataset includes parcel level information for every property in the eighteen counties that comprise the Atlanta, Georgia metropolitan market.[28] The parcel file specifies whether there is a structure built on the property and, if so, the type of structure (single-family detached, multi-family, commercial, etc.). The parcel file also includes detailed information about the physical characteristics of the structure, such as the square feet of living area, number of bedrooms, number of bathrooms, and its lot size.

The second CoreLogic dataset includes every property transaction recorded in the eighteen counties from January 1st, 2000 through December 31st, 2014. I use several fields in the dataset to identify and isolate single-family detached sales transactions. After applying several

[27] Atlanta was the clear leader in terms of institutional investor purchase volume. Mills et al. (2015) estimate that institutional investors purchased approximately 17,660 single-family homes in metro-Atlanta from 2012-2014. Of the other markets listed – institutional investment volume was second highest in Tampa, FL where they purchased approximately 7,498 single-family homes from 2012-2014 (*Note: only the top 10 markets are listed for each year so it is possible that a market that was only listed once or twice had a higher volume than Tampa, FL).
[28] The counties included in the dataset are Barrow, Bartow, Carroll, Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Newton, Paulding, Rockdale, and Walton. A map of the counties is available in Appendix A.

filters that remove (i) single-family attached, multi-family, and commercial sales transactions, (ii) interfamily transactions, and (iii) non-purchase transactions, the final dataset includes approximately 1.25 million sales transactions. The data is well suited for the issues I address in this paper as it contains detailed information about the parties involved in the transaction (i.e. buyer and seller), terms of the transaction, and the type of deed conveyed. Thus, I can determine whether an owner-occupier or investor purchased the property, it was part of a portfolio sale, or it was a foreclosure, REO, or short sale.

The third data source I utilize was provided by the Georgia Multiple Listing Service (GAMLS). The GAMLS dataset includes houses that were listed for sale or rent in the eighteen counties in and around Atlanta, GA. The GAMLS sales data is available between 2000 and 2014 and the rental data is available between 2003 and 2014. The data collected from the GAMLS includes detailed property characteristics (bedrooms, baths, etc.), listing information (list date, sale date, etc.), and sale conditions (foreclosure, REO, etc.). As noted by Levitt and Syverson (2008), MLS data is manually entered by real estate agents and is prone to error. Thus, I augment and validate the MLS records with the CoreLogic tax assessor and sales transaction data.

6.1 Repeat Sales House Price Index

I create a quarterly repeat sales housing price index using the CoreLogic sales transaction data that includes all single-family detached houses that were listed and sold at least twice during the sample period of 2000 to 2014. The initial dataset contains 1,255,075 sales transactions, over 30% of which are attributable to houses that only sold once during the sample period. After creating matched pairs, I remove records whose sales transactions occurred within six months of each other. The final repeat sales sample includes 420,809 records. Following Case and Shiller (1989) I estimate the index as follows:

$$\text{Log}\left(\frac{P_{it}}{P_{if}}\right) = \sum_q \beta_q D_{iq} + \varepsilon_{itf}, \quad q = 1, 2, \dots, Q \tag{13}$$

$$\text{where } D_{iq} = \begin{cases} 1, \text{if } q = t \\ -1, \text{if } q = f \\ 0, \text{otherwise} \end{cases}$$

P_{if} is the price of property *i* at the time of the first sale *f*

P_{it} is the price of property *i* at the time of the second sale *t*

β_q is the estimated coefficient for quarter q

Q is the number of quarters in the study period

ε_{itf} is the error term

I report exponentiated values that are scaled to 100 in relation to the first quarter of 2001. Figure 3 presents the results for Equation 13 in the form of a repeat sales index. House prices in Atlanta were relatively stable through the early to mid-2000s, increasing an average of 5.8% per year from 2000 to 2006. Although Atlanta's prices did not increase as much as other cities during its boom period, its bust period was equally dramatic. House prices dropped by almost 50% during the real estate crisis and remained at levels below those experienced in 2001 until the second quarter of 2014.

[Insert Figure 3]

Single-family detached sales volume mirrored the growth of house prices as displayed in Figure 4. The total volume of sales in the Atlanta metro area rose steadily from 2000 through the second quarter of 2006, peaking at 32,831 quarterly sales transactions. Sales volume dropped dramatically during the real estate crash as the percent of distressed sales rose rapidly, reaching as high as 74.3% in the fourth quarter of 2010. Both home prices and sales volume increased after 2012 and were approaching their pre-boom levels in the final quarter of 2014.

[Insert Figure 4]

6.2 Classification of Sales Transactions

Much of the analysis going forward relies on the correct identification and classification of owner-occupiers and investors. As such, I meticulously identify and assign each transaction as follows. To identify owner-occupiers I rely on a field provided in the CoreLogic dataset. I also perform a validation using the legal mailing address of the properties that were flagged by CoreLogic as owner-occupied (where available). The validation checks whether an owner-occupier's mailing address is simultaneously used as the legal mailing address for two or more additional properties in the dataset.[29] If so, I assume those properties are not owner-occupied. If the owner-occupier's legal mailing address does not match any of the property addresses I assume that the first single-family house purchased by the owner-occupier is their primary residence and the remaining properties are investments.

All single-family detached housing transactions not attributed to owner-occupiers are considered investor activity. I segment the investor transactions into two categories using an indicator variable available in the CoreLogic dataset. The indicator variable identifies all transactions in which the buyer is a corporate entity. If the indicator variable is 0, the transaction is assigned to an individual investor. If the indicator variable is 1, I further segment the corporate entity transactions into one of four investor subcategories: government/non-profit, financial institution, institutional investor, or corporate investor. Government and non-profit transactions include all purchases by government entities, such as local city and county governments, as well as purchases by non-profit groups, such as Habitat for Humanity. Financial institution transactions include all purchases by credit unions, securitized mortgage trusts, and banks.

To identify institutional investors I take a more granular approach as they are the primary group of interest in this study. I classify a purchaser as an institutional investor if they (i) entered the Atlanta housing market after the real estate crash, (ii) raised equity to invest in single-family detached housing, (iii) purchased 200 or more single-family detached houses, and (iv) had a publicly stated investment strategy of converting the houses they purchased to rentals.[30] After identifying eleven institutional investors, I associate all their transactions to their parent company to ensure the classification is comprehensive and accurate.[31] If the company is publicly traded, I

[29] The legal mailing address is where the property's owner receives property tax statements from the county. I cleanse the legal mailing addresses using an address verification system to remove typos and to ensure consistency in the dataset.

[30] I investigated every company that purchased more than 25 single-family detached houses from 2007 to 2014. Several companies had more than 200 combined purchases, but were not classified as an institutional investor if their investment strategy differed. Opportunistic investors that purchased houses and sold them in a short period of time (i.e. flippers) are not included. In addition, local investors that already had a portfolio of single-family detached houses prior to the real estate crisis are not included in the classification. Thus, the classification identifies the institutional investors discussed in section 4.

[31] The companies included in the institutional investor classification include American Homes 4 Rent, American Residential Properties, Colony American Homes (Colony Capital), Invitation Homes (Blackstone Group), Main Street Revival (Amherst Holdings), Progress Residential, Silver Bay Realty Trust, Starwood Waypoint Residential Trust, Havenbrook Homes, Residential Capital Management, and Sylvan Road Capital. The first eight companies listed above match the eight companies identified as "buy-to-rent" investors by Mills, Molloy, and Zarutskie (2015).

identify and search the transaction records for every asset company name listed in their SEC filings. If the company is private, I search their website for rental properties, look up the properties' owner in the CoreLogic dataset, and flag the asset company name as a known subsidiary of the institutional investor (I also perform this task for institutional investors that are public companies to ensure I capture all of their transactions). If a transaction is not assigned to the government/non-profit, financial institution, or institutional investor classifications it is placed in the corporate investor classification. A breakdown of sales transactions by buyer type is available in Table 3, which I discuss in detail in the next section.

6.3 Atlanta's Housing Stock and Investor Activity

Increasing house prices incentivized new development in the Atlanta market during the early to mid-2000s as displayed in Table 3. The number of new single-family detached houses introduced to the market remained relatively steady from 2000 to 2006, peaking at 48,245 new units in 2006. The new houses represented an annual supply growth of approximately 4%, when compared to Atlanta's housing stock in 2000, and may explain why Atlanta's house prices did not rise as rapidly as other cities during the real estate boom. Development slowed during the real estate crisis as prices crashed and the number of financial institution transactions nearly doubled from 2005 to 2007. The number of individual and corporate investor transactions also increased rapidly after the crash, almost doubling from an average of 6,321 purchases per year (2000-2006) to 12,370 purchases per year (2012-2014).

[Insert Table 3]

6.3.1 Institutional Investment

Several market factors likely influenced institutional investors' decision to enter the single-family detached housing market including declining house prices, decreasing multi-family vacancy rates, a large number of delinquent borrowers, the capital markets acceptance of investments in residential Real Estate Investment Trusts (REITs), the prospect of bulk purchases, and higher expected returns relative to apartment buildings. The repeat sales price index in Figure 3 shows that house prices were falling in 2011 and bottomed out in the first quarter of

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Appendix A includes a brief description of the institutional investors included in this study and the location of the houses that they purchased.

2012 – which corresponds with the entrance of institutional investors.[32] Figure 5 shows that demand for rentals was increasing as multi-family vacancy rates decreased from 13.1% in the third quarter of 2009 down to 10.3% in the first quarter of 2012. In addition, there was very little multi-family construction in the pipeline. From 2000 through 2008, approximately 74,000 new multi-family units were started each quarter. In contrast, approximately 30,000 new multi-family units were started each quarter from 2009 through 2011.

[Insert Figure 5]

Figure 1 shows that over 10% of homeowners were delinquent in 2011. The increased demand for rentals was expected to continue because the delinquent homeowners would likely become renters after they were foreclosed on. The delinquencies also meant that a large supply of distressed single-family detached housing would be available for purchase in the near future. The upcoming liquidation of distressed single-family detached housing combined with an increasing demand for rentals and decreasing rental vacancies offered a unique opportunity for large scale investment in and conversion of single-family detached housing.

Another potential draw for institutional investors was the capital market's acceptance of residential REITS. In January 2007, residential REITs accounted for $67 billion or 16.8% of the equity REIT market capitalization (NAREIT 2007).[33] Prior to the real estate crash, residential REITs included apartment and manufactured home REITs. There were no single-family rental REITs, but the market had a history of accepting and investing in new asset classes.[34] The growth and innovation of capital markets may have played a role in institutional investors' entrance into the owner-occupied housing market in 2012.

Table 3 highlights the entry of institutional investors into the Atlanta owner-occupied housing market. Over a four year period, 2011 to 2014, institutional investors purchased 21,283 single-family detached houses in the metro Atlanta area. Although institutional investors purchased a few properties in late 2011, it wasn't until 2012 when they truly entered the Atlanta market and accounted for over 5% of all the single-family detached housing transactions. In

[32] The repeat sales price index in Figure 3 only includes sales transactions for metro-Atlanta. However, the start of Atlanta's housing market recovery coincides with the start of the recovery nationwide

[33] In December 2014, residential REITs accounted for $108 billion or 12.9% of the equity REIT market capitalization (NAREIT 2014).

[34] Single-family rental REITs are listed in the 'diversified' sector and not the 'residential' sector. Additional information about institutional investors who became single-family rental REITs is available in Appendix A.

2013, institutional investment in Atlanta more than doubled, accounting for over 13% of all the sales transactions in the market. Competition among investors and increasing prices curtailed institutional investment in 2014, although they still accounted for over 8% of all single-family detached sales transactions.

The publicly stated investment strategy of the institutional investors included in this study is to purchase single-family detached homes and operate them as rentals.[35] Prior to the real estate crash, it was difficult for institutional investors to amass a portfolio of single-family detached rental homes – as they usually were only available through one-off sales. Thus, the single-family rental market remained fragmented in terms of both ownership and operation until after the real estate crash when institutional investors had several avenues in which they could purchase and build a portfolio of single-family detach rentals quickly including: individual sales, auctions, short sales listed on the MLS, trustee sales (foreclosed and tax sale properties), bank-owned houses listed on the MLS, bank-owned houses purchased directly from banks, and in some cases bulk sales.[36,37]

Institutional investors purchased single-family detached houses in Atlanta through several avenues as displayed in Table 4. Approximately 46.7% of their purchases were foreclosures, 7.9% were REOs, 7.8% were short sales, and 5.5% were part of a bulk purchase.[38] Of the remaining non-distressed transactions approximately 18.8% were purchased directly from an owner-occupier, 12.7% were purchased from an investor who already converted the property to a rental, and 0.6% were purchased from investors who owned and rented the house prior to 2007. The largest institutional investor in Atlanta was the Blackstone Group, through their Invitation Homes subsidiary. The Blackstone Group accounted for over one-third of all

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[35] See, for example, the American Homes 4 Rent website - https://www.americanhomes4rent.com/ - which states that they are "focused on acquiring, renovating, leasing and operating attractive, single-family homes as rental properties."
[36] Citing a 1996 Property Owners and Managers Survey, Mills et al. (2015) state that three quarters of the single-family detached rental units were owned by individuals or partnerships that owned fewer than 10 units.
[37] Auctions, short sales, trustee sales, and bank-owned sales were available prior to the real estate crash – but their volume paled in comparison to their post-crash volume (see Figure 4).
[38] I use the same definition of a bulk sale as Mills et al. (2015). I consider a transaction part of a bulk sale if there are three or more properties with the exact same transaction price, sales date, and buyer name with a sales amount greater than $225,000. I modify the sales price of each property that is part of a bulk sale to reflect the average price paid per house – because the sales price is estimated I remove bulk sales in most of the empirical analysis. If a property is listed as a bulk sale and a foreclosure it is only displayed in Table 4 as a bulk sale.

institutional purchases and was the primary bulk purchaser in Atlanta.[39] Although bulk sales only represented 5.5% of institutional investors' single-family purchases in the Atlanta - the prospect of bulk purchases may have drawn institutional investors into the market. In February 2012, the Federal Housing Financing Authority (FHFA) and Fannie Mae announced a REO-to-Rental Pilot Initiative to determine if bulk sales would generate private investment in single-family rental housing.[40]

[Insert Table 4]

6.4 Institutional Investors' Expected Return

The liquidation of distressed single-family housing may offer a unique investment opportunity, but institutional investors are rational and will only enter the owner-occupied market if it offers higher returns than apartment buildings in the rental market. In this section, I compare institutional investors' competing investment alternatives in rental housing (apartment buildings) with owner-occupied housing (single-family detached houses).

6.4.1 Mean Reversion Expectations

To examine institutional investors' mean reversion expectations I use the same dataset described in Section 6.2 to create a repeat sales index by investor type. The results displayed in Figure 6 show that institutional investors were able to identify and purchase single-family detached houses that offered higher expected mean reverting returns relative to individual investors and owner-occupiers. Institutional investors place a lower value on owner-occupied housing because they must convert it to rental housing, so the higher expected mean reverting returns are a product of, among other things, owner-occupied housing's asset illiquidity and preferential tax treatment.

[Insert Figure 6]

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[39] The overwhelming majority of Blackstone's transactions that are flagged as bulk purchases can be attributed to one deal that they completed in April 2013 with Building and Land Technology's single-family rental business.
[40] Additional information on the REO-to-Rental Pilot Initiative is available on the FHFA website: http://www.fhfa.gov/PolicyProgramsResearch/Policy/Pages/Real-Estate-Owned-(REO).aspx. Although bulk sales would allow institutional investors to build a large portfolio of single-family detached homes quickly – investors may shy away from bulk sales if the properties included in the sale were not in their target markets or if the properties were spread across large geographical areas - as it would undermine their stated goal of creating economies of scale.

Figure 7 plots an annual repeat sales index that that has been stratified into twenty home size segments based on each houses' square feet of living area. The stratified home size segments are a proxy for housing quality and that help identify the housing segments that institutional investors targeted. I stratify the home size segments in ascending order, so the smaller the house is, the lower the percentile it is segmented into (i.e. 0-5 percentile contains the smallest houses and 95-100 percentile contains the largest houses). Although the boom period in Atlanta was relatively mild compared to other cities, Figure 7 suggests that prices in two segments of Atlanta's single-family detached housing market, the 0-5 and 5-10 percentile, increased at a rate much higher than the rest of the market. The same two segments also experienced the largest decline during the crash.

[Insert Figure 7]

Next, I quantify and compare the mean reversion expectations by home size segment and buyer type in Table 5. The top section of Table 5 is stratified into the same twenty home size segments that correspond with Figure 7 – it details each home size segments' size distribution, number of properties purchased by institutional investors, and mean reversion expectations. Although institutional investors were active in every home size segment, the majority (over 85%) of their purchases fell in the 5-75 percentile range. The top right section of Table 5 provides the price index levels by home size segment for the pre-boom index level (P^E) in 2001, the pre-crash price apex (P^B) in 2006, the post-crash nadir (P^C) in 2012, and the recovery price in (P^R) in 2014. I also calculate each home size segment's pre-crash price appreciation (P^B - P^E), post-crash price depreciation (P^C - P^B), and mean reversion expectations in 2012 (P^E - P^C) and 2014 (P^E - P^R). The last two columns of Table 5 clearly show that smaller houses offered higher expected mean reversion returns in both 2012 and 2014. The monotonic price declines explain why institutional investors preferred smaller houses and were not as active in the 75-100 percentile home size segments.

[Insert Table 5]

In the bottom section of Table 5 I create price index levels by buyer type to compare institutional, corporate, and individual investors. The price index levels correspond with the repeat sales index in Figure 6. When institutional investors entered the Atlanta market in 2012 their expected return, based on mean reversion to pre-boom price levels in 2001, was 46% for the properties they purchased, which outpaced individual investors (36%) and was comparable to corporate investors (48%). The results support the asset illiquidity framework in Section 4, as institutional investors paid lower prices and demanded higher expected returns compared to owner-occupiers and local landlords (i.e. individual investors).

6.4.2 Income-producing Expectations

Although the expectation of large capital gains played a role in institutional investors' entrance into the owner-occupied housing market, housing's income-producing component is equally, if not more, important to institutional investors because, unlike the capital appreciation component, it is not affected by market illiquidity. To examine the income-producing component of owner-occupied housing, I calculate its gross rent-price ratio and compare institutional investors' competing real estate investment alternatives both before and after the crash. Rent-price ratios are a fundamental component of real estate returns and have a major role in investor's portfolio management decisions (Plazzi, Torous and Valkanov 2011). When comparing rent-price ratios, I restrict the sample to single-family detached houses that were both sold and rented within six months of each other.[41] The approach allows me to compare actual rent-price ratios over time across investor and property types.

I identify 10,144 single-family detached houses that were both sold and rented within six months of each other in the MLS rental and CoreLogic sales data. Summary statistics for the combined dataset and rent-price matches are displayed in Table 6. The median rent for a single-family detached house in the matched rental dataset is $1,150, which is identical to the median rent in the complete rental dataset. The median sales price for the matched dataset is much lower ($109,900) than the median sales price in the entire dataset ($154,670). However, the matched dataset is heavily weighted towards post-crash prices, whereas, the entire dataset is more evenly distributed. This is expected as single-family detached houses were not frequently purchased as rental properties prior to the real estate crash. Table 6 also provides summary statistics by period for the matched and entire dataset - including the median gross rent-price ratio for the boom, bust, and recovery time periods. The median rent was relatively flat over the three periods,

[41] My approach to calculating rent-price ratio is similar to the approach employed by Bracke (2014) in his study of the central London Housing market.

however, house prices declined after the real estate crash. As a result, the median gross rent-price ratio increased from 10% during the boom to 14% during the recovery.

[Insert Table 6]

Next I compare rent-price ratios for owner-occupied housing (single-family detached) and rental housing (apartment buildings) over the length of the study. If rents are relatively stable across the two housing submarkets, the model predicts that as owner-occupied house prices decrease, institutional investors will substitute some of their investment in rental housing with single-family detached rentals, thereby determining owner-occupied housing's liquidation value. I calculate the gross rent-price ratio for apartment buildings using data from CoStar for the Atlanta market from 2003 to 2014. Table 7 provides an overview of the gross rent-price ratio for apartment buildings in the Atlanta market by period. The CoStar data includes a total of 277 transactions over the 12 year period.

[Insert Table 7]

From 2003 to 2006, the median rent-price ratio for apartment buildings was approximately 15% (compared to 10% for single-family detached housing). After the crash, the median rent-price ratio dropped to 11%, which was 2% lower than the single-family detached housing market. During the recovery, 2012 to 2014, the median rent-price ratio rose to 17%, once again exceeding single-family detached housing. In Figure 8, I plot the rent-price ratios for the two property types. In the mid-2000s, the rent-price ratios for apartments are clearly superior to those offered by single-family detached housing. However, after the crash rent-price ratios for single-family detached houses rose rapidly and exceeded those offered by apartment buildings until the third quarter of 2013.

[Insert Figure 8]

In Figure 9, I examine the single-family detached gross rent-price ratios by investor type. In the mid-2000s, prior to the real estate crash, rent-price ratios averaged approximately 10% regardless of investor type. After the real estate crash, rent-price ratios climbed rapidly and peaked in 2011 when both corporate and individual investors purchased properties with gross rent-price ratios above 20%. In 2012, institutional investors entered the market and started to build their large single-family detached rental portfolios. The introduction of a new market participant increased competition and likely contributed to the sharp decline in rent-price ratios for single-family detached houses.

[Insert Figure 9]

6.4.3 Expected Returns

In Table 8, I provide a rough estimate of institutional investors' expected return that includes both their expected rental income and capital appreciation yields. For simplicity's sake, I assume that rents will remain the same over time, so an investors' rental yield equals the houses' rent-price ratio when it was purchased. Investors' capital appreciation yield is calculated based on the assumption that house prices will revert back to 2001 levels. To allow for a back of the envelope comparison and keep things simple, I divide the mean reversion expectation by the investors' holding period. I estimate the mean reversion return using holding periods of 3, 5, and 10 years. I tabulate the returns for houses purchased in 2012, 2013, and 2014 separately as market conditions changed over time.

[Insert Table 8]

In 2012, institutional investors' expected returns were particularly attractive. If institutional investors hold their purchases until 2017 (5 years) and house prices revert back to 2001 levels, they will receive an annualized gross return of approximately 23.7%. Given the fact that house prices in some segments have already reverted back to their 2001 levels in the Atlanta market, I believe this is a reasonable, if not conservative, assumption. If the market returns to its pre-crash (2006) levels by 2017, institutional investors' gross return would increase to a 26.6% annualized return. In 2013 and 2014, the Atlanta market started to recover, so the rental and capital appreciation returns available to institutional investors in single-family detached housing decreased. In 2013, single-family detached housing yields were still clearly favorable relative to the yields offered by apartment buildings in the Atlanta market. However, in 2014 a sharp increase in apartment building yields combined with the increase in house prices made the two markets' returns comparable.[42]

[42] To allow for ease of comparison, I assume that the apartment buildings included in the analysis were operating at capacity when purchased and their rent-price ratio will stay the same over time. Thus, the rent-price ratio listed represents the investors' expected return.

I recognize that a portion of the higher return offered by single-family detached rental housing may be offset by higher renovation, maintenance, and operating expenses. However, due to a lack of available data, I cannot quantify and compare the impact of single-family detached housing's higher expenses on its return. Instead, I assume renovation costs of 20% of the purchase price for single-family detached housing and recalculate institutional investors' expected income and appreciation yields in Table 8.[43] I also assume that the renovation adds no value and has no impact on the yield – this assumption is made to highlight the attractiveness of the investment opportunity.[44] After adjusting for renovation costs, institutional investors' returns still outpace returns offered by apartment buildings in the Atlanta market in 2012 and 2013, regardless of the holding period chosen.

7. Empirical Methodology and Results

The intuition behind the identification strategy employed in the empirical analysis going forward can be understood through a simple example. Consider two single-family detached houses which I will refer to as house A and house B. The two houses have similar physical characteristics and are located in the same neighborhood. Initially, both houses are owner-occupied and benefit from preferential tax treatment. Then suppose there is a crisis in which house prices rapidly decline and mortgage defaults increase. As a result of the crisis, demand simultaneously decreases for owner-occupied housing and increases for rental housing. Next suppose that house A and house B are both put on the market by their respective homeowners and are sold around the same time. House A is purchased by an owner-occupier and house B is purchased by an institutional investor. The institutional investor converts house B to a rental. As noted in Section 4, institutional investors incur an extra set of costs when investing in single-family detached housing and, because they convert the house to a rental, they do not benefit from the preferential tax treatment for owner-occupied housing. Thus, I expect institutional investors

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[43] According to their 2014 Annual Report, Starwood Waypoint spent, on average, 17% of the purchase price of a house on its renovation to ensure it was in "rent ready" condition. In Atlanta, which is Starwood Waypoint's second largest market in terms of aggregate investment ($312 mm), they spent 24% of the purchase price, on average, to renovate their homes (Starwood Waypoint Residential Trust 2014). I use a 20% renovation estimate as I do not know what other institutional investors' spent on renovation costs and I am not adjusting the comparison group (apartment buildings) for renovation costs.

[44] Institutional investors would never rationally renovate under these conditions. If institutional investors expect zero NPV, then the discounted cash flows post-renovation, including price reversion and increased rents, should equal the cost of renovation – in which case the institutional investor's return would be similar to their expected return in the absence of the renovation costs.

to pay a lower price for owner-occupied housing – in which the pricing differential represents an estimate of owner-occupied housing's asset illiquidity risk.

7.1 Single-family Detached Rental Conversions

Prior to running the empirical analysis I identify owner-occupied houses that were converted to rentals. Several obstacles exist in identifying these conversions. Although I identified institutional investor transactions and I know that institutional investors plan on renting the houses they purchase based on their publicly stated investment strategy - I have yet to determine whether the houses they purchased were conversions. It's possible that a portion of the houses institutional investors purchased were rental properties for the entire length of the study. Another obstacle is determining whether individual and corporate investors convert the houses they purchase to rental properties because investment strategies vary both across and within the two groups of investors. Thus, I recognize that the identification and categorization of conversions in my analysis is not perfect. However, I develop a set of reasonable assumptions to classify every single-family detached house as either (i) owner-occupied, (ii) rental [*Rent*], (iii) owner-occupied to rental [*O2R*] conversion, or (iv) rental to owner-occupied [*R2O*] conversion.

I begin the classification process by identifying houses that have no transactions during the study period. If a house has no transactions and is owner-occupied in 2014, I classify it as owner-occupied. If a house is investor-owned in 2014, I classify it as a rental. Approximately 51.8%, or 724,060, of the 1,399,067 single-family houses in the Atlanta metro market did not transact between 2000 and 2014. Of the non-transacting houses, approximately 84.6% are owner-occupied and 15.4% are rentals. Next I classify houses that only transacted during the pre-crisis subperiod (2000-2006). Approximately 21.3%, or 297,433 houses transacted during the pre-crisis subperiod, but did not transact in the post-crisis subperiod (2007-2014). Of these houses, approximately 82.9% are owner-occupied and 17.1% are rentals.

The remaining 377,574 houses transacted at least once in the post-crisis subperiod and therefore may be a conversion. Using the CoreLogic tax assessor and transaction data I begin by identifying the houses' baseline tenure status in the pre-crisis (2000-2006) subperiod. I classify a house as pre-crisis owner-occupied if the house was owner-occupied for more than five years from 2000 to 2006. I classify a house as a pre-crisis rental if it was investor owned for two or more of the seven years in the pre-crisis subperiod. Each houses' pre-crisis tenure serves as a baseline for the identification strategy where a house is classified as (i) owner-occupied if it was owner-occupied pre-crisis and post-crisis; (ii) rental if it was a rental pre-crisis and post-crisis; or (iii) conversion if it was owner-occupied (rental) pre-crisis and converted to rental (owner-occupied) post-crisis.[45] I estimate that approximately 76,138 houses, or 5.5% of metro Atlanta's single-family detached housing stock, were converted from owner-occupied to rental [*O2R*] from 2007 to 2014 and 5,328 houses were converted from rental to owner-occupied housing [*R2O*]. The total number of *O2R* conversions I identify is comparable to the single-family detached housing growth highlighted in Table 2. The American Community Survey (ACS) estimates that the number of occupied single-family detached rental houses in Atlanta increased by approximately 75,873 between 2007 and 2013.

7.2 Transaction Data and Matched Samples

After classifying every single-family detached house into one of four categories I merge the classifications with the sales transaction data. When running the empirical analysis in the following sections I remove records with missing data in a key field. I also remove houses that have more than six bedrooms or bathrooms, more than five acres of land, and winsorize the top and bottom .5 percent of sales prices. Select summary statistics for the full sample and two matched samples are displayed in Table 9 - where the treatment group in columns 1, 4, and 7 of the top section represent houses classified as owner-occupied to rental [*O2R*] conversions and the treatment group in the bottom section of Table 9 identifies houses that were purchased by institutional investors [*Institution*]. The control group in column 2 of the top section includes all sales transactions that were not included in the treatment group. The large t-statistics in column 3 - which compare the difference between the means of the treatment and control groups - highlight a potential sample selection issue. To address this potential issue I create matched samples for houses classified as *O2R* conversions in the top section of the table and houses purchased by institutional investors in the bottom section of the table.

[45] A pre-crisis owner-occupied house is classified as an *O2R Conversion* if (i) it was purchased by an investor(s) and held for a total of at least two years in the post-crisis period, (ii) it was purchased by an investor in 2013 and held through the end of the study period, or (iii) it was purchased by an institutional investor whose investment strategy is to buy and rent single-family housing. Thus, if a house was owner-occupied in the pre-crisis period, purchased by an investor in 2010, held by the investor for six months, and then sold to an owner-occupier – it would not be classified as a conversion. The number of conversions may be understated as first time non-institutional investor purchases in 2014 are not classified as conversions due to an "unknown" holding period.

[Insert Table 9]

I create the matched samples using two matching processes. The first process is a characteristic matching technique that identifies every unique combination of the following characteristics in the treatment group: transaction year, census block-group, number of bedrooms and number of bathrooms. I then limit the control sample to only include owner-occupied houses that match at least one of the records in the treatment group on every characteristic.[46] The second matching process I employ matches each observation in the characteristic matched treatment group with its nearest neighbor in the control group using a one-to-one propensity score matching technique with replacement.[47] The second matching process requires an exact match on the census block-group and transaction year fields – if there is no exact match the treatment record is dropped. If there are multiple exact matches the process then identifies the nearest neighbor by calculating a propensity score using the following fields: age, living area, lot size, bedrooms, and bathrooms. The second matching process is executed with replacement, so there are duplicate observations in the control sample. This approach increases the matching precision, but results in fewer independent control observations. As noted in Wiley (2014), having fewer independent control observations reduces the likelihood of finding statistically significant differences between the two groups (i.e. selection bias), but it does so at the expense of statistical power. The t-statistics for the matched samples are reported in columns 6 and 9 of Table 9. The t-statistics are smaller in magnitude which suggests that running the empirical analysis on the matched samples will help address potential empirical problems that may result from sample selection bias.

7.3 Transaction Level Analysis of Institutional Investor and Conversion Activity

In this section I examine the transaction-level correlates of institutional investor purchases and conversion activity using a series of linear probability models (LPM):

$$Institution_i = c + \sum_{k=1}^{K} \beta_k X_{ikt} + F_t + \varepsilon_{it} \qquad (14a)$$

[46] Houses purchased in bulk sales were removed from both the treatment and control groups in both the characteristic and nearest neighbor matching processes. I remove bulk purchases in the majority of the analysis going forward because their transaction price is estimated and they represent a small fraction of the transactions during the time period.
[47] Propensity score matching techniques (Rosenbaum and Rubin 1983) have been been employed in residential (McMillen 2012) and commercial (Eichholtz, Kok and Quigley 2010; Wiley 2014) real estate studies.

$$Non–Institution_i = c + \sum_{k=1}^{K} \beta_k X_{ikt} + F_t + \varepsilon_{it} \tag{14b}$$

$$O2R_i = c + \sum_{k=1}^{K} \beta_k X_{ikt} + F_t + \varepsilon_{it} \tag{14c}$$

where $Institution_i$ is an indicator variable that equals 1 if the house was purchased by an institutional investor and 0 otherwise, $Non–Institution_i$ is an indicator variable that equals 1 if the house was purchased by a non-institutional investor and 0 otherwise, and $O2R_i$ is an indicator variable that equals 1 if the house was pre-crisis owner-occupied and converted to a rental after the crisis and 0 otherwise. In all three LPM specifications c is a constant, X_{ikt} represents a vector of K transaction level characteristics that are potentially related to conversion activity, F_t represents year fixed effects, and ε_{it} is the error term. The specifications provide insight into the house characteristics and neighborhood attributes that institutional and non-institutional investors targeted. Institutional investors entered the Atlanta housing market in late-2011, so the correlate estimates displayed in Table 10 only include sales transactions from the beginning of 2012 through the end of 2014. The results in columns 1 and 3 are based on (14a), column 2 is based on (14b), and column 4 is based on (14c).

[Insert Table 10]

The property level characteristics in X_{ikt} include the house's age, square feet of living area, square feet of lot size, number of bedrooms, number of bathrooms and indicator variables for whether the house has a fireplace, garage, carport or pool. The results in column 1 suggest that institutional investors targeted 3 to 6 bedroom houses with 2 or 3 bathrooms and a garage. The presence of a carport or pool reduced the probability that the house would be purchased by an institutional investor. Houses located on larger lots were also less likely to be purchased by institutional investors. In most cases, non-institutional investors targeted houses with similar physical characteristics – however, column 2 suggests that they were more likely to purchase older houses with more bathrooms that do not have a garage.

In addition to the houses' physical characteristics - X_{ikt} includes distressed sales condition and neighborhood variables. The distressed sale condition variables identify whether the transaction was a short sale, foreclosure, REO, or part of a bulk sale and include a measure of the percent of distressed sales transactions over the past six months.[48] The results in column 1 show that a house was more likely to be purchased by an institutional investor if it was a bulk sale, foreclosure, or short sale. Houses that were REOs were less likely purchased by institutional investors – although they were more likely to be purchased by non-institutional investors. Both institutional and non-institutional investors targeted houses located in census tracts with higher levels of distressed sales transactions – which suggests that they were providing liquidity to the market.

The following neighborhood controls from the 2008-2012 American Community Survey are also included in X_{ikt} at the census tract level: unemployment rate, percent of household with kids, median income, median age, percent of population without a high school degree, and percent of the population with a college degree. The results in column 1 suggest that a house was more likely to be purchased by an institutional investor if it was located in a census tract with higher levels of unemployment – which serves as another proxy for distressed market conditions - and a higher percentage of households with children.

Additional census tract level variables were constructed to examine the neighborhoods that institutional investors purchased single-family detached houses in. Census tracts' gross rent-price ratio was calculated as the median census tract rent from 2012 to 2014 divided by the median census tract transaction price in the year that the house was purchased.[49] The results in column 1 suggest that institutional investors did not purchase houses located in neighborhoods with the highest rent-price ratios – which collaborates with the transaction-level rent-price estimates displayed in Figure 9. Attractive rent-price ratios likely attracted institutional investors into the single-family detached housing market, but it was not the deciding factor in their purchase decisions. Houses located in zip codes with higher mean reversion expectations were more likely to be purchased by institutional investors.[50] Note, however, that non-institutional investors were more likely to purchase houses in zip codes with higher mean reversion

[48] The 'Percent Distressed Prev 6 Months' variable is measured at the census tract level as the number of distressed sales transactions over the past six months divided by the total number of transactions over the past six months.
[49] The median rent was calculated using three years of data to increase the number of rental transactions at the census tract level and avoid dropping records. The measure assumes that rents were relatively stable over the three year period.
[50] Mean reversion expectations are estimated using a zip code repeat sales home price index where the mean reversion estimate equals the difference between the zip code's index in the year the house was purchased and the zip codes' 2001 price index level (the calculation is similar to the calculation employed in Table 5 except its conducted at the zip code level instead of home size segments).

expectations. These findings suggest that other factors, such geographical location and economies of scale, likely played a role in institutional investors' purchasing decisions.[51]

Pre-crisis rental and market liquidity measures are also included in X_{ikt} at the census tract level. The pre-crisis rental measure identifies and controls for the percent of single-family detached houses that were already rentals prior to the crisis (2000-2006). Houses located in traditional single-family rental markets (i.e. housing markets with a higher fraction of single-family detached rental units prior to 2007) were less likely to be purchased by institutional investors – which suggests that institutional investors were purchasing houses in census tracts that were traditionally owner-occupied. This finding supports the owner-occupied housing asset illiquidity framework in section 4 – which states that owner-occupied housing has to be sold to institutional investors during times of market wide distress because they do not require financing.

Berkovec and Goodman (1996) find that housing turnover is the most appropriate proxy for housing demand. As such, I include two turnover variables and a time-on-market (TOM) variable to estimate the market liquidity (i.e. demand for housing) in the census tracts where institutional investors purchased houses. The first turnover variable estimates market liquidity prior to the real estate crisis (2000-2006) and the second turnover variable estimates market liquidity in the two years leading up to the entrance of institutional investors (2010-2011). The turnover measures are calculated at the census tract level as the average annual number of sales transactions divided by the tract's housing stock. The results in column 1 suggest that houses located in census tracts with lower levels of turnover (i.e. market liquidity) from 2010-2011 were more likely to be purchased by institutional investors. Similarly, the average time-on-market (TOM) variable suggests that houses in census tracts with longer average TOM (i.e. less market liquidity) were more likely to be purchased by institutional investors.

Table 3 documents the large increase in new residential structures in the metro-Atlanta housing market. From 2000-2006, the supply of single-family detached housing grew approximately 4% per year relative to Atlanta's housing stock in 2000. The next measure examines whether houses located in census tracts that experienced high levels of growth in their

[51] The maps in Appendix A suggest that institutional investors tried to concentrate a large portion of their purchases in a geographical area. Additionally, in an interview with a large scale investor in Fulton County, GA Immergluck (2013) reports that the investor discussed a "hub and spoke" model of property management, in which the investor had multiple local offices that serviced rental units within a twenty-mile radius.

single-family detached housing stock were more likely to be purchased by institutional investors. In column 1, houses located in census tracts with higher fractions of new residential structures were more likely to be purchased by institutional investors - which suggests that those markets were oversupplied in the early to mid-2000s. The final two measures of interest examine investment in existing single-family detached structures. The first remodel variable identifies whether the house purchased by the institutional investor was remodeled between 2000 to 2011. The second remodel measure is a proxy for private investment in residential structures in the surrounding census tract – which I calculate using the CoreLogic tax assessor records as the percent of houses in the census tract in 2000 that were remodeled from 2000 to 2011. I create the two remodel measures using the 'effective year built' field in the CoreLogic tax assessor data.[52] The results in column 3 suggest that houses that were recently remodeled or were located in census tracts with a higher fraction of remodeled houses were less likely to be purchased by institutional investors.

7.4 Owner-occupied to Rental Conversion Pricing Differential

Using a difference in difference framework and the identification strategy described in the beginning of section 7, I estimate the difference in price paid for house A (control/*owner-occupied*) and house B (treatment/*O2R conversion*) using the following specification:

$$p_{it} = c + \beta_1 X_{it} + \beta_2 Cash_{it} + \beta_3 Distress_{it} + \beta_4 O2R_i + \beta_5 R2O_i + \beta_6 Rent_i + \beta_7 Post_t + \beta_8 Cash_{it} * Post_t + \beta_9 O2R_i * Post_t + \beta_{10} R2O_i * Post_t + \beta_{11} Rent_i * Post_t + F_t + \varepsilon_{it} \quad (15)$$

where p_{it} is log of the sales price for house *i* at time *t*. The sales price is a function of a vector of the house's physical characteristics [X_{it}], distressed sale conditions [$Distress_{it}$], whether the purchaser financed the purchase or paid cash [$Cash_{it}$], and the house's tenure classification [$O2R_i$, $R2O_i$, $Rent_i$].

[52] The effective year built field identifies the first year the building was assessed with its current components. If a house was constructed in 1980 and an additional bedroom and bathroom were built in 2005 – then the effective year built would be 2005 and it would be flagged as a remodeled property. Five counties (Barrow, DeKalb, Fayette, Forsyth, and Paulding) do not report an effective year built so they are removed in column 3. Smaller remodeling projects that do not require a permit from the county are not included in the measure. The numerator for the measure is the number of houses built prior to 2000 that were remodeled from 2000 to 2012 and the denominator is the number of houses built prior to 2000. I calculate the measure at the census tract level. Approximately 1.3% of the houses were remodeled in the 13 county subsample displayed in column 3.

The X_{it} vector of variables includes the house's age, square feet of living area, lot size, number of bedrooms, and number of bathrooms. It also includes indicator variables to identify if the house has a garage, carport, fireplace, and pool. The $Distress_{it}$vector includes indicator variables that identify whether the transaction was a bulk sale, short sale, foreclosure, or real estate owned (REO) transaction. The $O2R_i$ variable identifies houses that were owner-occupied prior to the crisis (2000 – 2006), but were then converted to rental housing after the crisis (2007 – 2014). The $R2O_i$ variable identifies houses that were rentals prior to the crisis (2000 – 2006), but were then converted to owner-occupied housing after the crisis (2007 – 2014). The $Rent_i$ variable identifies houses that were rentals both before and after the crisis.[53] Indicator variables for quarter and year time fixed effects [F_t] and post crisis [$Post_t$] are also included. Of particular interest is the coefficient for the interaction between the post crisis and own-to-rent conversion variables [$Post_t * O2R_i$], as it represents an estimate of the asset illiquidity risk inherent in housing's mildly segmented market structure.

Next I run a difference in difference model where the treatment groups are delineated by institutional and non-institutional investor purchases:

$$p_{it} = c + \beta_1 X_{it} + \beta_2 Cash_{it} + \beta_3 Distress_{it} + \beta_4 Institution_i + \beta_5 Non\text{–}institution_i + \beta_6 Post_t + \beta_7 Cash_{it} * Post_t + \beta_8 Institution_i * Post_t + \beta_9 Non\text{–}institution_i * Post_t + F_t + \varepsilon_{it} \qquad (16)$$

where the notation in (16) is similar to (15) expect for the $Institution_i$ and $Non\text{–}institution_i$ variables that identify whether the house was purchased by an institutional investor or non-institutional investor, respectively. As noted earlier, asset illiquidity is the difference between an asset's value in best use and its liquidation value. Thus, the [$Institution_i * Post_t$] interaction coefficient represents an estimate of the asset illiquidity risk inherent in housing's mildly segmented market structure.

I also estimate the pricing differential over time by interacting the $O2R_i$ and $Institution_i$ variables with annual indicator variables that identify the year the house sold. Ex ante, I expect houses that were converted after the crisis, as indicated by $O2R_i$, to appreciate at a rate similar to owner-occupied housing prior to the real estate crash, as they were trading in the same housing

[53] In subsequent specifications I filter out $R2O_i$and $Rent_i$ properties to isolate the impact of a conversion on owner-occupied house prices.

market. However, after the real estate crash, when the previously owner-occupied houses were converted to rental housing, I expect the returns to differ due to, among other things, owner-occupied housing's preferential tax treatment and the market's mildly segmented structure.

7.5 Empirical Results

Prior to the real estate crash, *O2R* conversions were trading in the owner-occupied market, so I expect them to sell for a price similar to owner-occupied houses. However, after the crash when the conversions trade in the rental market, I expect them to sell for a discount relative to owner-occupied houses that were not converted. In column 1 of Table 11, I find that owner-occupied houses that were subsequently converted to rentals [*O2R*] sold for approximately 3.2% more than owner-occupied houses that were not converted. However, after the crash when the houses were purchased as rental housing, they sold at an 11.2% discount relative to owner-occupied houses that were not converted. Although the post-crash discount was expected because the house was converted from the owner-occupied market to the rental market, the pre-crash premium is unexpected. The pre-crash premium suggests that either the *O2R* conversions were of superior quality, previous buyers overpaid for them, or there is a sample selection issue with the full dataset.

[Insert Table 11]

In column 1, the post-crisis and cash purchase interaction variable highlights the increased discount for cash purchases after the real estate crash. Prior to the real estate crash (2000 – 2006), houses sold for a 13.3% discount if the buyer paid cash. After the real estate crash (2007 – 2014), houses sold for a 26.0% discount when the buyer paid cash. The increased discount represents the value placed on liquidity during the financial crisis when a large proportion of potential homebuyers were credit constrained. The large discount also highlights the financial incentive offered to institutional investors, who did not require credit to make their purchases, when they entered the market in 2012.

In column 1, rental houses that were subsequently converted to owner-occupied houses [*R2O*] sold for approximately 2.7% less than owner-occupied houses prior to the crisis. After the crash when they were purchased as owner-occupied housing, the pricing differential remained the same. Single-family detached houses that were rentals for the entire study period [*Rent*] sold for a discount relative to owner-occupied housing prior to the real estate crash and, similar to *O2R* conversions, dropped significantly relative to owner-occupied houses after the crash. In column 2, I filter out *R2O* conversions, rental properties, and bulk sales as I am primarily interested in estimating the price effect of converting a house from owner-occupied to the rental.[54] The results in column 2 are similar to column 1 - *O2R* conversions sold for approximately 3.6% more than owner-occupied houses prior to the crash and a 12.2% discount after the crash.[55]

In column 3, indicator variables are included to identify houses purchased by institutional and non-institutional investors. Houses that were purchased by institutional investors were not significantly different than owner-occupied houses prior to the real estate crash. However, after the crash, when the houses were converted to rental properties, they sold for a 14.6% discount relative to owner-occupied houses that were not converted. In contrast, houses that were purchased by non-institutional investors sold for a 4.8% premium prior to the real estate crash and an 11.4% discount after the real estate crash.

Columns 4 and 5 use the same specifications as columns 2 and 3, but are run using the characteristic matched samples in Table 9. The sign and significance for all of the variables in column 4 remain the same, but the magnitude of the coefficients decrease. In column 5, the sign and significance of the institutional investor variable changed from positive and insignificant to negative and significant. The magnitude of the post-crisis institutional investor interaction variable decreased but still represents an 11.1% discount. Columns 6 and 7 run the same specifications using the nearest neighbor matched sample in Table 9. The results in column 6 are similar to columns 2 and 4 – although the sign on the *O2R* conversion variable flipped and the magnitude of the coefficients decreased further. Based on the nearest neighbor matched sample, *O2R* conversions sold for a 1.5% discount prior to the crisis and a 6.2% discount after the crisis. The results in column 7 are similar to columns 3 and 5 – except the post-crash cash discount is no longer significant. Houses purchased by institutional investors sold for a 2.5% discount prior to the crash and an 8.5% discount after the crash. The estimated discounts are in addition to the

[54] Bulk sales are included in column 1 of Table 11. The coefficient for the bulk sale variable is -0.5844 and it is significant at the 1% level. The empirical analysis going forward does not include bulk sales transactions.
[55] Table B1 in the appendix provides a full set of estimates for columns 1 and 2 in Table 11.

cash and distressed sale discounts (i.e. REO, foreclosure, and short sale) displayed in Table 11 and highlight the low liquidation values for single-family detached housing.

Table 12 examines the pricing differential on an annual basis. Ex ante, as the single-family housing market becomes more integrated, I expect the price of single-family homes to be bid up and returns to fall until the single-family detached housing market becomes fully integrated. However, segmentation may still exist due to, among other things, the preferential tax treatment associated with owner-occupied housing. To test this conjecture I interact the *O2R* conversion and *Rent* variables with annual indicator variables to examine the relationship over time. The first column of Table 12 examines the degree of segmentation between the owner-occupied and rental property markets. I am particularly interested in the relationship between the owner-occupied houses that were converted to rentals and the houses that were rentals for the entire study period. After the crash *O2R* conversions should sell for the same price as rental properties unless the buyers value the option to convert the property back to the owner-occupied market in the future. In which case, *O2R* conversions will sell for a discount compared to owner-occupied housing, but at a premium compared to rental housing.

[Insert Table 12]

In column 1, the *O2R* conversion (*Rent*) interactions are displayed to the left (right) of the pipe delimiter. Table 12 does not include *R20* conversions or bulk sales. The results show that rental properties sold for a discount relative to both owner-occupied and *O2R* conversions prior to crisis (2000-2006). From 2007 to 2011, rentals continued to sell for a discount (25.8%) relative to *O2R* conversions (10.4%). Additionally, from 2012 to 2014 the gap widened as rentals sold for a 43.3% discount relative to owner-occupied houses, compared to *O2R* conversions' 15.3% discount. Although institutional investors purchased owner-occupied houses and converted them to rentals they still sold for a premium relative to rental housing. The premium paid for the *O2R* conversions - relative to rental housing - is likely a function of the buyer's ability to convert the property back and sell it to an owner-occupier when the market recovers.

In column 2 of Table 12 I remove the rental transactions and focus solely on *O2R* conversions. The annual interactions in column 2 show that *O2R* conversions sold for a discount relative to other owner-occupied houses soon after the real estate crash. From 2007 to 2011 *O2R* conversions sold for an average discount of 10.7%. From 2012 to 2014 – which aligns with the entrance of institutional investors - the average discount for conversions relative to owner-occupied properties was 15.2%. Columns 3 and 4 run the same specification as column 2 using the characteristic and nearest neighbor matched samples. Similar to Table 11, the magnitude of the estimates decreased when using the matched samples. Using the nearest neighbor (characteristic) matched sample, *O2R* conversions sold for a 6.5% (8.6%) discount from 2007-2011 and a 6.7% (11.3%) discount from 2012-2014.

In Figure 10, I plot separate repeat sales price indexes for owner-occupied houses that were converted to rentals [*O2R*] and were not converted to rentals after the real estate crisis. I also include 95 percent confidence intervals for both indexes. The two indexes track each other closely from 2001 to 2006, but begin to diverge prior to the real estate crash. After the crash, *O2R* conversions clearly sell for a discount relative to owner-occupied housing that was not converted. In 2012, house prices started rising - likely due to increased competition among institutional investors and owner-occupants - but market segmentation still existed. These results suggest that the *O2R* conversions do not fully integrate into the rental housing market, but instead trade in a new conversion market that resides somewhere between the pre-existing owner-occupied and rental housing markets.

[Insert Figure 10]

Table 13 examines the pricing differential for houses that institutional and non-institutional investors purchased on an annual basis. The table does not include *R20* conversions, rentals, or bulk sales. In column 1, the annual institutional (non-institutional) investor interactions are displayed to the left (right) of the pipe delimiter. Similar to column 3 of Table 11, non-institutional investor properties sold for a premium prior to crisis (2000-2006). From 2007 to 2011, houses that institutional investors eventually purchased sold for a discount (17.4%) relative to non-institutional investor purchases (9.5%). However, when institutional investors entered the market in 2012 the discount dropped for the institutional investor houses (15.9%) and increased for non-institutional investor houses (15.3%).

[Insert Table 13]

Columns 2 to 4 compare houses purchased by institutional investors to owner-occupied houses that were not converted. Column 2 displays estimates for the full sample, column 3 displays estimates for the characteristic matched sample, and column 4 displays estimates for the nearest neighbor matched sample. Summary statistics for each sample are displayed in the bottom section of Table 9. Based on the nearest neighbor matched sample, houses purchased by institutional investors sold for, on average, a 5% discount from 2012 to 2014. The discount was the largest in 2012 (9.9%) and dropped considerably in 2013 (1.9%) and 2014 (3.1%) as institutional investors competed against each other. The 5% discount was in addition to cash purchase and distressed sale discount - highlighting owner-occupied housing's low liquidation value.

7.4 Alternative Specifications

Although I attribute the results in the previous section to owner-occupied housing's asset illiquidity, I examine several alternative specifications to test the robustness of my findings. I examine whether the *O2R* conversions were (i) in markets with less historical market liquidity, (ii) in markets with less current market liquidity, (iii) in markets with higher percentages of distressed sales, (iv) in markets with less investment in residential structures, (v) of differing quality, or (vi) a combination of all the above.

If the previously owner-occupied houses that were purchased and converted to rentals are located in markets that historically have less market liquidity (i.e. lower demand) - I would expect them to sell for a larger discount during times of distress. To examine the market liquidity for the houses I calculate the average turnover of existing homes prior to the real estate crisis. I calculate housing turnover at the census tract level as the average annual number of sales transactions divided by the tract's housing stock from 2000 to 2006. Column 1 of Table 14 uses the nearest neighbor matched dataset and is similar to column 6 of Table 11 except for the inclusion of the pre-crisis turnover measure and the use of zip code fixed effects. The average pre-crisis turnover variable is not significant in column 1 and has little impact on the *O2R* conversion coefficient. Column 2 includes a rolling 6 month turnover variable as a proxy for the current market liquidity when the house was purchased and converted. Similar to the turnover variable in column 1, it is not significant and does not impact the *O2R* conversion coefficient.

[Insert Table 14]

Several recent studies document a negative relationship between house sales prices and the number of nearby foreclosures (e.g. Immergluck and Smith 2006; Lin et al. 2009). Harding, Rosenblatt and Yao (2009) find a foreclosure contagion discount that reached as high as 1% for each nearby foreclosed property. If the converted properties in this study were located in areas with higher percentages of distressed sales I would expect them to sell for considerably less, which could potentially explain the large discount I find in the previous section. To examine the impact of nearby foreclosures on house prices I calculate the percent of distressed sales as the number of distressed sales transactions divided by the total number of sales transactions at the census tract level. In column 3 of Table 14 I find that a 5% increase in the percentage of distressed sales results in a 2.2% decrease in house prices. However, an increase in distressed sales does not explain why conversions sold for a discount after the real estate crash as the *O2R* conversion discount increased to 6.2% in the post-crisis period.

Another possible explanation for the *O2R* conversion discount is that the conversions are located in previously under-invested housing submarkets. Information on private investment in residential structures at the submarket level is not available, so I use two proxies available in the current dataset. The proxies examine private investment in new and existing structures. Column 4 includes a variable that identifies the fraction of the housing stock within the census tract that was built in 2000 or later. Investment in new housing structures likely creates a positive externality for the surrounding neighborhood and incentivizes current owners to maintain and invest in their existing structures. The variable is positive and significant – although it does not have a material impact on the *O2R* conversion discount. Column 5 includes a variable that identifies the percent of the census tract's existing housing stock in 2000 that were remodeled from 2000-2014. The variable is not significant and although the *O2R* conversion coefficient is smaller – its decrease can be attributed to use of the 13 county subsample.[56]

Next, I examine whether the *O2R* conversion discount for previously owner-occupied houses can be attributed to differences in housing conditions. I use a 'condition' variable in the CoreLogic dataset as a proxy for the house's condition. The condition variable identifies whether

[56] As noted in Table 10 – five counties do not report the effective year built in the CoreLogic tax assessor data. In unreported results the coefficient for the *O2R* conversion variable is -.0373 using the 13 county subsample in the absence of the 'Percent Houses Remodeled' variable. Thus, the inclusion of the variable only increases the coefficient by .0001.

the house was in excellent, very good, good, average, fair, poor, or unsound condition - according to the local county tax assessor's office – in 2014. The variable is not available for every parcel and is not populated for every county, so I remove records in which it is missing. The results in column 6 of Table 14 show that houses in excellent condition sell for a premium and that, ceteris paribus, house prices decrease as the condition of the house deteriorates. Additionally, after controlling for house quality the *O2R* conversion discount remains at 5.7% in the post-crisis subperiod.[57] In column 7 I include the additional controls in a single specification. Note that the sample size drops due to the missing remodeled and condition fields. The magnitude and significance of several variables change – although their signs remained the same. In unreported results the *O2R* conversion discount for the 126,202 subsample was 5.7% in the post-crisis subperiod. After including all the controls the discount dropped to 4.7% in column 7.

In the final three columns of Table 14 I run a series of alternative specifications for houses located in Fulton County. I restrict the nearest neighbor subsample to Fulton County to further examine the property condition variable in column 6. As noted in the previous paragraph the property condition variable in the CoreLogic dataset is a static measure as of 2014. Using property tax assessor records obtained directly from Fulton County tax assessor's office I examine whether the *O2R* conversion discount can be attributed to differences in the condition of the houses that were converted using a property condition variable that is updated annually. Column 8 provides a baseline model of the Fulton County subsample and column 9 incorporates the annual condition variables. The inclusion of the annual property condition variables does explain a small portion of the *O2R* conversion discount as it drops from 4.1% in column 8 to 3.6% in column 9. Column 10 incorporates all the controls for Fulton County and the *O2R* conversion discount increases to 3.9%.

The results of the alternative specifications – several of which include proxies for property condition – confirm the earlier results. Although I use a nearest neighbor matched sample, include distressed sale indicator variables, and include proxies for property condition - I recognize that the true condition of the property may not be captured in my model. If property

[57] The condition variable may vary across counties as it is populated by the county's local tax assessors. To address this potential issue I run a regression that interacts the condition variable with indicator variables for each county. The results are similar to those reported in Table 14. The condition variable in column 6 is also a static measure of the house's condition in 2014. Using a subset of data from Fulton County and annual tax assessor data from 2002 to 2014 I further examine the impact of the condition variable in columns 8-10.

condition is not properly controlled for and is correlated with the *O2R* conversion or *Institution* variable then my estimates may be biased. For example, it may be the case that the properties purchased by institutional investors require a certain amount of capital expenditure and that the price they paid was a no-arbitrage price that brought the house's value to the same level as a comparable house that did not require the same capital expenditure.

7.5 Impact on Local Markets

In the post-crash housing market model (Section 5), I argue that as institutional investors purchase owner-occupied houses and convert them to rental housing they reduce the available owner-occupied housing stock and push the market back towards equilibrium. In this section I examine whether lagged institutional investor activity had an impact on local house prices from 2012 to 2014. As noted by Mills et al. (2015) it is difficult to test the causal effect of institutional investor activity on house prices without exogenous variation in the activity of institutional investors. In addition, I also recognize that it is difficult to estimate the impact of institutional investor activity while they are still active in the market. Thus, the estimates presented in this section are meant to provide insight into the likely sign and magnitude of institutional investors' impact on local housing markets. If the data were available - it would be more appropriate to estimate the impact of institutional investor activity from 2012 to 2014 on local house prices from 2015 to 2016.

I examine institutional investors' impact on local housing markets using two specifications. The first (second) specification examines whether house prices increase in zip codes with increased institutional investment (conversion) activity. Both specifications are conducted at the zip code level by creating a repeat sales home price index for all zip codes that have a housing stock of at least 10,000 single-family detached houses. As a robustness check I also run the specifications using house price data from Zillow. The results of the first specification are presented in columns 1 and 2 of Table 15 - where the change in a zip code level home price index from 2012 through 2014 is regressed on the lagged market share of the following investor types: institutional, corporate, and individual. All zip codes with a single-family detached housing stock of 10,000 or more are included in the analysis (61 zip codes in total). I find that zip codes with increased institutional activity in previous years experienced higher house price appreciation the following year. Column 1 suggests that a 10% increase in institutional investor transaction share results in a .9% increase in house prices the following year.

[Insert Table 15]

In column 2, I include additional controls for zip code characteristics that may influence investor activity and have an independent effect on house prices within the zip code. I include the lagged log of house price and rent, the lagged percent of distressed sales in the zip code, as well as the following variables obtained from the 2008-2012 American Community Survey: percent of population without a high school degree, with an associate's degree or higher, with income in the first quintile, with income in the fifth quintile, households with kids, the poverty rate, and unemployment rate. I also include a pre-crisis rental and turnover measure. The pre-crisis rental measure identifies and controls for the percent of houses that were already rentals within the zip code and the turnover measure controls for the liquidity of the market prior to the crisis. The results in column 2 suggest that an increase in institutional investor activity within a zip code during the previous year increases house prices the following year. Institutional investors are the only investor type that significantly impact local house prices in the first specification.[58]

In columns 3 and 4 of Table 15, I present the results of the first specification using zip code level house pricing data from the Zillow website. Zillow uses a proprietary formula to estimate the value for every residential property in their coverage area and provides monthly averages of their house price estimates on their website. After downloading the monthly data for the Atlanta metro area at the zip code level I convert it to an annual average and regress the change in log of house prices from 2012 to 2014. Zillow's extensive coverage allows the inclusion of additional zip codes in the analysis (150 compared to 61 in columns 1 and 2). Similar to columns 1 and 2, I find that zip codes with increased institutional activity in previous years experienced higher house price appreciation the following year. Unlike the first specification, I find that individual and corporate investors do have a significant impact on local house prices. Although the sign for corporate investor changes when I include the control variables in column 4.

[58] Coefficient estimates for the control variables are available in Table B2 in the appendix.

Using the *O2R* conversions identified in Section 7.1, I aggregate the data at the zip code level and calculate their market share. I then regress the change in the log of house prices on lagged conversion market share as I expect an increase in *O2R* conversion activity in previous periods will help stabilize the local market and increase prices in subsequent periods. I present the results in columns 5 and 6 of Table 15.[59] The results suggest that a 10% increase in conversion activity results in a price increase in the range of .8% to 1.2% the following year.

8. Conclusion

House price declines together with large scale foreclosures, an increase in demand for rental housing resulting from the foreclosures, and the tightening of the mortgage market created a large supply of available owner-occupied housing. The large supply of available housing made economies of scale possible and represented a potential arbitrage opportunity. I show that owner-occupied housing offered higher returns than rental housing after the real estate crash. The higher returns coupled with potential economies of scale attracted institutional investors into the owner-occupied housing market. When institutional investors entered the owner-occupied housing market they not only increased demand, but also decreased the market's supply as they converted the houses they purchased to rentals.

The primary contribution of this study is to empirically isolate the mechanism, magnitude, and consequence of a single-family detached house's shift across the mildly segmented housing market. Although institutional investors entered the owner-occupied housing market which, in effect, should have decreased the two housing markets' degree of segmentation, I show that segmentation still exists. I find that although house prices did increase when institutional investors' entered the market, the premium associated with owner-occupied housing persisted. Using a propensity score nearest neighbor matched sample I estimate that from 2012 to 2012 – when institutional investors were active in the market- owner-occupied housing sold for 6.7% more than similar owner-occupied housing that was converted to rental housing after the crisis.

[59] I also ran analysis using a zip code level home price index similar to the first section of Table 15, but did not get significant results due to the zip code HPI's limited coverage area.

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Table 1: Overview of the United States Housing Market

	2006	2007	2008	2009	2010	2011	2012	2013
United States Housing								
Total	126,311,823	127,895,430	129,060,383	129,949,960	131,791,065	132,316,248	132,452,249	132,808,137
Owner-occupied	86,540,505	87,643,446	87,861,487	87,490,240	88,406,949	88,200,051	87,432,289	87,494,001
Rental	39,771,318	40,251,984	41,198,896	42,459,720	43,384,116	44,116,197	45,019,960	45,314,136
% Rental	31.49%	31.47%	31.92%	32.67%	32.92%	33.34%	33.99%	34.12%
Occupied Housing								
Total	111,617,402	112,377,977	113,101,329	113,616,229	114,567,419	114,991,725	115,969,540	116,291,033
Owner-occupied	75,086,485	75,515,104	75,373,053	74,843,004	74,873,372	74,264,435	74,119,256	73,843,861
Rental	36,530,917	36,862,873	37,728,276	38,773,225	39,694,047	40,727,290	41,850,284	42,447,172
% Rental	32.7%	32.8%	33.4%	34.1%	34.6%	35.4%	36.1%	36.5%
Occupied Rental Market Share								
% Single Family	31.0%	31.6%	32.4%	33.3%	33.5%	34.0%	34.8%	35.1%
Detached	*25.3%*	*25.9%*	*26.6%*	*27.4%*	*27.4%*	*27.9%*	*28.5%*	*28.8%*
Attached	*5.7%*	*5.7%*	*5.8%*	*5.9%*	*6.1%*	*6.1%*	*6.3%*	*6.3%*
% 2-4 Family	20.0%	19.7%	19.6%	19.0%	18.7%	18.5%	18.3%	18.1%
% 5-9 Family	12.6%	12.5%	12.3%	12.0%	11.8%	11.5%	11.5%	11.6%
% 10+ Family	31.3%	31.2%	30.8%	30.9%	31.2%	31.2%	30.8%	30.6%
% Other	5.1%	5.0%	4.9%	4.8%	4.8%	4.8%	4.6%	4.6%

Source: U.S. Census Bureau, American Community Survey (1-Year Estimates)

Table 2: Overview of the Atlanta Housing Market

	2007	2008	2009	2010	2011	2012	2013
Atlanta Metropolitan Area							
Occupied Housing							
Total	1,730,713	1,771,302	1,785,968	1,792,474	1,795,706	1,808,739	1,831,653
Owner-occupied	1,193,896	1,222,054	1,218,509	1,202,078	1,186,736	1,171,460	1,163,736
Rental	536,817	549,248	567,459	590,396	608,970	637,279	667,917
% Rental	31.0%	31.0%	31.8%	32.9%	33.9%	35.2%	36.5%
Occupied Rental Market Share							
% Single-Family	29.0%	29.4%	31.1%	32.0%	34.2%	35.4%	36.5%
Detached	*25.4%*	*25.5%*	*26.9%*	*27.6%*	*29.5%*	*30.7%*	*31.7%*
Attached	*3.7%*	*3.9%*	*4.2%*	*4.4%*	*4.7%*	*4.7%*	*4.7%*
% 2-4 Family	11.6%	10.8%	10.9%	10.4%	10.3%	10.1%	9.6%
% 5-9 Family	18.6%	17.4%	15.5%	14.6%	14.3%	14.4%	14.6%
% 10+ Family	37.6%	39.2%	39.4%	40.2%	38.5%	37.3%	36.5%
% Other	3.1%	3.2%	3.1%	2.9%	2.7%	2.7%	2.8%

Source: U.S. Census Bureau, American Community Survey (3-year Estimates)

Table 3: Atlanta's Single-Family Detached Housing Stock and Transaction Summary

	Housing Stock (1)	New Stock (2)	Remodeled Stock (3)	*Transaction Activity* Owner Occupied (4)	Individual Investor (5)	Corporate Investor (6)	Financial Institution (7)	Gov't & Non-profit (8)	Institutional Investor (9)	Market Share (10)
2000	1,040,483	44,237	5,332	64,296	367	2,126	2,001	8	-	-
2001	1,084,090	43,607	4,352	68,250	387	2,509	3,079	9	-	-
2002	1,125,080	40,990	4,065	68,801	1,407	3,534	5,145	15	-	-
2003	1,170,540	45,460	3,870	73,607	1,689	4,191	7,399	29	-	-
2004	1,217,918	47,378	2,451	79,298	4,311	4,301	8,495	19	-	-
2005	1,265,669	47,751	3,360	89,578	4,690	4,876	9,932	22	-	-
2006	1,313,914	48,245	4,042	89,369	4,865	4,992	14,098	32	-	-
2007	1,344,649	30,735	3,258	69,616	2,476	4,850	19,543	11	-	-
2008	1,357,631	12,982	2,429	50,925	1,869	5,789	27,006	24	-	-
2009	1,362,181	4,550	962	44,490	1,547	6,143	24,912	57	-	-
2010	1,367,764	5,583	783	36,596	1,613	6,469	27,709	78	-	-
2011	1,372,774	5,010	467	34,988	1,952	7,076	24,590	57	16	0.0%
2012	1,380,280	7,506	936	41,539	2,152	11,266	13,848	24	3,903	5.4%
2013	1,390,140	9,860	2,597	50,402	2,072	10,338	4,925	175	10,955	13.9%
2014	1,399,067	8,927	2,941	53,349	2,165	9,117	4,148	159	6,409	8.5%

Columns 1 - 3 provide an overview of metro Atlanta's single-family detached housing stock. The section was created using the CoreLogic tax assessor parcel files. Column 3 identifies houses whose 'effective year built' changed in the tax assessor data. The number of 'remodeled' houses is likely understated in column 3 as the field is not populated for 5 counties in the study. Columns 4 - 9 summarize every single-family detached housing transaction in metro Atlanta by buyer type and year. Column 10 displays institutional investors' share of the transaction activity. Their market share represents the number of sales transactions they were involved in divided by the total number of sales transactions that year.

Table 4: Institutional Investment in Atlanta's Single-Family Detached Housing Market

	Total		Bulk		Foreclosure		REO		Short sale		Owner-Occupier		Prev Conversion		Prev Rental	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Invitation Homes	7,258	34.1%	973	13.4%	3,151	43.4%	212	2.9%	738	10.2%	1,346	18.5%	804	11.1%	34	0.5%
Colony American Homes	3,141	14.8%	7	0.2%	2,514	80.0%	21	0.7%	85	2.7%	219	7.0%	289	9.2%	6	0.2%
Starwood Waypoint Residential Trust	2,678	12.6%	10	0.4%	1,235	46.1%	436	16.3%	140	5.2%	526	19.6%	317	11.8%	14	0.5%
American Homes 4 Rent	1,973	9.3%	54	2.7%	1,277	64.7%	216	10.9%	69	3.5%	199	10.1%	142	7.2%	16	0.8%
Progress Residential	1,325	6.2%	-	-	202	15.2%	151	11.4%	218	16.5%	599	45.2%	147	11.1%	8	0.6%
Silver Bay Realty Trust	1,082	5.1%	31	2.9%	387	35.8%	370	34.2%	92	8.5%	101	9.3%	92	8.5%	9	0.8%
American Residential Properties	924	4.3%	24	2.6%	419	45.3%	35	3.8%	74	8.0%	224	24.2%	143	15.5%	5	0.5%
Havenbrook Homes	826	3.9%	8	1.0%	-	-	70	8.5%	101	12.2%	295	35.7%	338	40.9%	14	1.7%
Sylvan Road Capital	762	3.6%	66	8.7%	-	-	103	13.5%	46	6.0%	275	36.1%	264	34.6%	8	1.0%
Main Street Revival	684	3.2%	-	-	129	18.9%	63	9.2%	97	14.2%	218	31.9%	167	24.4%	10	1.5%
Residential Capital Management	630	3.0%	-	-	627	99.5%	-	-	-	0.0%	-	0.0%	3	0.5%	-	0.0%
Total Institutional Investment	21,283		1,173	5.5%	9,941	46.7%	1,677	7.9%	1,660	7.8%	4,002	18.8%	2,706	12.7%	124	0.6%

Only sales transactions in which the buyer is an institutional investor are included in Table 4. Nominal transactions in which the institutional investor transfers a property internally from one asset company to another have been removed. Columns 1 and 2 display the total number of transactions for each institutional investor and their respective market share among all institutional investors. Columns 3 to 16 identify how the property was obtained. Properties purchased through bulk sales and distressed sales transactions are displayed in columns 3 to 10. If the property was purchased directly from an owner-occupier it is included in columns 11 and 12. Properties purchased from an investor who already converted the property to a rental are displayed in columns 13 and 14 and properties purchased from investors were renting the property prior to 2007 are included in columns 15 and 16.

Table 5: Institutional Investment by Home Size Segment and Expected Mean Reversion

Home Size Percentile	Size Range (Sqft)	Median Size (Sqft)	Mean Size (Sqft)	Institutional Investor Transactions	2001 Pre-Boom Price (P^E)	2006 Pre-Crash Price (P^B)	2012 Pre-Recovery Price (P^C)	2014 Recovery Price (P^R)	Pre-Crash Appreciation (P^B - P^E)	Post-Crash Depreciation (P^C - P^B)	2012 Mean Reversion Expectation (P^E - P^C)	2014 Mean Reversion Expectation (P^E - P^R)
0 to 5	330 - 1,066	976	948	539	100	153	58	88	53	-96	42	12
5 to 10	1,067 - 1,207	1,144	1,142	1,075	100	139	60	92	39	-78	40	8
10 to 15	1,208 - 1,315	1,263	1,262	1,295	100	128	62	90	28	-66	38	10
15 to 20	1,316 - 1,412	1,366	1,365	1,333	100	127	62	90	27	-65	38	10
20 to 25	1,413 - 1,504	1,458	1,459	1,342	100	126	67	95	26	-60	33	5
25 to 30	1,505 - 1,597	1,551	1,551	1,360	100	126	70	97	26	-56	30	3
30 to 35	1,598 - 1,696	1,646	1,647	1,387	100	123	70	96	23	-53	30	4
35 to 40	1,697 - 1,800	1,749	1,749	1,398	100	122	71	97	22	-51	29	3
40 to 45	1,801 - 1,906	1,852	1,853	1,426	100	124	72	101	24	-52	28	-1
45 to 50	1,907 - 2,024	1,966	1,965	1,400	100	122	75	100	22	-48	25	0
50 to 55	2,025 - 2,150	2,086	2,087	1,327	100	122	76	101	22	-46	24	-1
55 to 60	2,151 - 2,280	2,214	2,214	1,305	100	123	79	103	23	-43	21	-3
60 to 65	2,281 - 2,422	2,349	2,350	1,234	100	124	81	109	24	-43	19	-9
65 to 70	2,423 - 2,581	2,500	2,501	1,198	100	127	88	113	27	-40	12	-13
70 to 75	2,582 - 2,758	2,668	2,669	1,089	100	126	85	111	26	-40	15	-11
75 to 80	2,759 - 2,957	2,853	2,854	903	100	129	90	116	29	-39	10	-16
80 to 85	2,958 - 3,213	3,075	3,079	683	100	131	95	117	31	-36	5	-17
85 to 90	3,214 - 3,581	3,378	3,384	517	100	130	94	117	30	-36	6	-17
90 to 95	3,582 - 4,251	3,859	3,876	345	100	132	98	120	32	-34	2	-20
95 to 100	4,252 - 35,721	4,975	5,372	127	100	131	98	120	31	-33	2	-20
Buyer Type	**Size Range (Sqft)**	**Median (Sqft)**	**Mean (Sqft)**	**Transaction Count**	**Pre-Boom Price**	**Pre-Crash Price**	**Pre-Recovery Price**	**Recovery Price**	**Pre-Crash Appreciation**	**Post-Crash Depreciation**	**2012 Expectation**	**2014 Expectation**
All	330 - 35,721	1,958	2,210	1,255,075	100	128	77	104	28	-51	23	-4
Owner-Occupier	330 - 35,721	1,958	2,210	915,104	100	127	84	110	27	-43	16	-10
Institutional	575 - 7,003	1,870	1,983	21,283	100	115	54	76	15	-60	46	24
Corporate	360 - 23,179	1,610	1,876	87,577	100	126	52	75	26	-74	48	25
Individual	336 - 15,516	1,823	2,083	33,562	100	125	64	90	25	-61	36	10

The Pre-Boom (2001), Pre-Crash (2006), Pre-Recovery (2012), and Recovery Price (2014) were calculated using an annual repeat sales index in which we report exponentiated values that are scaled to 100 in relation to the pre-boom price in 2001. The top section of Table 5 is stratified by home size segments in ascending order. The bottom section of Table 5 is stratified by buyer type.

Table 6: Summary statistics for single-family detached houses from 2003 to 2014

	2003 - 2014			2003 - 2006			2007 - 2011			2012- 2014		
	Matched	Sales	Rentals	Matched	Sales	Rentals	Matched	Sales	Rentals	Matched	Sales	Rentals
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Transactions	10,144	842,122	101,502	896	340,272	5,976	3,524	321,893	46,914	5,724	179,957	48,612
Median Monthly Rent	1,150		1,150	1,200		1,150	1,123		1,200	1,150		1,105
Median Sales Price	109,900	154,670		149,900	165,700		100,000	144,500		100,000	139,000	
Median R/P Ratio	0.13			0.10			0.13			0.14		
Average Age	20.4	23.8	22.1	15.7	21.7	23.8	19.9	23.3	21.0	21.4	28.7	23.6
Average Living Area (Sqft)	1,997	2,190	2,075	1,933	2,136	2,190	2,058	2,209	2,154	1,969	2,257	2,019
Average Lot Size (Sqft)	17,411	25,207	20,152	16,806	26,327	16,740	17,686	23,589	21,226	17,336	25,982	19,535
Bedroom %												
1 Bedroom	0.1%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.1%	0.2%	0.2%
2 Bedrooms	3.2%	6.2%	5.1%	3.6%	3.2%	5.9%	3.7%	5.9%	5.5%	2.9%	5.3%	4.7%
3 Bedrooms	61.2%	56.4%	57.3%	61.2%	61.2%	60.2%	59.2%	55.7%	54.3%	62.5%	55.1%	59.9%
4 Bedrooms	29.1%	29.3%	29.6%	29.4%	29.1%	28.3%	29.8%	29.2%	31.0%	28.6%	30.6%	28.3%
5 Bedrooms	5.7%	7.1%	6.7%	5.4%	5.7%	4.6%	6.3%	8.2%	7.7%	5.4%	7.9%	6.1%
6 Bedrooms	0.7%	0.8%	1.1%	0.4%	0.7%	0.9%	1.0%	0.9%	1.3%	0.6%	0.9%	0.9%
Bathroom %												
1 Bathroom	8.1%	9.1%	10.8%	9.3%	10.3%	12.3%	8.9%	8.9%	11.3%	7.4%	7.0%	10.2%
2 Bathrooms	74.2%	37.1%	69.4%	75.8%	38.4%	73.9%	70.4%	36.2%	66.4%	76.4%	36.1%	71.8%
3 Bathrooms	14.3%	40.0%	14.8%	12.4%	39.0%	10.8%	15.6%	40.3%	16.1%	13.7%	41.4%	14.1%
4+ Bathrooms	3.4%	13.8%	4.9%	2.6%	12.2%	2.9%	5.1%	14.6%	6.3%	2.4%	15.4%	3.9%

The rental (sales) data displayed in this table is from the Georgia Multiple Listing Service (CoreLogic) dataset. The summary statistics include all single-family detached sale and rental transactions from 2003 to 2014. The matched dataset includes houses that have a sales and rental transaction within six months of each other. The subperiods displayed represent the pre-crisis (2003 - 2006), post-crisis (2007 - 2011), and recovery (2012 - 2014) periods in the Atlanta housing market.

Table 7: Gross Rent-Price Ratio for Apartment Buildings

		Median		
Time Period	Transactions	Gross Rent	Sales Price	R/P Ratio
Entire (2003 - 2014)	277	2,206,380	16,000,000	0.14
2003 - 2006	186	2,048,827	13,225,000	0.15
2007 - 2011	73	2,877,696	25,800,000	0.11
2012 - 2014	18	1,835,600	10,750,000	0.17

The data displayed represents the Atlanta apartment building market. The data was obtained from CoStar and includes all sales transaction between 2003 - 2014. The subperiods displayed correspond with the pre-crisis (2003 - 2006), post-crisis (2007 - 2011), and recovery (2012 - 2014) periods in the Atlanta housing market.

Table 8: Rough Estimate of Institutional Investors' Expected Returns

Purchase Year	Rent-Price Ratio: Purchase Price	Rent-Price Ratio: Purchase Price + Renovation	Expected Mean Reversion Estimate for Various Holding Periods (Years): Purchase Price 3	Purchase Price 5	Purchase Price 10	Purchase Price + Renovation 3	Purchase Price + Renovation 5	Purchase Price + Renovation 10	Apartment Rent-Price Ratio
2012	14.6%	12.1%	15.2%	9.1%	4.6%	11.6%	7.0%	3.5%	15.2%
2013	13.5%	11.3%	10.0%	6.0%	3.0%	5.3%	3.2%	1.6%	13.5%
2014	12.6%	10.5%	8.0%	4.8%	2.4%	3.0%	1.8%	0.9%	18.2%

The SFD rent-price ratios are estimated using the matched dataset. The expected mean reversion columns are a rough estimate of institutional investors' expected capital return for various holding periods using the same dataset utilized in Table 5. We estimate rent-price ratio and expected mean reversion using both the purchase price and the purchase price plus renovation costs of 20%. The mean reversion estimates are calculated by simply dividing the mean reversion expection by the holding period. The apartment rent-price ratio is calculated using the CoStar dataset and listed for ease of comparison.

Table 9: Summary statistics for matched samples

	Full Sample			Characteristic Match			Nearest Neighbor Match		
	Treatment	Control	t-Stat	Treatment	Control	t-Stat	Treatment	Control	t-Stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment: O2R Conversion									
Sale Price	142,723	198,184	143.1	141,986	173,826	91.8	141,986	151,440	21.8
Age	24.56	22.25	-39.7	23.26	18.73	-77.0	23.26	23.12	-1.8
Living Area (sqft '000s)	1.95	2.21	95.9	1.94	2.11	63.8	1.94	1.93	-3.3
Lot Size (sqft '000s)	16.96	19.88	50.1	16.54	18.46	32.7	16.54	15.46	-18.3
Bedrooms	3.30	3.39	42.7	3.28	3.33	27.8	3.28	3.27	-2.4
Bathrooms	2.48	2.64	57.7	2.47	2.55	31.1	2.47	2.47	-2.9
Observations	146,218	877,584		123,249	413,398		123,249	123,249	
Treatment: Insitutional Investor									
Sale Price	119,588	202,202	113.0	122,173	151,799	72.9	122,173	133,919	23.2
Age	19.81	21.33	14.7	18.86	15.64	-37.7	18.86	18.95	0.8
Living Area (sqft '000s)	1.92	2.26	65.8	1.92	2.03	27.1	1.92	1.93	0.3
Lot Size (sqft '000s)	15.50	19.98	41.4	15.48	18.14	25.0	15.48	15.02	-5.1
Bedrooms	3.34	3.42	22.3	3.32	3.31	-1.6	3.32	3.31	-1.0
Bathrooms	2.51	2.69	38.1	2.51	2.50	-2.2	2.51	2.50	-1.5
Observations	38,599	860,372		32,961	202,362		32,961	32,961	

This table reports descriptive statistics for a select group of variables for the full data sample and two matched samples. The treatment groups in columns 1, 4, and 7 of the top section represent sales transactions for owner-occupied houses that were converted to rentals after 2006. Bulk sales are only included in the full sample *O2R Conversion* grouping (they are filtered out in the majority of the empirical analysis). The treatment group in column 2 of the top section includes all transactions that are not included in the treatment group. The control group in column 2 of the bottom section includes all houses that were purchased by institutional investors - bulk sales are not included in this section or in columns 4-9. The control groups in column 5 include sales transactions that match at least one of the treatment records on all of the following criteria: transaction year, census block-group, bedrooms, and bathrooms. Treatment records were dropped if they had no matches in the control group. The control group in column 8 was matched using a one-to-one nearest neighbor matching technique with replacement.

Table 10: Correlates for Institutional Investment and Conversion Activity (2012-2014)

	Institution	Non-Institution	Institution	02R Conversion
	(1)	(2)	(3)	(4)
Age	-0.0009***	0.0008***	-0.0009***	-0.0001
	(-7.26)	(4.18)	(-6.03)	(-0.56)
Age Squared	0.0000***	-0.0000***	0.0000***	-0.0000***
	(3.14)	(-4.79)	(3.24)	(-2.67)
Living Area [Sqft '000s]	-0.0446***	-0.1084***	-0.0433***	-0.1495***
	(-16.23)	(-23.57)	(-13.57)	(-30.66)
Living Area Squared [Sqft '000s]	0.0000***	0.0000***	0.0000***	0.0000***
	(10.99)	(19.47)	(8.49)	(23.36)
Lot Size [Sqft '000s]	-0.0008***	-0.0014***	-0.0009***	-0.0022***
	(-12.90)	(-13.63)	(-11.92)	(-19.68)
Lot Size Squared [Sqft '000s]	0.0000***	0.0000***	0.0000***	0.0000***
	(5.75)	(10.37)	(5.95)	(12.48)
1 Bed [0,1]	-0.0157	0.0250	-0.0140	0.0085
	(-1.43)	(0.90)	(-1.00)	(0.30)
3 Beds [0,1]	0.0362***	0.0292***	0.0400***	0.0648***
	(14.25)	(5.61)	(12.74)	(11.77)
4 Beds [0,1]	0.0479***	0.0318***	0.0527***	0.0791***
	(15.32)	(5.50)	(14.02)	(12.87)
5 or 6 Beds [0,1]	0.0463***	0.0326***	0.0523***	0.0779***
	(12.42)	(4.98)	(11.75)	(11.06)
1 Bath [0,1]	-0.0299***	-0.0239***	-0.0322***	-0.0527***
	(-10.75)	(-4.57)	(-9.12)	(-9.58)
3 Baths [0,1]	0.0092***	0.0102***	0.0117***	0.0183***
	(4.40)	(3.59)	(4.80)	(5.93)
4 to 6 Baths [0,1]	-0.0226***	0.0079*	-0.0232***	-0.0152***
	(-7.85)	(1.91)	(-7.02)	(-3.34)
Fireplace [0,1]	0.0056***	0.0069**	0.0098***	0.0121***
	(3.04)	(2.47)	(4.60)	(4.08)
Garage [0,1]	0.0215***	-0.0353***	0.0215***	-0.0148***
	(13.59)	(-15.49)	(11.21)	(-6.04)
Carport [0,1]	-0.0040*	-0.0151***	-0.0040	-0.0182***
	(-1.76)	(-3.69)	(-1.33)	(-4.21)
Pool [0,1]	-0.0157***	-0.0209***	-0.0172***	-0.0362***
	(-6.26)	(-4.79)	(-6.21)	(-7.68)
Bulk Sale	0.4336***	-0.0620***	0.4415***	0.3511***
	(35.08)	(-5.37)	(33.19)	(33.85)
REO [0,1]	-0.0205***	0.0205***	-0.0170***	0.0012
	(-11.43)	(6.65)	(-8.33)	(0.36)
Foreclosure [0,1]	0.1746***	0.0573***	0.1825***	0.2270***
	(67.32)	(19.63)	(61.13)	(69.97)
Shortsale [0,1]	0.0087***	0.0201***	0.0113***	0.0291***
	(3.57)	(5.70)	(4.02)	(7.53)
Percent Distressed Prev 6 Months	0.0371***	0.0819***	0.0286***	0.1172***
	(6.59)	(10.24)	(4.21)	(13.42)

*Table 10 is continued on next page

Table 10: Correlates for Institutional Investment and Conversion Activity (cont.)

	Institution	Non-Institution	Institution	02R Conversion
	(1)	(2)	(3)	(4)
Unemployment Rate	0.1060***	0.3675***	0.0782***	0.4734***
	(5.31)	(12.47)	(3.09)	(15.05)
Percent Household with Kids	0.0705***	0.0493***	0.0416***	0.1134***
	(7.16)	(3.20)	(3.54)	(6.86)
Median Income [000s]	-0.0004**	-0.0018***	-0.0009***	-0.0021***
	(-2.43)	(-7.89)	(-5.12)	(-8.49)
Median Income Squared [000s]	0.0000**	0.0000***	0.0000***	0.0000***
	(2.23)	(9.11)	(5.67)	(9.54)
Median Age	0.0023	-0.0056**	0.0000	-0.0035
	(1.46)	(-2.23)	(0.00)	(-1.32)
Median Age Squared	-0.0000**	0.0001**	0.0000	0.0000
	(-2.10)	(2.12)	(-0.49)	(0.87)
Percent Less Than High School Diploma	-0.1891***	-0.3709***	-0.1847***	-0.5575***
	(-11.70)	(-15.75)	(-9.30)	(-21.93)
Percent College Degree	-0.0903***	0.0361**	-0.0855***	-0.0549***
	(-9.23)	(2.56)	(-7.49)	(-3.57)
Gross Rent Price Ratio	-0.2773***	-0.0412**	-0.3039***	-0.3061***
	(-21.83)	(-2.53)	(-22.18)	(-15.97)
Mean Reversion Expectation	0.0370***	0.1337***	0.0327***	0.1675***
	(8.16)	(18.08)	(6.63)	(21.30)
Percent Rental Housing Pre-crisis	-0.0989***	0.3558***	-0.1177***	0.2611***
	(-4.89)	(11.07)	(-4.90)	(7.55)
Average Turnover (2000-2006)	0.5660***	-0.6800***	0.6254***	-0.1730*
	(9.50)	(-7.93)	(8.88)	(-1.85)
Average Turnover (2010-2011)	-1.7389***	0.8742***	-1.8956***	-0.7888***
	(-16.99)	(5.44)	(-15.14)	(-4.55)
Average TOM (2010-2011)	0.0013***	-0.0003	0.0017***	0.0009*
	(4.48)	(-0.71)	(5.02)	(1.66)
Percent Houses Built (2000-2014)	0.0607***	-0.0109	0.0857***	0.0477***
	(11.40)	(-1.45)	(13.35)	(5.83)
Remodeled [0,1]			-0.0231***	
			(-4.03)	
Percent Houses Remodeled (2000-2011)			-0.5364***	
			(-12.93)	
Year 2013	0.1111***	-0.0017	0.1122***	0.1058***
	(56.29)	(-0.64)	(48.18)	(36.28)
Year 2014	0.0743***	0.0293***	0.0730***	0.1016***
	(31.46)	(8.73)	(25.89)	(27.94)
Number of Observations	176,467	176,467	133,430	176,467

This table presents OLS regression results where an indicator variable for houses that were purchased institutional investors is the dependent variable in columns 1 and 3; an indicator variable for houses that were purchased by non-institutional investors is the dependent variable in column 2; and an indicator variable for pre-crisis owner-occupied houses that were converted to rentals in the post-crisis period is the independent variable in column 4. Columns 1, 2 and 4 include all sales from 2012 to 2014. Column 3 does not include sales for Barrow, DeKalb, Fayette, Forsyth, and Paulding county because the effective year built field is not poplulated for these counties. Numbers in parentheses are t statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Owner-occupied Housing's Asset Illiquidity Risk

	Full Sample			Characteristic Match		Nearest Neighbor Match	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own-to-Rent Conversion	0.0318***	0.0356***		0.0156***		-0.0153***	
	(0.00)	(0.00)		(0.00)		(0.00)	
Post * Own-to-Rent Conversion	-0.1441***	-0.1571***		-0.1158***		-0.0468***	
	(0.01)	(0.01)		(0.01)		(0.00)	
Cash Purchase	-0.1327***	-0.1110***	-0.1109***	-0.1195***	-0.0969***	-0.1673***	-0.1520***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Post * Cash Purchase	-0.1270***	-0.1233***	-0.1221***	-0.1152***	-0.1083***	-0.0515***	0.0064
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
REO	-0.3578***	-0.3428***	-0.3436***	-0.3273***	-0.2868***	-0.3530***	-0.2840***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Foreclosure	-0.2120***	-0.2263***	-0.2253***	-0.2073***	-0.1713***	-0.2096***	-0.1582***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Short Sale	-0.1027***	-0.1100***	-0.1105***	-0.0973***	-0.0917***	-0.1013***	-0.0841***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Rent-to-Own Conversion	-0.0271***						
	(0.01)						
Post * Rent-to-Own Conversion	0.0062						
	(0.01)						
Rental	-0.0341***						
	(0.00)						
Post * Rental	-0.3171***						
	(0.01)						
Institutional Investor			0.0000		-0.0173***		-0.0248***
			(0.00)		(0.00)		(0.00)
Post * Institutional Investor			-0.1459***		-0.0940***		-0.0602***
			(0.00)		(0.01)		(0.01)
Non-Institutional Investor			0.0484***				
			(0.00)				
Post * Non-Institutional Investor			-0.1621***				
			(0.00)				
Time Fixed Effects	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bulk Sales	Yes	No	No	No	No	No	No
Location Control	Census Tract	Census Tract	Census Tract	Census Tract	Census Tract	Census Tract	Census Tract
Number of Observations	1,023,802	898,971	898,971	536,647	235,323	246,498	65,922
Adjusted R-squared	0.76	0.77	0.77	0.74	0.69	0.72	0.67

The dependent variable in every column is the log of house price. Columns 1, 2, 4, and 6 use a difference-in-difference model to estimate the impact of a conversion from the owner-occupied market to the rental market. Columns 3, 5, and 7 use a difference-in-difference model to examine the price differential for institutional investor purchases. Column 1 uses the full sample. Columns 2 and 3 do not include *R20* conversions, rentals, or bulk sales transactions (i.e. the bottom left section of Table 9). Column 4 (5) uses the characteristic matched sample from the top (bottom) section of Table 9 and column 6 (7) uses the nearest neighbor matched sample from the top (bottom) section of Table 9. All columns include the following property characterstics: age, square feet living area, lot size, bedrooms, and bathrooms. Indicator variables for a garage, carport, and pool are also included. The coefficient and signs for the property characteristics are all as expected and all significant. They are not listed for the sake of brevity, but are available upon request. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Housing Market Segmentation

	Full Sample (1)		Full Sample (2)	Characteristic Match (3)	Nearest Neighbor (4)
Own-to-Rent Conversion	0.0110**		0.0129**	-0.0083	-0.0185**
	(0.01)		(0.01)	(0.01)	(0.01)
Rental	-0.0120***				
	(0.01)				
Cash Purchase	-0.1259***		-0.1106***	-0.1190***	-0.1679***
	(0.01)		(0.00)	(0.00)	(0.01)
Post * Cash Purchase	-0.1304***		-0.1210***	-0.1139***	-0.0534***
	(0.01)		(0.00)	(0.00)	(0.01)
Y_2001 * [O2R Conversion	Rental]	0.0053	-0.0171***	0.0057	0.0041	-0.0049
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2002 * [O2R Conversion	Rental]	0.0191**	-0.0244***	0.0196***	0.0152**	0.0037
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2003 * [O2R Conversion	Rental]	0.0243***	-0.0308***	0.0248***	0.0225***	0.0082
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2004 * [O2R Conversion	Rental]	0.0273***	-0.0557***	0.0278***	0.0316***	0.0017
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2005 * [O2R Conversion	Rental]	0.0325***	-0.0676***	0.0333***	0.0369***	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2006 * [O2R Conversion	Rental]	0.0295***	-0.0618***	0.0309***	0.0343***	0.0079
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2007 * [O2R Conversion	Rental]	-0.0093	-0.0853***	-0.0108*	0.0013	-0.0097
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2008 * [O2R Conversion	Rental]	-0.0781***	-0.2087***	-0.0806***	-0.0580***	-0.0177*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2009 * [O2R Conversion	Rental]	-0.1430***	-0.3301***	-0.1467***	-0.1008***	-0.0487***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2010 * [O2R Conversion	Rental]	-0.1658***	-0.2487***	-0.1678***	-0.1257***	-0.0853***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2011 * [O2R Conversion	Rental]	-0.1901***	-0.3566***	-0.1918***	-0.1435***	-0.0826***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2012 * [O2R Conversion	Rental]	-0.2069***	-0.4271***	-0.2064***	-0.1462***	-0.0829***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2013 * [O2R Conversion	Rental]	-0.1321***	-0.4674***	-0.1327***	-0.0835***	-0.0227***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2014 * [O2R Conversion	Rental]	-0.1523***	-0.3678***	-0.1554***	-0.1088***	-0.0402***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Property Characteristics	Yes		Yes	Yes	Yes
Location Control	Census Tract		Census Tract	Census Tract	Census Tract
Number of Observations	1,005,319		898,971	536,647	246,498
Adjusted R-squared	0.76		0.77	0.74	0.71

The dependent variable in every column is the log of house price. R2O Conversions and bulk sales transactions are not included. In column 1 annual *O2R Conversion* and Rental interactions are displayed in the same row. The *O2R Conversion* (Rental) interaction variable is displayed to the left (right) of the pipe delimiter. Rentals are not included in columns 2-4. All columns include the following property characterstics: age, square feet living area, lot size, bedrooms, and bathrooms. Indicator variables for a garage, carport, pool, REO sale, foreclosure sale and short sale are also included. The coefficient and signs for the property characteristics and distressed sale indicators are all as expected and all significant. They are not listed for the sake of brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Institutional Investment

	Full Sample (1)		Full Sample (2)	Characteristic Match (3)	Nearest Neighbor (4)
Institutional Investor	0.0034		0.0007	-0.0261***	-0.0380***
	(0.01)		(0.01)	(0.01)	(0.01)
Non-Institutional Investor	0.0163***				
	(0.01)				
Cash Purchase	-0.1107***		-0.1038***	-0.0969***	-0.1529***
	(0.01)		(0.00)	(0.00)	(0.01)
Post * Cash Purchase	-0.1216***		-0.1317***	-0.1131***	-0.0005
	(0.01)		(0.00)	(0.00)	(0.01)
Y_2001 * [Institutional | Non-Institutional]	0.0046	0.0063	0.0049	0.0071	0.0208
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2002 * [Institutional | Non-Institutional]	0.0109	0.0231***	0.0107	0.0069	0.0296
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2003 * [Institutional | Non-Institutional]	0.0081	0.0311***	0.0072	0.0097	0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2004 * [Institutional | Non-Institutional]	0.0014	0.0369***	0.0007	0.0169	0.0124
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2005 * [Institutional | Non-Institutional]	-0.0163	0.0498***	-0.0165	0.0072	0.0045
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2006 * [Institutional | Non-Institutional]	-0.0175	0.0470***	-0.018	0.0088	0.0147
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2007 * [Institutional | Non-Institutional]	-0.0495***	-0.0057	-0.0499***	-0.0183	-0.0097
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2008 * [Institutional | Non-Institutional]	-0.0782***	-0.0827***	-0.0787***	-0.0417***	-0.0091
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2009 * [Institutional | Non-Institutional]	-0.1821***	-0.1429***	-0.1828***	-0.1074***	-0.0448**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2010 * [Institutional | Non-Institutional]	-0.2252***	-0.1618***	-0.2280***	-0.1210***	-0.1170***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2011 * [Institutional | Non-Institutional]	-0.3346***	-0.1704***	-0.3391***	-0.2339***	-0.1710***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2012 * [Institutional | Non-Institutional]	-0.2358***	-0.1884***	-0.2410***	-0.1417***	-0.0989***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2013 * [Institutional | Non-Institutional]	-0.0956***	-0.1602***	-0.0990***	-0.0372***	-0.0187***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Y_2014 * [Institutional | Non-Institutional]	-0.1466***	-0.1583***	-0.1492***	-0.0676***	-0.0313**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Property Characteristics	Yes		Yes	Yes	Yes
Location Control	Census Tract		Census Tract	Census Tract	Census Tract
Number of Observations	898,971		793,122	235,323	65,922
Adjusted R-squared	0.77		0.78	0.68	0.67

The dependent variable in every column is the log of house price. R2O Conversions, Rentals, and bulk sales transactions are not included. In column 1 annual Institutional and Non-Institutional investor interactions are displayed in the same row. The Institutional (Non-Institutional) interaction variable is displayed to the left (right) of the pipe delimiter. Non-institutional investor transactions are not included in columns 2-4. All columns include the following property characterstics: age, square feet living area, lot size, bedrooms, and bathrooms. Indicator variables for a garage, carport, pool, REO sale, foreclosure sale and short sale are also included. The coefficient and signs for the property characteristics and distressed sale indicators are all as expected and all significant. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: Alternative Specifications using O2R Conversion Nearest Neighbor Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Own-to-Rent Conversion	-0.0146***	-0.0146***	-0.0157***	-0.0146***	-0.0153***	-0.0115***	-0.0136***	0.0017	-0.0002	-0.0020
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.01)	(-0.01)	(-0.01)
Post * Own-to-Rent Conversion	-0.0449***	-0.0448***	-0.0466***	-0.0449***	-0.0372***	-0.0459***	-0.0337***	-0.0406***	-0.0357***	-0.0390***
	(-0.01)	(-0.01)	(0.00)	(-0.01)	(0.00)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)
Cash Purchase	-0.1650***	-0.1647***	-0.1609***	-0.1655***	-0.1608***	-0.1662***	-0.1528***	-0.2794***	-0.2637***	-0.2596***
	(-0.02)	(-0.02)	(-0.02)	(-0.02)	(-0.02)	(-0.02)	(-0.02)	(-0.04)	(-0.03)	(-0.03)
Post * Cash Purchase	-0.0614***	-0.0624***	-0.0605***	-0.0606***	-0.0572***	-0.0718***	-0.0675***	-0.0998***	-0.1030***	-0.0953***
	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.02)	(-0.02)	(-0.02)
Average Turnover (2000-2006)	0.2682						-0.6592			-1.4573**
	(-0.55)						(-0.63)			(-0.55)
Turnover Prev 6 Months		0.7496					2.0779*			3.6886***
		(-0.70)					(-1.12)			(-0.88)
Percent Distressed			-0.4453***				-0.5192***			-0.6670***
			(-0.06)				(-0.07)			(-0.13)
Percent Houses Built (2000-2014)				0.0863***			0.0495*			-0.0408
				(-0.03)			(-0.03)			(-0.07)
Percent Houses Remodeled (2000-2014)					0.6711		2.1045***			4.9580**
					(-0.45)		(-0.68)			(-2.38)
Very Good Condition						-0.0100	-0.0183		-0.1333***	-0.1134***
						(-0.03)	(-0.02)		(0.00)	(0.00)
Good Condition						-0.0775***	-0.0655***		-0.2538***	-0.2180***
						(-0.03)	(-0.02)		(0.00)	(0.00)
Average Condition						-0.1208***	-0.0911***		-0.3844***	-0.3369***
						(-0.03)	(-0.03)		(0.00)	(0.00)
Fair Condition						-0.1595***	-0.1271***		-0.4612***	-0.4196***
						(-0.03)	(-0.03)		(0.00)	(0.00)
Poor Condition						-0.1934***	-0.1591***		-0.4321***	-0.3825***
						(-0.04)	(-0.04)		(0.00)	(0.00)
Unsound Condition						-0.2649**	-0.3481***		-0.6689***	-0.5745***
						(-0.12)	(-0.09)		(0.00)	(0.00)
Time Fixed Effects	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Control	Zip Code	Zip Code	Zip Code	Zip Code	Zip Code	Zip Code	Zip Code	Zip Code	Zip Code	Zip Code
Number of Counties Included	18	18	18	18	13	13	13	1	1	1
Number of Observations	246,470	246,470	246,470	246,470	185,472	181,008	126,202	39,020	39,020	39,020
Adjusted R-squared	0.70	0.70	0.70	0.70	0.70	0.70	0.71	0.71	0.72	0.73

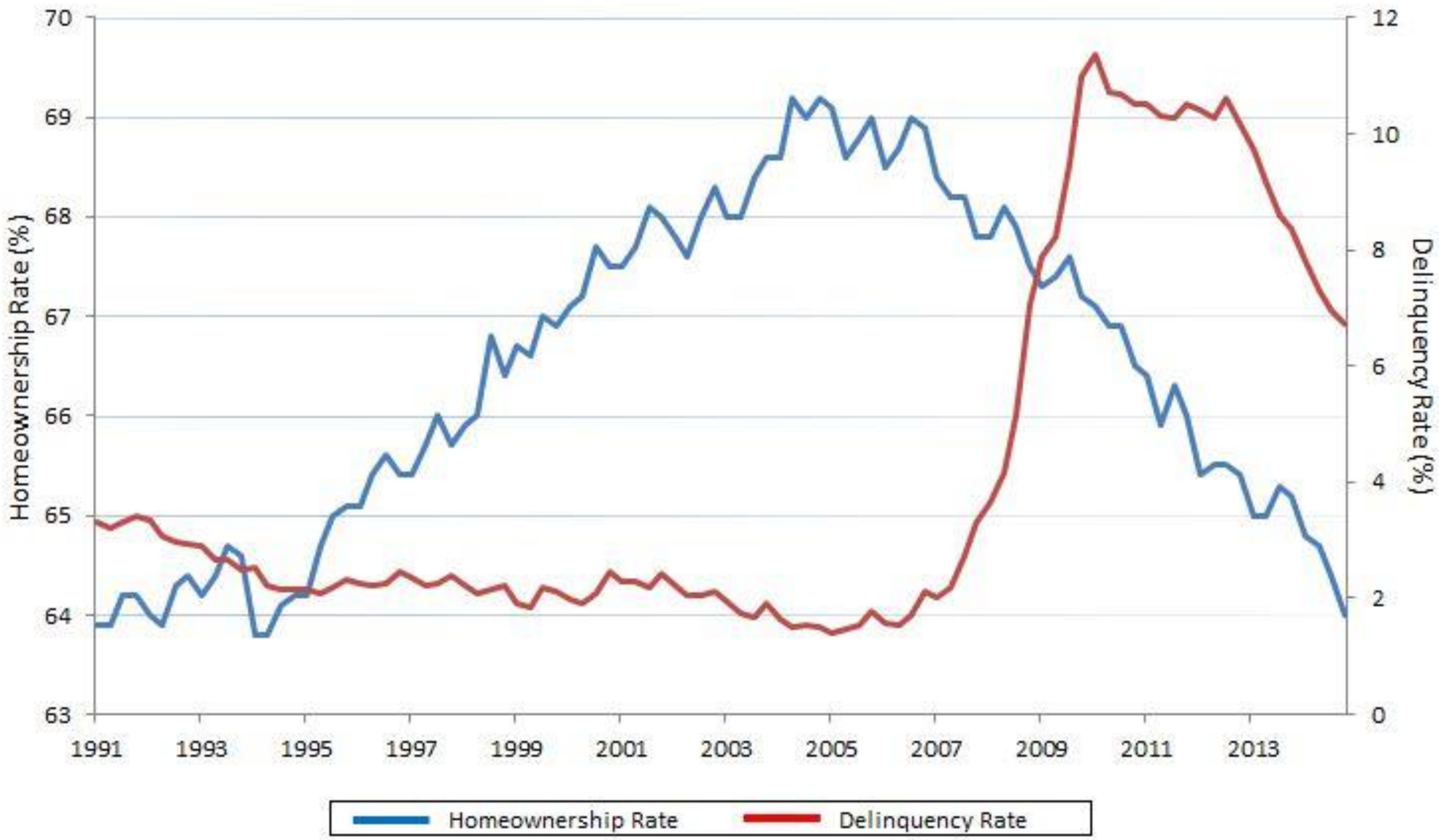
The dependent variable in every column is the log of house price. All columns include the following property characterstics: age, square feet living area, lot size, bedrooms, and bathrooms. Indicator variables for REOs, foreclosures, and short sales are also included. The coefficient and signs for the property characteristics and distressed sale indicators are as expected and all significant. The O2R nearest neighbor matched sample is used in every column. Columns 1 to 4 include all 18 counties, columns 5 to 7 include 13 counties, and columns 8-10 include only Fulton County. The condition variable in column 6 represents the properties condition in 2014. Whereas, the condition variables in columns 9 and 10 were updated annually. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 15: Change in house prices by investor share and conversion activity (2012-2014)

	Δ Zipcode HPI		Δ ln(House Prices)		Δ ln(House Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)
Institution share$_{t-1}$	0.09**	0.13*	0.23***	0.38***		
	(0.05)	(0.07)	(0.04)	(0.05)		
Corporate share$_{t-1}$	0.05	-0.02	-0.13***	0.16**		
	(0.04)	(0.10)	(0.03)	(0.06)		
Individual share$_{t-1}$	-0.08	-0.08	-0.39***	-0.22**		
	(0.11)	(0.17)	(0.09)	(0.09)		
Conversion share$_{t-1}$					0.08**	0.12***
					(0.03)	(0.04)
Y_2013	0.10***	0.13***	0.09***	0.07***	0.10***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Y_2014	0.14***	0.16***	0.13***	0.09***	0.16***	0.15***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Controls	No	Yes	No	Yes	No	Yes
Number of Observations	183	183	450	450	450	450
Adjusted R-squared	0.56	0.65	0.60	0.65	0.55	0.59
Dependent Variable Source	CoreLogic	CoreLogic	Zillow	Zillow	Zillow	Zillow

The dependent variable in columns 1 and 2 is the change in the zipcode level home price index that is calculated using the CoreLogic data for all zipcodes with a housing stock greater than 10,000. The dependent variable in columns 3, 4, 5 and 6 is the change in the log of average house prices (zipcode level) reported by Zillow. The controls in columns 2, 4 and 6 include percent distressed sales$_{t-1}$, log(rent$_{t-1}$), log(house price$_{t-1}$), poverty rate, unemployment rate, percent of household with kids, percent of households with income in the first quintile, percent of households with income in the fifth quintile, percent with less than a high school degree, percent with a college degree or higher education level, pre-crisis percent rental, and pre-crisis turnover. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Figure 1: United States Homeownership Rate



The quarterly homeownership rate represents the proportion of households that are owner-occupiers in the United States. The homeownership rate data was obtained from the U.S. Census Bureau. The delinquency rate represents the proportion of residential real estate loans that are past due thirty days or more and still accruing interest, as well as those in nonaccrual status at commercial banks. Residential real estate loans include loans secured by 1- to 4-family properties, including home equity lines of credit. The delinquency rate data was obtained from the Federal Reserve website.

Figure 2: Post-Crash House Price Dynamics

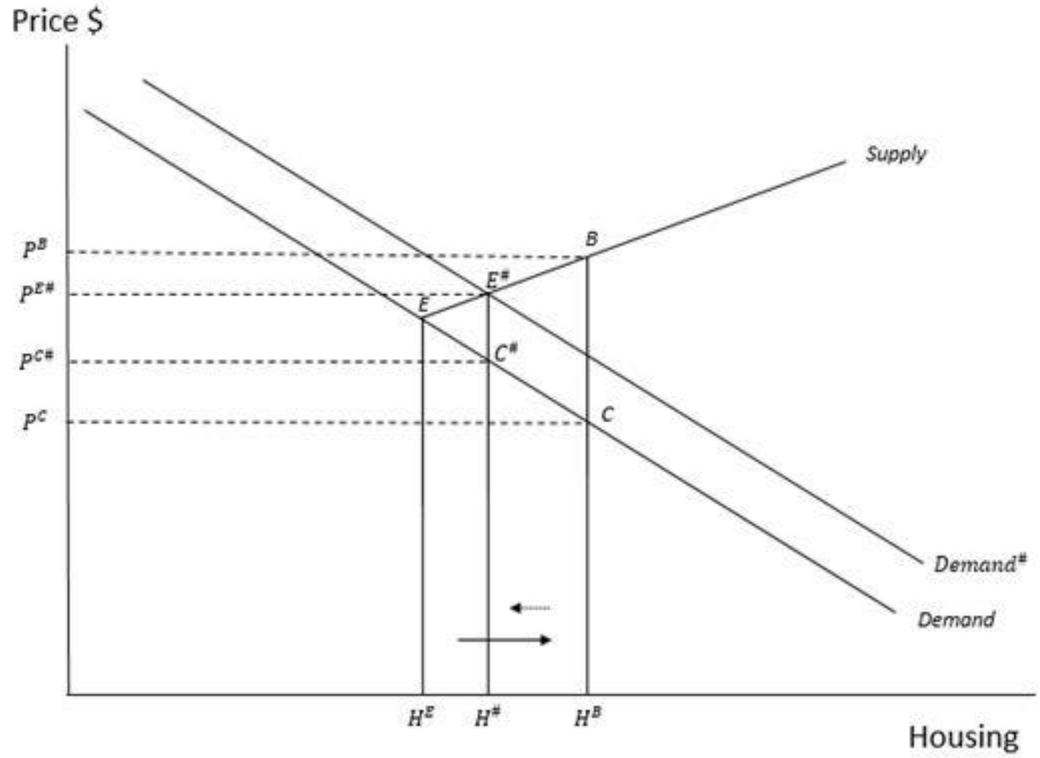
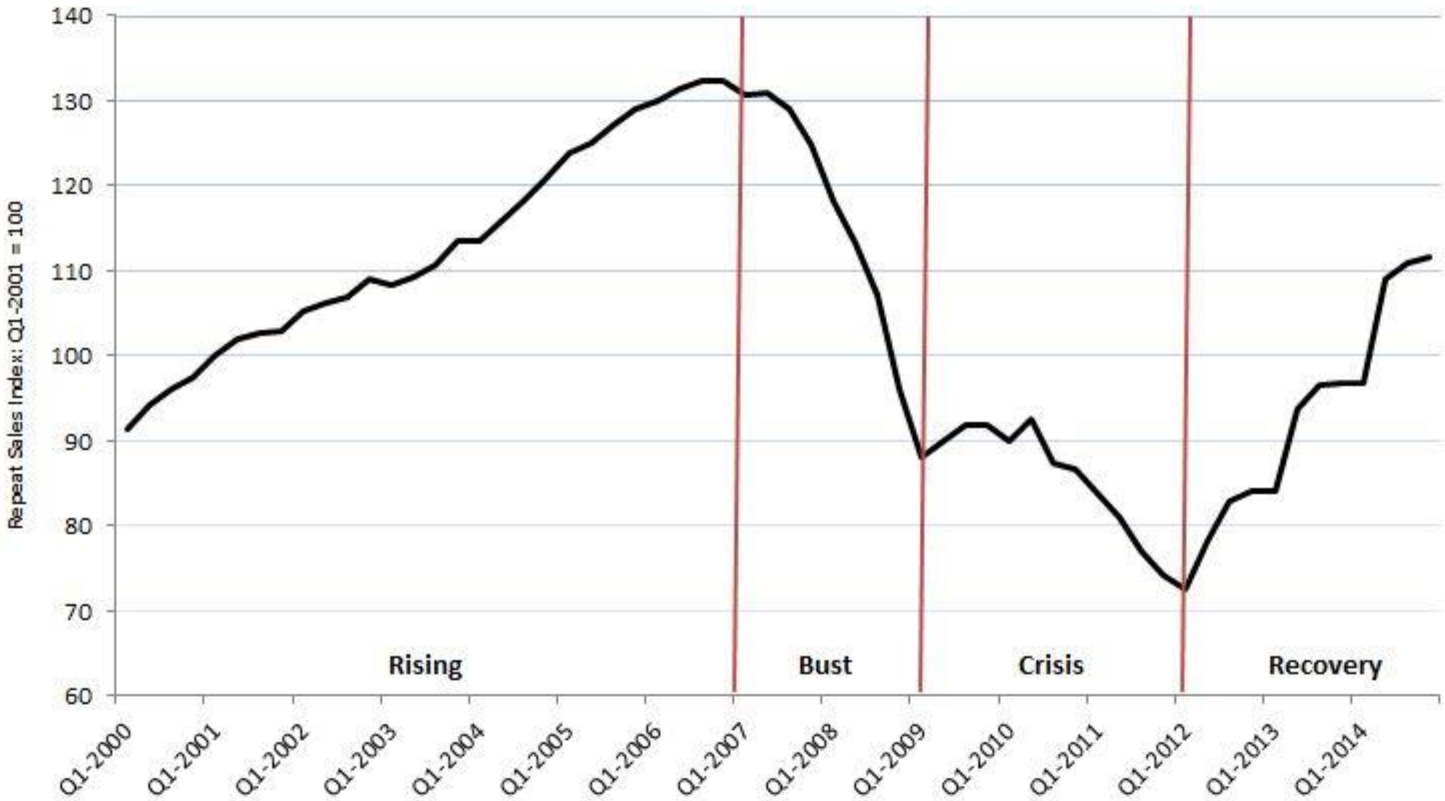
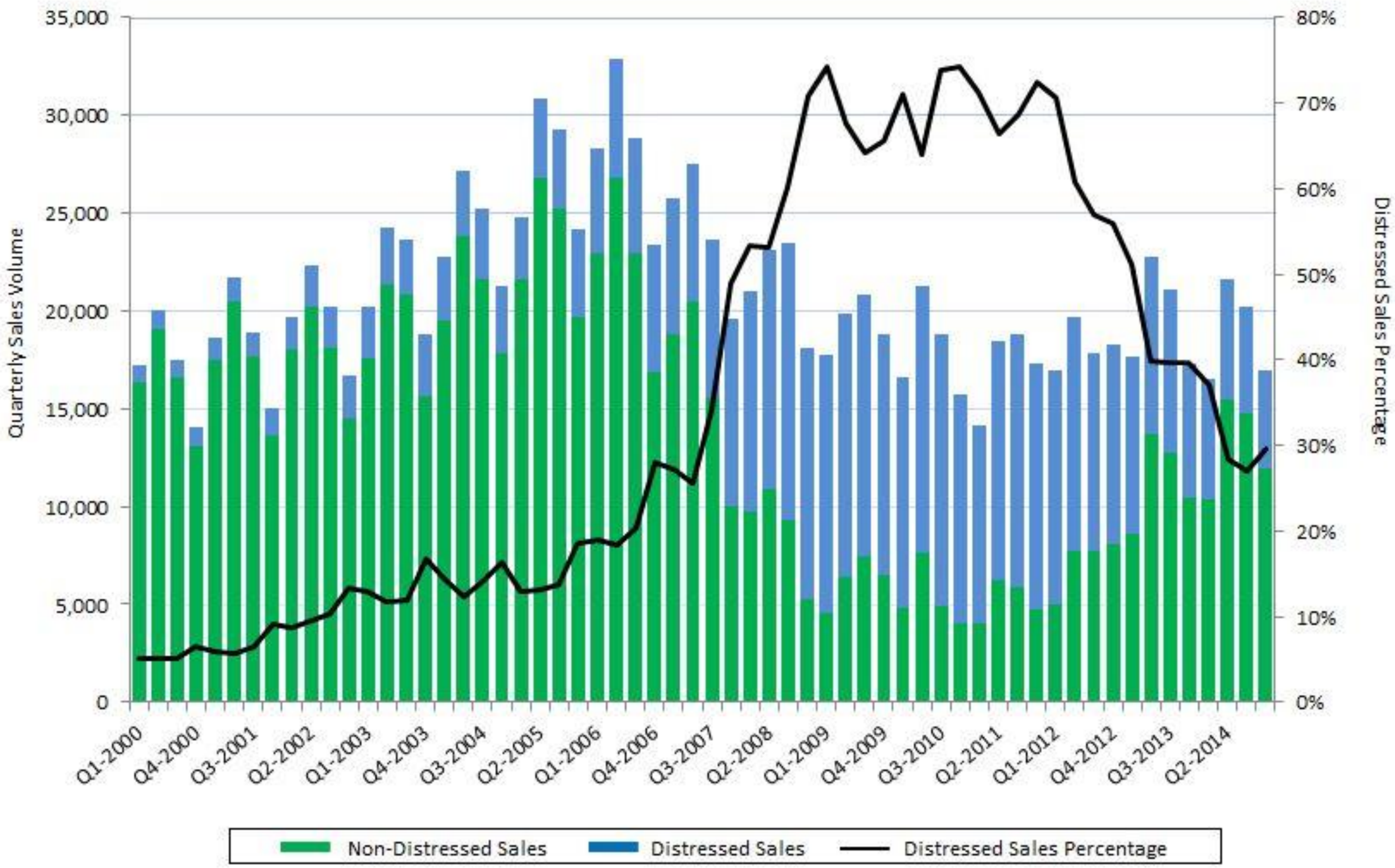


Figure 3: Metro Atlanta Repeat Sales Index



The repeat sales index was constructed using single-family detached sales transactions from the Corelogic dataset.

Figure 4: Metro Atlanta Sales Volume

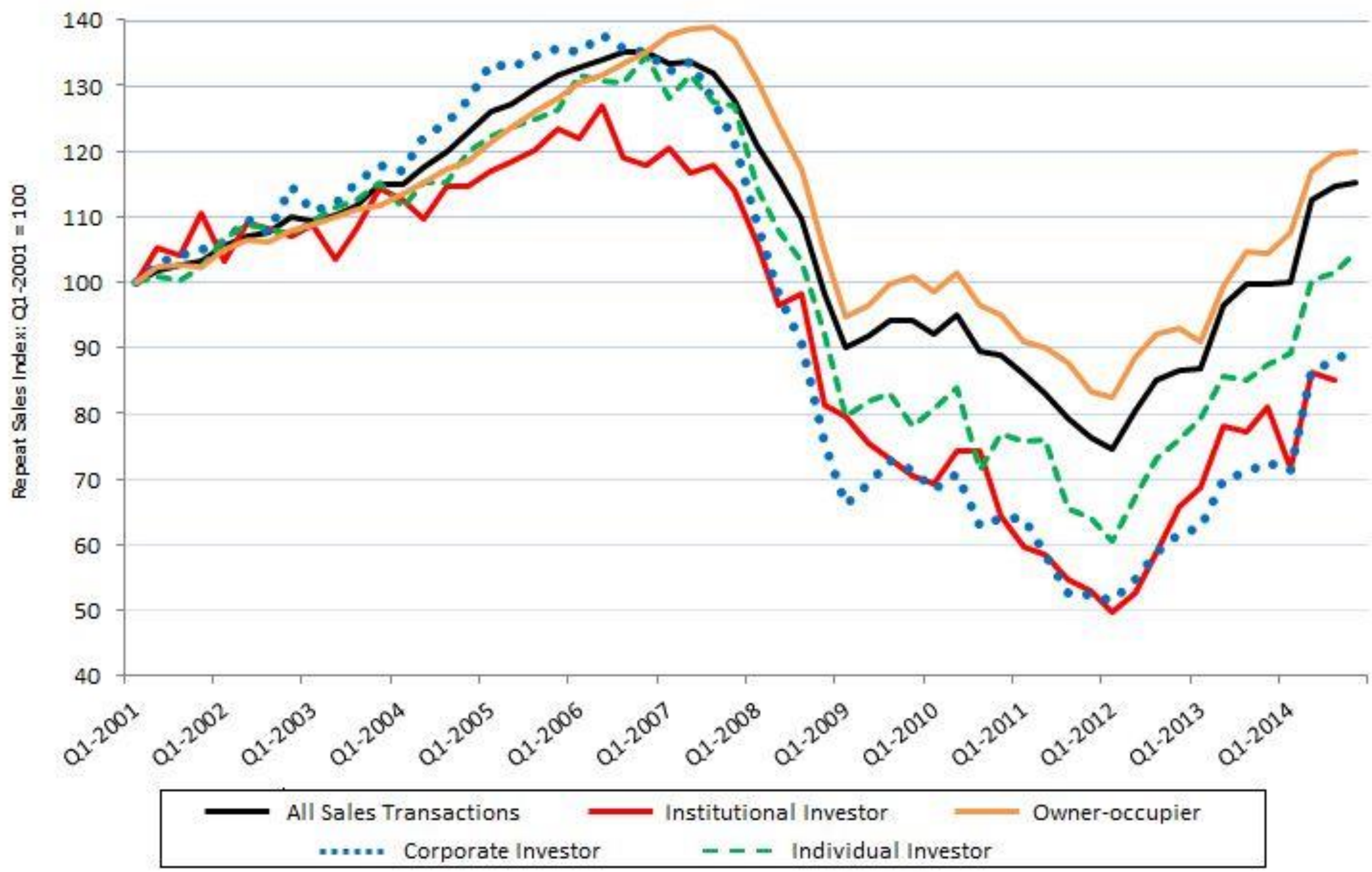


Includes all single-family detached sales transactions from the Corelogic sales transaction dataset. Distressed sales include all short-sale, foreclosure, and Real Estate Owned (REO) sales transactions.

Figure 5: Multi-family Starts and Vacancy Rate

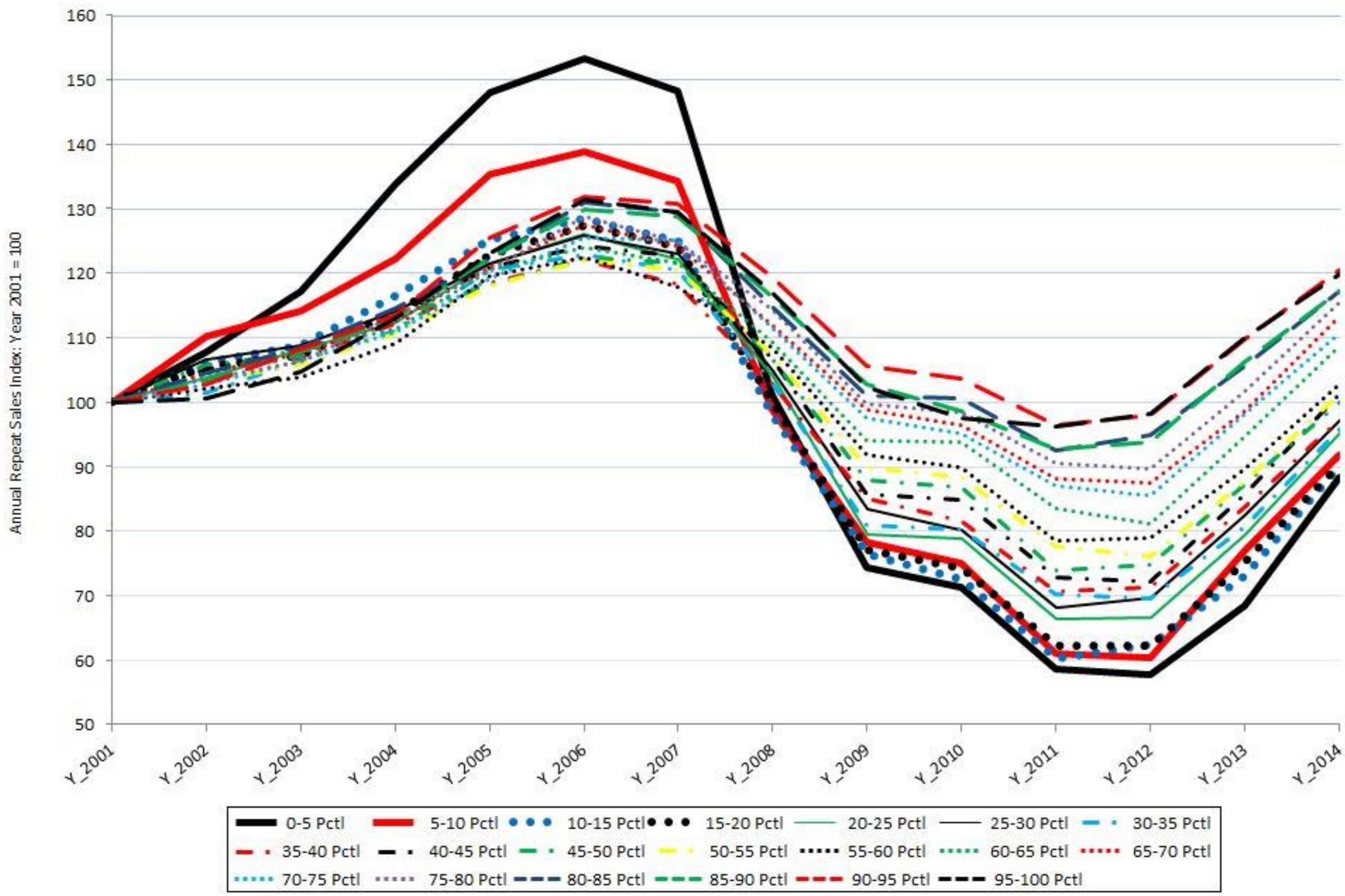
Multi-family starts is a rolling 4 quarter average that measures the number of new privately owned multi-family units that were started in the United States. The measure includes all buildings with five or more units. The multi-family starts data was obtained from the U.S. Census Bureau's Survey of Construction. The rental vacancy rate represents the proportion of the rental inventory in buildings with five or more units that is vacant. The rental vacancy rate data was obtained from the U.S. Census Bureau's Housing Vacancy Survey.

Figure 6: Repeat Sales Index by Investor Type



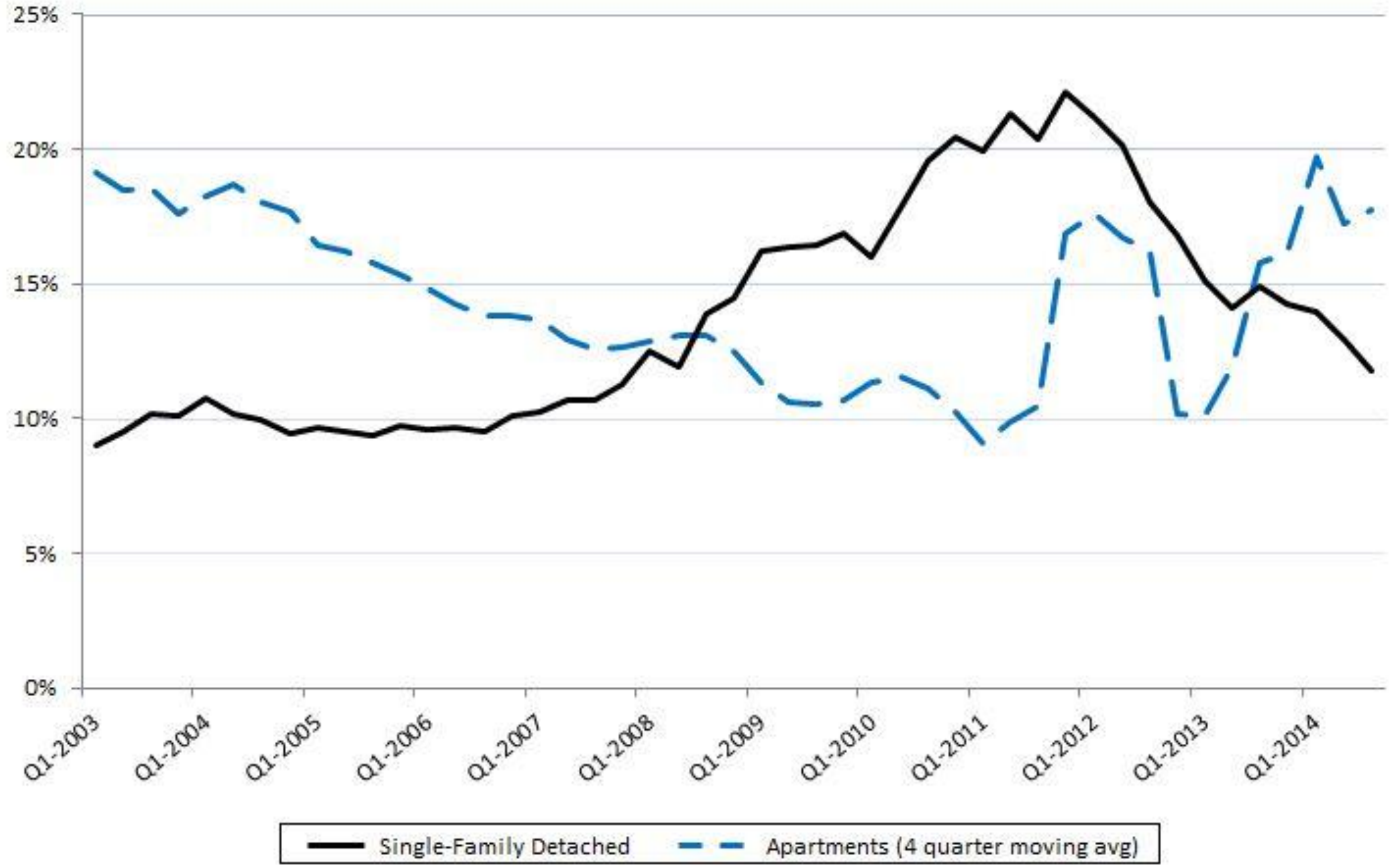
The quarterly repeat sales index was constructed using the same CoreLogic single-family detached sales transactions data as Figure 3. Separate indexes are constructed for owner-occupiers and institutional, corporate, and individual investors.

Figure 7: Annual Repeat Sales Index for 20 Home-Size Segments



The annual repeat sales index was constructed using the same CoreLogic single-family detached sales transactions data as Figure 3. However, the data is stratified into twenty home-size segments based on the house's square feet of living area. The 0-5 Percentile represents the smallest houses in the Atlanta market and the 95-100 Percentile represents the largest houses in Atlanta.

Figure 8: Gross Rent-Price Ratios by Property Type

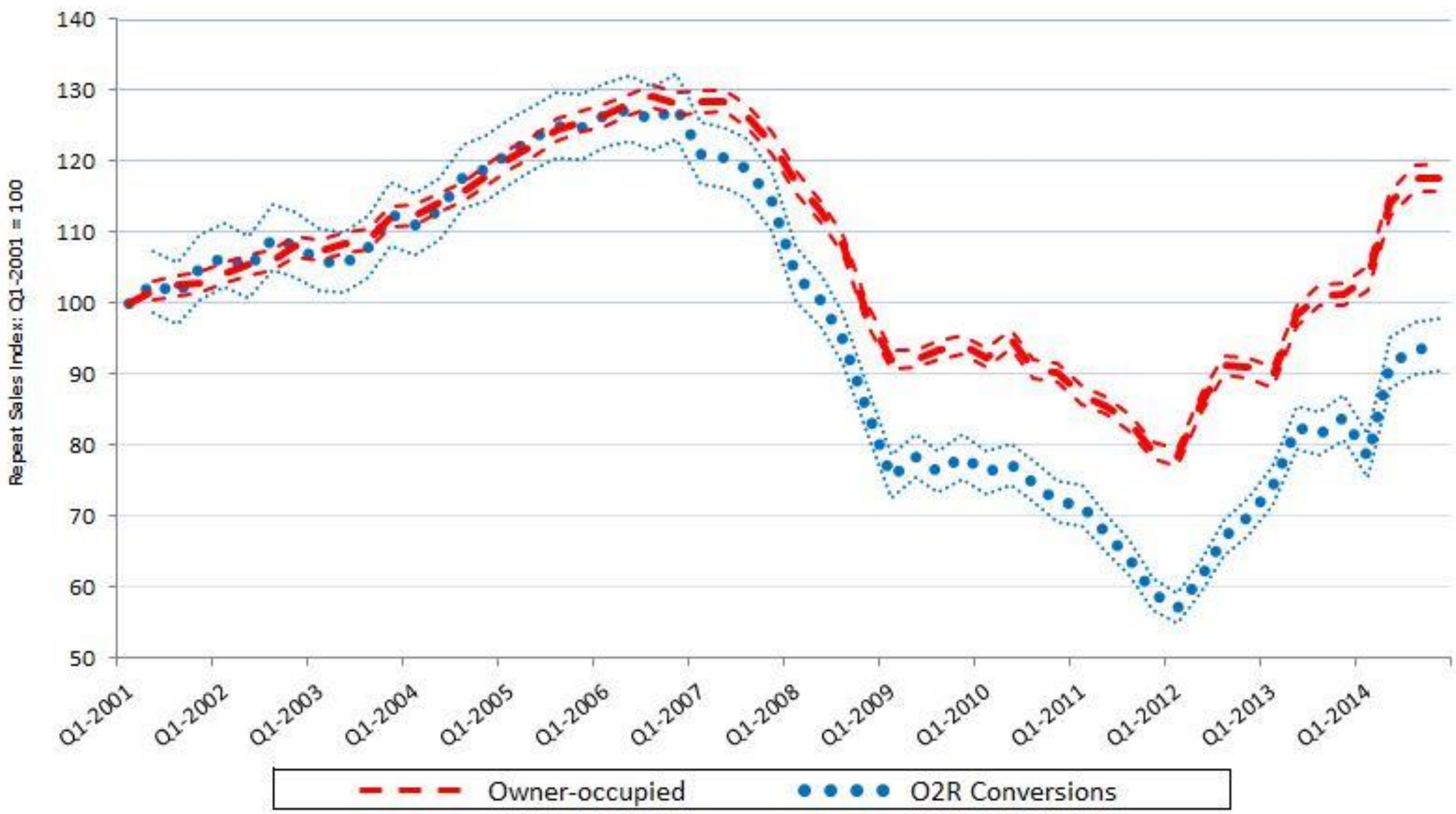


The single-family detached rent-price ratio represents the entire matched rental dataset. The matched dataset includes houses that were both sold and rented within six months of each other. The rent-price ratio for apartment buildings was tabulated on a rolling 4 quarter average using CoStar data.

Figure 9: Single-Family Detached Rent-Price Ratios By Investor Type

The single-family detached gross rent-price ratios are broken out by investor type using the matched rental dataset. The matched dataset includes houses that were both sold and rented within six months of each other.

Figure 10: Repeat Sales Index for Pre-crash Owner-occupied Housing



Quarterly repeat sales indexes are constructed for owner-occupied houses that were converted to rentals after the real estate crisis (O2R Conversions) and owner-occupied houses that were not converted to rentals after the crisis (Owner-occupied).

Appendix A – Institutional Investor Overview

American Homes 4 Rent: www.americanhomes4rent.com

American Homes 4 Rent is an internally managed real estate investment trust (REIT) that is publicly traded on the New York Stock Exchange (NYSE: AMH). American Homes 4 Rent is focused on acquiring, renovating, and leasing single-family homes as rental properties. They recently merged with American Residential Properties (see below) and now own and operate approximately 47,910 single-family properties in select housing markets across 22 states. American Homes 4 Rent was originally founded by self-storage (NYSE: PSA) billionaire B. Wayne Hughes. Its IPO data was August 1st, 2013.

American Residential Properties: www.amresprop.com [redirects to AMH website]

American Residential Properties was a publicly traded REIT (NYSE: ARPI) that acquired, owned, and managed single-family homes as rental properties. In March 2016, American Residential Properties merged with American Homes 4 Rent. American Residential Properties owned and operated approximately 8,938 single-family properties in 12 states when they merged with American Homes 4 Rent. Its IPO date was May 9th, 2013.

Colony American Homes: www.cah.com [redirects to www.waypointhomes.com]

Colony American Homes merged with Starwood Waypoint Residential Trust (NYSE:SWAY) in January 2016 to form Colony Starwood Homes. Colony Starwood Homes (NYSE:SFR) acquires, renovates, leases, maintains and manages single family homes. Prior to the merger Colony American Homes owned and operated approximately 17,796 single-family homes. After the merger, Colony Starwood Homes owned and operated approximately 30,667 single-family homes. Before merging with Starwood Waypoint, the Colony American Homes filed for an IPO on May 2nd, 2013, but postponed the pricing of its offering in June 2013.

Invitation Homes: www.invitationhomes.com

Invitation Homes is a subsidiary of the Blackstone Group (NYSE: BX). Invitation Homes owns and operates the largest single-family housing stock – not only in Atlanta, but nationwide. According to their website Invitation Homes owns over 50,000 single-family homes across 14 of the country's most popular cities.

Havenbrook Homes: www.havenbrookhomes.com

Havenbrook Homes owns and operates approximately 4,000 single-family homes in 5 housing markets that are spread across 4 states. Pacific Investment Management Co. (PIMCO) owns a controlling stake in Havenbrook Homes and recently bought out Sylvan Road Capital – who had an 8% stake in Havenbrook Homes.[60]

[60] Additional information on the transaction is available in the following article: http://www.bloomberg.com/news/articles/2015-03-25/pimco-bets-on-rental-homes-in-buyout-of-former-analyst

Main Street Renewal: www.msrenewal.com

Main Street Renewal is a subsidiary of Amherst Holdings LLC (www.amherst.com). Main Street Renewal's investment strategy is focused on acquiring, renovating, leasing, and managing single-family homes across the United States. Main Street Renewal owns and operates single-family housing rentals in 19 major cities across 12 states.

Progress Residential: www.rentprogress.com

Progress Residential focuses on acquiring, renovating, leasing, and managing single-family rental homes in 20 housing markets across the United States. Progress Residential owns and leases over 8,000 single-family rental homes. Progress Residential is backed by over $1 billion of equity capital.

Residential Capital Management: http://www.resicap.com/

Residential Capital Management is a "vertically integrated single source solution for institutional level single family real estate needs." Residential Capital Management has acquired, renovated and manages over 7,700 single family homes. Residential Capital Management operations are focused in 7 housing markets in the Southeast United States.

Silver Bay Realty Trust: www.silverbayrealtytrustcorp.com

Silver Bay Realty Trust is a publicly traded REIT (NYSE: SBY) that focuses on the acquisition, renovation, leasing and on-going management of single-family rental properties. Silver Bay owns and operates approximately 9,000 single-family properties that are spread across 9 states. Silver Bay was the first single-family rental REIT – its IPO date was December 17th, 2012.

Starwood Waypoint Residential Trust: http://colonystarwood.com/

Starwood Waypoint Residential Trust (NYSE:SWAY) merged with Colony American Homes in January 2016 to form Colony Starwood Homes. Colony Starwood Homes (NYSE:SFR) acquires, renovates, leases, maintains and manages single family homes. Prior to the merger Starwood Waypoint Residential Trust owned and operated approximately 12,881 single-family homes. Starwood Waypoint's original IPO date was January 22nd, 2014.

Sylvan Road Capital: https://www.sylvanroad.com/

Sylvan Road Capital is an asset management firm that focuses on the buy-to-rent market in single family housing. Sylvan Road Capital raised more than $500 million to acquire and rehabilitate homes in Atlanta and surrounding markets.

Figure A1: County Map

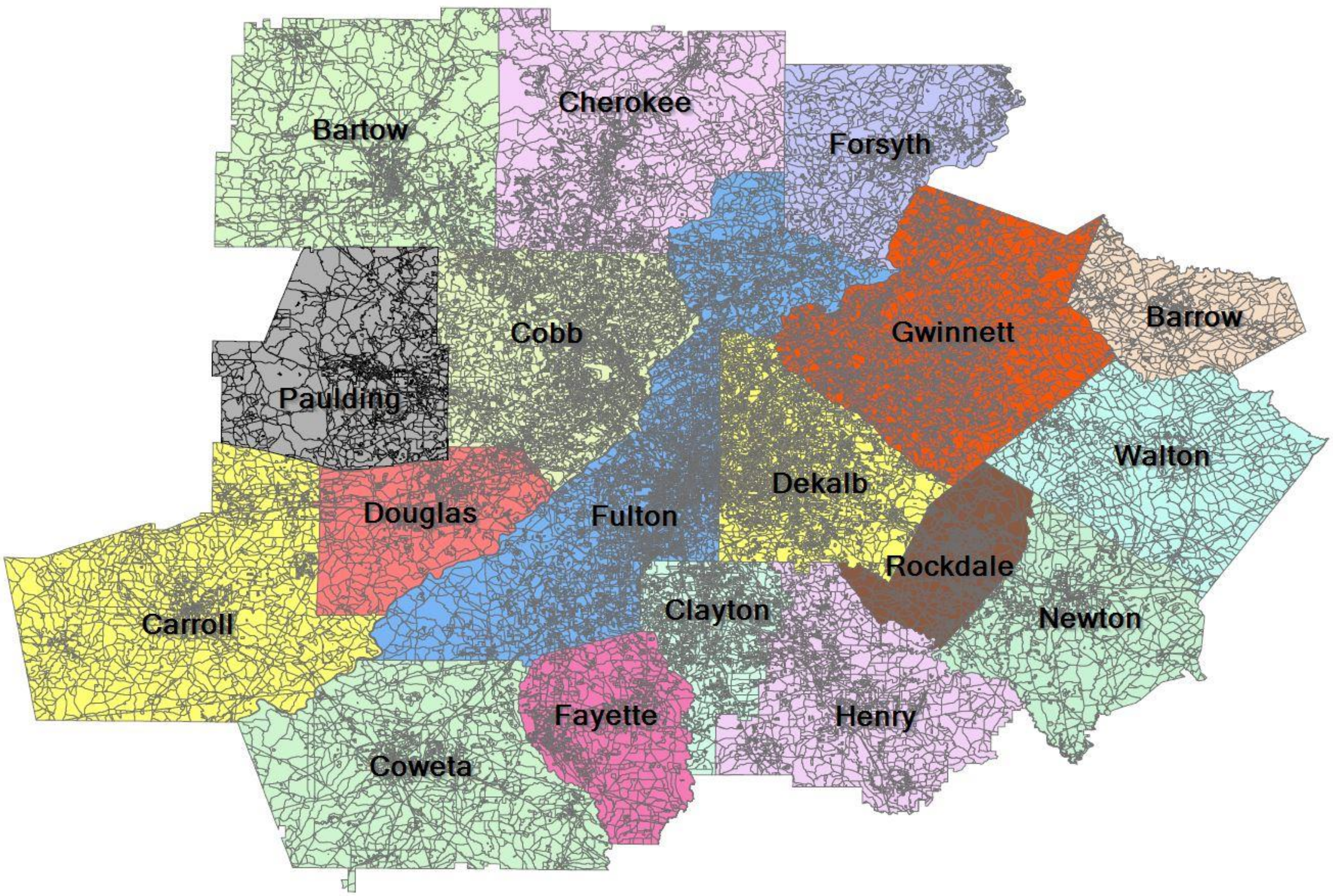


Figure A2: American Homes 4 Rent Purchases

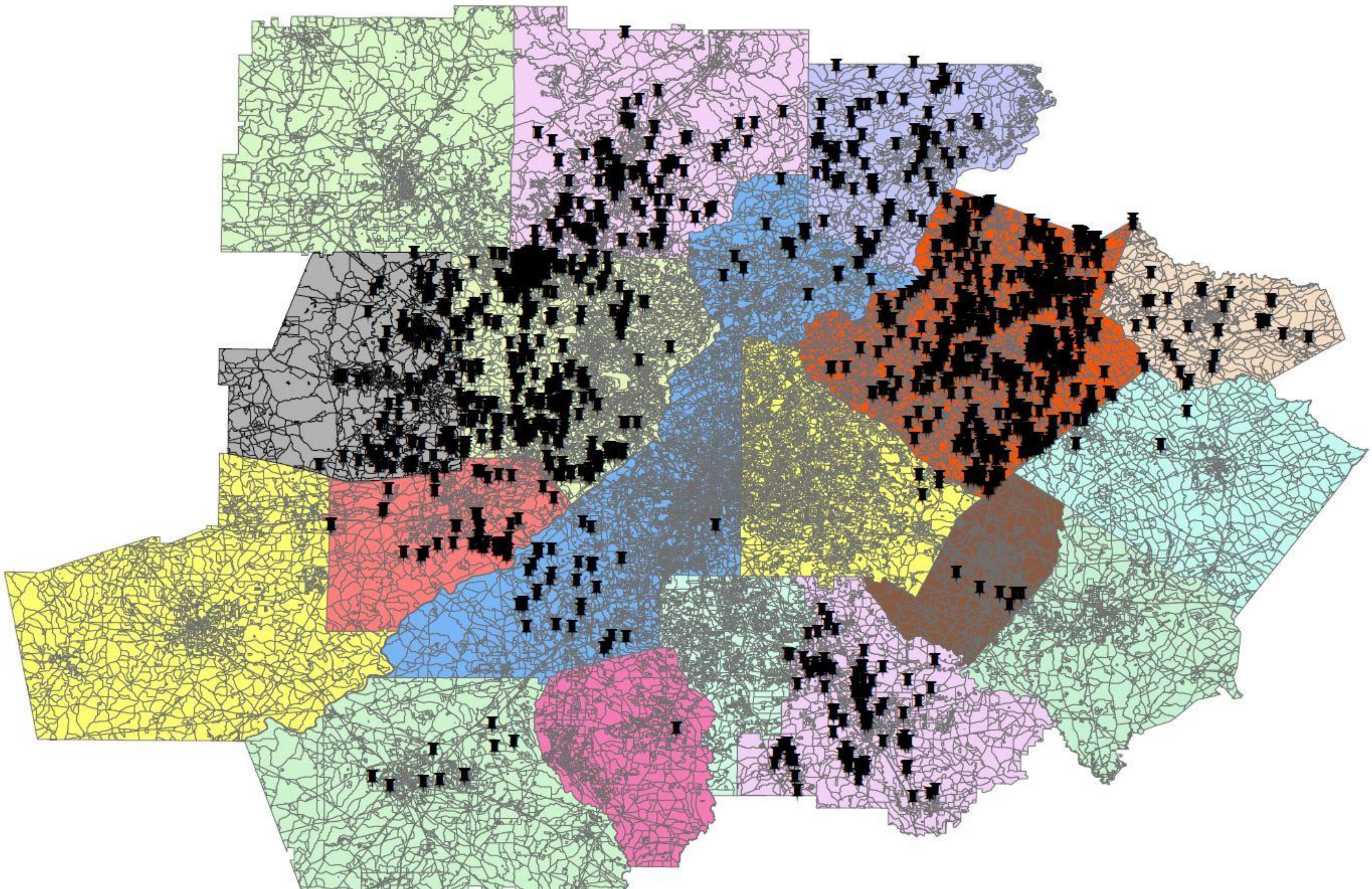


Figure A3: American Residential Purchases

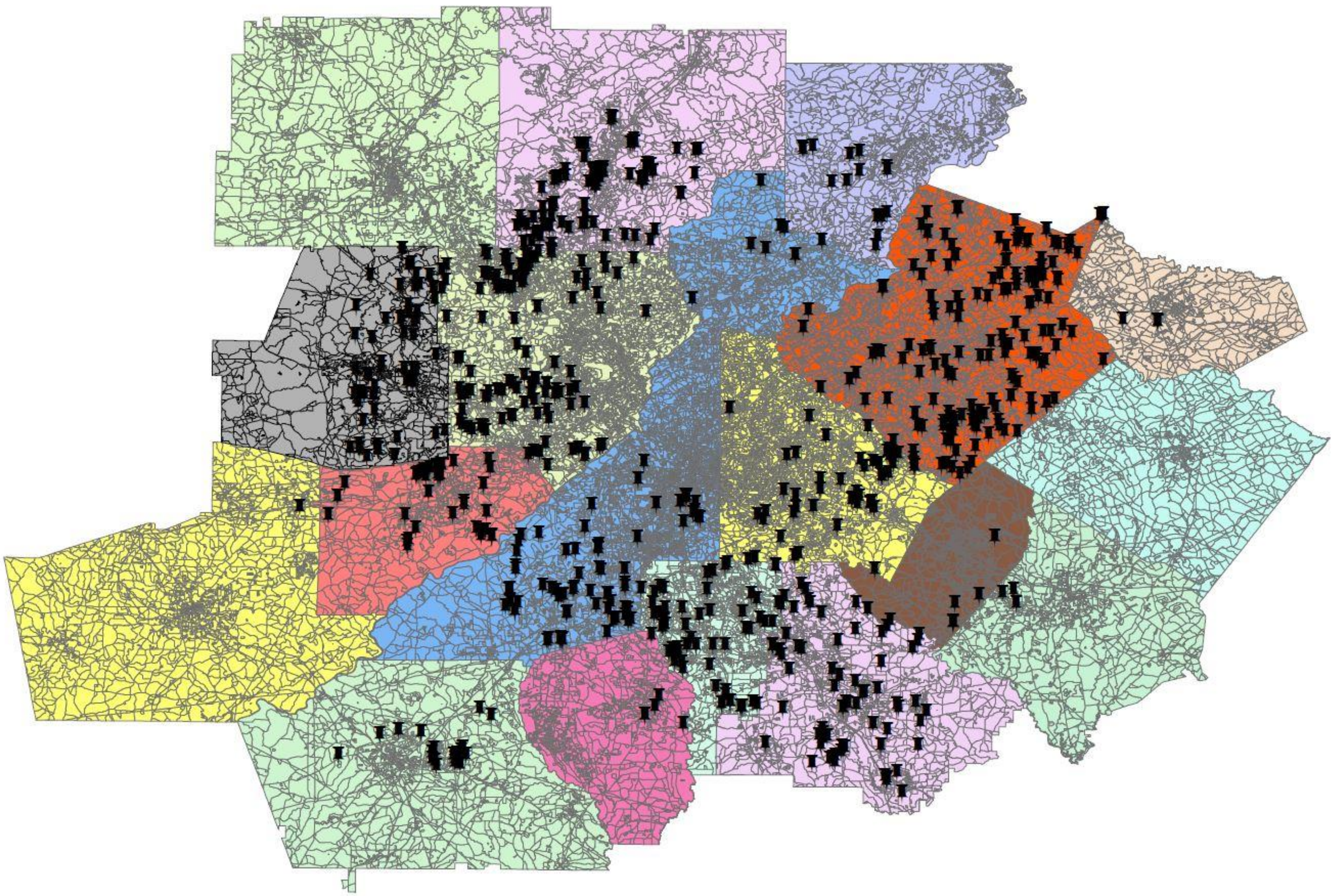


Figure A4: Colony American Homes Purchases

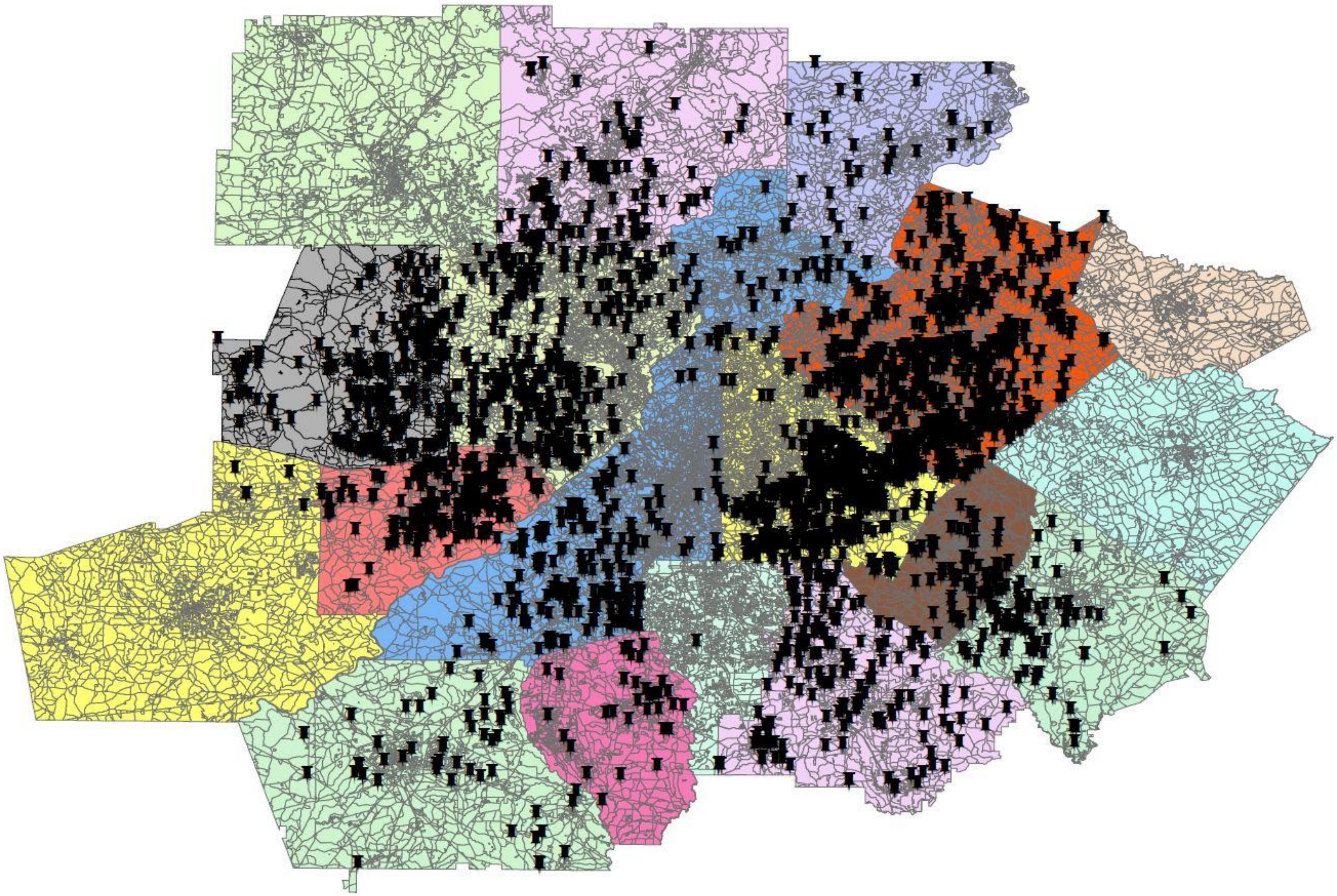


Figure A5: Havenbrook Homes Purchases

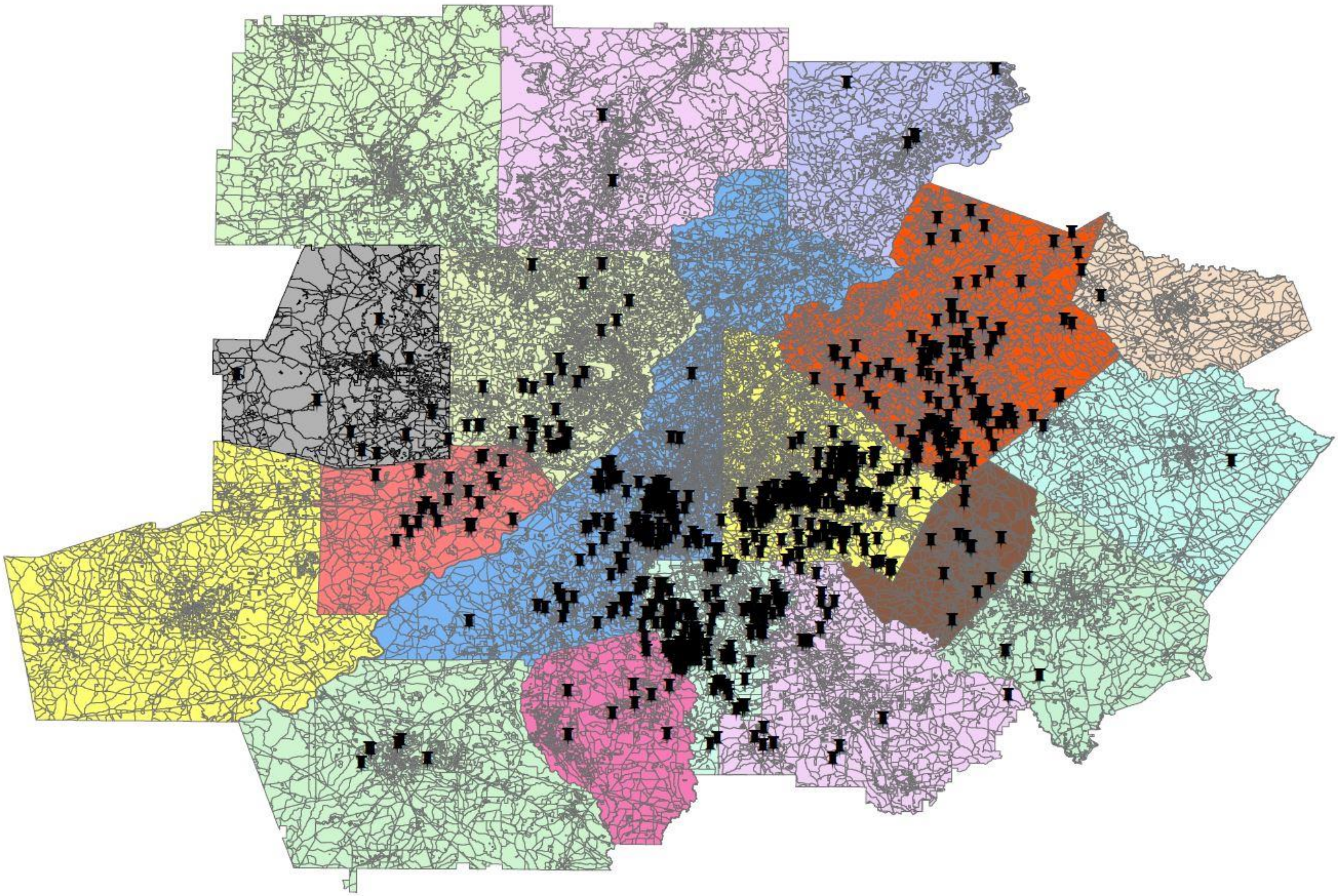


Figure A6: Invitation Homes Purchases

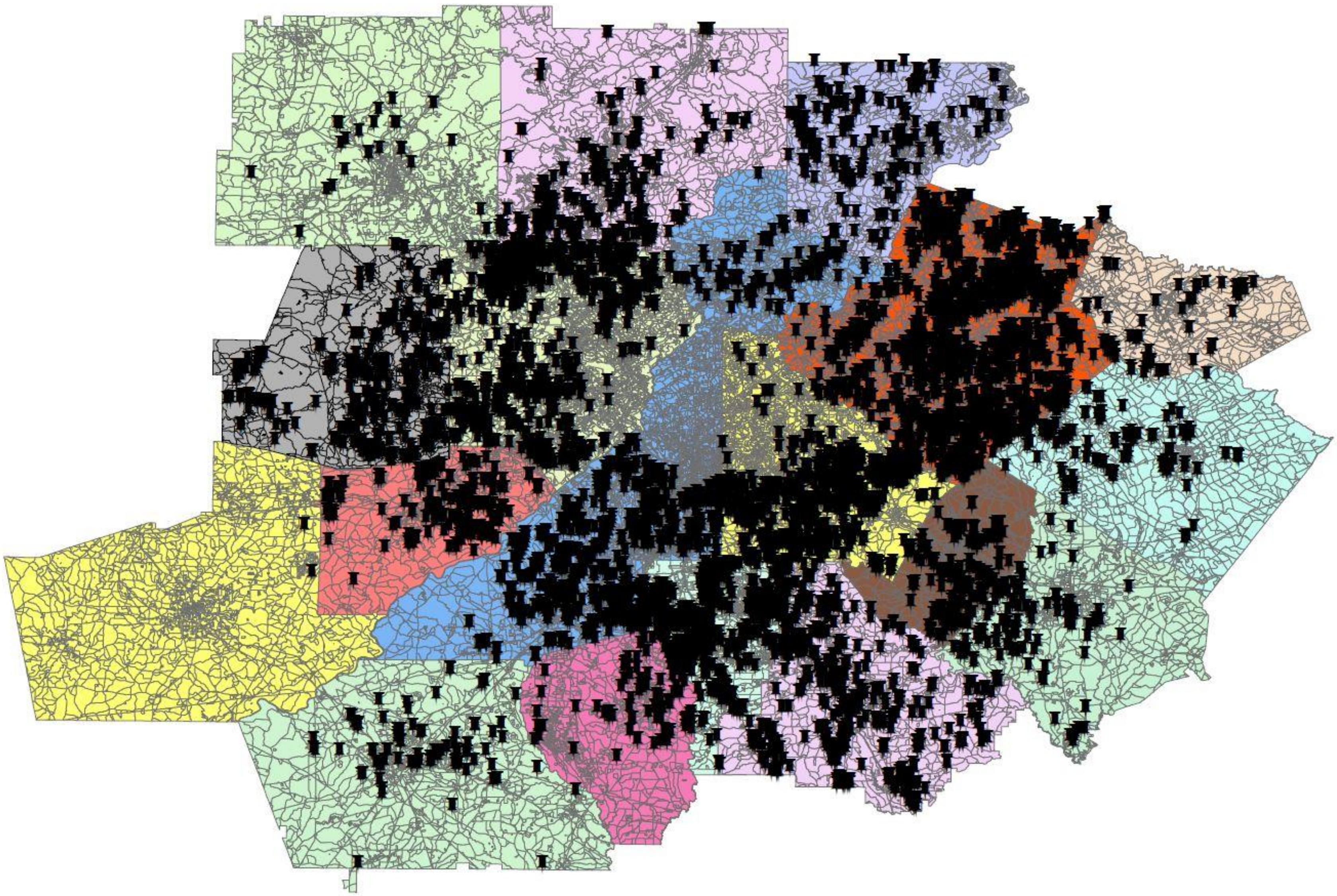


Figure A7: Main Street Renewal Purchases

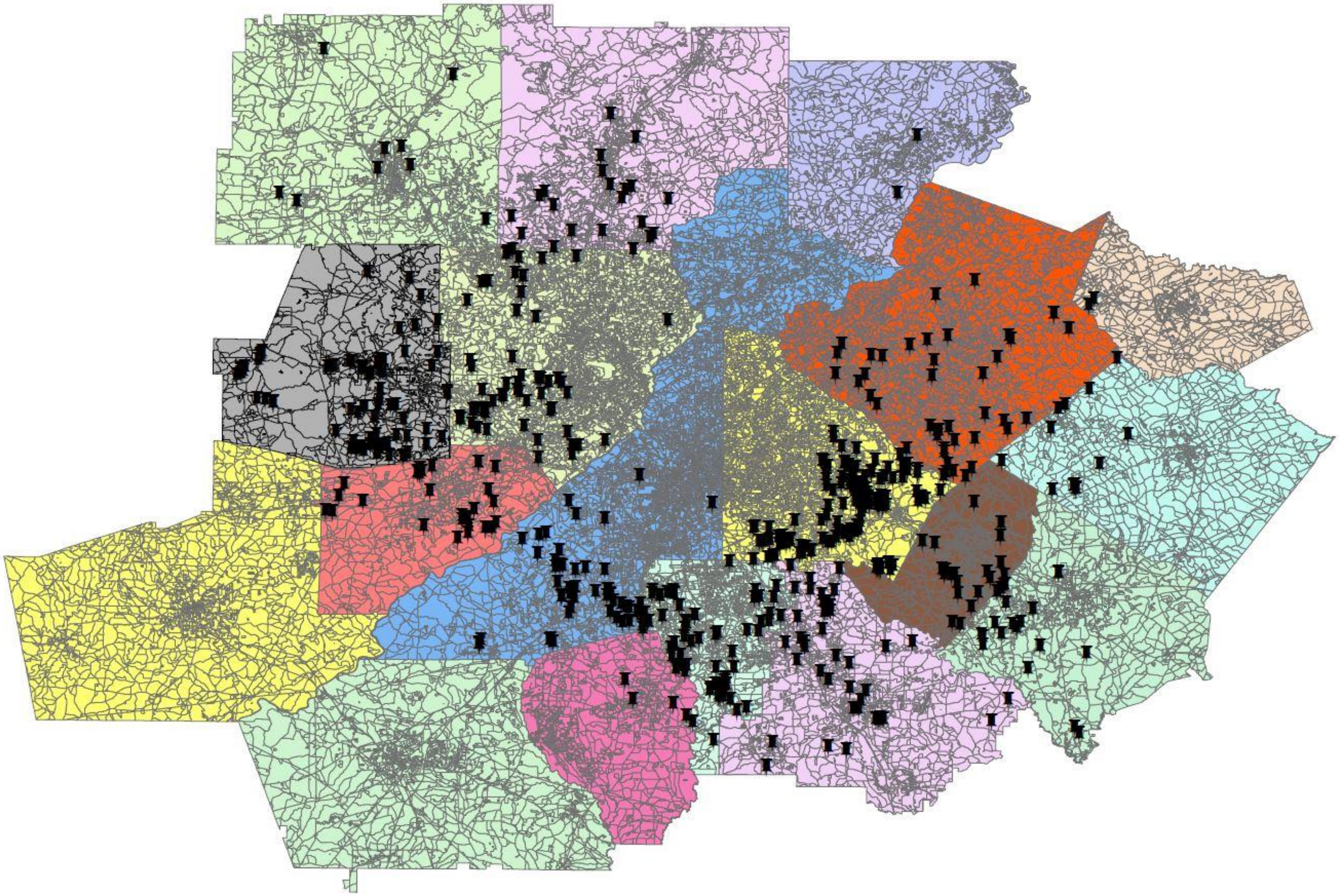


Figure A8: Progress Residential Purchases

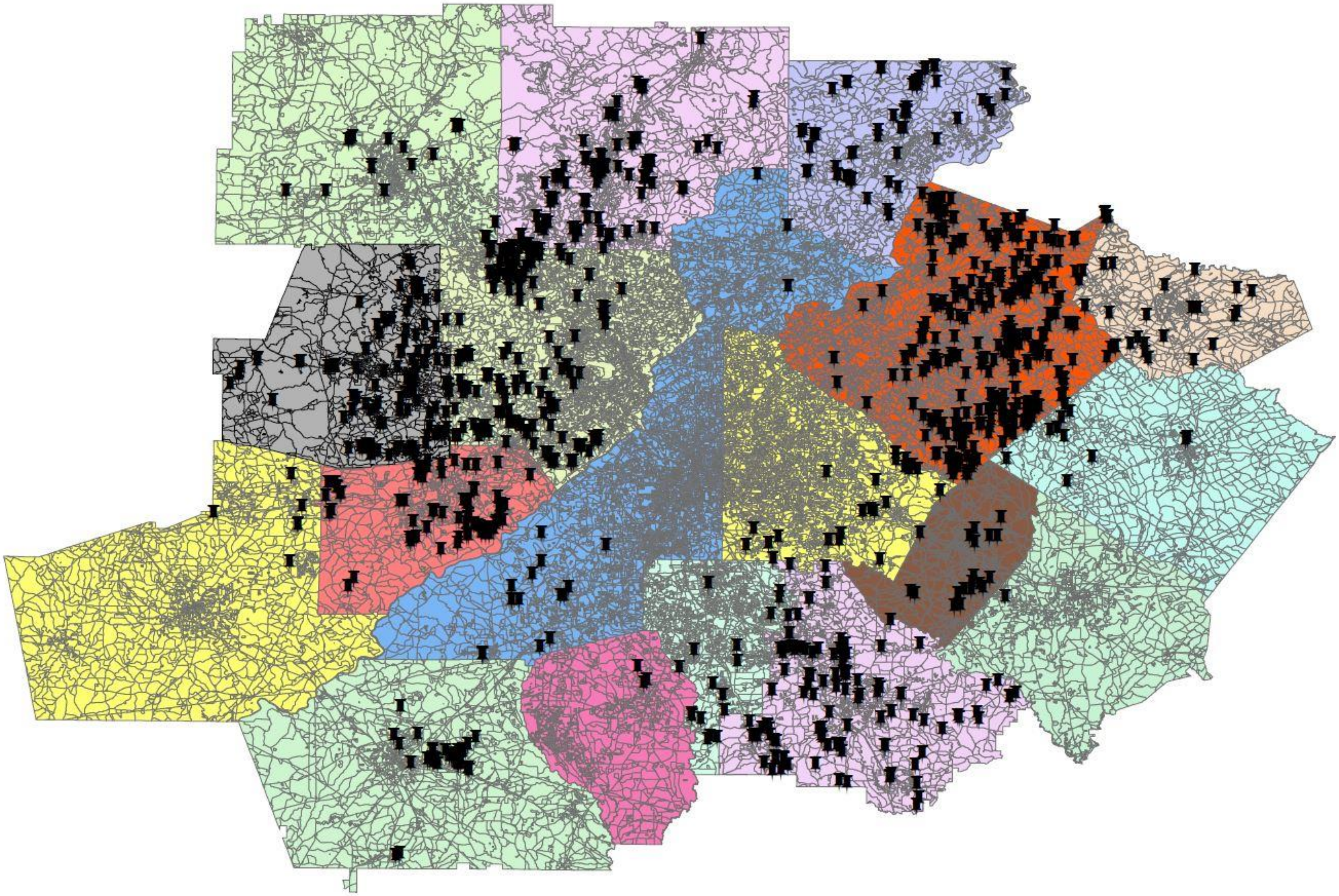


Figure A9: Residential Capital Management Purchases

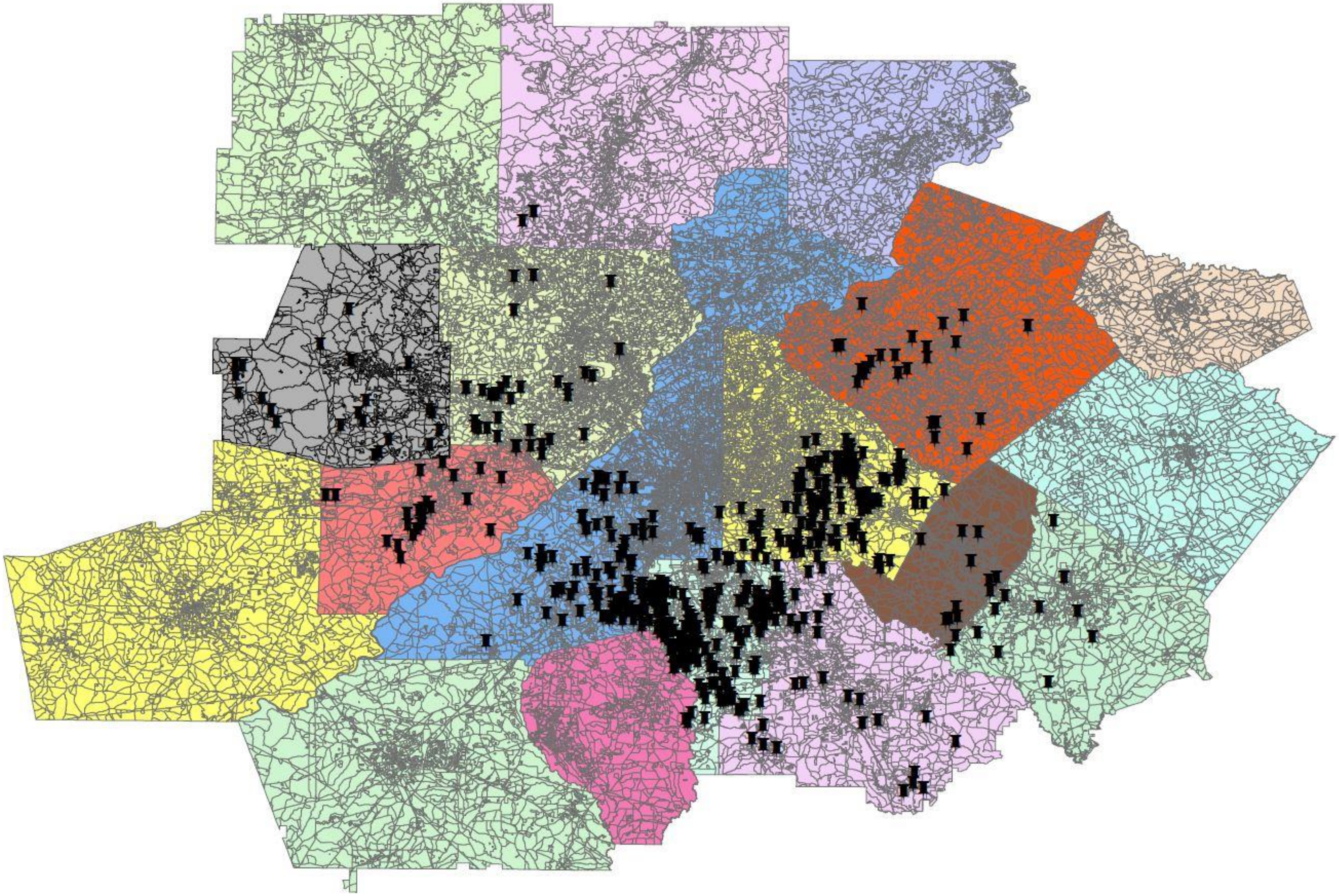


Figure A10: Silver Bay Realty Purchases

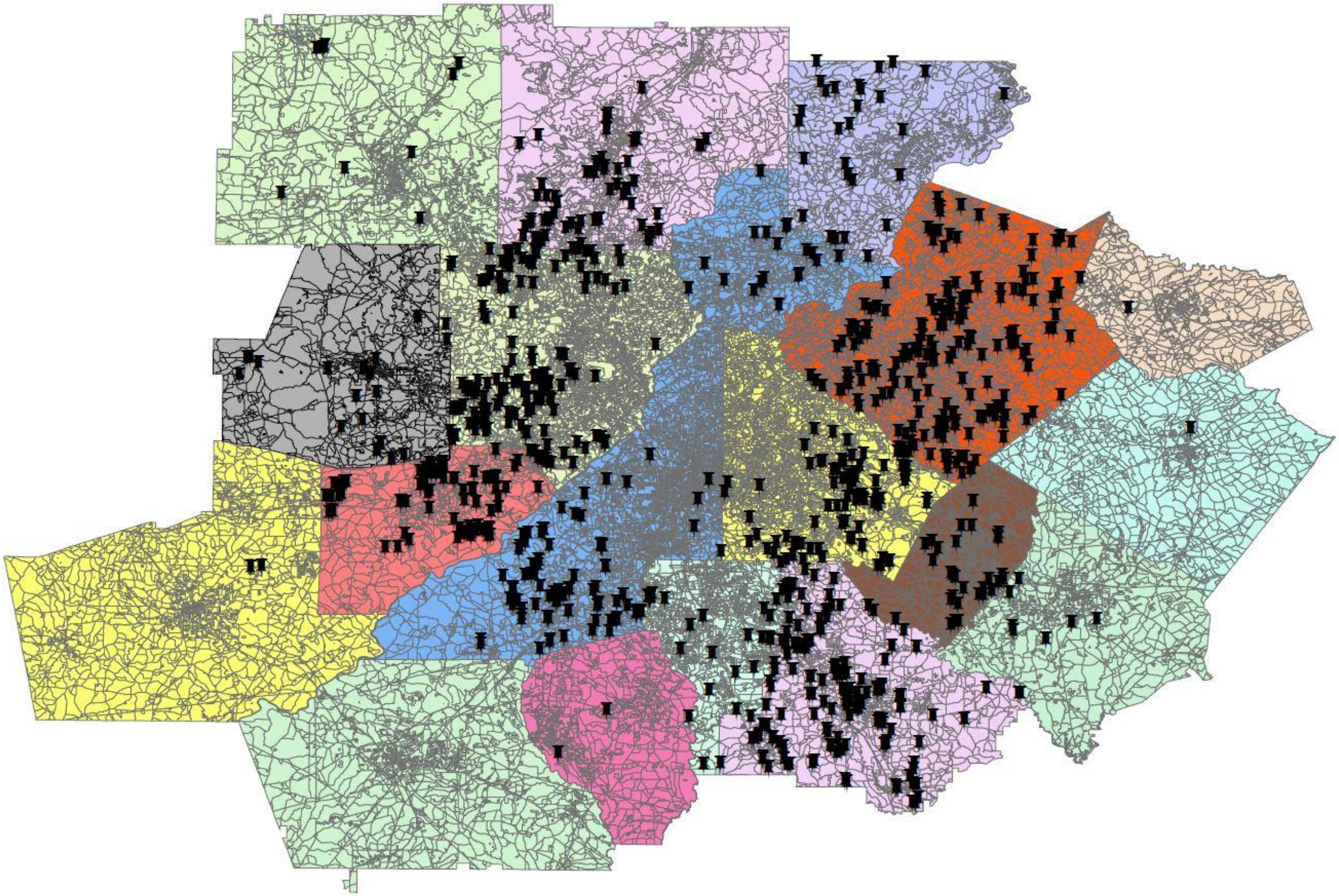


Figure A11: Starwood Waypoint Purchases

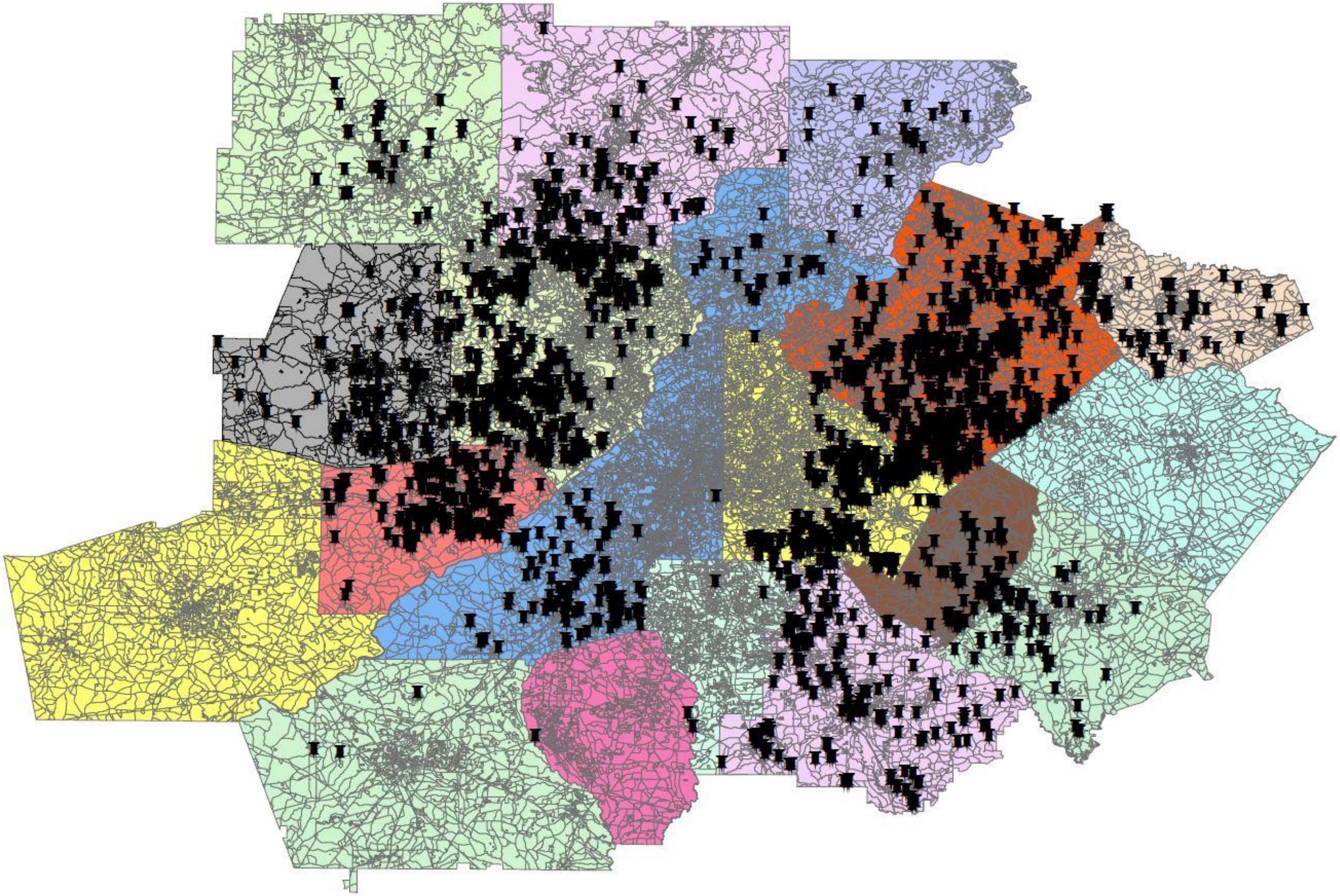


Figure A12: Sylvan Road Capital Purchases

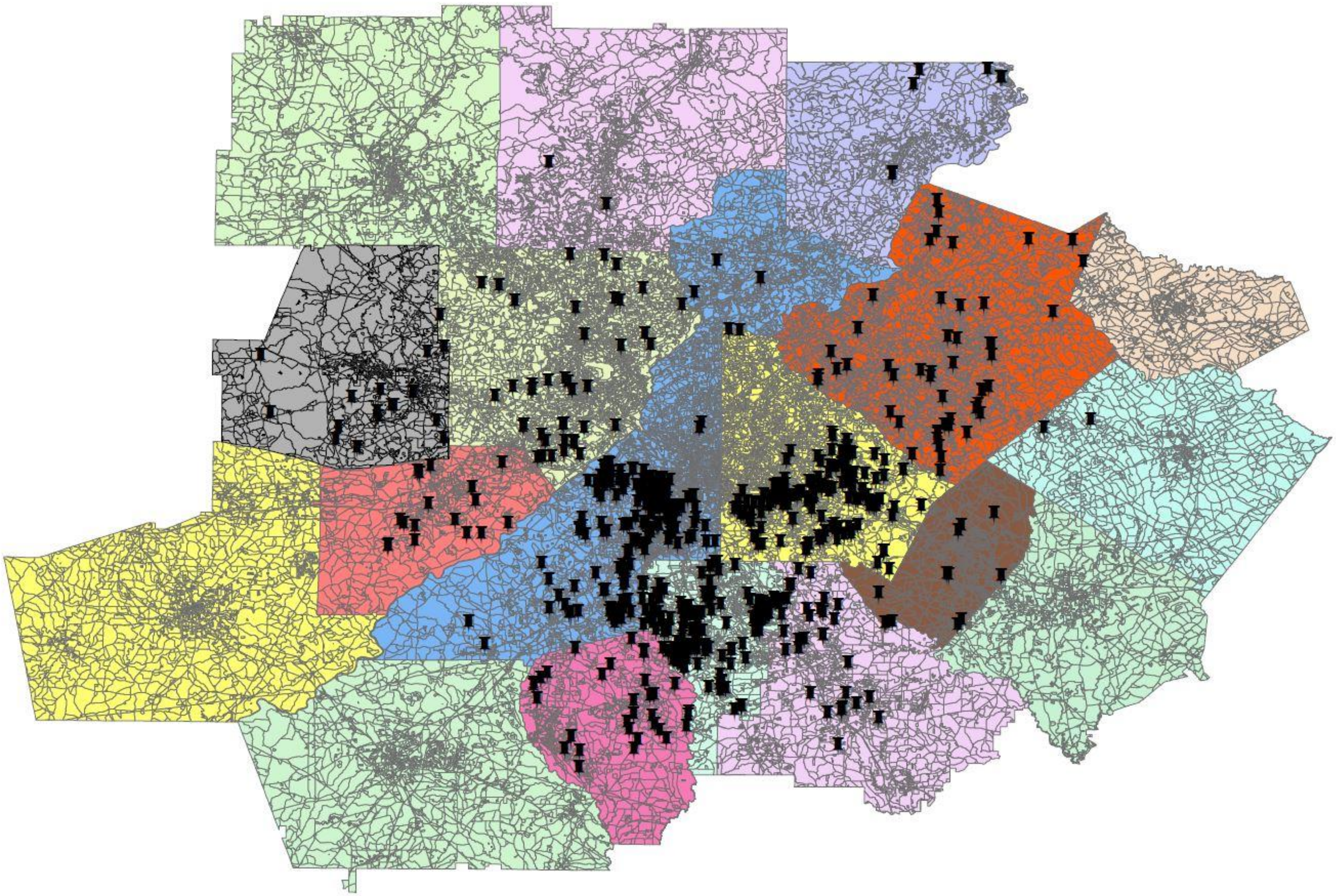


Table B1: Owner-occupied Housing's Asset Illiquidity

	Full Sample	
	(1)	(2)
Own-to-Rent Conversion	0.0318***	0.0356***
	(0.00)	(0.00)
Post * Own-to-Rent Conversion	-0.1441***	-0.1571***
	(0.01)	(0.01)
Cash Purchase	-0.1327***	-0.1110***
	(0.01)	(0.01)
Post * Cash Purchase	-0.1270***	-0.1233***
	(0.01)	(0.00)
Rent-to-Own Conversion	-0.0271***	
	(0.01)	
Post * Rent-to-Own Conversion	0.0062	
	(0.01)	
Rental	-0.0341***	
	(0.00)	
Post * Rental	-0.3171***	
	(0.01)	
Age	-0.0117***	-0.0124***
	(0.00)	(0.00)
Age Squared	0.0001***	0.0001***
	(0.00)	(0.00)
Living Area [Sqft '000s]	0.3363***	0.3401***
	(0.01)	(0.01)
Living Area Squared	-0.0000***	-0.0000***
	(0.00)	(0.00)
Lot Size [Sqft '000s]	0.0028***	0.0028***
	(0.00)	(0.00)
Lot Size Squared	-0.0000***	-0.0000***
	(0.00)	(0.00)

*Table B1 is continued on next page

Table B1: Owner-occupied Housing's Asset Illiquidity (cont.)

	Full Sample	
	(1)	(2)
1 Bedroom [0,1]	-0.0413***	-0.0333*
	(0.02)	(0.02)
3 Bedrooms [0,1]	0.0161***	0.0091**
	(0.00)	(0.00)
4 Bedrooms [0,1]	0.0455***	0.0393***
	(0.01)	(0.01)
5 or 6 Bedrooms [0,1]	0.0735***	0.0687***
	(0.01)	(0.01)
2 Bathrooms [0,1]	0.0539***	0.0497***
	(0.01)	(0.01)
3 Bathrooms [0,1]	0.0878***	0.0837***
	(0.01)	(0.01)
4 to 6 Bathrooms [0,1]	0.2207***	0.2161***
	(0.01)	(0.01)
Fireplace [0,1]	0.0355***	0.0351***
	(0.00)	(0.00)
Garage [0,1]	0.0324***	0.0316***
	(0.00)	(0.00)
Carport [0,1]	0.0324***	0.0315***
	(0.00)	(0.00)
Pool [0,1]	0.0709***	0.0720***
	(0.00)	(0.00)
REO [0,1]	-0.3578***	-0.3428***
	(0.01)	(0.01)
Foreclosure [0,1]	-0.2120***	-0.2263***
	(0.00)	(0.00)
Short Sale [0,1]	-0.1027***	-0.1100***
	(0.00)	(0.00)
Bulk [0,1]	-0.5884***	
	(0.10)	
Time Fixed Effects	Quarterly	Quarterly
Location Control	Census Tract	Census Tract
Number of Observations	1,023,802	898,971
Adjusted R-squared	0.76	0.77

Table B2: Change in house prices by investor share and conversion activity (2012-2014)

	Δ Zipcode HPI		Δ ln(House Prices)		Δ ln(House Prices)	
	Coeff	SD	Coeff	SD	Coeff	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Institution share$_{t-1}$	0.13*	(0.07)	0.38***	(0.05)		
Corporate share$_{t-1}$	-0.02	(0.10)	0.16**	(0.06)		
Individual share$_{t-1}$	-0.08	(0.17)	-0.22**	(0.09)		
Conversion share$_{t-1}$					0.12***	(0.04)
Y_2013	0.13***	(0.01)	0.07***	(0.01)	0.09***	(0.01)
Y_2014	0.16***	(0.02)	0.09***	(0.01)	0.15***	(0.01)
Percent Distress$_{t-1}$	-0.09***	(0.05)	-0.08**	(0.04)	-0.06	(0.04)
Log(Rent)$_{t-1}$	-0.04	(0.08)	-0.04	(0.03)	-0.01	(0.03)
Log(House Price)$_{t-1}$	0.12***	(0.04)	0.03	(0.02)	0.01	(0.02)
Poverty Rate	0.00	(0.0)	0.00	(0.00)	0.00	(0.00)
Unemployment Rate	0.00	(0.0)	0.00	(0.00)	0.00	(0.00)
% with Kids	0.00	(0.0)	0.00**	(0.00)	0.00	(0.00)
% 1st Income Quintile	0.01	(0.01)	-0.02**	(0.01)	-0.01*	(0.01)
% 5th Income Quintile	0.00	(0.0)	0.00	(0.00)	0.00	(0.00)
% Less High School Degree	0.00	(0.0)	0.00**	(0.00)	0.00	(0.00)
% College Grad	0.00	(0.0)	0.00	(0.00)	0.00	(0.00)
% Rental Pre-crisis	-0.20**	(0.12)	-0.28***	(0.10)	-0.24**	(0.11)
Turnover	0.07	(0.39)	0.05	(0.19)	0.14	(0.21)
Number of Observations	183		450		450	
Adjusted R-squared	0.65		0.65		0.59	
Dependent Variable Source	CoreLogic		Zillow		Zillow	

The dependent variable in columns 1 and 2 is the change in the zipcode level home price index that is calculated using the CoreLogic data for all zipcodes with a housing stock greater than 10,000. The dependent variable in columns 3, 4, 5 and 6 is the change in the log of average house prices (zipcode level) reported by Zillow. The controls in columns 2, 4 and 6 include percent distressed sales$_{t-1}$, log(rent$_{t-1}$), log(house price$_{t-1}$), poverty rate, unemployment rate, percent of household with kids, percent of households with income in the first quintile, percent of households with income in the fifth quintile, percent with less than a high school degree, percent with a college degree or higher education level, pre-crisis percent rental, and pre-crisis liquidity. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Homeownership: An examination of its effect on house prices

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Abstract

Subsidizing homeownership is only justifiable if it increases homeownership attainment and creates external benefits that outweigh their costs. Using parcel-level panel data I isolate and examine the effect of homeownership on surrounding house prices. Homeownership has a causal effect on house prices, but substantial variation exists across quantiles. Changes in homeownership have a lesser (greater) effect on house prices in the upper (lower) deciles of the conditional house price distribution - despite the fact that households in the upper deciles are the primary beneficiaries of the federal tax subsidies for homeownership.

1. Introduction

In the United States, homeownership is often considered the “American Dream” and has long been a central focus of housing policy. Homeowners benefit from various local, state and federal programs whose primary purpose is fostering homeownership. In 2014 alone, the federal government provided over $209 billion in homeownership subsidies (U.S. Department of the Treasury 2015).[1] Justifications for such programs are derived from the belief that homeownership creates positive externalities. While homeownership may create positive externalities questions regarding its impact on house prices remain. What is the monetary value of the positive externalities associated with homeownership? Does the monetary value of the positive externalities exceed their cost? Are the positive externalities allocated equally? Although these questions have important policy implications, difficulty in designing and implementing a study that isolates homeownership’s effect on house prices has limited previous research on the topic.

This paper provides a framework to address these questions and offers new insight into the distributional effect of homeownership on house prices. It has two primary goals: (i) to isolate the effect of homeownership, and changes to homeownership rates, on nearby house prices and (ii) to examine the effect of homeownership across the full distribution of house prices. To the best of my knowledge, this is the first study to use parcel-level data to isolate the effect of homeownership, and changes to homeownership rates, on nearby house prices. Isolating the extent and nature of price differentials related to homeownership is difficult because a variety of other factors may be correlated with sales prices and homeownership levels. For example, house prices in neighborhoods with high homeownership likely vary in quality, both structurally and in terms of neighborhood amenities, compared to houses in neighborhoods with low homeownership. Additionally, to properly isolate the effect of homeownership on house price, one needs to compare the effect homeownership has on prices for identical properties. However, due to the heterogeneous nature of real estate this is extremely difficult in practice.

I address these concerns and extend the extant literature using a unique dataset that provides information on sales prices, house characteristics, neighborhood quality, and buyer

[1] To provide a sense of magnitude, the federal government’s subsidy for rental housing was $8.3 billion or just under 4% of the homeownership subsidy.

attributes. The dataset includes every single-family detached sales transaction that occurred in Fulton County, Georgia from 2002-2014. For each transaction I observe the sales price, location, and detailed housing characteristics. I then merge information about the race, sex, mortgage, and income of the buyer to the sales transactions. The dataset also includes annual panel data for the entire housing stock, allowing me to isolate homeownership rates while controlling for differing property type compositions and neighborhood amenities.

High-income households are the primary beneficiaries of the federal government's subsidization of homeownership.[2] Despite this well documented fact, previous studies tend to focus on the average causal effect of homeownership on house prices, so little is known about the relationship over the full distribution of house prices. Understanding the distributional effect of homeownership is important because promoting homeownership, particularly low and moderate income as well as first time homeownership, has been a primary focus for policymakers for several decades.[3] Additionally, knowledge of the distributional effect of homeownership provides a clearer picture of what is driving the mean results and provides insight into the allocation of the positive externalities associated with homeownership.

The results of this study have several important policy implications. First, using a research design that explicitly controls for the unobserved quality of the individual house as well as time-varying neighborhood effects I find that the average causal effect of homeownership on house prices is much lower than previously reported. I estimate that a 10% increase in homeownership results in a 2.6% increase in surrounding house prices.[4] I also document the existence of quantile effects. Ex ante, I would expect changes to homeownership rates to have a greater effect on house prices in the upper deciles of the conditional house price distribution, as the federal tax subsidies for homeownership combined with a progressive income tax favors high income households. However, I find that changes in homeownership rates have a lesser (greater) effect on house prices in the upper (lower) deciles of the conditional house price distribution.

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[2] Poterba and Sinai (2008) show that the mortgage interest tax deduction saves the average homeowner $1,060. However, the average savings for households who make more than $250,000 is $5,459, compared to $91 in savings for households whose annual income is less than $40,000.

[3] For example, the Federal Housing Enterprises Financial Safety and Soundness Act of 1992 established performance standards for the Government Sponsored Enterprises to make homeownership available to a wider variety of households (Case et al., 2002).

[4] Coulson and Li (2013) estimate that a 10% increase in homeownership increases house prices by approximately 6%.

The subsidization of homeownership should also, in theory, directly affect a household's tenure choice. However, the lesser effect of homeownership on house prices in the higher deciles suggests that the federal tax subsidies for homeownership, which provide greater benefits to high-income households, are ineffective. Thus, if promoting homeownership is one of the primary goals of the federal tax subsidies, they are, at a minimum, poorly allocated.

The remainder of the paper is organized as follows. In the next section I provide a survey of the related literature. The paper then proceeds with a detailed overview of the dataset and homeownership measures used in this study. I then present the paper's methodology and empirical results. The paper concludes with a discussion of the potential implications of the findings.

2. External Benefits of Homeownership

Homeownership is heavily subsidized in the United States. Owner-occupiers benefit from the tax exemption of their implicit rental income and the exclusion of capital gains from the sale of their house. Owner-occupiers can also deduct their mortgage interest and property tax payments from their federal income taxes. In addition to the federal government's preferential tax treatment of owner-occupied housing, there are numerous state and local programs designed to promote homeownership.[5]

Several studies offer justifications for subsidizing homeownership by showing that the actions of homeowners create positive external benefits for their surrounding neighborhoods. Green and White (1997) find that children who grow up in owner-occupied housing, especially those in low-income households, have higher high school graduation rates. However, Aaronson (2000) notes that owner-occupiers have longer tenure than renters, so the positive effect may not be a result of the type of housing and instead a result of the length of tenure. Haurin et al. (2002) find that owning a house, compared to renting, results in greater cognitive ability and fewer child behavior problems; although follow-up studies by Barker and Miller (2009) and Holupka and Newman (2012) contradict Haurin et al.'s (2002) findings. DiPasquale and Glaeser (1999) argue that homeowners, who are less mobile, have an incentive to invest more social capital in their

[5] For example, in the Atlanta market that this study focuses on the *Georgia Dream Homeownership Program* provides first mortgage loans and down payment assistance to low income home buyers. To be eligible for the program the borrower must meet income and purchase price limits, have limited assets, and invest at least $1,000 into the sales transaction.

neighborhoods. Thus, they are more likely to get involved with local organizations and vote. In contrast, Engelhardt et al. (2010) find little evidence that homeowners are more involved in neighborhood organizations and Hilber and Mayer (2009) find that the positive externalities related to homeownership are likely confined to places with an inelastic supply of housing. Additionally, Hilber and Turner (2014) show that in areas with an inelastic housing supply the federal tax subsidies, the MID specifically are often capitalized into house prices, adding costs rather than boosting homeownership attainment. In addition to the conflicting results above, the studies are unable to quantify the monetary value of the external benefits.

The use of microdata allows me to estimate the monetary value of the positive externalities created by homeownership. Similar to Coulson and Li (2013), I argue that the subsidization of homeownership is only justifiable if the external benefits created as a result of the subsidies exceed their cost (i.e. forgone tax revenue). Coulson and Li (2013) measure the external benefits of homeownership in the form of higher house prices using data from the American Housing Survey. Using neighborhood clusters ranging in size from 4 to 11 units, Coulson and Li (2013) estimate the average causal effect of homeownership on house prices. The authors find that a transition in housing tenure from renting to owning creates positive external benefits (i.e. increases nearby house prices). This study is similar, in that, I measure the external benefit of homeownership in terms of higher house prices. However, this study differs in several key ways. First, I use negotiated sales transactions, instead of self-reported value estimates from homeowners. Second, the use of microdata allows me to examine the sensitivity of the empirical results to the areal unit (i.e. scale) at which homeownership is measured. I use both predefined geographical units and continuous spatial measures to estimate homeownership, which allows me to examine how house prices are affected by the overall tenure composition of a neighborhood, in addition to the tenure status of properties in the immediate vicinity of a house.[6] The comprehensive dataset allows me to employ a research design that explicitly controls for the unobserved quality of the individual house as well as time-varying neighborhood effects. I also show that homeownership's effect on house prices varies across the house price

[6] The American Housing Survey data used in Coulson and Li (2013) includes neighborhood clusters that range in size from 4 to 11 units. If house prices are affected by the tenure composition of the surrounding neighborhood (outside the neighborhood clusters) then the coefficient estimates may be biased.

distribution and, as such, the effectiveness of programs that promote homeownership among targeted groups, such as low and moderate income households, will vary as well.

3. Data and Summary Statistics

3.1 Homeownership Distributions

When examining the external benefits of homeownership, I argue that the distributional effect should be estimated to provide a clearer picture of what is driving the mean results. To support this conjecture I tabulate homeownership levels based on income and home value deciles. Table 1 displays homeownership rates by median income deciles. Median income is assigned at the block-group level using five year estimates from the 2013 American Community Survey (ACS). As expected, homeownership rates rise as the median income of the census block-group increases. The relationship is clearly displayed in the top section of Table 1 as homeownership rates monotonically decline from 91.8% (91.0%) for the tenth decile to 69.9% (56.0%) for the first decile in 2002 (2014). The upward sloping relationship holds over the entire length of the study regardless of market conditions (i.e. pre- and post-crisis).

[Insert Table 1]

In the middle and bottom sections of Table 1 I partition the data based on the property type composition of the census block in which the house is located. The middle section includes homogeneous census blocks that contain only single-family detached housing. Whereas, the bottom section of the table includes census blocks that contain a mix of single-family detached, single-family attached and multi-family housing units. I separate the data in this manner as previous research has shown that homeownership is strongly associated with single-family detached housing structures (Glaeser and Shapiro 2003) and including multiple structure types complicates the analysis (Coulson and Li 2013). Although the relationship between income and homeownership remains in both sections, homeownership rates are noticeably lower in the lower income deciles of the heterogeneous housing stock sample.

Table 2 presents homeownership rates by assessed value deciles.[7] The assessed value deciles are assigned based on the house's assessed value in 2002 or the year in which it was built if after 2002. The assessed value represents the houses' value prior to the real estate boom. Table 2 shows that a house's tenure status is highly correlated with its assessed value. Similar to the median income deciles, the relationship between assessed value and homeownership rate is upward sloping. In 2002 (2014) the homeownership rate in the first decile was 62.3% (49.1%) compared to 90.5% (90.3%) in the tenth decile. Table 3 displays the average assessed values for the median income deciles presented in Table 1. As expected, the average assessed value of a neighborhood increases as the median income of the census block-group in which the house is located increases.

[Insert Table 2]

The stylized facts presented in this section set the stage for the analysis going forward. The summary statistics show that homeownership increases as the average assessed value and income of the neighborhood increases. Although the summary statistics do not show that homeownership has an effect on house prices, they do suggest that a relationship exists and that it may vary across the distribution of house prices.

[Insert Table 3]

3.2 Data Overview

The Fulton County Tax Assessor's office provided two complementary datasets. Fulton County is the most populous county in the state of Georgia and includes the city of Atlanta. The assessment dataset includes property-level information for every parcel in Fulton County on an annual basis from 2002 to 2014. The dataset includes detailed information about the parcel itself, such as lot size and land use codes, as well as the physical characteristics of the dwelling unit(s) built on it. The transaction dataset includes every real estate transaction that was recorded from 2002 to 2014. The sales transaction file includes information about the buyer and seller, such as their name and address, which I use to identify owner-occupiers. It also includes, among other things, the sales date, purchase price, and the type of deed that was conveyed.

[7] I use assessed values, instead of sales price, to create the deciles because they are available on an annual basis for every house in the study. Whereas, sales price (i.e. transaction value) is only available when and if a house is sold. 51.9% of the single-family detached houses did not transact from 2002 – 2014.

Later in this study I use a subset of the Fulton County Tax Assessor data that has been merged with publicly available loan application registry data gathered under the Home Mortgage Disclosure Act (HMDA). The subset is created by merging the Fulton County data with proprietary transaction data obtained from CoreLogic. The CoreLogic data includes additional loan level information such as the lender name and loan amount. I then match the combined transaction dataset with the HMDA dataset based on each transaction's (i) census tract, (ii) year of the transaction, (iii) lender name, and (iii) loan amount. The HMDA dataset provides detailed demographic and economic information about the buyer.

3.3 Measuring Homeownership

To the best of my knowledge, this is the first study to use parcel-level data to isolate the effect of homeownership, and changes to homeownership rates, on nearby house prices. The use of microdata allows the examination of the external benefits of homeownership over time across areal units of differing size, as I expect the external benefits of homeownership to depend not only on the tenure status of the house itself, but also on the overall tenure composition of its surrounding neighborhood. If homeowners create positive external benefits for their surrounding neighborhoods then households should be willing to pay more to live near other homeowners; thereby allowing me to quantify the monetary value of homeownership by examining whether households are willing to pay more to live in neighborhoods with higher homeownership levels.

One of the primary goals of this paper is to isolate the effect of homeownership, and changes to homeownership rates, on nearby house prices. To achieve this goal I create a series of variables that measure homeownership rates at several areal units of differing size. I estimate homeownership rates over time using predefined geographical groupings based on the United States Census Bureau's census tract, block-group, and block levels.[8] I also estimate homeownership rates by neighborhood based on geographical groupings designated by the Fulton County Tax Assessor's office. I use several measures as previous research shows that the results of linear regressions are sensitive to the areal unit chosen (Openshaw and Taylor 1979; Fotheringham and Wong 1991). In addition to the predefined geographical groupings I create continuous spatial measures of homeownership.

[8] I associate every housing unit in Fulton County to its 2010 census tract, block-group, and block.

I use the annual tax assessment datasets that contain Fulton County's entire housing stock to estimate the homeownership rate measures. For each single-family detached record in the dataset, I observe the property's address *and* the mailing address where the county sends the property's tax bill. If the mailing address matches the property's address I assume the property is owner-occupied. If the mailing address does not match the property's address, but the mailing address is a local post office box – I then examine if the post office box is associated with multiple single-family detached houses. If the post office box is only associated with one single-family detached house I consider that house owner-occupied. If the mailing address does not match the property's address, the post office box is not local, or the post office box is associated with multiple single-family detached houses I assume the property is not owner-occupied. The annual homeownership measures represent the homeownership rate at the beginning of the year (i.e. January). I then create monthly homeownership measures by merging and incorporating the transaction data. If a property was owner-occupied in the annual file, but then was sold to an investor between January 1st and January 31st, the house's change in tenure would be included in February's homeownership measure.[9]

Table 4 provides an overview of the average size of the housing stock and homeownership rate for each predefined areal unit that contains a minimum of five single-family detached houses for the entire length of the study. The first column of each section in Table 4 presents a summary of the housing stock and homeownership rate for the complete data sample in four year increments using the annual parcel files. As displayed in the first column of 2002, census tracts represent the largest areal unit with an average housing stock of approximately 856 units. Census block-group is the second largest (~335 units), tax assessor neighborhood is the third largest (~160 units), and census blocks are the smallest (~29 units).[10] The second column of

[9] When merging the homeownership measures with the transaction data I associate each transaction with the previous month's homeownership measure for each predefined areal unit grouping. This ensures that a change in tenure status of the house in the current transaction is not included in the homeownership measure used in the analysis. The approach also aligns the homeownership measure so it reflects the market conditions when the sales contract was signed (instead of when the sale was closed). I also associated the homeownership measures using a two month lag. The results are similar to those reported using a one month lag. They are not reported in this paper, but are available upon request from the authors.

[10] Census blocks are the smallest geographic area at which the Census Bureau collects data. According to the census website (www.census.gov), census blocks are "formed by streets, roads, railroads, bodies of water, other visible physical and cultural features, and the legal boundaries shown on Census Bureau maps." Census block-groups consist of a cluster of census blocks and generally contain between 600 and 3,000 people. Block-groups can contain up to 999 unique census blocks.

each section contains areal units that only include single-family detached housing (i.e. there are no single-family attached or multi-family housing units in the areal unit) for the length of the study. As expected, as the size of the areal unit increases, there are fewer observations that include only single-family detached housing. The third column of each section contains areal units that include a mix of single-family detached, single-family attached and multi-family housing.

[Insert Table 4]

A comparison of the April 2010 block-group homeownership rates to the census 2010 SF1 homeownership rates shows that the two measures are highly correlated (~.96). A direct comparison for every block-group is not possible because the census homeownership rates are based on housing units - whereas the homeownership rate in this study is based on single-family detached houses only.[11] Additionally, the census homeownership rate only includes occupied housing units – whereas this study includes every single-family detached house regardless of occupancy.[12] Thus, when comparing the two homeownership rate measures I limited the comparison to the 46 census block-groups that contain only single-family detached housing in April 2010.

The use of predefined areal units is a convenient way to aggregate and estimate homeownership measures. However, the size and shape of census blocks, block-groups and tracts vary within and between areas. Additionally, the location of a house within the areal unit may potentially bias the effect of homeownership on its price. For example, the census block homeownership rate measure is likely more appropriate for a house centrally located within the census block compared to a house located on its border. As a robustness check - I create monthly spatial homeownership measures using radiuses of 0.05, 0.10, 0.25, 0.50, and 1.00 mile.[13] In addition to accurately estimating the homeownership rate, the continuous spatial measures allow

[11] The census bureau defines a housing unit as "a house, apartment, mobile home or trailer, group of rooms, or a single room that is occupied, or, if vacant, is intended for occupancy as separate living quarters."
[12] The census bureau defines an occupied housing unit as a housing unit where someone was staying or living on Census Day (April 1, 2016) and the unit was their usual residence (i.e. they stayed their most of the time).
[13] The .05 mile radius represents a radius of approximately 264 feet, .10 mile radius = 528 feet, .25 mile radius = 1320 feet, .5 mile radius = 2640 feet, and 1.0 mile radius = 5,280 feet. See Figure A1 for a visualization of the radiuses employed in this study.

me to precisely partition the data into subsamples based on surrounding property type compositions.

Table 5 provides an overview of the average size of the housing stock and homeownership rate for each radius distance. A house is only included if there are five single-family detached houses within the given radius distance. The summary statistics presented in Table 5 are cumulative, so the .10 mile radius for each house includes the housing stock in the .05 mile radius measure. The first column of each section presents a summary of the housing stock and homeownership rate for the entire housing stock, regardless of the property type composition, in four year increments. As displayed in the first column of 2002, the 1.00 mile radius represents the largest continuous spatial measure with an average housing stock of approximately 1,771 units, which is approximately twice the size of a census tract in Table 4. The half mile radius measure averages 533 single-family detached housing units placing it somewhere between the average size of a census tract and a block-group. The quarter mile radius averages 167 units making it comparable in size to the tax assessor neighborhood grouping (~160 units). The second column of each section contains houses in which the radius specified only contains single-family detached housing. Similar to the areal units in Table 4, as the size of the radius increases, there are fewer observations that contain only single-family detached housing. The third column of each section contains houses in which the radius specified contains a mix of single-family detached, single-family attached and multi-family housing.

[Insert Table 5]

In Table 6, I present changes in homeownership rates at the block, neighborhood, and block-group levels on an annual basis for the length of the study. As the size of the areal unit increases, the range of the change in homeownership rates contracts. The likelihood that an areal unit experiences no change in homeownership increases as the size of the areal unit decreases. This represents a classic case of the modifiable areal unit problem (MAUP) in which the effect of homeownership on house prices may be sensitive to the scale at which the analysis is run (i.e. the spatial size of the areal unit). Openshaw and Taylor (1979) empirically show that changing the scale of an areal unit alters the findings in statistical tests. As such, I run the analysis using multiple areal units of differing sizes to demonstrate the sensitivity of the homeownership measure and the robustness of my findings.

[Insert Table 6]

Fulton County was created in 1853 from the western half of DeKalb County and grew into a "strange, elongated shape by absorbing the counties of Milton (to the north) and Campbell (to the south) during the Great Depression."[14] Figure 1 provides a rough outline of Fulton County and displays the change in homeownership rates at the census block level for the entire study period (2002 to 2014). The change in homeownership rate is only plotted for homogeneous census blocks that contain only single-family detached housing for the entire study period. In the appendix Figure A2, A3, and A4 provide similar information for changes in homeownership rates from 2002 to 2006, 2006 to 2010, and 2010 to 2014, respectively.[15]

[Insert Figure 1]

3.3 Sales Transactions

After merging the two Fulton County tax assessor datasets, I remove sales transactions that had empty key fields (such as number of bathrooms or square feet of living area), were located in census blocks with less than five single-family detached houses, or included multiple parcels. I also filter out all records that had more than six bedrooms, six bathrooms, lot size greater than five acres, or that was in "unsound" physical condition. Finally, I winsorize the data to remove transactions with sales prices in the 1st and 99th percentile. The final cleansed full dataset contains 1119,793 sales transactions. Table 7 displays the means and standard deviations for the variables used in the analysis.

[Insert Table 7]

A change in a house's tenure from owner-occupied (rental) to a rental (owner-occupied) is often associated with a sales transaction. If an increase in transaction volume coincides with the change in homeownership, then a portion of the effect on house prices may be the result of a liquidity shock. To disentangle changes in homeownership and market liquidity I include a turnover variable that measures the number of sales transactions over the past six months divided

[14] Additional information on Fulton County's history is available on Georgia's website: https://georgia.gov/cities-counties/fulton-county
[15] The time periods in Figures A2, A3, and A4 align with the data presented in Table 4.

by the housing stock within the areal unit.[16] I also include two proxies for private investment in new and existing structures. An increase in the number of new houses or investment in existing structures likely creates positive externalities that increase surrounding home values. As such, I include two variables that identify the fraction of the housing stock that was (i) built within the last three years or (ii) remodeled within the last three years. I identify whether a house was remodeled using the 'effective year built' field in the Fulton County tax assessor data. The 'effective year built' field identifies the year in which the house underwent a major addition, but does not identify minor remodeling projects that do not require a permit.[17]

In addition to the market liquidity and private investment variables I control for several additional neighborhood characteristics. Given the time period of the study, house prices may be influenced by distressed sales of surrounding properties (Harding, Rosenblatt, and Yao 2009). To address this potential concern, I include a distressed turnover variable that I calculate as the number of distressed sales over the past six months divided by the housing stock within the areal unit. I also include a school test score variable that represents the average elementary school test score on the annual state administered Criterion-Referenced Competency Test (CRCT). The remaining neighborhood variables (median income, percent poverty, percent white, percent with less than a high school education, and percent with college degree) are all gathered at the census block-group level from the 2010 census.

The first section of Table 7 displays summary statistics for the complete cleansed dataset. The second (columns 3 and 4) and third (columns 5 and 6) sections are partitioned by buyer type. If an owner-occupier purchased the house it is included in columns 3 and 4, otherwise the sales transaction is included in columns 5 and 6. The average sales price over the length of the study is just over \$261,000 – although the average sales price for houses purchased by owner-occupiers (\$312,547) was considerably higher than investors (\$161,414). This is not surprising because, on average, the owner-occupied houses are, among other things, more expensive, larger, in better condition, and less likely to be part of a distressed sales transaction. Of the 119,793 sales

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[16] I append transaction data from CoreLogic that extends back to 2000 to the Fulton County transaction data to create the turnover variable, so that no records are dropped.
[17] If a house was built in 1985 and had a major addition in 2004 (i.e. an additional bedroom and bathroom were added to the structure) then the house's 'effective year built' in the Fulton County tax assessor data would be 2004. The house would be included in the remodeled variable for the next three years.

transactions in the cleansed dataset, 79,104 were owner-occupied sales transactions and 40,689 were investor sales transactions.

Table 8 stratifies the owner-occupied transactions into two property composition subgroupings by time period. Columns 1 to 4 include summary statistics for sales transactions that took place in homogeneous census blocks that do not contain single-family attached or multi-family housing and columns 5 to 6 include summary statistics for sales transactions that took place in heterogeneous census blocks that contain a mix of property types. The property type composition subgroupings show that houses in homogeneous census blocks are, on average, more expensive, younger, bigger, and in better condition.

[Insert Table 8]

4. Methodology and Results

4.1 Average Effect of Homeownership

Using parcel-level data that includes individual property characteristics and homeownership information for every single-family house allows me to employ a hedonic pricing method, similar to the method popularized by Rosen (1974), to examine households' valuation of nearby homeownership levels. I begin with a log-linear hedonic model of house prices:

$$p_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 S_{it} + \beta_3 N_{jt} + \beta_4 H_t + \gamma_{it} + \phi_{jt} + \varepsilon_{ijt} \qquad (1)$$

where p_{ijt} is the log of the sales price for house *i* in areal unit *j* at time *t*. Sales price is a function of a vector of the house's physical characteristics X_{it}, sales conditions S_{it}, neighborhood characteristics N_{jt}, and nearby homeownership levels H_t. Unobserved characteristics of the house and areal unit are represented by γ_{it} and ϕ_{jt}, and ε_{ijt} is a random error term. I recognize that variations in homeownership may be correlated with unobservable factors, so Equation 1 controls for spatial heterogeneity using a standard fixed effects approach at various levels (census tract, census block-group, and tax assessor neighborhood). I further allow error terms to be clustered at the census tract, block-group, and neighborhood level, respectively. Indicator variables are also included to control for quarterly time fixed effects.

The X_{it} vector includes the house's age, square feet of living area, lot size, number of bedrooms, and number of bathrooms. It also includes indicator variables to identify if the house has a fireplace, garage, carport, fireplace, pool, and the condition of the house. The S_{it}vector includes indicator variables that identify whether the transaction was a cash purchase, short sale, foreclosure, or real estate owned (REO) transaction. The N_{jt} vector includes market liquidity, private investment, percent of distressed sales, and census variables discussed in the data section.

Table 9 presents estimation results for the mean effect of homeownership on house prices using several specifications of Equation 1. The estimates reported represent a total of 47 regressions that differ only in the combination of the areal unit or radius distance in which homeownership is measured, the neighborhood's property type composition, and the location fixed effect used. Homeownership is measured at the census block, tax assessor neighborhood, and census block-group levels as well as several continuous radius distances as denoted by the row names. I run the regression analysis on the entire transaction sample in the first section, and then partition the data in the second and third section based on the property type composition within the homeownership measure. I control for location fixed effects at several levels. The first column of each section (columns 1, 4, and 7) controls for spatial heterogeneity at the census tract level. The second and third column of each section controls at the census block-group and tax assessor neighborhood levels, respectively. The dependent variable in every column is log of sales price.

[Insert Table 9]

In Table 9 the coefficient on the key variable of interest, homeownership rate, is positive and significant regardless of the measure used. [18] The homeownership rate is a decimal in the dataset, so the coefficients in Table 9 can be interpreted as the percentage change in house prices as homeownership rates move from 0% to 100%. The coefficient in the first row of Column 1 can be interpreted such that a 10% increase in homeownership results in a 4.7% increase in sales price. The coefficients for the census block homeownership measure in the first row are relatively similar across each column, ranging from 4.1% to 4.9% (based on a 10% increase in homeownership rates).

[18] Table A1 in the appendix presents results for all the variables in the block level regressions using data from the entire study period.

The results for the homeownership rates measured at the tax assessor neighborhood and census block-group level are displayed in the second and third row, respectively. As the size of the areal unit at which homeownership is measured increases, the magnitude of its coefficient increases in the regression results. This is expected because the results of spatial analysis are sensitive to the scale at which they measured. The range of coefficients in the second row, where homeownership is measured at the tax assessor neighborhood level, is wide compared to the first row. When homeownership is measured at the tax assessor neighborhood level, a 10% increase in homeownership results in an increase in sales price from 6.9% (column 5) to 17.1% (column 8). Note that the coefficients in homogeneous neighborhoods, where the entire housing stock is single-family detached, are more comparable to the first row. However, the coefficients in neighborhoods with a heterogeneous housing stock are much higher which suggests that including neighborhoods with multiple structure types complicates the analysis. When homeownership is measured at the census block-group level, a 10% increase in homeownership results in an increase in sales price ranging from 17.4% (column 7) to 31.1% (column 6). The larger coefficients are now in the homogeneous neighborhoods.[19]

The results for the continuous homeownership radius measures are similar to the predefined areal units, in that, as the size of the radius increases, the magnitude of the homeownership coefficient increases. At first glance, the results suggest that the value of a house is impacted not only by the properties that immediately surround it (census block), but also by the ownership composition of the surrounding area (census block-group). However, when interpreting the results it’s important to keep the scale of the homeownership measure in mind, as a 10% increase in homeownership in a census block-group is less likely to occur compared to a 10% increase in a census block. For example, a 10% decrease in homeownership rate at the block-group level in 2014 would, on average, represent a change in tenure status of 49 houses. Whereas, a 10% decrease in homeownership at the block level would, on average, only represent a change in tenure status of 3 houses.

In Table 10 I further partition the dataset into pre-crisis (2002-2006) and post-crisis (2007-2014) time period subsamples. The subsamples only include areal units that have a homogeneous housing stock (i.e. single-family detached housing only). I re-estimate the mean

[19] As displayed in Table 4, only 9.2% (46 of the 501) of the block-groups have a homogeneous housing stock (i.e. 100% single-family detached).

effect of homeownership on house prices using several specifications of Equation 1. The estimates reported represent a total of 38 regressions that differ only in the combination of the homeownership measure, neighborhood property type composition, and location fixed effects used. The pre-crisis subperiod represents an up market in Atlanta; whereas the post-crisis market represents a down market. The results highlight the impact homeownership rates have on house prices across housing market cycles and suggest that market conditions differed in the pre- and post-crisis subperiods. Thus, the use of individual time and location fixed effects in Equation 1 may not be optimal.

[Insert Table 10]

The estimates reported in Tables 9 and 10 may also suffer from an omitted variable bias as the standard fixed effects approach using in Equation 1 assumes that the unobservable house (γ_{it}) and areal unit (ϕ_{jt}) characteristics are constant over time. However, if γ_{it} and ϕ_{jt} are changing over time and their change is correlated with changes to homeownership then the fixed effect coefficient estimates will be inconsistent. In the next step of the analysis I address these concerns by explicitly controlling for the unobserved quality of the individual house and neighborhood. To do so, I capitalize on the extended timeframe of the study using a repeat-sales specification with time-varying census tract effects. Equation 2 is a repeat sales specification that includes house fixed effects:

$$p_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 S_{it} + \beta_3 N_{jt} + \beta_4 H_t + \mu_i + \Omega_{jt} + \varepsilon_{ijt} \qquad (2)$$

where p_{ijt} is the log of the sales price for house *i* in areal unit *j* at time *t*. Sales price is a function of a vector of variables that include the house's physical characteristics X_{it}, neighborhood characteristics N_{jt}, and the surrounding homeownership rate H_t.[20] House-specific fixed effects and a set of tract-by-time fixed effects are denoted by μ_i and Ω_{jt}, respectively.[21] The inclusion of house fixed effects ensure that the homeownership coefficient is estimated by comparing identical houses, while the tract-by-time fixed effects ensure that the comparisons are made

[20] The majority of the house and neighborhood variables do not change over time, so they are differenced out (see Equation 3). Thus, in Equation 2 X_{it} represents the physical condition of the house and N_{jt} represents the distressed contagion variables.

[21] The house fixed effects variables assume that the house characteristics and quality remain constant over the study period. I include the tax assessor house condition variables to control for changes in the condition of the house over time.

within the same areal unit during the same time period. To demonstrate how the effect of homeownership is identified in Equation 2 I rewrite the equation by differencing observations for consecutive pair of repeat transactions for house *i* at times *t* and t':

$$p_{ijt} - p_{ijt'} = \beta_1(X_{it} - X_{it'}) + \beta_2(S_{it} - S_{it'}) + \beta_3(N_{jt} - N_{jt'}) + \beta_4(H_t - H_{t'}) + (\Omega_{jt} - \Omega_{jt'}) + \epsilon_{ijt} \quad (3)$$

The house fixed effect and physical characteristics of the house drop out of Equation 3 because the same house is being compared.[22] One drawback of the repeat sales model is that it requires a minimum of two sales transactions for a house. Thus, if a house only sold once during the study period (2002-2014) it is not included in the analysis.

In the first row of Table 11, I estimate the effect of homeownership at the census block level. The results are relatively stable regardless of the time period chosen - a 10% increase in homeownership increases house prices between 2.6 to 2.9%. The results are similar, although the magnitude of the coefficient decreases, when I estimate the impact of homeownership on house prices using a 0.10 mile radius measure.

[Insert Table 11]

The relationship between household income, house values and homeownership displayed in Tables 1 to 3 shows that as income and house value increase, homeownership increases and rentership decreases. This is problematic, because it suggests that homeownership is endogenous and correlated with household income and house prices. To address this concern, I merge the Fulton County Tax Assessor datasets with HMDA data. The HMDA dataset includes demographic information about the buyer, allowing me to instrument for the decision to become a homeowner using the homebuyer's demographic information D_{it}.

$$O^*_{ijt} = \beta_1 D_{ijt} + \varepsilon_{ijt} \quad (4)$$

Equation 4 estimates a bivariate probit model where O^*_{ijt} represents the likelihood that a house *i* in census tract *j* at time *t* will be purchased by an owner-occupier. I use the estimated parameters

[22] To ensure the house fixed effect represents the same quality house (i.e. constant-quality model) I filter out repeat sales transactions in which I have reason to believe the house has undergone a major renovation between sales transactions. I also filter out repeat sales transactions that have an exceptionally high rate of appreciation (greater than 10% per quarter) as they likely underwent major renovations to justify the extraordinarily high rate of appreciation.

from Equation 4 to calculate an inverse Mills ratio, which I include as an additional explanatory variable in Equation 1.

The results reported in Table 12 are comparable to the results reported in Tables 9 and 10.[23] Note that the results in Table 12 are the product of specifications that include an inverse Mills ratio and the truncated HMDA data subset.[24] The inclusion of the inverse Mills ratio for homeownership does not change the relationship between homeownership and house prices. Thus, I conclude that an increase in surrounding homeownership rates causes an increase in house price, regardless of the specification, homeownership measure, or one's treatment of potential endogeneity issue. The initial estimates were relatively unstable across the housing market cycle (i.e. pre-crisis vs. post-crisis), however after controlling for time-varying census tract effects I find that a 10% increase in homeownership results in a 2.6% increase in house prices on average.

[Insert Table 12]

I find that the magnitude of the homeownership coefficient increases as the scale of its measure increases, so I would expect the estimate to be greater than or equal to previous estimates that used a smaller scale. However, the estimates are considerably lower than the 6% estimate reported in Coulson and Li (2013) despite the fact that the average size of the measures are, in terms of housing stock, nearly three times as big as the clusters used in their study. In the next section, I move beyond estimating the average effect of homeownership on house prices and instead test for the existence of quantile effects.

4.2 Distributional Effect of Homeownership

Koenker and Bassett (1978) originally proposed the quantile regression approach.[25] Quantile regression estimates a conditional quantile function in which a quantile of the dependent variable's conditional distribution is expressed as a function of covariates. Thus, quantile regressions differ from hedonic regressions that estimate a mean conditional function as

[23] Column 1 of Table 12 is similar to the specification used to estimate the first row of Column 4 in Table 9. Column 2 (3) of Table 12 is similar to the specification used to estimate the first row of Column 1 (4) in Table 10.

[24] The HMDA data does not include cash purchases, private party loans, unmatched records, or matched records with blank demographic fields. For example, the sample size for Column 4 of Table 9 is larger (N = 47,570) compared to Column 1 of Table 12 (N = 23,111).

[25] Several real estate studies have used quantile regression including, but not limited to Gyourko and Tracy (1999), McMillen and Thorsnes (2006), Coulson and McMillen (2007), and McMillen (2008).

they allow their estimates to vary with the corresponding quantile, so they are particularly useful when quantile effects exist. The primary difference between ordinary least squares regression and quantile regression is that quantile regression minimizes the weighted sum of absolute residuals instead of the sum of squared residuals. The quantile minimization procedure can be expressed as:

$$\widehat{\beta_\theta} = \underset{\beta_\theta \in R^K}{\arg\min} \sum_{a=1}^{A} |p_a - x_a\beta_\theta|\, w_a \tag{5}$$

where A is the complete sample of transactions, $\widehat{\beta_\theta}$ is a vector of coefficient estimates, p denotes a vector of A house prices, X denotes an $A \times K$ matrix in which the first column is all ones and the rest of the columns record the values of K - 1 independent variables, and $\theta \in (0,1)$ denotes the quantile estimated. Thus, p_a is the a^{th} entry of p, x_a is the a^{th} entry of X, and w_a is the a^{th} observation's weight that can be expressed as:

$$w_a = \begin{cases} 2\theta, & \text{if } p_a - x_a\beta_\theta > 0 \\ 2(1-\theta), & \text{otherwise} \end{cases} \tag{6}$$

At the median (θ = .5) equal weight is given to positive and negative residuals. Whereas, when examining the 80th percentile (θ = .8), $2\theta = 1.6$ and $2(1-\theta) = .4$, so more weight is given to positive residuals. I estimate the standard errors of the coefficient estimates using a bootstrap method that retains the assumption of independent errors but relaxes the assumption of identically distributed errors, which makes the bootstrapped standard errors equivalent to robust standard errors in linear regressions. One of the primary benefits of quantile regression is that it uses the full sample and avoids the truncation problem inherent in subsample hedonic regression analysis.[26] The quantile regression takes the following form:

$$p_{\mathrm{it}} = \beta_{1(\theta)}X_{it} + \beta_{2(\theta)}N_{jt} + \beta_{3(\theta)}H_{jt} + \varepsilon_{ijt,\theta} \tag{7}$$

where the housing characteristic, neighborhood characteristic, and homeownership rate coefficients vary by quantile θ. Similar to Equation 1, sales price is a function of a vector of the house's physical characteristics X_{it}, neighborhood characteristics N_{jt}, and nearby homeownership levels H_{jt}.

[26] Some studies subdivide their sample according to the unconditional distribution of their dependent variable and then run a hedonic regression for each subsample.

Ex ante, I expect that higher (lower) priced houses would be more (less) sensitive to changes in homeownership rates as the current federal tax subsidy for owner-occupied housing is directly related to the price of the house and indirectly, positively related to the owner occupier's income.[27] As an owner-occupier's house price and income increases the tax subsidy for homeownership increases.[28] Although previous research shows that high income households benefit the most from the owner-occupier tax subsidies (Poterba and Sinai, 2008) little is known about whether the subsidies promote homeownership. Glaeser and Shapiro (2003) argue that the federal tax policies appear to increase the amount spent on housing, but have almost no effect on the homeownership rate. They posit that the mortgage interest deduction (MID) is ineffective as it benefits wealthy households, who would likely be homeowners in its absence. In this section I run a series of quantile regressions to examine the effect of homeownership rates over the full distribution of house prices. I argue that if the tax subsidies for owner-occupied housing are effective instruments, house prices in the upper deciles will be more sensitive to changes in homeownership rates as they are the primary beneficiaries.

Table 13 includes quantile regression estimates for census blocks and 0.10 mile radiuses that contain only single-family detached housing. The dependent variable in every column is the log of sales price. The first column of Table 13 presents ordinary least squares (OLS) results that are comparable to Tables 9 and 10. Results for the 10th, 25th, 50th, 75th, and 90th quantiles are presented in order in columns 2 to 6. The results are displayed for the entire study period in the first (fourth) row for the block-level (.10 mile radius) homeownership measure. An increase (decrease) in homeownership has a positive (negative) effect in every quantile. The homeownership estimates exhibit a quantile effect as the magnitude of homeownership's effect on house prices is greater (lesser) in the lower (upper) deciles of the conditional house price distribution. Scatter plots of select explanatory variable coefficients by quantile are displayed in Figure 2. The scatter plots are available for several structural variables, property conditions, and neighborhood controls. Figure 3 displays a larger, isolated scatter plot of the homeownership rate

[27] Assuming that the owner-occupier's marginal tax rate increases with their income.

[28] The tax subsidy is not directly proportional to an owner-occupier's income because homeowners can only deduct interest on the *first* $1,000,000 in acquisition debt and *first* $100,000 in home equity debt that is secured by their primary residence and second home. If a homeowner has a second home and they rent it out for part of the year, they must use the second home more than 14 days or more than 10% of the number of days during the year that the home is rented at a fair market rental rate, whichever is longer. If they do not meet these requirements, the property is considered a rental and not a second home (IRS Publication 936).

coefficients by quantile with a 95% confidence interval. The figure shows that the magnitude of the homeownership's effect decreases from the lower to the upper deciles of the conditional house price distribution.

[Insert Table 13]

Two subperiods are created to examine the effect of homeownership on house prices across market conditions. The data is partitioned so that the subperiods represent the pre-crisis housing boom (2002-2006) and the post-crisis housing bust/recovery (2007-2014). The second and fifth rows of Table 13 present the results for the pre-crisis subperiod. During the pre-crisis subperiod, I find that an increase (decrease) in homeownership has a positive (negative) effect in all but the top quantile. Quantile effects are present as the magnitude of the coefficients decrease in the upper deciles of the conditional house price distribution. Figure 4 displays a scatter plot of the homeownership rate coefficients by quantile for the pre-crisis subperiod. Similar to Figure 3, the magnitude of the homeownership's effect on house prices decreases from the lower to the upper deciles of the conditional house price distribution.

The third and sixth rows of Table 13 present the results for quantile regressions using the post-crisis data subset. As noted earlier, the OLS homeownership rate coefficient estimate is noticeably larger in the post-crisis subperiod compared to the pre-crisis subperiod (.4450 in row 3 versus .1963 in row 2). According to the OLS estimates, a change in homeownership had a larger mean effect on house prices during the housing bust/recovery than during the housing boom. Similarly, the quantile homeownership coefficients in rows 3 and 6 are also all greater than the corresponding quantile coefficients in rows 2 and 5. Figure 5 displays a scatter plot of the homeownership rate coefficients by quantile for the post-crisis subperiod. Similar to Figures 3 and 4, the distributional effect of homeownership decreases as you move from the lower to the upper deciles of the conditional house price distribution.

4.3 Valuing the External Benefits of Homeownership

In this section, I calculate a back of the envelope estimate for the external benefits of homeownership's monetary value across the house price distribution. In Table 13, a 10% point increase (decrease) in homeownership at the census block level has an average effect of a 2.0% point increase (decrease) in pre-crisis house prices and a 4.5% point increase (decrease) post-crisis using OLS. Throughout the study period, the average housing stock in each census block was approximately 33 houses. If I assume that 28 of the 33 houses in a census block were owner-occupied, then the transition of the 29th house from rental to owner-occupancy would increase the homeownership rate in the census block by approximately 3% points. Using the OLS estimate for the pre-crisis (post-crisis) dataset, the other 28 owner-occupied houses in the block would increase in value by approximately 0.59% (1.34%) points. Following Coulson and Li (2013), if the average sales price is approximately $307,000 in the pre-crisis period and $355,000 in the post-crisis period, the monetary value of the house's tenure transition represents approximately $1,800 per house or $50,400 (1,800 * 28) prior to the crisis and approximately $4,730 per house or $132,440 (4,730 * 28) for the census block post-crisis. If a 3% annual capitalization rate is applied (assuming an infinitely-lived asset), the homeownership externality would, on average, yield an annuity of approximately $1,512 ($3,973) per year pre-crisis (post-crisis) for the owner-occupied properties.

The quantile regression results I report in the previous section provide additional insight into the distributional effect of homeownership and suggest that the external benefits of homeownership vary over the entire distribution of house prices (which serves as a proxy for income). In the pre-crisis period I find that a 10% point increase (decrease) has a greater effect, approximately 4.3%, on house prices in the lower decile compared to a 2.0% effect in the median decile and no effect in the upper decile of the conditional house price distribution. Taking the same approach as the previous paragraph, I estimate that the transition of one house would increase the other owner-occupied house values by approximately 1.30% points in the lower decile, 0.61% in the median decile, and have no effect in the upper decile. Taking into account the fact that the typical house value in the upper, median, and lower deciles differ, I estimate the monetary value of a house's tenure transition from rental to owner-occupied to be approximately $1,380 per house, or $38,640 per block, in the lower decile, and $1,480 per house, or $41,440 per block, in the median decile.[29] Using a 3% annual capitalization rate and assuming an infinitely-lived asset, the homeownership externality would, on average, yield an annuity of approximately $1,159 in the lower decile and $1,243 in the median decile for owner-occupied properties during the pre-crisis period. The homeownership externality has no effect on house

[29] The estimation uses an average sales price of $106,000 for the lower decile and $244,000 for the median decile during the pre-crisis time period.

prices in the upper, Q(0.90), decile. The results demonstrate that using the mean effect overestimates the monetary value of the external benefits of homeownership for both the lower and median deciles prior to the real estate crisis. It also demonstrates that homeownership has little effect on house prices in the upper deciles, despite the fact that they are the primary beneficiaries of the federal government's subsidization of homeownership in the United States. Using the same approach for the post-crisis period, I estimate the annuity to be approximately $1,050 in the lower decile, $2,822 in the median decile, and $1,806 in the upper decile.[30]

The estimates above provide insight into the distributional effect of homeownership on house prices and suggest that the federal tax subsidies are ineffective instruments for promoting homeownership. Households that rent, but would prefer to be homeowners are typically low income households. However, the primary beneficiaries of the federal tax subsidies are high income households who, as shown above, receive less homeownership externality benefits. Instead of increasing homeownership, the federal tax subsidies likely increase the amount spent on housing by high income households, subsidizing the amount spent on housing rather than increasing homeownership.

5. Conclusion

Using microdata that includes information for the entire housing stock in Fulton County, Georgia I isolate and examine the effect of homeownership on house prices. I exploit the extended timeframe of the data using a research design that explicitly controls for the unobserved quality of the individual house as well as time-varying neighborhood effects. I find that the average causal effect of homeownership on house prices is much lower than previously reported despite using a homeownership measure with a larger scale. I estimate that a 10% increase in homeownership results in a 2.6% increase in surrounding house prices. Recognizing that changing the scale of a measure alters findings in statistical tests, I run the analysis using areal units of differing sizes and several continuous spatial measures. My findings are robust and show a causal effect regardless of the homeownership measure employed. Although there are limitations to the study as I cannot – due to data limitations – control for several potentially endogenous factors such as the redistricting of school zones and crime.

[30] The estimation uses an average sales price of $79,000 for the lower decile and $302,000 for the median decile, and $600,000 for the upper decile during the post-crisis time period.

This paper also provides a first look at the distributional effect of homeownership on nearby house prices. Proponents of subsidizing homeownership contend that homeownership creates positive externalities and previous research supports the conjecture (see for example: DiPasquale and Glaeser 1999). I argue that the subsidization of homeownership is only justifiable if the external benefits created exceed their cost. I measure the external benefits of homeownership in the form of higher house prices over the entire distribution of house prices and estimate the benefits from a marginal homeowner across the house price distribution. I show that homeownership has a greater effect on house prices in the lower deciles of the conditional house price distribution despite the fact that they benefit the least, if at all, from the federal tax subsidies for homeownership. On the opposite end of the house price distribution, homeownership has little to no effect on house prices in the top decile, despite the fact that they benefit the most from the federal tax subsidies for homeownership.

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Table 1: Homeownership Rates by Median Income Deciles

Decile	Median Income		Homeownership Rate by Year												
	Min (1)	Max (2)	2002 (3)	2003 (4)	2004 (5)	2005 (6)	2006 (7)	2007 (8)	2008 (9)	2009 (10)	2010 (11)	2011 (12)	2012 (13)	2013 (14)	2014 (15)
Full Sample															
1st	7,399	23,482	69.9%	69.9%	68.5%	67.7%	66.9%	65.1%	61.8%	60.7%	59.6%	58.5%	57.6%	56.6%	56.0%
2nd	23,563	32,385	74.6%	74.6%	73.6%	72.8%	71.8%	70.1%	67.1%	65.9%	63.9%	62.4%	61.6%	60.4%	59.3%
3rd	32,515	43,468	79.8%	79.8%	79.9%	79.4%	78.8%	77.6%	76.2%	75.1%	73.7%	71.8%	70.9%	69.8%	68.3%
4th	43,570	56,125	81.7%	81.7%	82.5%	81.8%	81.3%	80.9%	79.6%	78.8%	77.2%	75.6%	74.5%	73.3%	72.2%
5th	56,159	72,829	85.9%	85.9%	86.7%	86.6%	86.4%	86.0%	85.3%	84.8%	83.5%	82.7%	82.1%	81.8%	81.1%
6th	73,171	86,563	88.7%	88.7%	89.5%	89.4%	89.5%	89.1%	88.8%	88.4%	87.5%	86.8%	86.6%	86.3%	85.6%
7th	86,731	104,054	90.1%	90.1%	91.2%	91.1%	91.7%	91.5%	91.3%	91.2%	90.3%	89.9%	89.5%	89.3%	88.9%
8th	104,236	126,985	90.3%	90.3%	91.5%	91.5%	91.6%	91.1%	91.0%	90.4%	89.4%	88.6%	88.2%	88.2%	87.7%
9th	128,667	151,250	91.3%	91.3%	93.3%	93.3%	93.7%	93.4%	93.3%	93.1%	92.3%	92.0%	91.7%	91.6%	91.3%
10th	151,295	250,000	91.8%	91.8%	93.3%	93.4%	93.6%	93.4%	93.0%	92.7%	91.7%	91.4%	91.3%	91.3%	91.0%
Census Blocks without Multi-Family Housing															
1st	7,399	23,482	74.6%	74.6%	73.1%	71.9%	70.8%	69.0%	66.0%	64.9%	63.5%	61.9%	61.1%	60.0%	59.0%
2nd	23,563	32,385	78.6%	78.6%	77.9%	77.1%	75.8%	74.0%	71.5%	70.2%	68.0%	66.7%	65.8%	64.7%	63.2%
3rd	32,515	43,468	82.5%	82.5%	82.1%	81.5%	81.0%	80.1%	78.8%	77.8%	76.3%	74.3%	73.3%	72.2%	70.6%
4th	43,570	56,125	83.5%	83.5%	84.5%	83.6%	82.9%	82.6%	80.9%	79.9%	78.3%	76.7%	75.4%	74.0%	72.8%
5th	56,159	72,829	87.8%	87.8%	88.6%	88.4%	88.1%	87.3%	86.8%	86.1%	84.8%	84.0%	83.4%	82.8%	82.0%
6th	73,171	86,563	90.0%	90.0%	90.9%	91.0%	91.0%	90.6%	90.4%	89.9%	89.0%	88.6%	88.4%	88.1%	87.1%
7th	86,731	104,054	90.8%	90.8%	92.2%	92.1%	92.6%	92.2%	92.1%	92.0%	90.9%	90.6%	90.3%	90.2%	89.7%
8th	104,236	126,985	91.0%	91.0%	92.3%	92.3%	92.3%	91.7%	91.5%	90.9%	90.1%	89.1%	88.8%	88.7%	88.4%
9th	128,667	151,250	91.7%	91.7%	93.7%	93.9%	94.3%	94.0%	93.9%	93.7%	92.8%	92.6%	92.3%	92.2%	91.7%
10th	151,295	250,000	91.5%	91.5%	93.1%	93.2%	93.5%	93.3%	92.9%	92.6%	91.5%	91.1%	91.0%	91.1%	90.6%
Census Blocks with Multi-Family Housing															
1st	7,399	23,482	65.6%	65.6%	64.5%	64.1%	63.5%	61.6%	58.1%	57.1%	56.1%	55.5%	54.5%	53.5%	53.2%
2nd	23,563	32,385	69.7%	69.7%	68.4%	67.6%	66.9%	65.2%	61.6%	60.6%	58.9%	57.1%	56.3%	55.1%	54.4%
3rd	32,515	43,468	75.7%	75.7%	76.5%	76.2%	75.3%	73.8%	72.1%	71.1%	69.7%	68.1%	67.2%	66.1%	64.8%
4th	43,570	56,125	78.2%	78.2%	78.5%	78.2%	78.2%	77.7%	77.0%	76.7%	75.2%	73.4%	72.6%	72.0%	71.0%
5th	56,159	72,829	83.3%	83.3%	84.0%	83.9%	83.9%	84.1%	83.1%	82.9%	81.6%	80.8%	80.2%	80.3%	79.8%
6th	73,171	86,563	86.5%	86.5%	87.3%	86.9%	87.0%	86.5%	86.2%	86.1%	85.0%	83.7%	83.5%	83.5%	83.2%
7th	86,731	104,054	88.9%	88.9%	89.6%	89.6%	90.2%	90.2%	90.0%	90.0%	89.2%	88.7%	88.1%	87.7%	87.5%
8th	104,236	126,985	88.7%	88.7%	89.9%	89.9%	90.3%	89.8%	89.9%	89.4%	87.9%	87.8%	87.0%	87.1%	86.5%
9th	128,667	151,250	89.8%	89.8%	91.8%	90.9%	91.3%	91.1%	91.2%	90.7%	90.2%	89.5%	89.3%	89.2%	89.6%
10th	151,295	250,000	92.8%	92.8%	94.0%	94.3%	94.3%	93.7%	93.8%	93.5%	93.0%	92.8%	92.6%	92.3%	92.5%

Median income is tabulated at the block-group level using 5-year estimates from the 2013 American Community Survery. The median income deciles are open on the lower end and closed on the higher end. Homeownership rates are tabulated on an annual basis using the Fulton County Tax Assessor parcel files. Houses located in a census block with less than five single-family detached houses or with an assessed value less than $5,000 are not included. If a house was built after 2002 the assessed value is based on the year the house was built.

Table 2: Homeownership Rates by Assessed Value Deciles

Decile	Assessed Value		Homeownership Rate by Year												
	Min	Max	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Full Sample															
1st	5,100	64,000	62.3%	62.3%	61.7%	61.0%	60.5%	58.8%	55.5%	54.2%	52.7%	51.6%	50.7%	49.9%	49.1%
2nd	64,100	79,600	75.0%	75.0%	73.6%	72.9%	71.6%	70.0%	67.2%	66.2%	64.2%	62.4%	61.4%	60.3%	59.0%
3rd	79,700	97,300	80.5%	80.5%	80.2%	79.3%	78.5%	77.5%	75.7%	74.5%	73.1%	71.4%	70.3%	68.9%	67.5%
4th	97,400	125,100	84.1%	84.1%	84.7%	84.1%	83.5%	82.4%	81.2%	80.5%	79.0%	77.6%	76.5%	75.3%	73.9%
5th	125,200	165,900	87.0%	87.0%	87.4%	87.3%	87.1%	86.7%	86.0%	85.3%	84.2%	83.1%	82.6%	82.3%	81.3%
6th	166,000	210,800	89.5%	89.5%	90.8%	90.7%	90.8%	90.5%	90.2%	89.9%	88.7%	87.8%	87.5%	87.3%	86.4%
7th	210,900	261,200	91.0%	91.0%	92.2%	92.2%	92.6%	92.3%	92.0%	91.9%	91.0%	90.5%	90.2%	90.0%	89.8%
8th	261,300	326,700	91.6%	91.6%	92.7%	92.8%	92.8%	92.7%	92.7%	92.6%	91.7%	91.6%	91.4%	91.2%	90.9%
9th	326,800	435,600	92.4%	92.4%	93.6%	94.0%	94.3%	93.8%	93.8%	93.6%	92.6%	92.5%	92.2%	92.1%	92.2%
10th	435,700	7,248,700	90.5%	90.5%	92.6%	92.6%	93.2%	92.8%	92.4%	91.9%	91.0%	90.4%	90.4%	90.5%	90.3%
Census Blocks without Multi-Family Housing															
1st	5,100	64,000	65.8%	65.8%	65.1%	64.2%	63.2%	61.5%	58.5%	57.3%	55.7%	54.4%	53.5%	52.8%	51.6%
2nd	64,100	79,600	78.5%	78.5%	77.2%	76.1%	75.1%	73.3%	70.8%	69.6%	67.6%	65.5%	64.6%	63.4%	62.1%
3rd	79,700	97,300	83.4%	83.4%	83.4%	82.4%	81.5%	80.5%	78.9%	77.4%	75.6%	74.0%	72.8%	71.3%	69.9%
4th	97,400	125,100	86.7%	86.7%	87.6%	87.1%	86.5%	85.3%	84.2%	83.4%	82.0%	80.5%	79.5%	78.2%	76.5%
5th	125,200	165,900	88.3%	88.3%	88.8%	88.6%	88.3%	88.1%	87.5%	86.8%	85.7%	84.5%	84.1%	83.5%	82.2%
6th	166,000	210,800	90.2%	90.2%	91.5%	91.7%	92.0%	91.6%	91.1%	90.7%	89.6%	88.8%	88.4%	88.2%	87.2%
7th	210,900	261,200	92.6%	92.6%	93.9%	93.7%	94.0%	93.7%	93.5%	93.4%	92.6%	92.1%	91.9%	91.6%	91.2%
8th	261,300	326,700	93.1%	93.1%	94.2%	94.4%	94.1%	93.9%	94.1%	94.1%	93.2%	93.3%	93.0%	93.0%	92.6%
9th	326,800	435,600	92.7%	92.7%	94.0%	94.5%	94.7%	94.5%	94.4%	94.1%	93.2%	93.0%	92.9%	93.0%	93.0%
10th	435,700	7,248,700	90.4%	90.4%	92.6%	92.5%	93.2%	92.8%	92.4%	91.9%	91.0%	90.4%	90.3%	90.4%	90.1%
Census Blocks with Multi-Family Housing															
1st	5,100	64,000	59.0%	59.0%	58.4%	57.9%	58.0%	56.1%	52.5%	51.2%	49.8%	48.9%	48.0%	47.0%	46.6%
2nd	64,100	79,600	70.4%	70.4%	69.0%	68.6%	67.0%	65.7%	62.5%	61.6%	59.8%	58.4%	57.3%	56.2%	55.0%
3rd	79,700	97,300	75.1%	75.1%	74.5%	73.7%	73.0%	71.9%	69.7%	69.2%	68.6%	66.7%	65.7%	64.3%	63.2%
4th	97,400	125,100	78.9%	78.9%	79.2%	78.2%	77.6%	76.7%	75.5%	74.9%	73.4%	71.8%	70.6%	69.6%	68.8%
5th	125,200	165,900	84.8%	84.8%	85.2%	85.1%	85.2%	84.4%	83.4%	83.0%	81.7%	80.7%	80.1%	80.4%	79.8%
6th	166,000	210,800	88.1%	88.1%	89.4%	88.8%	88.6%	88.4%	88.6%	88.3%	86.9%	85.9%	85.7%	85.6%	85.0%
7th	210,900	261,200	88.0%	88.0%	89.0%	89.2%	89.9%	89.4%	89.3%	89.0%	88.1%	87.4%	86.9%	87.1%	87.0%
8th	261,300	326,700	89.0%	89.0%	90.2%	90.0%	90.6%	90.7%	90.1%	89.8%	89.2%	88.6%	88.5%	88.1%	88.0%
9th	326,800	435,600	91.6%	91.6%	92.7%	92.8%	93.3%	92.5%	92.6%	92.5%	91.5%	91.3%	90.6%	90.3%	90.4%
10th	435,700	7,248,700	91.0%	91.0%	92.7%	92.9%	93.2%	92.7%	92.4%	92.3%	91.0%	90.2%	90.8%	90.9%	91.0%

Deciles were created using assessed values in the 2002 Fulton County tax assessor files. If a house was built after 2002 the assessed value is based on the year it was built. The assessed value deciles are open on the lower end and closed on the higher end. Homeownership rates are tabulated on an annual basis using the Fulton County Tax Assessor parcel files. Houses located in a census block with less than five houses or with an assessed value less than $5,000 are not included in this table.

Table 3: Average Assessed Values by Median Income Deciles

Decile	Median Income		Average Assessed Value ($0,000s)												
	Min	Max	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Full Sample															
1st	7,399	23,482	75.4	75.4	75.4	75.4	75.5	75.6	75.8	75.9	76.0	76.0	76.1	76.1	76.1
2nd	23,563	32,385	80.8	80.8	80.9	80.9	81.0	81.0	81.0	81.1	81.1	81.1	81.0	81.1	81.1
3rd	32,515	43,468	110.0	110.0	110.0	110.0	110.0	110.0	109.9	109.9	109.9	109.9	109.8	109.8	109.8
4th	43,570	56,125	130.2	130.2	130.7	130.5	130.8	130.7	130.4	130.4	130.6	130.4	130.4	130.4	130.5
5th	56,159	72,829	171.7	171.7	171.6	171.7	171.6	171.7	171.8	171.8	171.9	171.9	171.7	171.8	171.9
6th	73,171	86,563	231.3	231.3	231.2	231.2	231.1	231.0	230.8	230.9	230.9	230.9	230.9	230.9	230.8
7th	86,731	104,054	269.2	269.2	269.4	269.6	269.5	269.7	269.8	269.8	269.8	269.9	269.9	269.9	270.0
8th	104,236	126,985	323.5	323.5	324.0	324.0	324.0	323.8	324.1	323.7	323.9	323.8	323.8	323.7	323.7
9th	128,667	151,250	358.0	358.0	358.1	358.2	358.4	358.2	358.3	358.3	358.4	358.3	358.3	358.1	357.9
10th	151,295	250,000	489.2	489.2	489.5	489.2	489.7	490.2	490.4	489.8	489.9	490.3	490.0	489.6	490.2
Census Blocks without Multi-Family Housing															
1st	7,399	23,482	74.6	74.6	74.7	74.7	74.7	74.9	74.9	74.9	74.9	75.0	75.0	75.0	75.1
2nd	23,563	32,385	81.7	81.7	81.7	81.7	81.7	81.8	81.8	81.8	81.8	81.9	81.9	81.9	81.9
3rd	32,515	43,468	110.3	110.3	110.3	110.3	110.3	110.2	110.1	110.0	110.0	110.0	109.9	109.9	109.8
4th	43,570	56,125	113.5	113.5	113.6	113.6	113.6	113.4	113.4	113.4	113.5	113.5	113.4	113.5	113.4
5th	56,159	72,829	156.2	156.2	156.3	156.4	156.3	156.4	156.5	156.4	156.3	156.5	156.3	156.5	156.5
6th	73,171	86,563	241.0	241.0	241.0	241.0	240.9	240.8	240.6	240.6	240.6	240.6	240.5	240.6	240.4
7th	86,731	104,054	277.1	277.1	277.3	277.5	277.5	277.6	277.7	277.7	277.8	277.9	277.8	277.8	278.0
8th	104,236	126,985	326.1	326.1	326.4	326.5	326.4	325.9	326.4	325.7	325.8	325.7	325.8	325.6	325.3
9th	128,667	151,250	365.5	365.5	365.6	365.8	366.1	365.9	366.1	365.9	366.0	366.0	365.9	365.6	365.4
10th	151,295	250,000	500.8	500.8	501.2	500.9	501.5	501.9	501.8	501.4	501.6	501.8	501.8	501.3	501.9
Census Blocks with Multi-Family Housing															
1st	7,399	23,482	76.0	76.0	76.0	76.0	76.2	76.3	76.6	76.7	76.9	77.0	77.0	77.0	77.1
2nd	23,563	32,385	79.8	79.8	79.8	79.9	80.0	80.0	80.1	80.1	80.3	80.1	80.0	80.0	80.1
3rd	32,515	43,468	109.5	109.5	109.6	109.6	109.5	109.7	109.7	109.7	109.7	109.6	109.7	109.8	109.8
4th	43,570	56,125	162.8	162.8	164.0	163.5	164.3	164.4	163.6	163.7	163.9	163.5	163.8	163.7	164.0
5th	56,159	72,829	194.0	194.0	193.7	193.9	193.7	193.9	194.0	194.1	194.4	194.2	194.1	194.2	194.3
6th	73,171	86,563	215.3	215.3	215.3	215.2	214.9	214.8	214.7	215.0	215.1	215.0	214.9	215.0	214.9
7th	86,731	104,054	256.3	256.3	256.7	256.8	256.6	256.8	257.0	257.0	256.9	257.0	256.9	257.0	257.0
8th	104,236	126,985	318.4	318.4	319.1	319.1	319.2	319.7	319.5	319.6	320.2	319.9	319.8	319.8	320.5
9th	128,667	151,250	329.2	329.2	329.3	329.3	328.8	328.6	328.6	329.1	328.9	328.6	328.8	329.0	328.8
10th	151,295	250,000	432.6	432.6	432.5	432.4	432.7	433.5	434.8	433.6	433.5	434.5	433.3	433.4	434.1

Median income is at the block-group level using 5-year estimates from the 2013 American Community Survery. The median income deciles are open on the lower end and closed on the higher end. The average assessed values were tabulated using the 2002 Fulton County Tax Assessor parcel files. If a house was built after 2002 the assessed value is based on the year the house was built. Houses located in a census block with less than five houses or with an assessed value less than $5,000 are not included in this table.

Table 4: Single-family detached housing stock and homeownership rates by selected year, areal unit, and property type composition

	2002			2006			2010			2014		
	Total	w/o MF	w/ MF	Total	w/o MF	w/ MF	Total	w/o MF	w/ MF	Total	w/o MF	w/ MF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Census Tract												
Mean Stock	856.0	703.0	856.7	944.1	713.0	945.3	1,003.5	719.0	1005.0	1,010.1	724.0	1011.6
Mean Owner-Occupied	719.3	638.0	719.7	799.3	665.0	800.0	807.3	661.0	808.0	789.9	638.0	790.6
Homeownership Rate	84.0%	90.8%	84.0%	84.7%	93.3%	84.6%	80.4%	91.9%	80.4%	78.2%	88.1%	78.2%
Observations	196	1	195	196	1	195	196	1	195	196	1	195
Census Block-Group												
Mean Stock	334.8	444.8	323.7	369.2	471.5	358.9	392.5	486.6	383.0	395.0	490.0	385.4
Mean Owner-Occupied	281.4	404.6	268.9	312.6	435.2	300.2	315.7	435.2	303.6	308.9	432.4	296.4
Homeownership Rate	84.0%	91.0%	83.1%	84.7%	92.3%	83.7%	80.4%	89.4%	79.3%	78.2%	88.2%	76.9%
Observations	501	46	455	501	46	455	501	46	455	501	46	455
Tax Assessor Neighborhood												
Mean Stock	160.0	98.1	330.4	167.2	103.9	341.7	169.8	105.0	348.5	169.5	105.1	346.8
Mean Owner-Occupied	134.5	88.5	261.3	140.9	95.1	267.2	136.0	93.3	253.5	131.6	91.2	242.6
Homeownership Rate	84.1%	90.2%	79.1%	84.3%	91.5%	78.2%	80.1%	88.9%	72.8%	77.6%	86.8%	70.0%
Observations	1,047	768	279	1,047	768	279	1,047	768	279	1,047	768	279
Census Block												
Mean Stock	29.3	29.7	28.6	31.6	32.0	30.9	32.9	33.1	32.7	33.1	33.3	32.8
Mean Owner-Occupied	24.7	25.8	22.9	26.8	27.9	24.8	26.6	27.7	24.1	25.9	27.0	24.1
Homeownership Rate	84.4%	86.9%	80.0%	84.8%	87.4%	80.2%	80.7%	83.6%	73.7%	78.3%	81.1%	73.5%
Observations	5,619	3,547	2,072	5,619	3,547	2,072	5,619	3,547	2,072	5,619	3,547	2,072

Census tracts, block-groups, blocks and neighborhoods must contain at least five single-family detached houses for the entire length of the study (2002-2014) to be included in the analysis. The second column in each section identifies tracts, block-groups, neighborhoods, and blocks that do not include multi-family and single-family attached housing. The third column in each section identifies census tracts, block-groups, neighborhoods, and blocks that do contain multi-family or single-family attached housing structures.

Table 5: Single-family detached housing stock and homeownership rates by selected year, radius, and property type composition

	2002			2006			2010			2014		
	Total	w/o MF	w/ MF	Total	w/o MF	w/ MF	Total	w/o MF	w/ MF	Total	w/o MF	w/ MF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Radius: 1.00 mile												
Mean Stock	1,770.9	690.9	1,829.1	1,865.9	796.4	1,923.5	1,924.3	851.3	1,982.1	1,927.1	860.9	1,984.6
Mean Owner-Occupied	1,473.5	621.8	1,519.4	1,550.2	731.6	1,594.3	1,510.8	758.6	1,551.4	1,465.9	758.1	1,504.0
Homeownership Rate	83.2%	90.0%	83.1%	83.1%	91.9%	82.9%	78.5%	89.1%	78.3%	76.1%	88.1%	75.8%
Observations	164,324	8,402	155,922	164,324	8,402	155,922	164,324	8,402	155,922	164,324	8,402	155,922
Radius: 0.50 mile												
Mean Stock	532.5	391.7	571.5	558.6	414.5	598.6	574.1	426.1	615.1	574.5	429.0	614.8
Mean Owner-Occupied	443.6	356.0	467.9	464.3	382.3	487.0	450.6	381.2	469.8	435.9	375.3	452.7
Homeownership Rate	83.3%	90.9%	81.9%	83.1%	92.2%	81.4%	78.5%	89.5%	76.4%	75.9%	87.5%	73.6%
Observations	164,245	35,655	128,590	164,245	35,655	128,590	164,245	35,655	128,590	164,245	35,655	128,590
Radius: 0.25 mile												
Mean Stock	166.9	140.1	191.3	173.8	145.7	199.1	177.6	147.9	204.5	177.5	148.5	203.8
Mean Owner-Occupied	139.3	125.9	151.3	144.4	131.7	155.9	139.4	129.1	148.8	134.5	125.6	142.5
Homeownership Rate	83.4%	89.9%	79.1%	83.1%	90.4%	78.3%	78.5%	87.2%	72.8%	75.7%	84.6%	69.9%
Observations	163,771	77,762	86,009	163,771	77,762	86,009	163,771	77,762	86,009	163,771	77,762	86,009
Radius: 0.10 mile												
Mean Stock	37.9	34.5	46.6	39.1	35.2	48.7	39.7	35.5	50.2	39.6	35.5	49.9
Mean Owner-Occupied	31.8	30.4	35.1	32.6	31.1	36.3	31.3	30.0	34.4	30.1	29.0	32.9
Homeownership Rate	83.7%	88.2%	75.3%	83.3%	88.2%	74.5%	78.7%	84.5%	68.7%	75.9%	81.5%	65.9%
Observations	160,580	114,616	45,964	160,580	114,616	45,964	160,580	114,616	45,964	160,580	114,616	45,964
Radius: 0.05 mile												
Mean Stock	14.0	13.7	15.5	14.3	13.9	16.3	14.4	13.9	16.8	14.4	13.9	16.7
Mean Owner-Occupied	11.8	11.9	11.4	12.1	12.1	11.9	11.6	11.6	11.4	11.1	11.2	10.8
Homeownership Rate	84.6%	87.2%	73.5%	84.4%	87.3%	73.0%	80.1%	83.3%	67.5%	77.3%	80.4%	64.9%
Observations	147,398	121,800	25,598	147,398	121,800	25,598	147,398	121,800	25,598	147,398	121,800	25,598

The first column in each section includes the entire single-family detached housing stock. The second column in each section includes houses in which only single-family detached housing structures are included in the specified radius. The third column in each section includes houses in which a mix of single-family detached, single-family attached, and multi-family housing units are included in the specified radius. Houses are only included if they have at least five single-family detached houses within the specified radius.

Table 6: Annual changes to homeownership rates by areal unit

	Entire Study Period (2002 - 2014)			Pre-crisis (2002 - 2006)			Post-crisis (2007 - 2014)		
	Block	Neighborhood	Block-Group	Block	Neighborhood	Block-Group	Block	Neighborhood	Block-Group
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
75 to 100%	0	0	0	0	0	0	0	0	0
50 to 75%	2	2	0	1	1	0	1	1	0
25 to 50%	73	18	0	40	16	0	33	2	0
10 to 25%	1,298	124	0	597	68	0	701	56	0
5 to 10%	2,622	321	0	956	162	0	1,666	159	0
0 to 5%	4,903	2,167	217	1,765	897	102	3,138	1,270	115
No change	21,709	3,419	35	7,848	1,246	20	13,861	2,173	15
0 to -5%	5,980	2,695	295	1,457	573	60	4,523	2,122	235
-5 to -10%	3,877	357	5	972	76	2	2,905	281	3
-10 to -25%	1,999	108	0	512	32	0	1,487	76	0
-25 to -50%	98	4	0	40	0	0	58	4	0
-50 to -75%	2	0	0	0	0	0	2	0	0
-75 to -100%	1	1	0	0	1	0	1	0	0

Census blocks, tax assessor neighborhoods, and census block-groups that contain only single-family detached housing are included. The homeownership rate intervals are open on the lower (higher) end and closed on the higher (lower) end for positive (negative) changes. Areal units with less than five single-family detached houses are not included in this table.

Table 7: Summary statistics for sales transactions, by purchaser

	Complete Sample		Owner-occupier		Investor	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
Price	261,213	214,430	312,547	225,393	161,414	146,711
Homeownership Rate	0.80	0.16	0.84	0.14	0.73	0.17
House Characteristics						
Age	36.7	26.6	33.8	25.8	42.4	27.1
Sqft Liv Area (000s)	2.12	1.06	2.32	1.09	1.74	0.88
Sqft Lot Size (000s)	17.97	17.73	19.18	18.15	15.61	16.65
Bedrooms	3.31	0.87	3.42	0.87	3.09	0.83
Bathrooms	2.06	0.94	2.21	0.96	1.75	0.81
Half Bathrooms	0.47	0.53	0.53	0.54	0.35	0.50
Fireplace'	0.69	0.46	0.77	0.42	0.55	0.50
Garage'	0.33	0.47	0.37	0.48	0.24	0.43
Carport'	0.09	0.28	0.08	0.27	0.10	0.30
Pool'	0.04	0.20	0.05	0.22	0.02	0.14
Physical Condition						
Excellent'	0.10	0.30	0.12	0.33	0.05	0.21
Very Good'	0.24	0.42	0.26	0.44	0.19	0.39
Good'	0.34	0.47	0.35	0.48	0.33	0.47
Average'	0.27	0.44	0.22	0.42	0.36	0.48
Fair'	0.05	0.22	0.04	0.20	0.07	0.25
Poor'	0.01	0.08	0.00	0.07	0.01	0.09
Very Poor'	0.00	0.03	0.00	0.02	0.00	0.04
Sales Condition						
Cash'	0.12	0.33	0.11	0.32	0.14	0.35
Distressed Sale'	0.33	0.47	0.14	0.35	0.70	0.46
Owner Occupant'	0.66	0.47				
Neighborhood Characteristics						
Turnover	0.07	0.05	0.06	0.06	0.07	0.07
Distressed Turnover	0.03	0.04	0.01	0.03	0.05	0.05
% New Houses	0.04	0.12	0.04	0.04	0.04	0.04
% Remodeled Houses	0.01	0.02	0.01	0.01	0.00	0.00
School Test Score	54.95	33.88	63.96	33.08	37.45	28.07
Median Income (000s)	75.49	48.84	86.97	49.87	53.16	37.84
% Poverty	0.14	0.14	0.11	0.13	0.20	0.16
% White	0.44	0.37	0.55	0.36	0.24	0.31
% Less High School	0.11	0.11	0.09	0.10	0.16	0.12
% College Degree	0.50	0.26	0.57	0.24	0.36	0.23
Transactions	**119,793**		**79,104**		**40,689**	

Houses located in a census block with less than five single-detached family houses are not included. The first section (columns 1 and 2) include the full sample, the second section (columns 3 and 4) includes sale transactions in which the buyer was an owner-occupier, and the third section (columns 5 and 6) includes sales transactions in which the buyer was an investor. Variable names followed by ' are indicator variables.

Table 8: Summary statistics for owner-occupied sales transactions, by property type composition and time period

	Without Multi-Family				With Multi-Family			
	2002 - 2006		2007 - 2014		2002 - 2006		2007 - 2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	307,028	217,153	355,062	254,375	260,463	176,008	311,395	224,935
Homeownership Rate	0.87	0.12	0.87	0.12	0.79	0.16	0.80	0.16
House Characteristics								
Age	27.9	21.4	27.7	19.9	44.9	29.1	40.5	30.7
Sqft Liv Area (000s)	2.34	1.09	2.69	1.15	1.88	0.89	2.20	0.97
Sqft Lot Size (000s)	20.90	18.70	23.33	20.45	14.22	14.01	15.38	15.19
Bedrooms	3.46	0.84	3.69	0.82	3.07	0.86	3.32	0.86
Bathrooms	2.22	0.96	2.52	0.99	1.82	0.83	2.15	0.89
Half Bathrooms	0.56	0.54	0.66	0.54	0.35	0.50	0.49	0.53
Fireplace'	0.76	0.42	0.85	0.35	0.66	0.47	0.76	0.42
Garage'	0.41	0.49	0.42	0.49	0.29	0.45	0.32	0.46
Carport'	0.09	0.28	0.07	0.26	0.08	0.27	0.07	0.26
Pool'	0.06	0.23	0.07	0.26	0.03	0.17	0.03	0.18
Physical Condition								
Excellent'	0.10	0.30	0.15	0.36	0.09	0.29	0.14	0.35
Very Good'	0.22	0.41	0.26	0.44	0.27	0.44	0.33	0.47
Good'	0.37	0.48	0.38	0.48	0.30	0.46	0.31	0.46
Average'	0.26	0.44	0.18	0.38	0.28	0.45	0.18	0.38
Fair'	0.04	0.20	0.04	0.18	0.05	0.22	0.03	0.18
Poor'	0.00	0.06	0.00	0.04	0.01	0.10	0.00	0.06
Very Poor'	0.00	0.02	0.00	0.02	0.00	0.04	0.00	0.02
Sales Condition								
Cash'	0.08	0.27	0.14	0.35	0.08	0.28	0.15	0.36
Distressed Sale'	0.04	0.21	0.23	0.42	0.05	0.23	0.23	0.42
Owner Occupant'	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Neighborhood Characteristics								
Turnover	0.07	0.05	0.05	0.04	0.08	0.06	0.06	0.05
Distressed Turnover	0.01	0.02	0.02	0.03	0.01	0.03	0.02	0.04
% New Houses	0.04	0.14	0.02	0.07	0.05	0.14	0.03	0.08
% Remodeled Houses	0.00	0.02	0.00	0.01	0.01	0.03	0.01	0.02
School Test Score	65.62	33.66	72.07	30.20	53.11	33.52	60.41	32.25
Median Income (000s)	91.54	51.17	102.29	50.11	66.99	43.96	77.51	43.86
% Poverty	0.10	0.12	0.07	0.09	0.17	0.16	0.12	0.13
% White	0.54	0.36	0.61	0.34	0.46	0.36	0.56	0.34
% Less High School	0.08	0.10	0.06	0.08	0.13	0.12	0.09	0.10
% College Degree	0.57	0.25	0.62	0.21	0.49	0.26	0.57	0.23
Transactions	**24,112**		**23,458**		**16,255**		**15,279**	

Property type composition is determined at the census block level. If a census block's housing stock is all single-family detached, then its sales transactions are included in the second section titled "Without Multi-Family". If a census block contains single-family attached or multi-family housing, then its sales transactions are included in the third section titled "With Multi-Family". The two time periods selected represent pre-crisis (2002 - 2006) and post-crisis (2007 - 2014) housing markets. Variable names followed by ' are indicator variables.

Table 9: Homeownership estimates by property type composition

	Complete Sample			Without Multi-Family			With Multi-Family		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Census Block	0.4652***	0.4649***	0.4241***	0.4910***	0.4849***	0.4328***	0.4551***	0.4634***	0.4059***
	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Neighborhood	1.1257***	1.2017***		0.7125***	0.6864***		1.4343***	1.7078***	
	(0.09)	(0.08)		(0.12)	(0.10)		(0.14)	(0.16)	
Census Block-Group	1.7504***		1.9154***	2.6663***		3.1074***	1.7356***		1.8970***
	(0.14)		(0.12)	(0.52)		(0.44)	(0.15)		(0.13)
Radius: 0.05 mile	0.2831***	0.2756***	0.2453***	0.2487***	0.2459***	0.2121***	0.3239***	0.3155***	0.2998***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Radius: 0.10 mile	0.5069***	0.5108***	0.4722***	0.4159***	0.4072***	0.3616***	0.6121***	0.6387***	0.6073***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Radius: 0.25 mile	1.0858***	1.1924***	1.1838***	0.8144***	0.7694***	0.7793***	1.1926***	1.3740***	1.3354***
	(0.08)	(0.07)	(0.08)	(0.12)	(0.10)	(0.09)	(0.09)	(0.08)	(0.11)
Radius: 0.50 mile	1.7749***	2.1635***	2.1143***	1.2790***	1.1751***	1.2646***	1.8701***	2.4088***	2.2912***
	(0.13)	(0.12)	(0.12)	(0.27)	(0.23)	(0.18)	(0.14)	(0.12)	(0.14)
Location Fixed Effects	Tract	Block-Group	Nbhd	Tract	Block-Group	Nbhd	Tract	Block-Group	Nbhd
Quarterly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The effect of homeownership on sales price is estimated at several continuous spatial radiuses in addition to census block, tax assessor neighborhood, and census block-group levels. Results in columns 1 to 3 are based on the entire owner-occupied purchase sample. Results in columns 4 to 6 are based on areal units (radiuses) that only contain single family detached housing units. Results in columns 7 to 9 are based on areal units (radiuses) that contain a mixed housing stock. The dependent variable in every column is log of house sales price. *, **, and *** denote significance at 10, 5,and 1 percent levels, respectively.

Table 10: Homeownership estimates by subperiod in areal units without multi-family housing

	Pre-crisis (2002 - 2006)			Post-crisis (2007 - 2014)		
	(1)	(2)	(3)	(4)	(5)	(6)
Census Block	0.1963***	0.1480***	0.1462***	0.4450***	0.4148***	0.2984***
	(0.03)	(0.03)	(0.032)	(0.06)	(0.05)	(0.04)
Neighborhood	0.1653*	0.0935		0.7622***	0.6994***	
	(0.09)	(0.08)		(0.12)	(0.11)	
Census Block-Group	0.2374		0.1337	1.9667***		2.5609***
	(0.29)		(0.243)	(0.44)		(0.47)
Radius: 0.05 mile	0.0911***	0.0791***	0.0738***	0.2454***	0.2256***	0.1629***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Radius: 0.10 mile	0.1563***	0.1341***	0.1284***	0.3819***	0.3445***	0.2437***
	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
Radius: 0.25 mile	0.2825***	0.1657*	0.1770**	0.6784***	0.5712***	0.4422***
	(0.10)	(0.09)	(0.07)	(0.12)	(0.09)	(0.09)
Radius: 0.50 mile	0.3801**	0.247	0.2584**	1.1201***	0.7993***	0.7629***
	(0.17)	(0.17)	(0.11)	(0.23)	(0.23)	(0.23)
Location Fixed Effects	Tract	Block-Group	Nbhd	Tract	Block-Group	Nbhd
Quarterly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood Controls	Yes	Yes	Yes	Yes	Yes	Yes

The effect of homeownership on sales price is estimated at several continuous spatial radiuses in addition to census block, tax assessor neighborhood, and census block-group levels. Similar to columns 4, 5 and 6 in Table 8, the analysis is based on areal units (radiuses) that contain *only* single-family detached housing. The results in columns 1 to 3 are further partitioned to include data from 2002 to 2006. The results in columns 4 to 6 include data from 2007 to 2014. The dependent variable in every column is log of house sales price. *, **, and *** denote significance at 10, 5,and 1 percent levels, respectively.

Table 11: Repeat sales specification with time-varying census tract effects

	Entire (2002-2014) (1)	Pre-crisis (2002-2006) (2)	Post-crisis (2007-2014) (3)
Census Block	0.2569***	0.2858***	0.2891***
	(0.13)	(0.16)	(0.14)
Radius: 0.10 mile	0.0767***	0.1385***	0.1243***
	(0.04)	(0.08)	(0.07)
Tract-by-Quarter Fixed Effects	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes
Neighborhood Contols	Yes	Yes	Yes
House Fixed Effects	Yes	Yes	Yes

The effect of homeownership rate on sales price is estimated using census blocks (.10 mile radiuses) that only contain single-family detached housing units. The results in column 1 represent a repeat sales specification in which the house transacted at least twice during the entire study period. Column 2 represents the pre-crisis subperiod in which the houses included in the analysis transacted at least twice between 2002-2006. Column 3 represents the post-crisis subperiod in which the houses included in the analysis transacted at least twice between 2007-2014. *, **, and *** denote significance at 10, 5,and 1 percent levels, respectively.

Table 12: Specifications with inverse Mills ratio for selection into homeownership

	Entire (2002-2014) (1)	Pre-crisis (2002-2006) (2)	Post-crisis (2007-2014) (3)
Census Block	0.4063***	0.1839***	0.3738***
	(0.05)	(0.04)	(0.05)
Radius: 0.10 mile	0.3474***	0.1391***	0.3476***
	(0.04)	(0.04)	(0.05)
Inverse Mills Ratio	Yes	Yes	Yes
Location Fixed Effects	Tract	Tract	Tract
Quarterly Fixed Effects	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes
Neighborhood Controls	Yes	Yes	Yes

The effect of homeownership on sales price is estimated at the census block level using census blocks that contain at least five single-family detached houses and no multi-family housing units. The results in column 1 include the entire HMDA merged dataset from 2002-2014. Column 2 includes the pre-crisis subperiod and is comparable to the first row of column 1 in Table 10. Column 3 includes data from the post-crisis subperiod (2007-2014) and is comparable to the first row of column 4 in Table 10. *, **, and *** denote significance at 10, 5,and 1 percent levels, respectively.

Table 13: Quantile regression homeownership estimates by period

		Without Multi-Family					
		OLS	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
Census Block	*Full Sample*	0.4910***	0.6102***	0.5277***	0.3301***	0.1739***	0.0761*
		(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)
	Pre-crisis (2002 - 2006)	0.1963***	0.4341***	0.3404***	0.2022***	0.0942**	0.0209
		(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
	Post-crisis (2007 - 2014)	0.4450***	0.5261***	0.4465***	0.3711***	0.2500***	0.1195**
		(0.06)	(0.06)	(0.04)	(0.04)	(0.03)	(0.04)
Radius: 0.10 mile	*Full Sample*	0.4159***	0.5976***	0.5191***	0.3668***	0.2038***	0.1320***
		(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	Pre-crisis (2002 - 2006)	0.1563***	0.3514***	0.2579***	0.1808***	0.1055***	0.0442
		(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)
	Post-crisis (2007 - 2014)	0.3819***	0.3743***	0.4216***	0.3901***	0.2825***	0.1774***
		(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Location Fixed Effects		Tract	Tract	Tract	Tract	Tract	Tract
Quarterly Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics		Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood Controls		Yes	Yes	Yes	Yes	Yes	Yes

Homeownership rate is measured at the census block (0.10 mile radius) level in every column. Areal units (radiuses) that contain only single-family detached housing in this table. The pre- and post-crisis subperiods represent up and down markets in our dataset. The dependent variable in every column is log of house sales price. *, **, and *** denote significance at 10, 5, and 1 percent levels, respectively.

Figure 1: Homeownership Rate Change 2002 – 2014

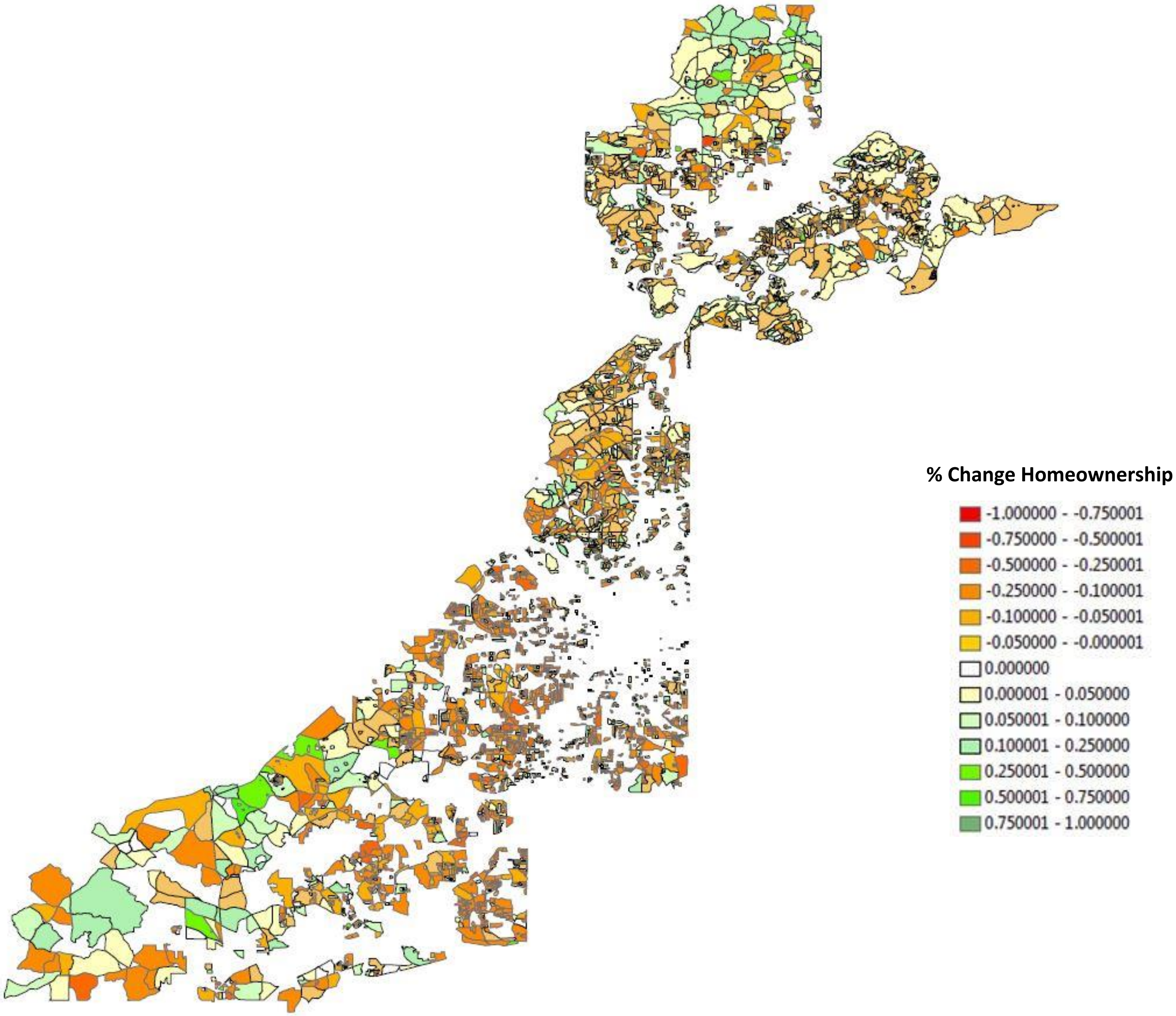


Figure 2: Quantile Regression – Independent Variable Coefficients

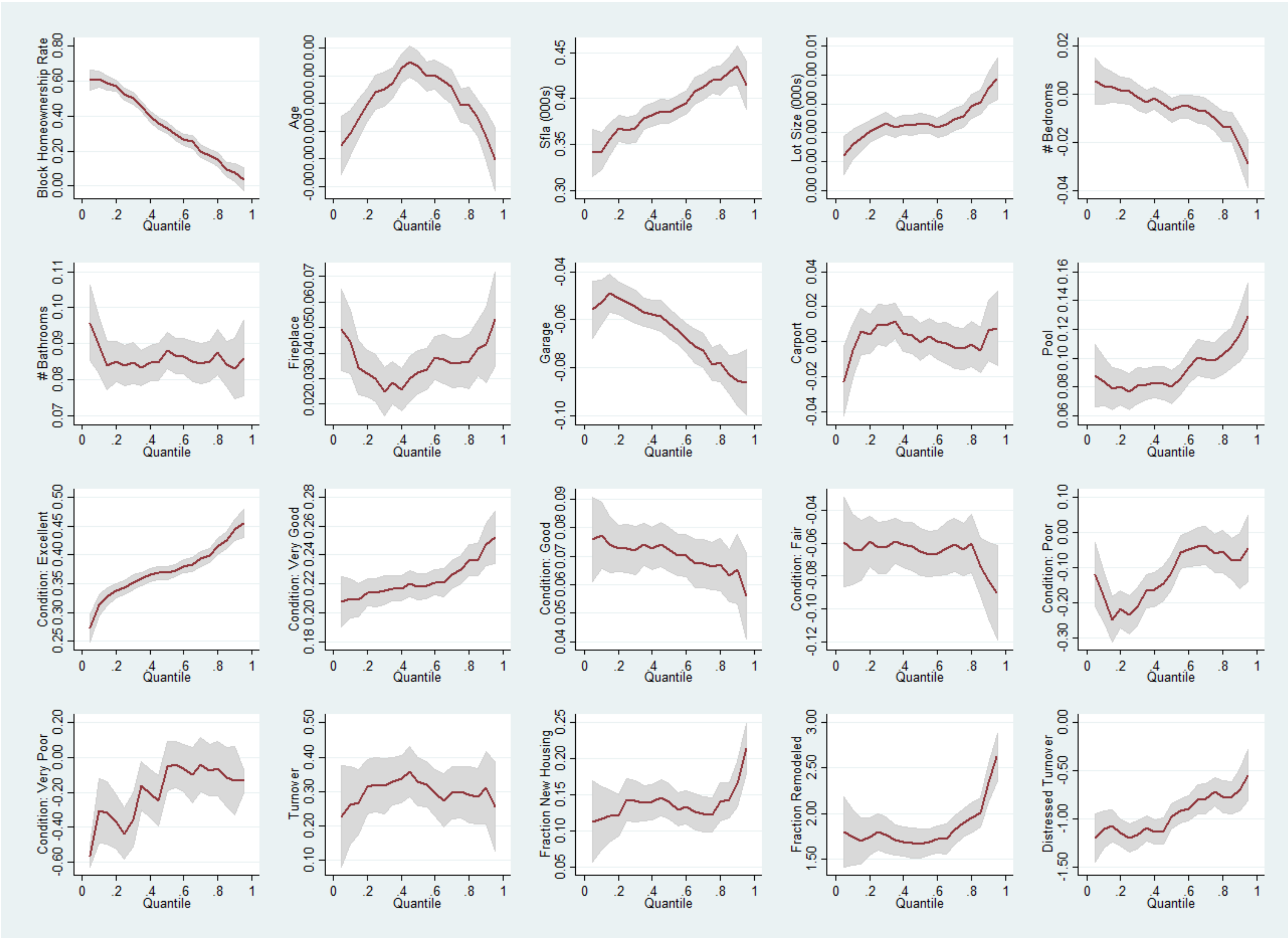


Figure 3: Census Block Homeownership Rate by Quantile (2002 – 2014)

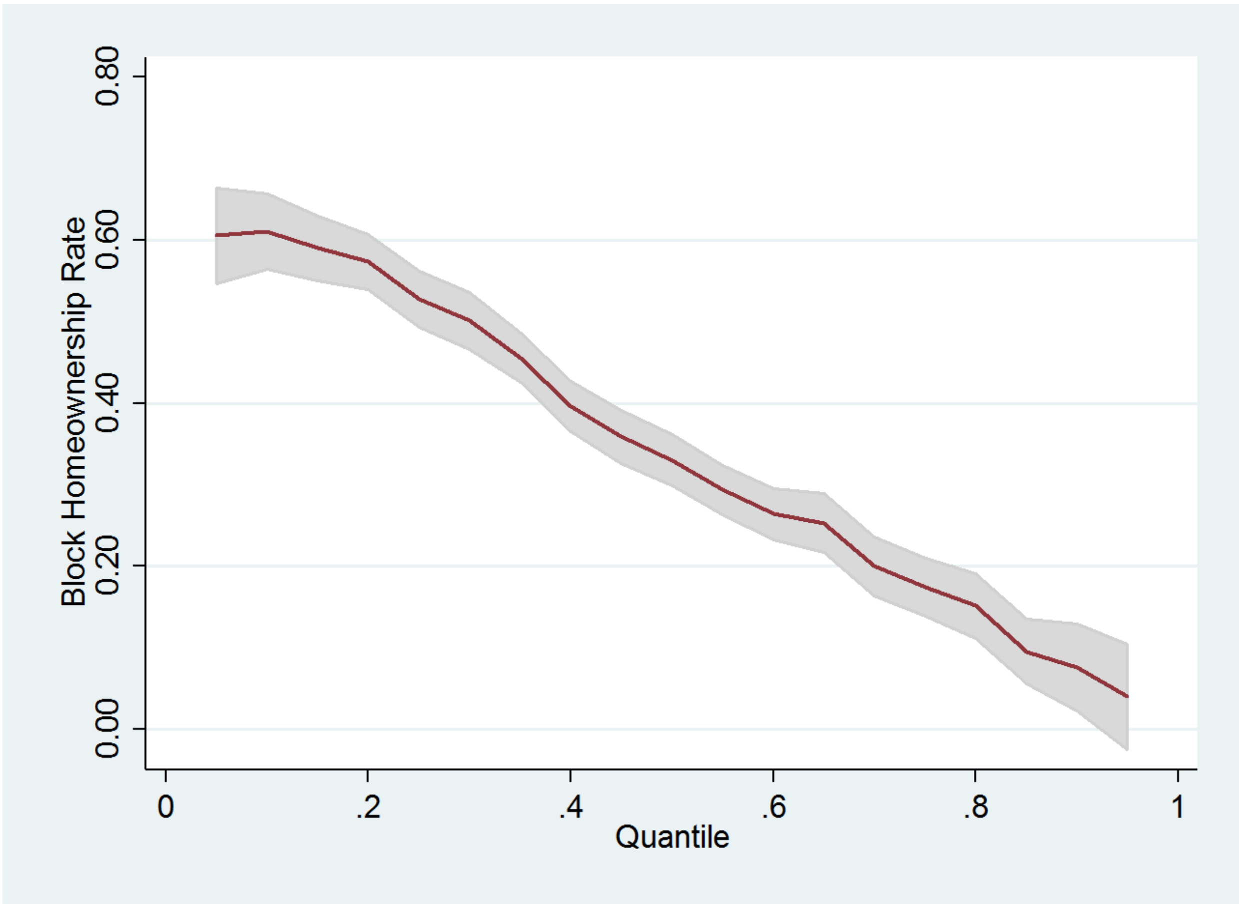


Figure 4: Pre-crisis Block Homeownership Rate by Quantile (2002-2006)

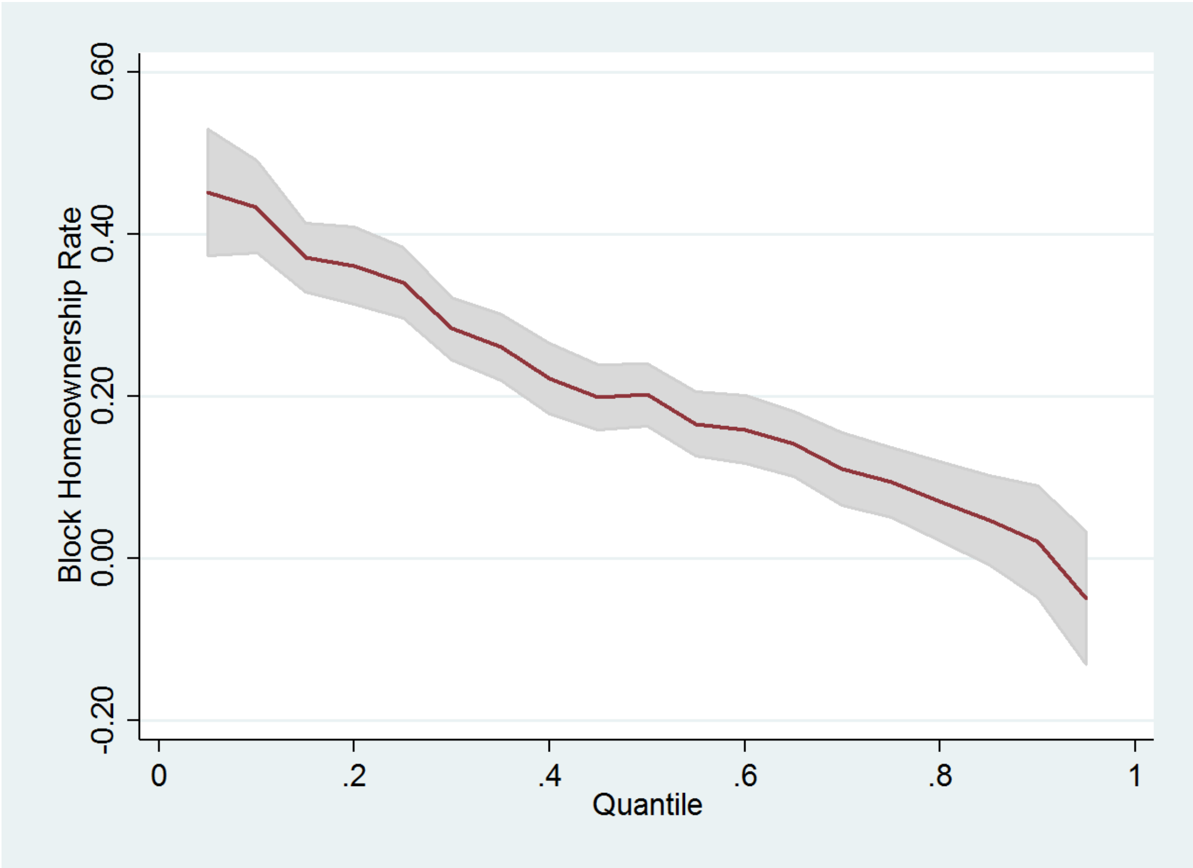


Figure 5: Post-crisis Block Homeownership Rate by Quantile (2007-2014)

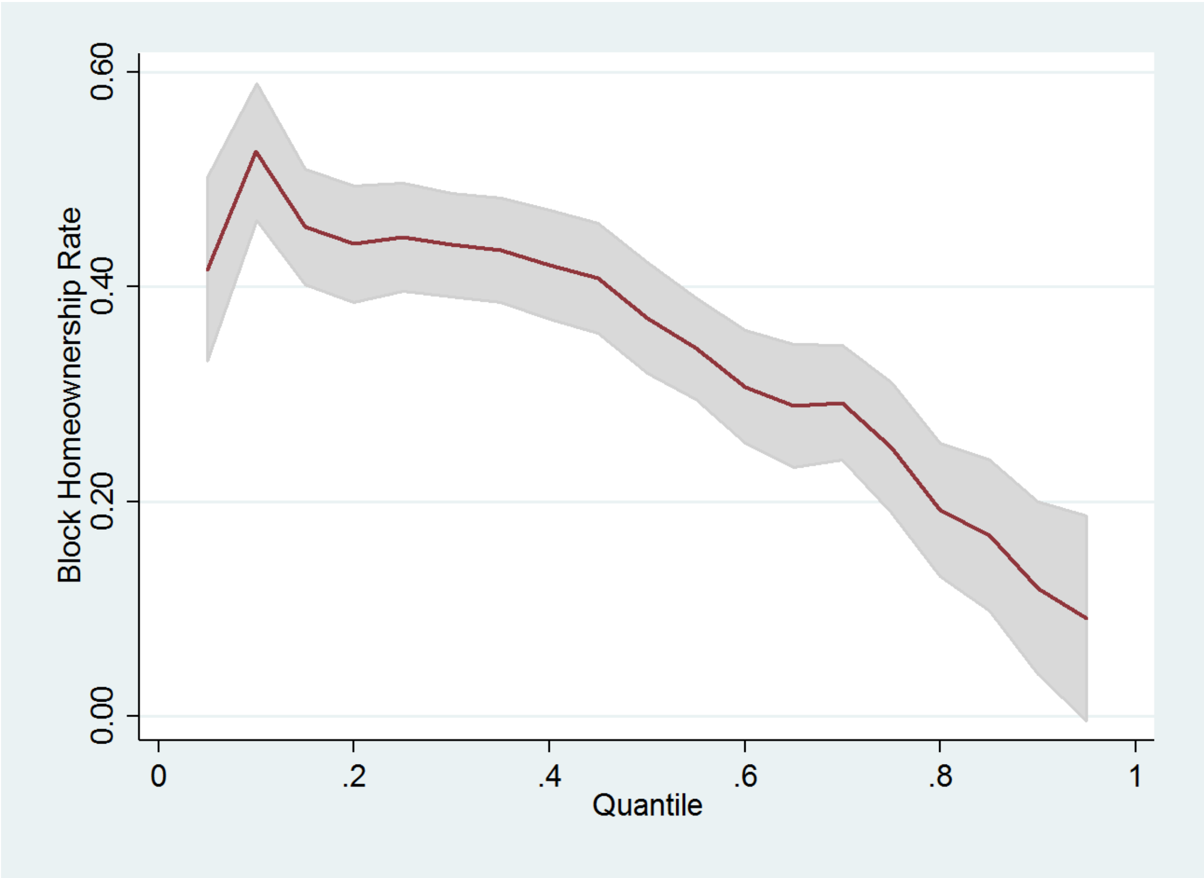


Table A1: Results for hedonic price model, by block level homeownership rates and property type compositions

	Complete Sample			Without Multi-Family		
	(1)	(2)	(3)	(4)	(5)	(6)
Homeownership Rate	0.4652***	0.4649***	0.4241***	0.4910***	0.4849***	0.4328***
	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)
Age	-0.0039***	-0.0044***	-0.0042***	-0.0035***	-0.0043***	-0.0032***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age Squared	0.0000***	0.0000***	0.0000***	0.0000**	0.0000***	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sqft Living Area (000s)	0.3109***	0.2887***	0.2434***	0.3265***	0.2880***	0.2034***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Sqft Squared (000s)	-0.0160***	-0.0148***	-0.0146***	-0.0191***	-0.0160***	-0.0099***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lot Size Sqft (000s)	0.0037***	0.0036***	0.0027***	0.0036***	0.0033***	0.0023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lot Size Sqft Squared (000s)	-0.0000***	-0.0000***	0.0000	-0.0000***	-0.0000**	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Bedrooms	0.0122***	0.0148***	0.0151***	0.0074*	0.0110***	0.0124***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Bathrooms	0.0679***	0.0633***	0.0440***	0.0736***	0.0673***	0.0453***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Number of Half Bathrooms	0.0316***	0.0290***	0.0295***	0.0342***	0.0306***	0.0282***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Fireplace	0.0189***	0.0215***	0.0248***	0.0161**	0.0198***	0.0256***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Garage	-0.0417***	-0.0375***	-0.0101***	-0.0464***	-0.0453***	-0.0170***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Carport	-0.0146*	-0.0163**	-0.0090	-0.0196**	-0.0197**	-0.0165**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pool	0.0796***	0.0795***	0.0754***	0.0756***	0.0756***	0.0742***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Excellent Condition	0.2148***	0.2064***	0.1796***	0.2316***	0.2218***	0.1836***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Very Good Condition	0.1364***	0.1308***	0.1193***	0.1455***	0.1348***	0.1192***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Good Condition	0.0561***	0.0528***	0.0600***	0.0543***	0.0475***	0.0514***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fair Condition	-0.0436***	-0.0399***	-0.0469***	-0.0451**	-0.0432***	-0.0532***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Poor Condition	-0.0697**	-0.0690**	-0.0762**	-0.0479	-0.0363	-0.0405
	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)
Very Poor Condition	-0.2140**	-0.1975*	-0.1866**	-0.2616**	-0.2613**	-0.2348**
	(0.11)	(0.11)	(0.09)	(0.12)	(0.12)	(0.11)
Turnover	0.3348***	0.3432***	0.3750***	0.2401***	0.2191***	0.2691***
	(0.05)	(0.04)	(0.04)	(0.07)	(0.06)	(0.05)
% New Houses	0.1583***	0.1527***	0.1405***	0.1430***	0.1288***	0.1226***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
% Remodeled Houses	0.1892	0.1418	0.1280	0.1107	0.0519	0.0305
	(0.12)	(0.09)	(0.10)	(0.15)	(0.14)	(0.14)
Distressed Turnover	-0.7275***	-0.7377***	-0.7458***	-0.7214***	-0.7216***	-0.7961***
	(0.08)	(0.07)	(0.07)	(0.11)	(0.10)	(0.09)
R-squared	0.84	0.84	0.85	0.86	0.87	0.88
Observations	79,104	79,104	79,104	47,570	47,570	47,570
Location Fixed Effects	Tract	Block-Group	Neighborhood	Tract	Block-Group	Neighborhood
Quarterly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Distressed Sales Controls	Yes	Yes	Yes	Yes	Yes	Yes
Census Controls	Yes	Yes	Yes	Yes	Yes	Yes
Homeownership Rate	Block	Block	Block	Block	Block	Block

Homeownership rate is measured at the census block level in every specification in this table. Results in columns 1 to 3 are based on the entire data sample. Results in columns 4 to 6 are based on census block that only contain single-family detach housing units. The dependent variable in every column is log of house sales price. *, **, and *** denote significance at 10, 5, and 1 percent levels, respectively.

Table A2: Quantile regression results for entire sample period

	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
	(1)	(2)	(3)	(4)	(5)
Homeownership Rate	0.6102***	0.5277***	0.3301***	0.1739***	0.0761*
	(-0.04)	(-0.03)	(-0.02)	(-0.02)	(-0.03)
Age	0.0009	0.0024***	0.0033***	0.0019***	0.0008
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age Squared	0.0000	0.0000	0.0000***	0.0000***	0.0001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sqft Living Area (000s)	0.3429***	0.3654***	0.3856***	0.4200***	0.4359***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sqft Squared (000s)	-0.0205***	-0.0225***	-0.0240***	-0.0281***	-0.0299***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lot Size Sqft (000s)	0.0016***	0.0022***	0.0023***	0.0026***	0.0035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lot Size Sqft Squared (000s)	-0.0000*	-0.0000***	-0.0000**	-0.0000**	-0.0000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Bedrooms	0.0034	0.0011	-0.0068*	-0.0100***	-0.0212***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Bathrooms	0.0896***	0.0839***	0.0881***	0.0850***	0.0831***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Half Bathrooms	0.0459***	0.0425***	0.0449***	0.0456***	0.0455***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Fireplace	0.0445***	0.0301***	0.0325***	0.0363***	0.0433***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Garage	-0.0527***	-0.0529***	-0.0614***	-0.0786***	-0.0851***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Carport	-0.0053	0.0099	-0.0002	-0.0042	0.0062
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pool	0.0837***	0.0766***	0.0800***	0.0985***	0.1166***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Excellent Condition	0.3127***	0.3429***	0.3684***	0.3990***	0.4433***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Very Good Condition	0.2099***	0.2138***	0.2181***	0.2296***	0.2473***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Good Condition	0.0772***	0.0727***	0.0723***	0.0665***	0.0653***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Fair Condition	-0.0638***	-0.0627***	-0.0652***	-0.0638***	-0.0827***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Poor Condition	-0.1871***	-0.2347**	-0.1140*	-0.0603*	-0.0814*
	(0.03)	(0.07)	(0.06)	(0.03)	(0.03)
Very Poor Condition	-0.3066	-0.4373	-0.0503	-0.0732	-0.1328
	(0.28)	(0.26)	(0.22)	(0.10)	(0.11)
Turnover	0.2610***	0.3189***	0.3298***	0.2988***	0.3117***
	(0.06)	(0.05)	(0.04)	(0.04)	(0.07)
% New Houses	0.1173***	0.1437***	0.1411***	0.1227***	0.1650***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.04)
% Remodeled Houses	1.7376***	1.7941***	1.6652***	1.8968***	2.3410***
	(0.15)	(0.12)	(0.11)	(0.12)	(0.21)
Distressed Turnover	-1.1066***	-1.1953***	-0.9728***	-0.7174***	-0.6956***
	(0.19)	(0.12)	(0.11)	(0.09)	(0.11)
Observations	47,570	47,570	47,570	47,570	47,570
Location Fixed Effects	Tract	Tract	Tract	Tract	Tract
Quarterly Fixed Effects	Yes	Yes	Yes	Yes	Yes
Distressed Sales Controls	Yes	Yes	Yes	Yes	Yes
Census Controls	Yes	Yes	Yes	Yes	Yes
Homeownership Rate	Block	Block	Block	Block	Block

Homeownership rate is measured at the census block level in every column. The analysis includes areal units that contain only single-family detached housing in this table. The dependent variable in every column is log of house sales price. *, **, and *** denote significance at 10, 5, and 1 percent levels, respectively.

Figure A1 – Continuous Spatial Measures of Homeownership

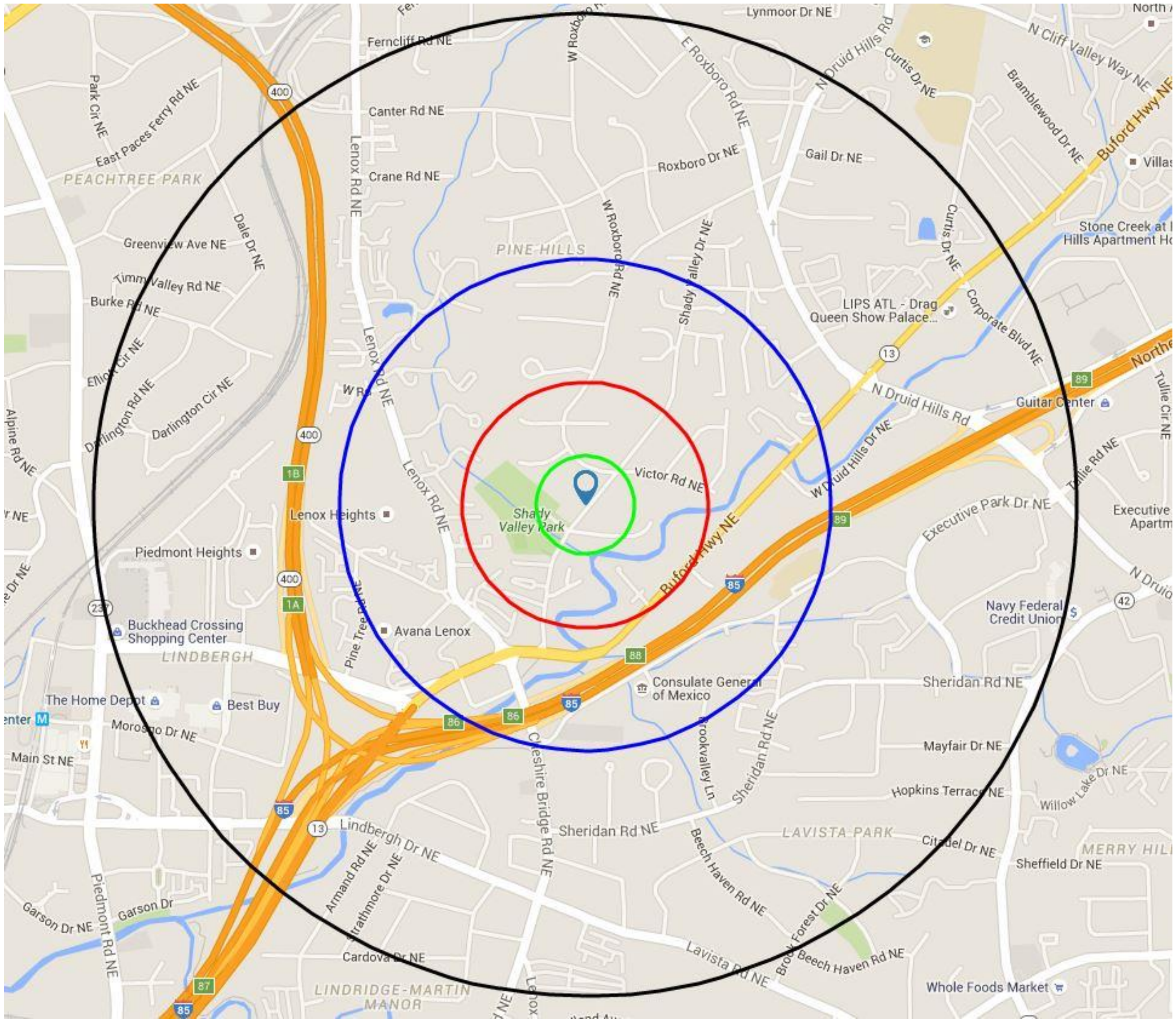


Figure A2: Homeownership Rate Change 2002 – 2006

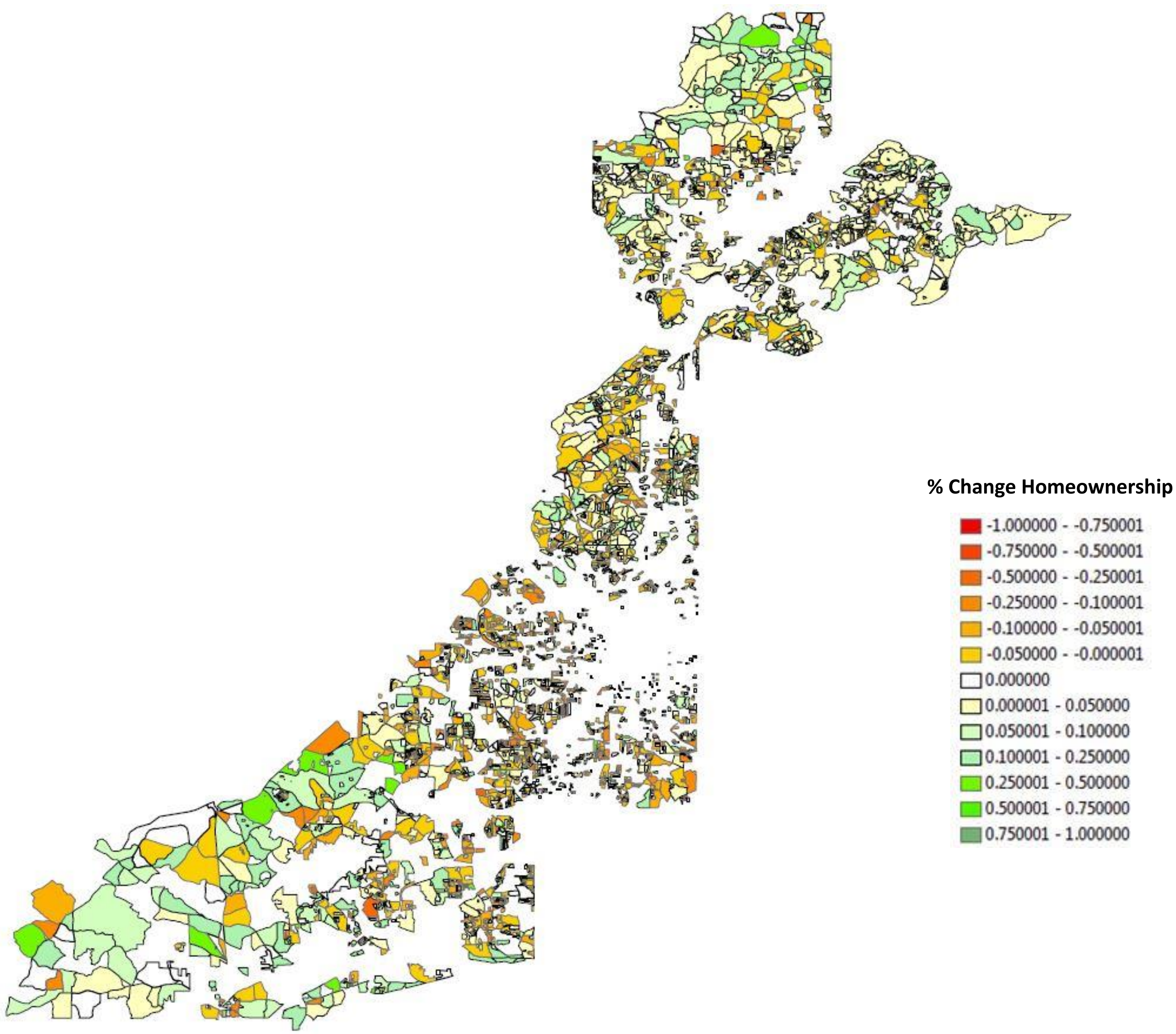


Figure A3: Homeownership Rate Change 2006 – 2010

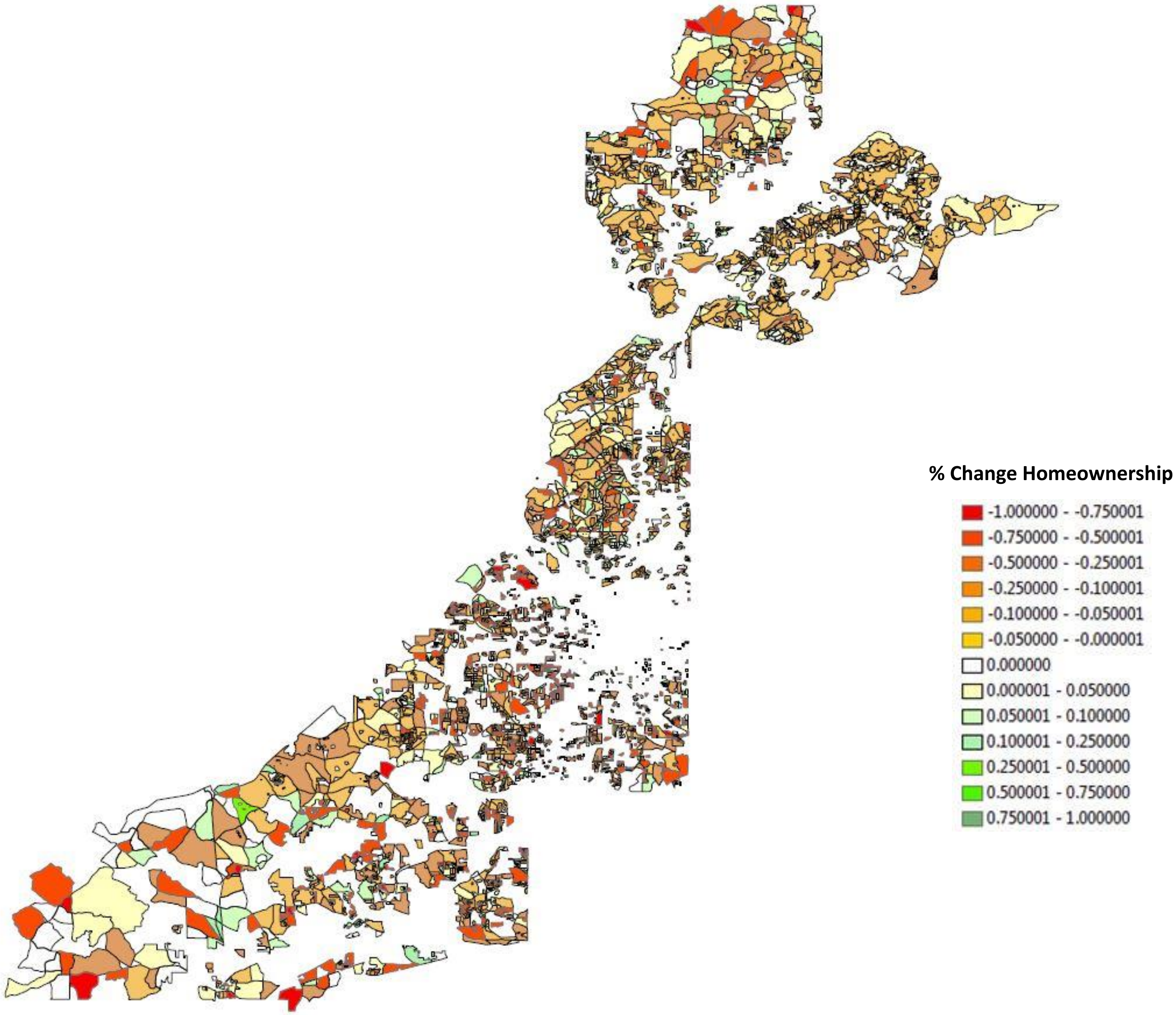
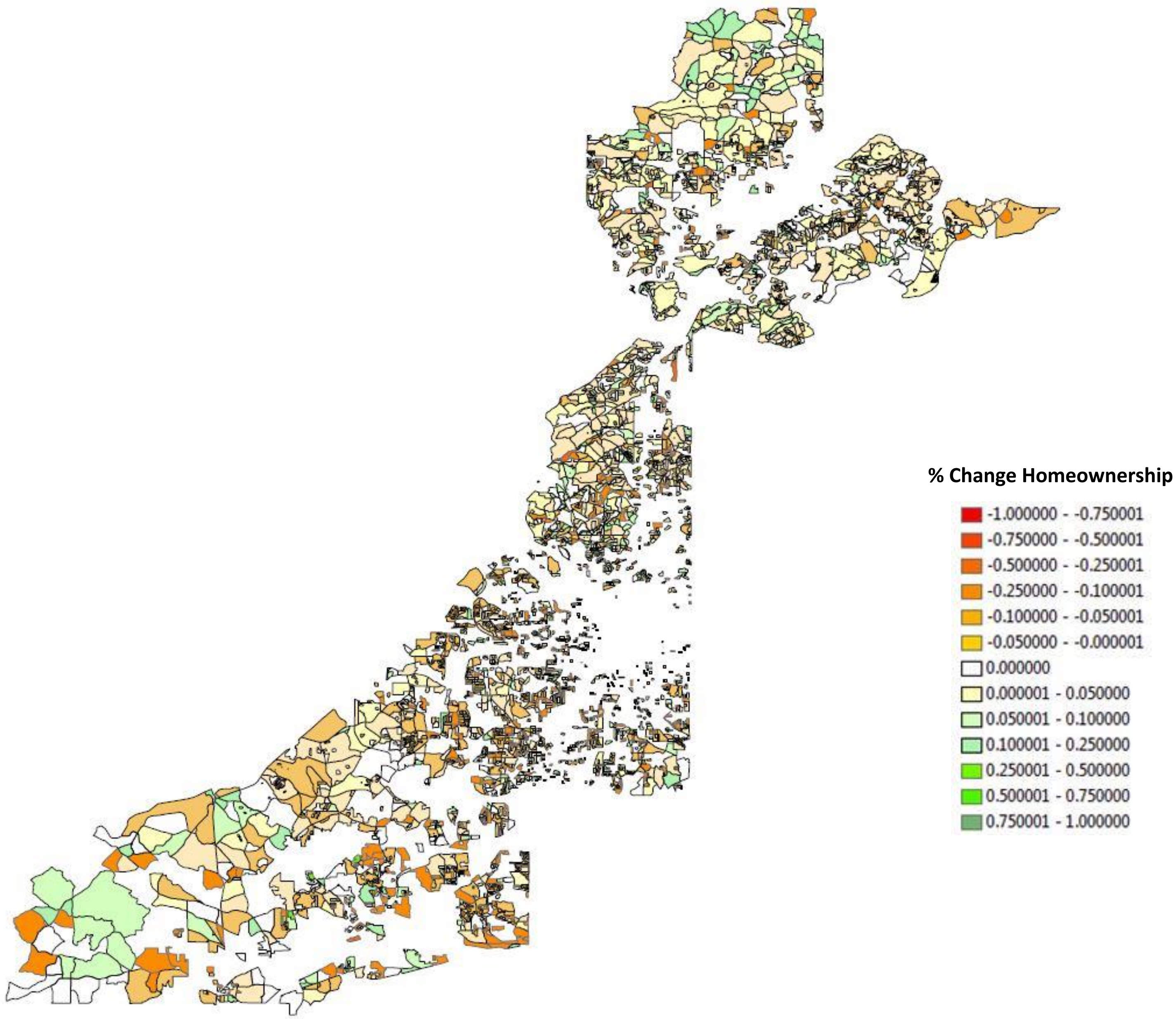


Figure A4: Homeownership Rate Change 2010 – 2014



Appendix B: Examination of Supply Shocks

Table 6 shows that some census blocks experienced large annual homeownership rate swings. The large annual homeownership swings (greater than 10% - increase or decrease) were often precluded by a large influx of newly developed single-family detached houses within the census block. When estimating the effect of homeownership on house prices in an area that has a large increase in newly developed houses it’s possible that the influx of new houses increases the homeownership rate and house prices simultaneously. As such, it’s important that the two effects are properly controlled for when estimating the effect of homeownership on house prices.

I identify 33 census blocks whose housing stock more than doubled in one year – which I flag using an indicator variable (*Shock*). I then create a control sample whereby I identify census blocks that (i) did not experience a supply shock (their housing stock did not increase by more than 10 percent in any given year) and (ii) are located in the same census tract, but not in the same census block-group (they are located in the same geographic area, but not in the immediate area). After identifying the control group I then construct a matched sample that identifies comparable properties that sold in the same calendar year, have the same number of bedrooms and bathrooms, and were built within five years of at least one of the *Shock* records. After dropping observations with no match - the control group of comparable properties (N=444) is over twice as large as the *Shock* group (N=1,100).

Properties in the census blocks are matched both before and after the supply shock, so that the control group’s house price trend serves as a counterfactual in the analysis. The approach assumes that the neighborhood characteristics in the treatment and control groups do not differ significantly. The approach also assumes that the control group’s house price trend is representative of the house price trend that the treatment group’s house price trend in the absence of the housing stock shock.[31] I then modify equation (1) to include the *Shock* indicator variable and two interaction terms: *Shock*After* and *Shock*After*Trend*. The coefficient on the *Shock* indicator variable estimates the constant price difference between houses in the treatment and control census blocks for the length of the study. The *Shock*After* interaction estimates a “permanent” price difference after the shock and the *Shock*After*Trend* interaction estimates the

[31] Wiley (2015) uses a similar approach to examine the impact of commercial development on surrounding residential house prices.

price difference after the shock over time. The *Trend* variable measures the number of years relative to the occurrence of the shock {…,-3,-2,-1,0,+1,+2,…} where 0 represents the year that the housing stock more than doubled.[32]

The results of the estimation are displayed in Table B1. Column 1 estimates the effect of homeownership on house prices using equation (1) - providing a baseline estimate (without the three additional variables) using the smaller subsample of data so that it can be compared to the full sample estimates in Table 9. Column 2 includes both the local market controls (Turnover, % Remodeled Houses, and Distressed Turnover) and the three additional supply shock variables. Whereas, column 3 includes the three shock variables, but not the local market controls. The results in both columns suggest that a supply shock does not have a significant effect on house prices. Whereas, the coefficient on the homeownership variable remains positive and significant.

[32] Only supply shocks that occurred in 2005 or later are included in the analysis in this section. Shocks that occurred earlier are not included in either the treatment or control groups. The 2005 cutoff was chosen to allow a minimum of three years of sales transactions in the "before" baseline trend.

Table B1: Examination of Housing Stock Shocks

	(1)	(2)	(3)
Homeownership Rate	0.2180***	0.2429***	0.2273***
	(0.00)	(0.00)	(0.00)
Age	-0.0113***	-0.0101***	-0.0102***
	(0.00)	(0.00)	(0.00)
Age Squared	0.0001***	0.0001***	0.0001***
	(0.00)	(0.00)	(0.00)
Sqft Living Area (000s)	0.3273***	0.3277***	0.3242***
	(0.00)	(0.00)	(0.00)
Sqft Squared (000s)	-0.0206***	-0.0211***	-0.0207***
	(0.00)	(0.00)	(0.00)
Lot Size Sqft (000s)	0.0035**	0.0035**	0.0035**
	(0.00)	(0.00)	(0.00)
Lot Size Sqft Squared (000s)	.0000	.0000	-0.0000*
	(0.00)	(0.00)	(0.00)
Number of Bedrooms	.0143	.0131	.0142
	(0.00)	(0.00)	(0.00)
Number of Bathrooms	0.0583***	0.0603***	0.0594***
	(0.00)	(0.00)	(0.00)
Number of Half Bathrooms	0.0397**	0.0399**	0.0396**
	(0.00)	(0.00)	(0.00)
Fireplace	.0054	.0081	.0081
	(0.00)	(0.00)	(0.00)
Garage	-.0353	-.0338	-.0337
	(0.00)	(0.00)	(0.00)
Carport	-.0209	-.0221	-.0229
	(0.00)	(0.00)	(0.00)
Pool	0.0840**	0.0856**	0.0858**
	(0.00)	(0.00)	(0.00)
Shock		.0432	.0466
		(0.03)	(0.03)
Shock * After		-.0307	-.0351
		(0.04)	(0.04)
Shock * After * Trend		.0041	.0038
		(0.01)	(0.01)
R-squared	0.90	0.90	0.90
Observations	1,544	1,544	1,544
Location Fixed Effects	Tract	Tract	Tract
Quarterly Fixed Effects	Yes	Yes	Yes
Distressed Sales Controls	Yes	Yes	Yes
Property Condition Controls	Yes	Yes	Yes
Census Controls	Yes	Yes	Yes
Market Controls	Yes	Yes	No
Homeownership Rate	Block	Block	Block

The dependent variable in every column is log of sales price. Homeownership is measured at the census block level.

School Quality, Latent Demand, and Bidding Wars for Houses

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Abstract

I examine the recent rise of bidding wars and their effectiveness relative to traditional listing strategies. A simple theoretical model predicts that underpricing a house to incite a bidding war will be most effective in housing markets with high levels of latent demand. I use school quality as a proxy for latent demand as households with children naturally want their kids to go to the best school possible. I posit that the limited supply of housing within high quality school districts creates latent demand for housing within those districts. Evidence from Atlanta supports the model - I find that underpricing a house to incite a bidding war is more effective in markets with latent demand. However, underpricing does not outperform traditional listing strategies.

1. Introduction

When a homeowner decides to list their house for sale they can choose either a "traditional" or "bidding war" listing strategy. The seller sets a list price that serves as an upper bound in a traditional listing strategy. The high list price is often adjusted downwards after a series of negotiations between the buyer and seller. In a bidding war strategy the seller sets a list price that serves as a lower bound. The low list price is meant to *incite* immediate activity and multiple competing bids, thereby, pushing the sale price upwards. Han and Strange (2014) estimate that a growing number of sales, over 30 percent in some markets, were involved in a bidding war. The increasing prevalence of bidding wars raises several questions. What are the underlying catalysts for bidding wars? Were the bidding wars intentional or unintentional? Can house sellers and/or their agent intentionally underprice a house to incite a bidding war? When a house is listed using a bidding war strategy (i.e. intentionally underpriced) does it outperform traditional listings? The purpose of this study is to test the hypothesis that latent demand, as proxied by school quality, along with supply constraints are two of the primary catalysts underlying the seller and/or agent's choice of listing strategy. While this is not the first to study the link between house price and school quality, the link to bidding wars has not been studied thus far and is one contribution of this paper.[1]

Any attempt to estimate bidding war's market share or causal effect on house prices is complicated by the fact that I do not know which listing strategy was employed or the number of bids received for each sales transaction. Previous studies simply assume that any house that sold for a price above its original list price was involved in a bidding war. Although the assumption satisfies the requirement that the seller's list price served as a lower bound, it does not identify whether the seller listed the house using a bidding war strategy. Another distinguishing feature of this study is the examination of whether the bidding war was intentional or unintentional. Sellers that want to intentionally start a bidding war will list their house for less than their expected sales price. Whereas, sellers that list their house above their expected sales price are not intentionally trying to start a bidding war. The delineation is important because the recent rise in bidding wars gives the impression that underpricing a house to incite a bidding war may be an effective listing strategy. Although it may be a false impression if a large fraction of the recent bidding wars are

[1] There is a rich literature that studies the link between house prices and school quality. See, for example, Black (1999), Bogart and Cromwell (2000), Downes and Zabel (2002), and Figlio and Lucas (2004).

unintentional. In addition, intentionally underpricing a house to start a bidding war may attract multiple competing offers that push the transaction price above the list price, but still result in an unfavorable outcome for the seller. In other words, underpricing a house may incite a bidding war, but not maximize the transaction price.

In this study, I identify neighborhoods with high levels of latent demand as they, by definition, contain multiple potential bidders who are waiting to purchase housing in that area. A high level of latent demand is a vital component of a bidding war strategy - as its goal is to incite immediate activity and multiple competing bids at the time of listing. Thus, neighborhoods that have high levels of built up latent demand offer the ideal setting for bidding wars. I use school quality as the primary measure of latent demand. School quality allows me to identify neighborhoods with built up latent demand because in most MSAs only children who live within a school's attendance boundary can attend the local public school. Households with children naturally want their children to attend the best school possible and are faced with two choices. They can either purchase housing services in a high quality school district or purchase housing services in a lower quality school district and send their children to a private school. For households of more modest means, sending their children to a private school may not be an option. The limited supply of housing in school districts that have the highest test scores creates latent demand for housing within the school district.

The level of latent demand in a given neighborhood is also a function of the neighborhood's housing supply elasticity. If the neighborhood has a large number of undeveloped residential lots, then a portion of the latent demand can be satisfied by building additional houses. However, if the neighborhood is highly developed (i.e. there are few undeveloped residential lots), then the latent demand for housing will persist as long as the local school's quality remains high relative to nearby school districts. Figure 1 presents a simple visualization of the theory. In the figure there are three neighborhoods that differ only in terms of school quality and housing supply elasticity. Each neighborhood's local average school test score is displayed in brackets and its housing supply elasticity is represented by the availability of undeveloped residential lots.[2] In this simple example, I would expect Market A to have the highest level of latent demand because it lacks developable lots and has the highest test scores.

Although bidding wars have received a good deal of media attention, some of which attributes partial blame to them for the housing boom and bust cycle of the 2000s, little is known about the forces that drive them or their effectiveness as a sales strategy. I show that built up latent demand, as proxied by high quality school districts with inelastic housing supplies, is one of the driving forces behind bidding wars. Additionally, real estate agents that advocate underpricing a house to incite a bidding war have come under scrutiny as critics argue that it is ineffective and constitutes a principal-agent conflict (Bucchianeri and Minson, 2013). The results of this study confirm that underpricing a house to incite a bidding war is ineffective. Although, I find that real estate agents use a bidding war listing strategy when selling their own house – which contradicts the assertion that real estate agents advocate bidding wars purely out of self-interest.

2. Background

Housing transactions are often modeled as a series of negotiations between buyers and sellers using a standard search model (Yinger 1981). In a traditional housing search model a seller hires a real estate agent to market their house for a given list price. The original list price set by the seller is assumed to be the ceiling at which the property can transact (i.e. the highest price the seller can possibly attain). When selecting a list price the seller faces a trade-off between sale price and time on the market (TOM) (e.g. Trippi 1977; Yavas and Yang 1995; Knight 2002).[3] The trade-off is a function of the seller's pricing strategy, as the house's list price directly affects the arrival rate of potential buyers. A low list price may increase the arrival rate and encourage potential buyers to look at the house sooner. However, a seller may set a higher list price as part of their bargaining strategy, because research shows that, on average, it produces a higher selling price.[4] Thus, the lower (higher) the seller lists their property, the more (fewer) potential buyers the listing will attract, the shorter (longer) the negotiation process, and the shorter (longer) the TOM.

[2] An increase in the average test score displayed in brackets represents an increase in the quality of the local school.
[3] Sirmans, MacDonald and Macpherson (2010) provide a detailed overview of previous studies.
[4] See for example Yavas and Yang (1995)

Anglin, Rutherford and Springer (2003) examine the degree to which a house is overpriced – which they measure as the percentage difference between the actual list price and the expected list price given the observable characteristics of the house. Anglin et al. (2003) argue that setting the initial list price too high may discourage participation by potential buyers – thereby increasing the property's TOM. Whereas, setting the initial list price too low may result in a quick sale – potentially lowering the sales price due to a lack of exposure. The degree of overpricing (DOP) measure in Anglin et al. (2003) implicitly assumes that every house uses a traditional listing strategy – where the list price is set higher than the expected sales price and negotiated downwards. Although 9.3% of the properties in their study sold for more than their list price Anglin et al. (2003) do not examine whether sellers intentionally underpriced their house to start a bidding war.

A bidding war listing strategy contains elements of two of the more common real estate sales approaches: standard search and auction. Similar to the traditional listing approach, a seller lists their house with a real estate agent, but instead of setting a list price that serves as a ceiling they intentionally list their house at a price below the expected sales price. The lower list price signals that they are not only serious about selling their house but also, similar to a real estate auction, attempts to attract multiple buyers that will bid the sales price higher than the original list price. If successful, a bidding war listing strategy can minimize the property's time-on-market (TOM) and holding costs, while maximizing its sales price.

Despite the extensive literature on listing price strategies and their impact on the relationship between sales price and TOM, there is a dearth of knowledge related to the underpricing of real estate in a search market, especially in regards to strategically underpricing real estate in an effort to create a bidding war. Bucchianeri and Minson (2013) examine the optimal pricing strategy that sellers should pursue in a search market and find that there is little or no benefit to underpricing a house, even in hot markets. They conclude that agents that advocate a bidding war listing strategy do so out of self-interest because it increases the probability of sale and their likelihood of receiving a commission. Han and Strange (2014) use survey data from the National Association of Realtors (NAR) to examine the frequency of bidding wars from 1986 – 2010. The authors document the rise of bidding wars, their determinants at the MSA level, and the individual characteristics of both buyers and sellers that participated in a bidding war. However, due to the nature of their data Han and Strange (2014) do not evaluate whether the seller intentionally underpriced their house to start a bidding war or if using a bidding war listing strategy is effective.

A related strand of literature on auction behavior is of particular interest to this study. Bidding wars are similar to auctions in that they have low starting prices and are likely to perform better in thicker markets with multiple known potential buyers. Recent studies on auction behavior find that auctions which open with low asking prices attract more bids and finish with higher prices (Simonsohn and Ariely 2007). Studies that examine auctions in a real estate setting offer conflicting evidence. Mayer (1995) develops a framework to compare the performance of auctions to negotiated sales (i.e. properties that were sold using the standard search process). Mayer (1998) finds that auctions result in a poor match and a discounted price, although he does note that auctions will perform worse in down markets with high vacancies. Quan (2002) develops a model in which buyers and sellers can choose between a search market and an auction. He then examines the two disposition alternatives and finds that vacant lots sold for a premium when sold at auction. A recent study by Chow, Hafalir and Yavas (2015) finds that auctions generate a higher relative price relative to negotiated sales when (i) demand for the house is strong, (ii) the asset is more homogeneous, and (iii) the asset attracts buyers with higher valuations.

In an efficient market, listing strategies should not affect house prices. However, researchers have shown that real estate markets are inefficient. For example, Lambson, McQueen and Slade (2004) find that out-of-state buyers paid a statistically significant and economically meaningful premium for apartment complexes in Phoenix, Arizona. Price distortions also exist when real estate agents sell houses that they personally own. Rutherford, Springer, and Yavas (2005) and Levitt and Syverson (2008) find that agent owned houses sell for approximately 4% more compared to non-agent owned houses. This study is similar to the aforementioned literature, in that I examine the inefficiency of real estate markets. However, I focus on listing strategies and their effect on house prices.

3. Identification Strategy

One limitation of this study is that it is impossible to identify whether a property was intentionally underpriced to incite a bidding war without contacting the previous owner or listing agent, which is time and cost prohibitive given the large dataset and extended timeframe of the study. Instead, I develop a detailed identification strategy based on several distinct criteria that are intrinsic to bidding wars. Similar to previous studies, the first criterion I propose is that the property must sell for more than its list price.[5] Second, the property must be intentionally underpriced. Third, the property must be listed in a thick market. Fourth, the property must not be atypical to ensure it appeals to as many potential buyers as possible. Fifth, there must be a high level of latent demand for the property.

The first criterion above identifies houses that were involved in a bidding war. The underlying logic is that the house's sale price was pushed above its list price by competing bids from multiple buyers. The first criterion, however, does not identify whether the house was listed using a bidding war strategy. The second criterion builds off the first and identifies houses whose list price was set below its expected sales price. The second criterion assumes that sellers are rational and set their list price based on recent comparable sales. Thus, if a seller sets their list price above the expected sales price they choose a traditional listing strategy where the list price is an upper bound and the final sales price is determined by a series of negotiations between the buyer and seller. If a seller sets their list price below the expected sales price they choose a bidding war listing strategy where the final sales price is determined by competition among multiple potential buyers who bid against each other in a quasi-auction framework.

The third criterion, that the property must be listed in a thick market, is indirectly related to the second criterion, as sellers must be reasonably confident in their sale price expectation to choose a bidding war strategy. In thin markets sellers have fewer comparable sales to draw from when setting their sales price expectations, so they are more likely to set a high list price. The high list price allows them to extract information from the market that is currently unavailable in the form of comparable sales. Additionally, thin markets, by definition, have fewer buyers so a low list price may not attract the requisite number of buyers for a successful bidding war.

[5] My approach differs slightly as I identify whether the *transaction price* is greater than both the original and terminal list price. The property's transaction price equals its sales price minus seller concessions. Previous studies do not include seller concessions. A property's terminal list price is its list price in the MLS when the buyer and seller reached an agreement and the property was taken off the market.

I draw the fourth criterion from previous research that finds that houses with atypical features take longer to sell and that sellers of atypical houses tend to set higher original list prices relative to the eventual sale price (Haurin 1988; Sass 1988). If a house is similar to recent comparable sales I expect its seller to be more confident in their sales price expectation. However, if the house is atypical the seller will not be as confident in their sales price expectation and is more likely to set a high list price to extract information from the market. Thus, I expect houses that are atypical to use a traditional listing strategy. Whereas, houses that are more homogeneous will choose between a traditional listing strategy and a bidding war strategy.

The fifth criterion, that the property is located in a neighborhood with a high level of latent demand is a vital component of a bidding war because the goal of the listing strategy is to incite immediate activity and multiple competing bids at the time of listing. A neighborhood with a high level of built up latent demand offers the ideal setting for a bidding war. I identify the level of latent demand in a neighborhood by identifying a strong positive externality. If a neighborhood offers a strong positive externality that only benefits households that reside within that neighborhood, then households who reside outside the neighborhood will compete for housing units in that neighborhood when they are listed for sale. The more difficult it is to reproduce the positive externality in surrounding neighborhoods, the higher the level of latent demand. The level of latent demand for the positive externality is also a function of the neighborhood's housing supply elasticity. If a property is located in a neighborhood that has a large number of undeveloped residential lots, then a portion of the latent demand can be satisfied by building additional houses in the neighborhood. However, if the neighborhood is fully developed then the latent demand for housing will persist over time as long as the positive externality remains.

I use school quality as an instrument for the positive externality mentioned above because it cannot easily be reproduced, its market delineations (i.e. school attendance boundaries) are clearly defined, and previous research finds that it is one of the most important criteria in the home buying process for households with children. For example, Black (1999) finds that parents are willing to pay 2.5 percent more for a 5 percent increase in school test scores and Figlio and Lucas (2005) find that families make location choices on the basis of school grades. School quality allows me to identify markets with built up latent demand because parents naturally want their children to attend the best schools possible and only children who live inside the school attendance boundaries can attend the local public school. As such, parents can (i) purchase housing services in a high quality school district or (ii) purchase housing services in a lower quality school district and send their children to a private school. For households of more modest means, private schooling may not be an option.

3.1 Implementation

I begin by identifying properties whose transaction price was greater than both its original listing price and terminal listing price. To construct the above list price indicator variable, $Above\ LP_i$, I define OLP_i as the original list price, LP_i as the terminal list price, TP_i as the transaction price, SP_i as the sales price, and SC_i as the seller concession for house i, where $TP_i = SP_i - SC_i$. I subtract seller concessions from sales price as concessions are often negotiated between the buyer and seller and their inclusion in the sales price could misclassify transactions as bidding wars.[6] Using the definitions above, I then define the $Above\ LP_i$ indicator variable as follows:

$$Above\ LP_i = \begin{cases} 0, if \ \max(OLP_i\ ,\ LP_i\ ) \geq TP_i \\ 1, if \ \max(OLP_i\ ,\ LP_i\ ) < TP_i \end{cases} \tag{1}$$

If $Above\ LP_i$ = 1 the house was involved in a bidding war. Next, I identify whether the seller used a traditional listing strategy – in which case the bidding war was unintentional – or if the seller intentionally underpriced the listing to incite a bidding war. To construct the underprice indicator variable, $Underprice_i$, I define $E(TP_i\ )$ as the expected transaction price when the house was initially listed on the MLS.[7]

$$Underprice_i = \begin{cases} 0, if \ \max(OLP_i\ ,\ LP_i\ ) \geq E(TP_i\ ) \\ 1, if \ \max(OLP_i\ ,\ LP_i\ ) < E(TP_i\ ) \end{cases} \tag{2}$$

Using (2) I further classify the bidding war transactions identified in (1) as intentional if $Underprice_i$ = 1 and unintentional if $Underprice_i$ = 0. As noted earlier, one drawback of this

[6] Over 53% of the sales transactions in the dataset included a seller concession. Of the transactions that included a seller concession the average concession was approximately 2.2%.
[7] The steps taken to estimate the expected transaction price for each listing are detailed in Appendix A.

study is that I do not know if houses that were underpriced ($Underprice_i$ = 1) and did not sell above their list price ($Above\ LP_i$ = 0) were involved in a bidding war that did not push their transaction price above their list price.

After classifying the bidding war transactions I examine how thick the market was when the house was listed. A bidding war requires multiple competing bids to push the sales price above the original list price, so I argue that bidding wars will be more likely in thick markets.[8] Additionally, sellers must be reasonably confident in their sales price expectation to be willing to employ a bidding war strategy. I create several measures of market thickness. First, I create two measures in the immediate vicinity of the subject property: competition and listing density. The two measures are similar to those employed in Turnbull et al. (2006) and Zahirovic-Herbert and Turnbull (2008). To construct the market competition variable I define l_i as the listing date and s_i as the sales date for house *i*. I then calculate house *i*'s time-on-market as s_i-l_i+1. If house *j* is also simultaneously listed for sale, then the two houses have an overlapping time-on-market of $O(i,j)$ = min[s_i, s_j] – max[l_i, l_j] + 1. Using the definitions above, the neighborhood market competition variable, *C*, measures the competition for house *i* as:

$$C^d = \sum\left(d - D(i,j)\right)^2 O(i,j) \qquad (3)$$

where $D(i,j)$ is the straight-line distance in miles between houses *i* and *j*. In this study, I measure C^d as the summation taken over all competing houses *j* within *d* miles of house *i*. I measure competition at several continuous spatial distances (radiuses of .25, .50, and 1 mile).

The next market competition variable, *L*, represents the listing density for house *i*. Listing density measures competing overlapping listings per day on the market. I estimate the listing density using a numerator similar to the competition variable in (3) and a denominator that is house *i*'s time-on-market as:

$$L^d = \sum \frac{\left(1-D(i,j)\right)^2 O(i,j)}{s(i)-l(i)+1} \qquad (4)$$

[8] This sentiment is echoed and confirmed in Han and Strange (2013) and Liu et al. (2015). Liu et al (2015) find that mansions, which have atypical features and trade in thin markets, never adopt a bidding war strategy. They argue, similar to Han and Strange (2013) that mansions' atypical features and thin market increases the risk that multiple bids for the mansion would not arrive at the same time even if the original list price was set well below the expected sale price.

In addition to the market competition and listing density variables, I also include an inventory and turnover variable at the elementary school level. *Inventory* measures the supply of single-family detached houses available for sale in the elementary school zone. I calculate *Inventory* as the total number of houses available for sale (i.e. listed on the MLS) during the month that the house was listed divided by the average number of sales per month over the previous year. *Turnover* measures the demand for housing over time within the elementary school zone. I calculate *Turnover* as the annualized average number of sales transactions over the previous three months divided by the housing stock.

Previous research finds that houses with unusual attributes sell for less and take longer to sell (Haurin 1988) and that real estate auctions generate a higher price relative to negotiated sales when the asset is more homogeneous (Chow et al. 2015). As such, I examine the atypicality of each house because I expect that houses with fewer unusual features will appeal to a broader market, thereby rendering a bidding war listing strategy feasible. Conversely, atypical houses will appeal to a smaller market segment, so a bidding war strategy is not feasible. I estimate the atypicality of each house following the framework in Turnbull et al. (2006) that measures atypicality as the extent to which a given house is either larger or smaller, in terms of its square feet of living area, relative to other houses in its surrounding neighborhood.[9] To create the atypicality measure, I index every house within a given radius of house *i* by *J* and estimate the house's relative size. The relative house size is estimated as follows:

$$Localsize_i = \frac{Livingarea_i - \sum_{j \in J} Livingarea_j / N_j}{\sum_{j \in J} Livingarea_j / N_j} \tag{5}$$

where N_j is the number of surrounding houses in the neighborhood *J*. I then define the relative size variables A_Larger_i and $A\_Smaller_i$ as the absolute value of the positive and negative values of $Localsize_i$ as follows:

$$A\_Larger_i = \begin{cases} 0 & , if\ Localsize_i \leq 0 \\ |Localsize|, & if\ Localsize_i > 0 \end{cases} \tag{6}$$

[9] Turnbull et al. (2006) estimate the atypicality of a house relative to other houses that were listed for sale, as their dataset did not include information on houses that were not listed for sale. If houses that are listed for sale are significantly different than houses that are not listed for sale then the measure employed in Turnbull et al. (2006) may be biased. The dataset includes information on houses that were and were not listed for sale, so I create the atypicality measure using the entire single-family detached housing stock.

$$A\_Smaller_i = \begin{cases} 0 & , if\ Localsize_i \geq 0 \\ |Localsize|, & if\ Localsize_i < 0 \end{cases} \quad (7)$$

where the relative size variables allow for asymmetric relative house size effects on a house i's market outcome. Similar to competition, I measure the atypicality of a house using several continuous spatial distances (radiuses of .25, .50, and 1 mile) and within elementary school districts.

I expect more bidding wars to occur in neighborhoods with a high level of latent demand because bidding wars require multiple competing bids to push the transaction price above its original list price. Assuming a thick market and low level of atypicality, a house located in a neighborhood with a high level of latent demand will, by definition, have multiple interested bidders waiting to bid on it when it is listed. Thus, neighborhoods with high levels of latent demand offer the ideal setting to employ a bidding war listing strategy. I estimate the latent demand for housing in a neighborhood using local school quality.

To estimate the local school quality for each transaction, I identify and assign each house to their local elementary school based on school attendance boundaries using a geographical information system. After assigning each house to the appropriate school, I then merge the transaction data with the average test score for the corresponding school. The local elementary school's average school test score serves as a proxy for local school quality.[10] I also measure the local housing supply elasticity as the percent of developed residential lots in the specified areal unit in which the house is located. To construct the housing supply elasticity measure I define u_J as the number of undeveloped lots and f_J as the total number of developed lots in neighborhood J. I then estimate the neighborhood's housing supply elasticity as:

$$E_J = u_J \,/\, (u_J + f_J) \quad (8)$$

In the empirical analysis I expect to find the highest levels of latent demand in housing markets that have high quality schools and are highly developed.

4. Data

[10] I describe the elementary attendance boundaries, redistricting of the boundaries, and school test score data in Section 4.

The dataset I employ in this study includes several data sources. The transaction level data was provided by the Georgia Multiple Listing Service (GAMLS). The transaction data includes every single-family detached house that was listed for sale on the GAMLS from January 1, 1997 to September 30, 2014, regardless of whether it sold or not. The data's coverage area includes four counties (Cobb, DeKalb, Fulton, and Gwinnett) that make up the core of Atlanta's metropolitan housing market. The GAMLS data contains detailed information on the property's location, lot size, age, structural characteristics (number of bedrooms, bathrooms, etc.), and sales conditions (foreclosure, short sale, etc.). The GAMLS data also includes listing information (listing date, list price, sales price, etc.) that I use to calculate time-on-market and identify houses that were marketed using a bidding war strategy.

I supplement and validate the GAMLS data with parcel level information from each county's tax assessor office. The tax assessor data contains information for the entire single-family detached housing stock regardless of whether the house was listed for sale or not during the study period. The tax assessor data was obtained from CoreLogic and includes additional information such as the house's square feet of living area that is not available in the GAMLS dataset. After merging the GAMLS and CoreLogic datasets I geocode the entire housing stock and identify the local elementary school that the occupant's children are eligible to attend based on the property's address. I use School Attendance Boundary Survey (SABS) files that were obtained from Department of Education's National Center for Education Statistics (NCES) to associate each housing transaction with its local elementary school and corresponding school district. Similar to previous research that examines school quality's impact on house prices I focus on elementary schools because it is the only school-level that allows for enough within-district variation.

The SABS files only include the school attendance boundaries for 2014. After assigning each house to its elementary school in 2014, I also identify whether the house is located in a school attendance zone that has been affected by redistricting during the study period. Redistricting is necessary in school districts where the school age population within the attendance zone outgrows the occupancy capacity of the school that serves it.[11] Information on

[11] This was a relatively common occurrence within in the metro-Atlanta area during the time period of this study due to the rapid growth in the student population. For example, Gwinnett County School District grew from

redistricting was obtained directly from the Atlanta Public School, City of Decatur, Cobb County, DeKalb County, Fulton County, Gwinnett County, and Marietta City school districts' planning departments.

Using data obtained from the Georgia Department of Education I create several measures of school quality based on each elementary school's average Criterion-Referenced Competency Test (CRCT) scores.[12] The CRCT was implemented in the spring of 2000 and retired in 2014 when it was replaced by the Georgia Milestones Assessment System. I create a static overall average test score variable using each elementary school's 2000 to 2014 CRCT test scores as well as a non-static annual average test score variable. I use the static overall average variable as a proxy for school quality when running the empirical analysis on the entire dataset (1997-2014). An obvious drawback of the static measure is that elementary school test scores will vary from year to year and the static measure does not take improvement (retrogression) into consideration. As such, I also use annual CRCT score averages and restrict the data to a subsample that includes the third quarter of 2000 through the third quarter of 2014.[13]

Students who take the CRCTs are not compared to each other based on their raw score, but are measured based on whether they meet specific academic standards outlined by the Georgia Department of Education. In addition to a raw test score, a student's achievement in each content area is classified into one of three performance levels: Student Met Standard, Student Did Not Meet Standard, or Student Exceeded Standard. Students' CRCT results are made available to the public at an aggregated school and system level each year. The primary test score variable used in the analysis is the average standard score for each elementary school that I calculate by normalizing and averaging each school's test scores across grades three

approximately 110,330 students in the 2000-2001 school year to approximately 175,800 in the 2014-2015 school year.

[12] Georgia law, as amended by the A+ Education Reform Act of 2000, requires that all students in first through eighth grade take the Reading, English/Language Arts, and Math CRCTs. Students in third through eighth grade also must take the Science and Social Studies CRCTs. The CRCTs are administered in late spring each year and the results are released prior to the end of the school year. The CRCT is designed to measure student achievement of state-mandated content standards. Additional information is available on the Georgia Department of Education's website (http://www.gadoe.org/).

[13] The CRCT test scores are typically released in June of the year they were administered. I associate the test scores from the 1999-2000 school year to sales in the third and fourth quarter of 2000 and the first and second quarter of 2001. The 2000-2001 test scores are then associated to sales in the third quarter of 2001 and so on.

through five.[14] Similar to previous research I focus on the average Math and Reading test scores for each elementary school.[15]

Seasonality variables are also included to examine school quality's role in a seller's decision to use a bidding war strategy. Seasonality likely plays a role because homebuyers with school-age children search within a narrow timeframe (i.e. spring and early-summer) – that way their children's education is not disrupted by a mid-year change of schools. To examine seasonality's role in bidding wars I create monthly and quarterly variables where *Winter* includes houses listed in January, February and March; *Spring* includes houses listed in April, May and June; *Summer* includes houses listed in July, August and September; and *Fall* includes houses listed in October, November and December.

Finally, I match each house with its 2010 census block, block-group, and tract. The predefined census groupings do not coincide with the school attendance boundaries. I use the census block-group identifications to match the houses with census data. After merging the datasets and removing records with missing fields there are 542,354 unique listing records, of which 408,959 resulted in a successful sales transaction. Two key fields, Agent Owned and Agent Related, are not populated for the entire length of the study so I parse the public remarks section of MLS data to populate the fields.[16] I also parse the public remarks section to identify and update missing information for every field used in the empirical analysis. For example, if the public remarks section states that the property is a "fixer-upper", but the listing agent did not

[14] From 2000 to 2003, I only use fourth grade CRCT test scores because only grades four, six, and eight were tested from 2000 to 2002. The test score variables from 2004 to 2014 include grades three through five.

[15] I also create a variable based on the percent of students in the elementary school that met or exceeded the CRCT standards. I create the variable by normalizing and averaging each school's percent of students that met or exceed the standards across grades three through five. This measure is the same as the average standard score assigned to each elementary school on the popular school ranking website schooldigger.com. As an additional robustness check I also create a variable that includes the following test scores for grades three through five: CRCT Reading, CRCT English Language Arts, CRCT Math, CRCT Science, and CRCT Social Studies. The findings are similar regardless of the school test score measure employed.

[16] The Agent Owned field is unavailable prior to 2006 and the Agent Related field is unavailable prior to 2009. I populate the fields by parsing the public remarks section of the MLS. For example, if the public remarks states that the "owner is agent", "agent is owner", "seller is agent", "agent is seller", "owner is real estate agent", "seller is real estate agent", "owner is licensed agent", "owner/agent", "seller/agent", or "seller is licensed agent" then I update the Agent Owned indicator variable accordingly. A similar string of key words is used to populate the Agent Related field.

mark the “fixer-upper” box when filling out the MLS input sheet I update the indicator variable accordingly.[17]

After updating the variables using the public remarks, I apply several filters to systematically clean the data. I winsorize the top and bottom 1 percent of sale and list prices and top 1 percent of time-on-market to remove potential outliers. I remove houses that were built prior to 1900 and exclude houses that have less than 500 square feet of living area, more than 5 acres of land, more than 6 bedrooms or bathrooms, a negative time-on-market, or a seller concession greater than 9 percent of the house’s sales price.[18] I also remove listings that included additional buildings/lots or were listed as a waterfront, rental, tear down, incomplete construction, new construction, or fixer upper property. The cleaned dataset includes 283,622 unique listings that resulted in successful transactions, of which 214,697 were non-distressed transactions. Summary statistics for the key variables of interest are available in Table 1. The average transaction price for the entire sample was $198,243 which was approximately $7,608, or 3.7 percent, less than the average list price at the time of sale. Approximately 9 percent of the sample sold for more than their original list price (*Above LP*) and an additional 4 percent sold for more than their reduced list price (*Above Reduced LP*).[19,20]

[Insert Table 1]

In the second and third sections of Table 1 the data is partitioned into non-distressed and distressed subsamples to show that the subsamples’ listing strategies, sales processes, and market outcomes differ. Houses in the distressed subsample were, on average, older, smaller, and in neighborhoods with lower school test scores. The distressed subsample also had a lower average sales price, took longer to sell, and were more likely to sell for more than their original list price. *Above LP* transactions represented approximately 15 percent of the distressed subsample compared to only 9 percent in the non-distressed subsample.

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[17] A complete list of the key words used when parsing the public remarks is available upon request.
[18] I remove all records that have a seller concession greater than 9% as that is the upper limit designated in Fannie Mae’s Interested Party Contributions (IPC) guidelines. FHA loans limit seller concessions to 6% of the sales price and require that each dollar that exceeds the six percent limit be subtracted from the property's sale price.
[19] Approximately 13 percent of the sample had a sales price that exceeded its original list price. The 4 percent difference highlights the fact that not accounting for seller concessions would result in a large number of transactions being misclassified as bidding wars.
[20] The above reduced list price grouping includes all sales transactions where the transaction price was greater than a list price that was reduced at least once over the course of its listing period.

The time-on-market measure in Table 1 was constructed using both sold and unsold listings where properties that were taken off the market and relisted within 60 days are treated as a continuous listing.[21] Approximately 4 percent of the transactions were relisted at least once prior to their sale. The average time-on-market for the entire sample was just under 84 days. In Figure 2 (3) I graph time-on-market kernel density estimates for all non-distressed sales transactions (with a TOM less than or equal to 90 days).[22] In both figures the transactions are partitioned into six groups: above original list price, above reduced list price, above increased list, below or equal to original list price, below or equal to reduced list price, and below or equal to increased list. As expected, sales transactions with a reduced list price have a longer time-on-market, as the list price reduction signals that the property did not transact earlier at the original list price. Sales transactions whose list price increased also have a longer average time-on-market compared to sales that did not change their list price.

[Insert Figure 2]

The two figures illustrate the fact that a high proportion of above original list price transactions sold quickly. However, there are a large number of above original list price transactions that took an extended amount of time to sell. If one of the primary goals of a bidding war is to incite immediate activity then Figures 2 and 3 highlight the need to further refine the proxy for bidding wars. As such, I create several bidding war measures using various TOM cutoffs. My preferred bidding war measure includes all above original list price transactions that sold within 28 days. The 28 day cutoff signifies that the listing incited immediate activity and multiple bids. Although I do not have information on the number of bids received, it is more plausible that a transaction price was pushed higher by multiple bids early in its listing cycle (i.e. four weeks or less) compared to a house that was listed for ten weeks.

[Insert Figure 3]

4.1 Underpriced Listings and Bidding Wars

[21] TOM = [Sale Date] – [Initial Listing Date] – [Days not on MLS]

[22] 90 days or 3 months represents the average length of a listing contract agreement between sellers and their agents in the sample.

Han and Strange (2014) classify a transaction as a bidding war if its sales price exceeded its list price.[23] Although this approach identifies houses that were likely part of a bidding war - it does not identify if the house was intentionally underpriced to incite a bidding war. If a house seller wants to start a bidding war the most effective strategy would be to set their list price lower than their expected sales price – similar to an auction. The results in the top section of Table 2 examine whether underpriced houses sold for more than their list price (columns 3 to 6) and expected transaction price (columns 7 to 10).

[Insert Table 2]

Underpricing a house results in a bidding war approximately 9 percent of the time – although only 1 percent of the houses in the underpriced subsample sold for more than their expected transaction price. The transaction price for the overpriced subsample was less likely to result in a bidding war (~5%), but much more likely to exceed its expected transaction price (~76%). The middle and bottom sections of Table 2 are filtered to only include houses that were part of a bidding war. In the middle section, columns 1 and 2 show that 50 percent of bidding wars, as proxied by *Above LP* transactions, were intentionally underpriced. The underpriced transactions represent a subset of houses that used a bidding war listing strategy and were successful in terms of inciting a bidding war. Of the houses that used a bidding war listing strategy, only 13 percent sold for more than their expected transaction price. Using the preferred proxy (*Above LP* [TOM ≤ 28 days]) in the bottom section, I estimate that 55 percent of the houses that were involved in a bidding war were intentionally underprice – of which only 11 percent exceeded their expected transaction price.

The results in the top section of Table 2 suggest that bidding wars occur more often when a house is underpriced and that inciting a bidding war by underpricing a house may come at the expense of a lower than expected transaction price. This fact is further reinforced in the middle and bottom sections of Table 2 - which only include transactions that involved a bidding war.[24] Even when conditioning on a successful bidding war, only 11 to 13 percent of the underpriced listings sold for more than their expected transaction price.

[23] As noted earlier, this study uses transaction price instead of sales price.
[24] In other words, underpriced houses that did not sell for more than their list price were removed.

4.2 Bidding War Frequency

To examine the frequency of bidding wars over time I partition the dataset into annual subsamples from 1998 to 2014 in Table 3. The average time-on-market, premium above list price, inventory, turnover, and the number of transactions are displayed for the entire sample and several distinct groupings. The number of houses that sold for more than their list price, which has been used as a proxy for bidding wars in previous literature, increased during the early- to mid-2000s, accounting for as much as 10.2 percent of the total non-distressed sales transactions in 2001. Bidding wars are often anecdotally associated with the housing boom and I do find that the number of sales that transacted above their list price decreased during the financial crisis. However, Table 3 shows that the decrease in bidding wars was temporary and that their market share started increasing back to pre-crisis levels in 2012. Bidding wars represented 7.5 percent of the market prior to the real estate crisis (2003 – 2006), 3.0 percent during the housing bust (2007-2011), and 7.1 percent during the housing recovery (2012-2014) in Atlanta.[25] The reemergence of bidding wars after the financial crisis suggests that they were not a temporary byproduct of the housing boom.

[Insert Table 3]

The results in the top section of Table 3 also highlight the relationship between bidding wars and market conditions. The time-on-market, inventory, and turnover measures represent the average market conditions for the elementary school zones where the bidding wars took place. When inventory decreased (increased), bidding wars' market share increased (decreased). Whereas, when turnover increased (decreased), bidding wars' market share increased (decreased). There was a relatively large increase in the premium above original list price from 2008 to 2012.[26] From 1997 to 2007, the premium ranged from 2.8 to 3.7 percent. However, from 2008 to 2012 the premium ranged from 4.5 to 6.0 percent - averaging approximately 5.4 percent. Although there were much fewer bidding wars, in terms of both volume and market share, from 2008 to 2012 - the houses that were involved in a bidding war benefited from a higher average

[25] For comparison purposes, Han and Strange (2014) estimate that 11.4% (9%) of all non-distressed sales sold for more than their list price during Atlanta's housing boom of 2003 – 2006 (housing bust of 2007 – 2010).
[26] Premium Above LP = [TP – max(OLP, LP)] / [max(OLP, LP)]

premium above list. In 2013 and 2014, the premium above list price returned to pre-crisis levels although the average TOM was considerably lower.

The average time-on-market for houses that were involved in a bidding war increased leading up to and during the financial crisis, but dropped below pre-crisis levels soon after. The high average TOM, especially from 2004 to 2008, does not seem plausible for bidding wars, so I report similar descriptive statistics for a subsample of transactions in which transaction price exceeded list price *and* the time-on-market was 28 days or less. As noted earlier, the 28 day time-on-market cutoff represents the preferred proxy for bidding wars. Using '% *Above LP* [TOM ≤ 28]' as the proxy, bidding wars represented 2.7 percent of the market prior to the real estate crisis (2003 – 2006), 1.6 percent during the housing bust (2007-2011), and 5.5 percent during the housing recovery (2012-2014) in Atlanta.

Next I partition the *Above LP* [TOM ≤ 28] grouping into intentional and unintentional bidding wars. A transaction is considered an intentional bidding war if (i) its transaction price exceeded list price, (ii) the house had a time-on-market of 28 days or less, *and* (iii) the house was underpriced. A transaction is considered an unintentional bidding war if its meets requirements (i) and (ii), but it was listed for more than its expected transaction price. Intentional bidding wars represented 1.5 percent of the market prior to the real estate crisis (2003 – 2006), 1.1 percent during the housing bust (2007-2011), and 3.0 percent during the housing recovery (2012-2014). Whereas, unintentional bidding wars represented 1.2 percent of the market prior to the real estate crisis (2003 – 2006), 0.5 percent during the housing bust (2007-2011), and 2.5 percent during the housing recovery (2012-2014).

4.3 School Quality, Housing Supply Elasticity, and Latent Demand

Table 4 provides summary statistics by school test score deciles for non-distressed sales transactions. Columns 1 to 3 display the average, minimum and maximum school test score for each decile.[27] The deciles were created such that the elementary schools with the lowest average school test scores are included in the 1st decile. As school test scores increase so too do their

[27] The school test scores in Table 4 represent the static overall average Math and Reading CRCT scores for each elementary school from 2000 through 2014.

corresponding decile. There are 323 elementary schools in the metro Atlanta area, so each decile represents 32 or 33 schools.[28]

[Insert Table 4]

Columns 4 to 10 of Table 4 display aggregated transaction level detail for each decile. The transaction detail shows that the average annual sales volume per school district and the average transaction price increase as the deciles increase. In contrast, the percent of above list price sales transactions decrease as the deciles increase. The percent of above list price sales represents all transactions in which the transaction price of the property exceeded both its original and terminal list price regardless of property's TOM. Whereas, the percent of bidding wars represents all transactions in which the property's transaction price exceeded its original and terminal list price *and* the property sold in 28 days or less. The bidding war proxy is further partitioned into intentional and unintentional bidding wars. Intentional bidding war shares exceed unintentional bidding war shares in the upper deciles. Whereas, the unintentional bidding war shares exceed or are on par with intentional bidding war shares in the lower school test score deciles. Also, note that the average transaction price for the 5th through 8th deciles is not monotonic which suggests that homebuyers may only be willing to pay a premium to live in neighborhoods located in the top two test score deciles.

Each decile's average housing supply elasticity is presented in the final section of Table 4. Column 11 represents the average number of single-family detached lots in each elementary school zone. For each decile, column 12 (14) displays the average number of undeveloped lots in an elementary school zone in 1997 (2014) and column 13 (15) displays the corresponding average percent of undeveloped lots. In 1997, there was no clear pattern across the deciles. In contrast, a clear pattern emerged over time and is visible in 2014. The percent of undeveloped lots in the higher quality school deciles decreased over time as demand increased for housing in neighborhoods with higher test scores. In 2014, the top two deciles had the lowest percentage of developable lots. This stylized fact combined with the upper decile price premium lends credence to the expectation that there is latent demand for housing in neighborhoods with higher school test scores.

[28] School quality is loosely correlated with median household income. High income neighborhoods generally have high quality schools. However, high quality schools are also located in lower income neighborhoods.

4.4 Transaction to List Price Ratios by School Decile

In Figure 4 I graph the transaction to original list price ratios for the school test score deciles presented in Table 4. Figure 4 includes all non-distressed sales in which the transaction price did not exceed its list prices ($\max(OLP_i\,,\ LP_i\,) \geq TP_i\,)$ and was not underpriced ($\max(OLP_i\,,\ LP_i\,) \geq E(TP_i\,))$. These transactions represent houses that were listed using a "traditional" listing strategy in which the house seller sets a list price that serves as an upper bound. Sellers who are uncertain about their expected sales price use the traditional listing strategy to extract information from the market. They often set their list price above their expected selling price by an amount that increases with their uncertainty about their home's market value (Liu et al. 2015). The high list price is then adjusted downwards after a series of negotiations between the buyer and seller. Figure 4 shows that sellers in the upper school test score deciles are more certain about their expected sales price, especially during the real estate bust and subsequent recovery (2007 – 2014). This suggests that sellers in the upper test score deciles are more likely to select a bidding war listing strategy because confidence in sales price expectations is a necessary condition when selecting a bidding war listing strategy.

[Insert Figure 4]

4.5 Listing Agents and Agent Owned Sales

The seller's decision to underprice their house in an attempt to start a bidding war was likely influenced by the real estate agent they chose to list their house. Table 5 displays the frequency in which bidding wars are employed by listing agents. Of the 23,340 distinct agents with at least one listing in the dataset over one-fourth (27.4%) of the agents had a listing that sold above its list price at least once – although that number drops to 16.7 percent when the using the preferred TOM ≤ 28 constraint. Approximately 10.4 percent of the agents were involved in at least one transaction in which they intentionally underpriced the house and it sold above the list price within 28 days. Of the 2,437 agents that employed an intentional bidding war listing strategy the majority (74.6%) only did so once. The frequency in which the bidding war listing strategy is employed varies greatly by listing agent, but Table 5 shows that numerous listing agents have repeatedly employed the strategy for their clients.

[Insert Table 5]

Real estate agents that advocate underpricing a house to incite a bidding war have come under scrutiny as critics argue that it constitutes a principal-agent conflict (Bucchianeri and Minson, 2013). Next, I examine whether real estate agents use a bidding war listing strategy when selling their own house – which would contradict the assertion that real estate agents advocate the listing strategy purely out of self-interest. If real estate agents – who are often better informed than their clients (Levitt and Syverson 2008) - advise their clients to use a bidding war strategy, but do not employ the strategy themselves it may signal that the agents' primary motive is a quick sale and not the maximization of sales price for their clients. However, if real estate agents use bidding wars when listing their own properties it may signal that they believe the listing strategy is an effective option.

The top portion of Table 6 is stratified by the number of agent owned sales transactions. Agents with a single agent owned sales transaction intentionally employed a bidding war listing strategy 1.3 percent of the time – which is slightly less than the 1.8 percent average for the non-agent owned sample. However, if the agent owned and sold multiple houses they were more likely to use a bidding war listing strategy. Overall, approximately 1.7 percent of the agent owned transactions were sold using a bidding war listing strategy – which is in line with the 1.8 percent average for the non-agent owned sample.

[Insert Table 6]

I also created a subsample of agent owned sales that I filtered to only include agents that used a bidding war strategy at least once for a client. After conditioning on the use of a bidding war listing strategy for a client, 4.9 percent of the agents in the subsample also used a bidding war strategy when they sold their own house.[29] Thus, real estate agents that advocate the use of a bidding war listing strategy for their clients are more likely to use the strategy themselves when listing their own house.

4.6 Transaction Level Analysis of Bidding Wars

[29] The subsample consisted of 628 agent owned sales transactions – of which, 31 were underpriced and sold for more than their list price.

To further examine the factors that influence bidding wars and a seller and/or agent's decision to use a bidding war listing strategy I estimate several linear probability models that take the following form:

$$W_{ijt} = \alpha + \sum_{k=1}^{K} \beta_k X_{jkt} + \varepsilon_{jt} \tag{9}$$

where W_{ijt} represents the probability that house *i* located in neighborhood *j* will (i) be involved in a bidding war, (ii) involved in an intentional bidding war, or (iii) involved in an unintentional bidding war at time *t*. X_{jkt} represents a vector of K potentially related transaction level correlates, β_k represents the corresponding coefficients, α is a constant, and ε_{jt} is the error term. In addition to the three specifications above, I run a specification that examines a house sellers decision to underprice their house and a specification the examines the transaction level correlates for underpriced houses that result in a bidding war.

Table 7 presents the results for the five specifications - all of which include census tract and time fixed effects in addition to the variables displayed. The first column presents the results for bidding wars as proxied by *Above LP* [TOM ≤ 28]. The second column presents the results for houses that used a traditional listing strategy that were involved in a bidding war (i.e. unintentional bidding wars) and the third column presents the results for underpriced houses that were involved in a bidding war (intentional bidding wars). The analysis was run using sales transactions that occurred in elementary school zones that were not affected by redistricting initiatives during the study period.

[Insert Table 7]

The results at the top of Table 7 show an interesting pattern among bidding wars and school test scores. The results in column 1 suggest that bidding wars are not correlated with school test scores. However, the results in column 2 suggest that an unintentional bidding war is more likely to occur in a school district with higher test scores. Whereas, an intentional bidding war is less likely to occur in a school district with higher test scores. Most of the physical characteristics of the house produce mixed results across the three specifications or are insignificant in all three – although larger houses are less likely to be involved in bidding wars. Using survey data, Han and Strange (2014) find that younger buyers are more likely to have purchased their houses through bidding wars. I include an indicator variable that identifies houses that were described as “starter homes” in the MLS listing. The indicator variable is positive and significant in column 1. The result confirms the finding in Han and Strange (2014) and suggests that “starter homes” – which are often marketed towards young, first-time homebuyers – are more likely to be purchased through a bidding war.

An indicator variable for agent owned houses is insignificant in all three models – although transactions in which the agent is related to the seller is significant and negative in two of the three specifications. An increase in inventory reduces the likelihood of a bidding war in all three specifications. Thus, when supply decreases (increases) bidding wars are more (less) likely to occur. Along the same line, as turnover increases (decreases) the likelihood of bidding war increases (decreases). Seasonality also plays a role in bidding wars. Houses are much more likely to be purchased through a bidding war when they are listed in the first six months of the year.[30]

The dependent variable in column 4 is the *Underprice* variable from equation (2). Thus, the estimates in column 4 identify the transaction level correlates for houses that were intentionally underpriced. The coefficient on school test scores is negative, large, and significant – which suggests that house sellers in high quality school districts are less likely to underprice their house. The coefficients on the physical characteristics of the house are mixed. Larger houses with more bathrooms are more likely to be underpriced. However, houses with five or six bedrooms are less likely to be underpriced. Houses listed as estate owned or corporate relocations are also less likely to be underpriced when they are listed. The decision to underprice a house is not correlated with agent owned, agent related, or the level of inventory on the market when the house was listed. It is, however, correlated with market turnover and the season in which it is listed. A house is more (less) likely to be underpriced as recent market turnover increases (decreases).

In column 5, the data is further partitioned to only include underpriced listings. The dependent variable in column 5 equals 1 if the house was underpriced and resulted in a bidding war and 0 if the house was underpriced and did not result in a bidding war. Although houses in

[30] In unreported results – a linear probability model that incudes indicator variables for each month instead of the seasons shows that houses listed in March, April, and May were more likely to be purchased through a bidding war (compared to the omitted category of January). Whereas, listings in October, November, and December were less likely to be purchased through a bidding war. Months not mentioned were insignificant in the model.

neighborhoods with high school test scores are less likely to be underpriced – they are more likely to result in a bidding war when they are underpriced. Smaller houses with three bedrooms are more likely to result in a bidding war when underpriced. Agent owned houses are also more likely to result in a bidding war when underpriced – which supports the narrative in previous literature that agents are better informed than their clients (Levitt and Syverson 2008). Surprisingly, underpricing a house to start a bidding war is not correlated to the inventory on the market or recent turnover within the market when the property was listed.

One dynamic not explored in this study is the relationship between bidding wars and redistricting of houses among the elementary school zones. If a house in a low (high) quality elementary school zone is suddenly redistricted to a high (low) quality school zone it will impact the demand for and value of the house (Bogart and Cromwell 2010; Ries and Somerville 2010). Although I have information on what elementary school zones were involved in a redistricting initiative, I cannot isolate the individual houses that were affected. To ensure the results reported in Table 7 are not biased by redistricting initiatives I remove every elementary school zone that was redistricted – simplifying the analysis to focus solely on bidding wars and latent demand, as proxied by school quality, over time. Thus, I do not explore the link between bidding wars and redistricting – primarily because of data restrictions – and leave it for examination in future studies on the topic.

5. Empirical Strategy

I recognize that a house's selling price and time-on-market are simultaneously determined when a traditional listing strategy, in which the seller sets a high original list price and the sales price is negotiated downward, is employed. As such I specify a joint determination model similar to Turnbull and Dombrow (2006) as:

$$P = \varphi_p(T, X, A, C) + \varepsilon_P \tag{10}$$

$$T = \varphi_T(P, X, A, C) + \varepsilon_T \tag{11}$$

where P is log of transaction price, T is time-on-market, X is a vector of property and location characteristics, A represents the atypicality of the house, C is a measure of market thickness that represents the current local housing market conditions, and ε_P and ε_T are the stochastic error terms.

As noted in Zahirovic-Herbert and Turnbull (2008) the sales price regression in (10) would yield the estimated effect of competition C on price as the partial derivative $\partial P/\partial C$ if time-on-market were held constant. Whereas a change in competition while holding time-on-market constant can be expressed as a change in listing density, such that $\partial P/\partial C = \partial P/\partial L$. Thus, I rewrite (10) and (11) as:

$$P = \varphi_p(T, X, A, L) + \varepsilon_P \tag{12}$$

$$T = \varphi_T(P, X, A, C) + \varepsilon_T \tag{13}$$

The primary goal of the empirical analysis is to isolate the effect of bidding wars on real estate market outcomes. Similar to previous research the joint determination framework in (12) and (13) assumes that sellers face a trade-off between sale price and time-on-market. In other words, the equations do not consider bidding wars. As such I modify the framework as follows:

$$P = \varphi_p(T, X, A, L, W, Q) \tag{14}$$

$$T = \varphi_T(P, X, A, C, W, Q) \tag{15}$$

where W is an indicator variable for a property that was involved in a bidding war and Q is the quality of the local elementary school.

I create several measures for the bidding war indicator variable as the original definition includes sales transactions with long marketing periods. My preferred measure only includes listings that have a time-on-market of 28 days or less.[31] The local school quality variable, Q, is created at the elementary school level based on local school boundaries and their corresponding average test scores. I use the school test scores as a proxy for latent demand in the housing market. I also include interaction terms between the underpriced indicator variable and the

[31] I also use measures that include underpriced listings that sold within 14 days (2 weeks), 42 days (6 weeks), and 56 days (8 weeks). If one of the primary goals of a bidding war is to incite immediate activity then the preferred measure of 28 days or less is the most appropriate. I report results for the 28 and 42 day cutoffs. The results for the 14 and 52 day cutoffs are similar – although the magnitudes of the coefficients differ.

continuous school quality variable to examine the effectiveness of bidding wars across neighborhoods of varying levels of latent demand.

5.2 Matched Samples

Prior to running the analysis I examine the data for potential sample selection biases. In Table 8, the non-distressed subsample from Table 1 has been partitioned into a treatment and control group – where *Above LP* is the proxy for the treatment group (i.e. bidding wars) in the top section and *Above LP* [TOM ≤ 28 days] is the treatment group in the bottom section. Similar to Table 7, the data only includes sales transactions from elementary school zones that were not affected by redistricting. The t-test results in column 3, which compare the difference between the means of the treatment and control groups, identify a potential issue. The list price and TOM variables should differ based on the listing approach employed by the seller, but the house characteristics should be similar – if not, the empirical analysis may be affected by sample selection bias.

[Insert Table 8]

To address this potential issue I create two matched samples. The first matching process identifies every unique combination of the following neighborhood and house characteristics in the treatment group: elementary school zone, transaction year, number of bedrooms, and number of bathrooms. I then limit the control sample to only include records that were not underpriced and that match at least one of the records in the treatment group on every characteristic. When creating the matched sample for the *Above LP* [TOM ≤ 28 days] treatment group I also remove records that sold above their list price (i.e. were not involved in a bidding war). The process matches transactions that were involved in a bidding war with transactions that were not.

The second matching process I employ matches each observation in the treatment group with its nearest neighbor in the control group using a one-to-one propensity score matching process with replacement.[32] The second matching process requires an exact match on the elementary school and transaction year fields – if there is no exact match then the treatment record is dropped. Conditional on an exact match, the process then identifies the nearest

[32] Propensity score matching techniques (Rosenbaum and Rubin 1983) have been been employed in residential (McMillen 2012) and commercial (Eichholtz, Kok and Quigley 2010; Wiley 2014) real estate studies.

neighbor(s) based on the following fields: age, living area, lot size, bedrooms, bathrooms, and the latitude and longitude coordinates of the house. The propensity score matching process allows replacement - which increases the matching precision, but does so at the expense of statistical power (Wiley 2014). The t-statistics for the matched samples in columns 6 and 9 are smaller in magnitude which suggests that running the empirical analysis on the matched samples will help address potential empirical problems resulting from sample selection bias.

6. Empirical Results

A question of primary interest to this study is whether properties that were involved in a bidding war sell for a premium (discount) relative to properties that were not involved in a bidding war. Table 9 presents the results from a 2SLS regression that controls for time-on-market. I use houses that sold above their original listing price within 28 days [columns 1, 3, and 5] and 42 days [columns 2, 4, and 6] as proxies for bidding wars. In addition to the bidding war indicator variables I include each school's annual test score and an interaction between the two variables. The results in the top section of Table 9 use the full sample, the middle section uses the characteristic matched sample, and the bottom section uses the nearest neighbor matched sample.

[Insert Table 9]

The results in the top section confirm my expectation that bidding war's effectiveness will vary across markets based on school test scores. Using the school test score data as a proxy for latent demand – the results in the top section show that houses that were purchased through a bidding war had higher prices neighborhoods with higher levels of latent demand. The results in the top section are sensitive to the TOM constraint imposed on the bidding war indicator variable and the market cycle. In column 1, I find that houses that were purchased through a bidding war resulted in higher prices in neighborhoods with school test scores above 61.9% which, according to the decile ranges in Table 5, would include all transactions that took place in neighborhoods in the top four deciles and a large portion of the 6th decile. Based on the results I estimate that a house in the top decile would, on average, sell for approximately 1.28% more if it was purchased through a bidding war. The 1.28% increase represents a premium of approximately $3,868 based on the decile's average sales price of $301,500. Turning my attention to neighborhoods on the lower end of the school test score range, I find that houses involved in a bidding war sell for a discount. A house located in a neighborhood in the bottom decile of school test scores would sell for approximately 2.51% less if it was purchased through a bidding war. The 2.51% decrease represents a discount of approximately $3,269 based on the decile's average sales price of $130,300. The results in column 2, which uses a TOM cutoff of 42 days are similar – although houses in neighborhoods with a test score above 54.4% would sell for a higher price if it were involved in a bidding war.

The extended time period of the study allows me to examine bidding war transactions throughout the housing market cycle. In columns 3 to 6, I partition the dataset into two subperiods that represent "up" and "down" markets. Columns 3 and 4 represent an up market in which house prices were rising in the metro Atlanta housing market. The results in column 3 (4), show that houses that were purchased through a bidding war sold for, on average, a 1.83% (2.49%) premium from 2000 to 2006. Columns 5 and 6 represent a down market in which house prices rapidly declined and then slowly recovered in the metro Atlanta housing market. The results in columns 5 and 6 suggest that houses that were involved in a bidding war only sold for a premium in neighborhoods that had a high level of latent demand from 2007 to 2014. . In column 5, houses that were purchased through a bidding war resulted in higher prices in neighborhoods with school test scores above 80.2% which, according to the decile ranges in Table 4, would include all transactions that took place in neighborhoods in the top two deciles and a portion of the 8th decile.

In the middle and bottom sections of Table 9, I re-run the analysis using the characteristic matched and nearest neighbor matched subsamples. The results in columns 2, 4, and 6 of Table 9 use the matched samples in the top section of Table 8. The results in columns 1, 3, and 5 of Table 9 use the matched samples in the bottom section of Table 8. After controlling for potential sample selection biases the results from the matched sample sections of Table 9 suggest that houses that were purchased through bidding wars sell for, on average, less than houses that used a traditional listing strategy. The results do, however, suggest that houses that were purchased through a bidding war fared better in neighborhoods with higher levels of latent demand. For example, in column 1 of the nearest neighbor matched section – houses that were purchased through a bidding war sold for a 7 percent discount. However, the interaction term shows that the discount decreased as the school test score increased.

6.1 Repeat Sales Specification

Although the dataset includes detailed information on every parcel, it may still be subject to an omitted variable bias - as it is impossible to include every physical attribute related to the house in a hedonic model. One potential concern with the results in the previous sections is that the houses that were purchased through bidding wars differed in quality relative to the houses that were sold using a traditional listing strategy. This is particularly important given the differing results in the full and matched sample analysis. In the next step of the analysis I address these concerns by explicitly controlling for the unobserved quality of the individual house using a repeat-sales specification with house fixed effects. In addition, I partition the bidding war sample into intentional and unintentional bidding wars to examine their performance separately.

[Insert Table 10]

The results in column 1 of Table 10 are comparable to the full sample results in column 1 of Table 9. Houses that were purchased through bidding wars result in higher prices in neighborhoods with school test scores above 61.8% which, according to the decile ranges in Table 5, would include all transactions that took place in neighborhoods in the top four deciles and a large portion of the 6^{th} decile. Based on the results in column 1 of Table 10 - I estimate that a house in the top decile would, on average, sell for approximately 1.79% more if it was involved in a bidding war. The 1.79% increase represents a premium of approximately $5,387 based on the decile's average sales price of $301,500. Turning my attention to neighborhoods on the lower end of the school test score range, I find that houses that sold through a bidding war fared much worse. A house in the bottom school score decile would sell for a discount of approximately 3.46% if it was acquired through a bidding war. The 2.51% decrease represents a discount of approximately $4,514 based on the decile's average sales price of $130,300.

In column 2, I include indicator variables that identify whether the bidding war was intentional or unintentional. A transaction is considered an unintentional bidding war if it was listed using a traditional listing strategy (i.e. its list price exceeded it expected transaction price) and it sold above its list price. A transaction is considered an intentional bidding war if its list price was set below its expected transaction price and it sold above its list price. Based on these definitions alone, I expect that unintentional bidding wars will outperform intentional bidding wars – in which case, unintentional bidding wars are likely biasing the coefficients in the earlier analysis upwards. The results in column 2 show that unintentional bidding wars sell for a 9.8% premium above traditional listings. Whereas, intentional bidding wars sell for a 1.3% discount relative to traditional listings. The stark difference between the two coefficients highlights the need to carefully delineate between the two types of bidding wars – especially when trying to decide whether to list a house using a bidding war strategy (i.e. underpricing).

In column 3, I interact the intentional and unintentional bidding war indicator variables with school test scores. Intentional bidding wars still sell for a discount, but that discount decreases as the school test scores increase. In contrast, unintentional bidding wars sell for a premium, but that premium decreases as school test scores increase. In column 4, I isolate the effect of intentional bidding wars by removing unintentional bidding wars. The results, similar to column 3, show that houses that are underpriced and purchased through a bidding war sell for a discount relative to traditional listings. Thus, it appears that using a bidding war listing strategy is ineffective – regardless of the latent demand within the market. This is especially true when one considers the fact that the measure does not include underpriced houses that did not sell above their list price.

6.2 Alternative Specifications

Up to this point, I've used school quality as the sole proxy for latent demand in the analysis. In Table 11 I interact the bidding war indicator variables with three additional proxies. In column 1 and 2, I use inventory as a proxy for latent demand. When inventory levels are low, the likelihood of a bidding war increases (see Table 7) and houses purchased through a bidding war sell at higher prices according to column 1. The results in column 2 suggest, similar to the previous results, that unintentional bidding wars sell for a premium. Unlike previous results, the results in column suggest that the effectiveness of bidding wars is tied to market inventory. As inventory decreases (increases), house prices for intentional bidding wars increases (decreases). Thus, column 2 suggests that underpricing to incite a bidding war may be effective in markets with low inventory levels – although it's important to note that houses that were underpriced and did not result in a bidding war are not included in the measure.

In columns 3 and 4, I interact the bidding war indicator variables with the turnover measure. The interaction variables in both columns are insignificant. In column 3, houses that were purchased through a bidding war sold for a premium. However, column 4 shows that the positive coefficient is largely due to unintentional bidding wars. In columns 5 and 6, I interact the bidding war indicator variables with a measure of the average time-on-market. The average time-on-market variable is calculated at the elementary school level based on the last 12 months of sales transactions. If there is latent demand for housing in the elementary school zone then the average TOM should be lower. The results in column 5 show that houses purchases through a bidding war sell for higher prices when the average time-on-market is lower. Interestingly, this result carries over to intentional bidding wars in column 6 – suggesting that intentional bidding wars are effective if the recent time-on-market within the elementary school zone was less than 55.2 days.[33]

7. Conclusion

Using transaction level data that accounts for seller concessions, I find that bidding wars' market share increased over the past two decades; albeit at a slower rate than previously reported. Despite bidding wars' increasing prevalence little is known about the factors that drive them or their effectiveness as a listing strategy. I develop a simple theory that predicts that bidding wars will be more effective in markets with high levels of latent demand. I use school quality as a proxy for latent demand because households with children naturally want their kids to attend the best school possible. I argue that the limited supply of housing within high quality school districts creates latent demand for housing within those districts. Sellers that list their houses using a bidding war strategy attempt to incite immediate activity and multiple competing bids. Thus, neighborhoods with known latent demand offer the ideal setting for a bidding war.

The results suggest that intentional bidding wars are more effective in neighborhoods with latent demand. However, I show that intentionally underpricing a house to incite a bidding war is risky and, on average, does not outperform houses that were sold using a traditional listing strategy. I also find that a large fraction of the recent rise in bidding wars can be attributed to unintentional bidding wars – in which the house seller did not intentionally underprice their

[33] Approximately 328 of 1,022 intentional bidding war records had an average time-on-market less than 55.2 days in the repeat sales subsample.

house in an attempt to start a bidding war. Thus, although bidding wars market share has increased over the past two decades – a large portion of the increase is not due to house sellers using a bidding war listing strategy.

The results confirm previous research that that finds that underpricing a house is an ineffective listing strategy – although I find some evidence that discredits the claim that real estate agents advocate bidding wars purely out of self-interest (Bucchianeri and Minson 2013). I show that real estate agents are just as likely to use a bidding war listing strategy when selling their own house and after conditioning on the real estate agent using a bidding war listing strategy for a client - they are actually more likely to use the strategy themselves when selling their own house. While this study focused primarily on latent demand and its impact on bidding wars, additional research that examines the effectiveness of bidding wars warrants further exploration. For example, the examination of bidding wars in a less elastic, supply constrained market may find that bidding wars are even more effective than reported in this study.

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Table 1: Summary statistics

	Entire Sample				Non-Distressed Transactions				Distressed Transactions			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Transaction Details												
Sales Price	200,282	113,551	28,875	655,000	221,378	113,462	28,888	655,000	134,569	85,162	28,875	654,000
Seller Concession	2,038	2,654	0	48,849	2,191	2,703	0	48,849	1,564	2,433	0	41,740
Transaction Price	198,243	113,318	27,298	655,000	219,187	113,438	27,405	655,000	133,005	84,463	27,298	654,000
1st Original List Price (OLP)	213,538	122,106	35,000	789,000	232,936	122,892	35,000	789,000	153,113	97,401	35,000	785,900
Original List Price	211,133	120,464	34,900	769,900	231,316	121,159	34,900	769,900	148,266	93,632	34,900	765,000
List Price (LP)	205,851	118,225	30,000	749,900	227,375	118,478	30,000	749,900	138,806	88,613	30,000	749,900
Time-on-Market	84.0	84.4	0	450	79.4	80.9	0	450	98.2	93.1	0	450
Cash Purchase	0.14	-	0	1	0.09	-	0	1	0.31	-	0	1
Distressed	0.24	-	0	1								
School Quality												
Avg Test Score	0.61	0.24	0.03	0.90	0.63	0.23	0.03	0.90	0.51	0.25	0.03	0.90
Annual Avg Test Score	0.61	0.26	0.00	0.99	0.65	0.25	0.00	0.99	0.53	0.26	0.00	0.99
House Characteristics												
Age	22.5	19.0	2	115	22.3	19.0	2	115	23.3	18.7	2	115
Living Area (Sqft [000s])	2.26	0.87	0.52	16.00	2.30	0.88	0.53	16.00	2.15	0.85	0.52	9.67
Lot Size (Sqft [000s])	16.88	13.75	0.12	217.80	17.09	13.52	0.12	217.80	16.24	14.39	0.44	217.80
Bedrooms	3.75	0.84	2	6	3.76	0.85	2	6	3.71	0.82	2	6
Full Bathrooms	2.35	0.76	1	6	2.37	0.77	1	6	2.30	0.73	1	6
Half Bathrooms	0.54	0.53	0	4	0.54	0.53	0	4	0.53	0.53	0	4
Deck/Patio	0.55	-	0	1	0.58	-	0	1	0.45	-	0	1
Finished Basement	0.34	-	0	1	0.35	-	0	1	0.29	-	0	1
Garage	0.72	-	0	1	0.72	-	0	1	0.71	-	0	1
Carport	0.09	-	0	1	0.09	-	0	1	0.08	-	0	1
Pool	0.03	-	0	1	0.03	-	0	1	0.03	-	0	1
Private Backyard	0.67	-	0	1	0.72	-	0	1	0.53	-	0	1
Sprinkler System	0.06	-	0	1	0.06	-	0	1	0.03	-	0	1
Recent Renovation	0.11	-	0	1	0.13	-	0	1	0.05	-	0	1
Historic	0.00	-	0	1	0.00	-	0	1	0.00	-	0	1
Pond	0.01	-	0	1	0.01	-	0	1	0.00	-	0	1
Gated Community	0.00	-	0	1	0.00	-	0	1	0.00	-	0	1
Neighborhood Assoc	0.37	-	0	1	0.40	-	0	1	0.26	-	0	1
Starter Home	0.02	-	0	1	0.01	-	0	1	0.02	-	0	1

*Table 1 is continued on the next page

Table 1: Summary statistics (cont.)

	Entire Sample				Non-Distressed Transactions				Distressed Transactions			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Listing Details												
Above LP	0.09	-	0	1	0.07	-	0	1	0.15	-	0	1
Above LP [TOM ≤ 28]	0.05	-	0	1	0.03	-	0	1	0.09	-	0	1
Above Reduced LP	0.04	-	0	1	0.02	-	0	1	0.08	-	0	1
Agent Change	0.06	-	0	1	0.04	-	0	1	0.11	-	0	1
Relisted	0.04	-	0	1	0.05	-	0	1	0.04	-	0	1
Agent Owned	0.01	-	0	1	0.01	-	0	1	0.01	-	0	1
Agent Related	0.00	-	0	1	0.00	-	0	1	0.00	-	0	1
Estate Owned	0.02	-	0	1	0.02	-	0	1	0.01	-	0	1
Corporate Relocation	0.02	-	0	1	0.02	-	0	1	0.02	-	0	1
Location												
Cobb County	0.21	-	0	1	0.22	-	0	1	0.16	-	0	1
DeKalb County	0.22	-	0	1	0.21	-	0	1	0.25	-	0	1
Fulton County	0.20	-	0	1	0.20	-	0	1	0.22	-	0	1
Gwinnett County	0.37	-	0	1	0.37	-	0	1	0.36	-	0	1
Seasonality												
Winter	0.27	-	0	1	0.28	-	0	1	0.26	-	0	1
Spring	0.30	-	0	1	0.31	-	0	1	0.27	-	0	1
Summer	0.24	-	0	1	0.24	-	0	1	0.24	-	0	1
Fall	0.19	-	0	1	0.18	-	0	1	0.22	-	0	1
Transactions	**283,622**				**214,697**				**68,925**			

This table reports descriptive statistics for the variables of interest to our study. GAMLS is the data source of record for every field except for house's square feet of living area, lot size (sqft), and school test scores. The square feet of living area and lot size variables were obtained from the CoreLogic tax assessor dataset. The school test scores were obtained from the Georgia Department of Education.

Table 2: Transaction summary by listing strategy

			Above LP				Above E(TP)			
			0		1		0		1	
			#	%	#	%	#	%	#	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Full Sample										
Underpriced (DOP ≤ 0)	78,339	0.36	71,055	0.91	7,284	0.09	77,361	0.99	978	0.01
Overpriced [DOP > 0]	136,358	0.64	128,986	0.95	7,372	0.05	32,706	0.24	103,652	0.76
# Transactions	214,697		200,041	0.93	14,656	0.07	110,067	0.51	104,630	0.49
Above LP										
Underpriced (DOP ≤ 0)	7,284	0.50					6,306	0.87	978	0.13
Overpriced [DOP > 0]	7,372	0.50					-	-	7,372	1.00
# Transactions	14,656						6,306	0.43	8,350	0.57
Above LP [TOM ≤ 28]										
Underpriced (DOP ≤ 0)	3,884	0.55					3,446	0.89	438	0.11
Overpriced [DOP > 0]	3,232	0.45					-	-	3,232	1.00
# Transactions	7,116						3,446	0.48	3,670	0.52

A transaction is classified as underpriced (overpriced) if its list price was less than or equal to (greater than) its expected sales price. Columns 3 to 6 identify whether the house's transaction price exceeded its list price. If the house's transaction price exceeded its list price it is included in column 5, otherwise it is included in column 3. Columns 7 to 10 identify whether the house's transaction price exceeded its expected transaction price. If the house's transaction price exceeded its expected transaction price it is included in column 9, otherwise it is included in column 7.

Table 3: Bidding war frequency and market conditions by year

	1998 (1)	1999 (2)	2000 (3)	2001 (4)	2002 (5)	2003 (6)	2004 (7)	2005 (8)	2006 (9)	2007 (10)	2008 (11)	2009 (12)	2010 (13)	2011 (14)	2012 (15)	2013 (16)	2014 (17)
Entire Sample																	
Average TOM	*50.3*	*56.8*	*55.0*	*61.3*	*67.4*	*73.0*	*73.6*	*80.7*	*97.9*	*114.2*	*137.6*	*129.8*	*110.6*	*119.8*	*94.4*	*63.6*	*60.7*
Inventory	*4.0*	*3.5*	*3.2*	*3.5*	*3.5*	*4.0*	*4.0*	*6.3*	*7.7*	*9.4*	*12.6*	*13.5*	*12.5*	*12.3*	*7.9*	*5.3*	*4.5*
Turnover (%)	*4.1*	*4.2*	*3.9*	*4.1*	*3.9*	*4.1*	*4.4*	*4.8*	*4.7*	*4.0*	*2.9*	*2.5*	*2.4*	*2.6*	*2.9*	*3.3*	*3.6*
Premium Above LP (%)	*-3.9*	*-3.6*	*-3.3*	*-3.6*	*-3.9*	*-4.0*	*-4.0*	*-3.7*	*-3.9*	*-5.1*	*-7.6*	*-9.5*	*-9.7*	*-10.8*	*-7.7*	*-5.3*	*-5.1*
Number Transactions	*9,909*	*13,764*	*13,760*	*15,776*	*15,113*	*17,091*	*18,819*	*20,834*	*19,079*	*13,600*	*8,068*	*6,357*	*6,053*	*6,646*	*7,748*	*11,115*	*10,965*
% Above LP	3.9	6.8	8.7	10.2	9.4	9.4	7.7	7.0	5.8	3.8	2.6	2.4	2.8	3.6	5.5	8.6	7.2
Average TOM	*37.8*	*50.9*	*47.4*	*52.1*	*57.7*	*62.2*	*69.0*	*72.9*	*81.5*	*84.1*	*83.0*	*44.9*	*38.1*	*39.5*	*36.2*	*24.2*	*21.3*
Inventory	*3.7*	*3.5*	*3.2*	*3.6*	*3.5*	*4.0*	*4.3*	*6.7*	*8.1*	*9.8*	*13.5*	*12.1*	*10.3*	*10.6*	*6.3*	*4.8*	*4.2*
Turnover (%)	*3.6*	*4.3*	*4.1*	*4.4*	*4.3*	*4.4*	*4.6*	*5.1*	*4.9*	*4.1*	*3.2*	*3.0*	*3.0*	*3.1*	*3.2*	*3.3*	*3.7*
Premium Above LP (%)	*3.4*	*3.4*	*3.7*	*3.5*	*3.4*	*2.9*	*2.8*	*3.1*	*3.5*	*3.6*	*4.5*	*5.5*	*6.0*	*5.3*	*5.8*	*4.0*	*3.3*
Number Transactions	*383*	*938*	*1,196*	*1,614*	*1,421*	*1,610*	*1,458*	*1,459*	*1,113*	*518*	*208*	*152*	*169*	*240*	*424*	*959*	*794*
% Above LP [TOM ≤ 28]	2.2	3.7	4.9	4.8	3.7	3.3	2.7	2.5	2.3	1.4	1.1	1.5	1.8	2.2	3.5	6.9	6.1
Average TOM	*12.7*	*13.2*	*14.3*	*15.2*	*16.2*	*16.3*	*15.4*	*14.6*	*14.3*	*14.7*	*14.9*	*15.8*	*15.2*	*15.3*	*13.0*	*10.3*	*9.9*
Inventory	*3.5*	*3.2*	*3.0*	*3.4*	*3.4*	*3.9*	*4.0*	*6.9*	*7.8*	*9.5*	*13.9*	*11.9*	*10.4*	*10.3*	*6.0*	*4.8*	*4.0*
Turnover (%)	*3.5*	*4.2*	*4.1*	*4.4*	*4.2*	*4.5*	*4.5*	*5.1*	*4.8*	*3.7*	*3.0*	*3.0*	*3.0*	*3.1*	*3.3*	*3.4*	*3.8*
Premium Above LP (%)	*2.7*	*3.1*	*2.6*	*3.3*	*2.8*	*2.5*	*2.6*	*2.5*	*3.4*	*2.9*	*3.7*	*6.0*	*5.6*	*5.5*	*5.0*	*3.8*	*3.2*
Number Transactions	*214*	*514*	*680*	*761*	*563*	*569*	*510*	*530*	*436*	*193*	*87*	*95*	*109*	*148*	*270*	*770*	*667*
% Intentional	1.3	2.1	2.5	2.3	1.8	1.6	1.5	1.5	1.4	0.9	0.6	1.1	1.4	1.5	2.1	3.9	3.1
Average TOM	*12.2*	*13.1*	*13.9*	*14.5*	*15.8*	*15.4*	*15.3*	*14.7*	*14.0*	*14.6*	*15.6*	*16.1*	*15.9*	*15.8*	*14.3*	*10.9*	*10.5*
Inventory	*3.7*	*3.2*	*3.0*	*3.4*	*3.4*	*3.9*	*3.9*	*7.0*	*7.7*	*10.0*	*15.6*	*11.6*	*9.7*	*9.8*	*5.7*	*4.8*	*4.1*
Turnover (%)	*3.2*	*4.2*	*4.1*	*4.4*	*4.1*	*4.6*	*4.5*	*5.3*	*4.9*	*3.6*	*3.1*	*3.1*	*3.1*	*3.3*	*3.4*	*3.2*	*3.5*
Premium Above LP (%)	*2.7*	*2.8*	*2.3*	*2.8*	*2.9*	*2.5*	*2.7*	*2.5*	*3.9*	*2.9*	*4.7*	*7.8*	*6.9*	*6.8*	*6.7*	*5.0*	*3.9*
Number Transactions	*128*	*289*	*345*	*367*	*266*	*277*	*282*	*305*	*268*	*122*	*51*	*67*	*82*	*103*	*166*	*430*	*336*
% Unintentional	0.9	1.6	2.4	2.5	2.0	1.7	1.2	1.1	0.9	0.5	0.4	0.4	0.4	0.7	1.3	3.1	3.0
Average TOM	*13.5*	*13.3*	*14.6*	*15.9*	*16.5*	*17.1*	*15.6*	*14.5*	*14.8*	*14.9*	*14.0*	*15.1*	*13.4*	*14.1*	*11.0*	*9.5*	*9.3*
Inventory	*3.3*	*3.1*	*3.0*	*3.5*	*3.3*	*3.9*	*4.3*	*6.9*	*8.0*	*8.6*	*11.6*	*12.6*	*12.5*	*11.4*	*6.6*	*4.8*	*4.0*
Turnover (%)	*3.8*	*4.1*	*4.1*	*4.4*	*4.2*	*4.4*	*4.4*	*4.9*	*4.6*	*3.7*	*2.9*	*2.8*	*2.7*	*2.6*	*3.1*	*3.7*	*4.0*
Premium Above LP (%)	*2.7*	*3.6*	*3.0*	*3.7*	*2.7*	*2.4*	*2.5*	*2.4*	*2.5*	*2.8*	*2.2*	*1.7*	*1.6*	*2.5*	*2.1*	*2.2*	*2.5*
Number Transactions	*86*	*225*	*335*	*394*	*297*	*292*	*228*	*225*	*168*	*71*	*36*	*28*	*27*	*45*	*104*	*340*	*331*

This table reports the mean percentage of transactions for which the sales price exceeds the list price each year from 1998 to 2014. The '% Above LP' section includes sales transactions in which transaction price exceeds both the 1st original list price and list price at the time of sale. The '% Above LP [TOM ≤ 28]' section is a subsample of the '% Above LP' section that only includes sales transactions that had a time-on-market of 28 days or less. The '% Above LP [TOM ≤ 28]' section is further partitioned into intentional bidding wars and unintentional bidding wars.

Table 4: Summary Statistics by School Test Score Decile

Test Score Decile	Test Scores Avg (1)	Min (2)	Max (3)	Transaction Detail Annual Sales Per School (4)	Avg TOM (Days) (5)	Avg TP ($0,000s) (6)	% Above List (7)	% Bidding Wars (8)	% Intentional (9)	% Unintentional (10)	Supply Elasticity Avg # SFD Lots (11)	Avg Undevel Lots 1997 (12)	% Undevel Lots 1997 (13)	Avg Undevel Lots 2014 (14)	% Undevel Lots 2014 (15)
1st	10.8	3.0	15.9	21	82.7	130.3	11.7%	5.0%	2.1%	2.9%	2,021	444	22.0%	80	3.9%
2nd	21.3	16.2	25.4	20	82.6	160.1	9.4%	4.3%	2.2%	2.1%	1,761	407	23.1%	94	5.3%
3rd	31.6	26.1	35.8	18	85.9	152.4	9.5%	4.1%	2.1%	2.0%	1,639	413	25.2%	60	3.7%
4th	39.5	35.9	44.0	26	85.3	182.8	9.7%	4.2%	2.2%	2.0%	1,853	530	28.6%	101	5.4%
5th	51.3	44.2	56.3	43	82.0	214.0	6.3%	3.1%	1.7%	1.5%	2,485	728	29.3%	92	3.7%
6th	62.6	56.4	67.4	53	78.2	206.9	7.7%	3.7%	1.9%	1.8%	2,565	711	27.7%	69	2.7%
7th	72.1	68.0	76.5	59	81.7	211.2	6.3%	3.0%	1.8%	1.2%	3,038	953	31.4%	88	2.9%
8th	79.4	76.5	81.8	55	81.0	209.4	6.1%	3.0%	1.9%	1.1%	2,667	1,010	37.9%	78	2.9%
9th	84.9	83.0	86.5	50	77.5	277.3	4.8%	2.7%	1.6%	1.1%	2,493	872	35.0%	60	2.4%
10th	88.0	86.5	90.1	50	75.9	301.5	4.2%	2.6%	1.4%	1.2%	2,807	649	23.1%	45	1.6%

This table reports the average transaction level detail and supply elasticity for each decile. The deciles were created by grouping elementary schools based on their average test scores. Each decile's average, minimum and maximium school test scores are reported in the first section of the table. Each decile represents 32 or 33 of the 323 elementary schools in this study. Distressed transactions are not included in this table. Bidding wars are proxied by the Above LP [TOM ≤ 28] variable.

Table 5: Frequency of Bidding Wars by Listing Agent

Freq of Above LP Listings	Number of Listing Agents		
	No TOM Restriction	TOM ≤ 28 Days	Intentional
	(1)	(2)	(3)
1	3,916	2,682	1,819
2 to 5	2,042	1,052	553
6 to 10	278	123	50
11 to 25	129	34	13
26 to 50	15	7	2
51 to 100	6	1	0
101+	1	0	0
Total	6,387	3,899	2,437
Total List Agents		23,340	
% Agents	27.4%	16.7%	10.4%

Columns 1 and 2 display the frequency in which a house listed by an agent is part of a bidding war. Column 3 displays the frequency in which listing agents intentionally employ a bidding war listing strategy. The bottom section of the table calculates the percentage of listing agents that have been involved in a bidding war (columns 1 and 2) and the percentage of agents that have intentionally listed a house using a bidding war listing strategy (column 3). Distressed sales transactions are not included in this table.

Table 6: Agent Owned Listing Strategies

# of Agent Owned Listings	% Above Original List Price		
	No TOM Restriction	TOM ≤ 28 Days	Intentional
	(1)	(2)	(3)
1	5.1%	3.3%	1.3%
2 to 5	5.2%	3.3%	1.9%
6 to 10	4.8%	3.8%	2.9%
11 to 25	4.8%	3.6%	3.6%
26 to 50	3.6%	3.6%	3.6%
# Bidding Wars	93	62	31
Total Agent Own		1,846	
% Bidding Wars	5.0%	3.4%	1.7%

Columns 1 and 2 tabulate how often real estate agents' own houses are involved in bidding wars. Column 3 tabulates how often real estate agents use a bidding war listing strategy when selling their own house. The top portion of the table partitions real estate agents based on the number of agent owned houses they sold and the listing strategy they used. The bottom portion of the table aggregates the data and displays the overall bidding war market share for agent owned sales transactions.

Table 7: Bidding War Correlates

	Bidding War (1)	Unintentional (2)	Intentional (3)	Underprice (4)	Bidding War (5)
Annual Test Score	0.0040	0.0102***	-0.0059*	-0.1107***	0.0079*
	(1.00)	(3.68)	(-1.91)	(-9.48)	(1.66)
Age	0.0002	0.0002**	0.0000	-0.0030***	-0.0001
	(1.44)	(2.53)	(-0.36)	(-9.71)	(-0.64)
Age Squared	0.0000	0.0000	0.0000	0.0000***	0.0000
	(-0.16)	(-0.61)	(0.38)	(8.09)	(1.19)
Living Area (Sqft [000s])	-0.0151***	-0.0078***	-0.0079***	0.0397***	-0.0127***
	(-5.41)	(-4.08)	(-3.72)	(4.87)	(-4.21)
Living Area Squared	0.0016***	0.0010***	0.0007**	-0.0063***	0.0018***
	(3.77)	(3.31)	(2.20)	(-5.02)	(3.87)
Lot Size (Sqft [000s])	-0.0001	-0.0001**	0.0000	0.0004	-0.0002*
	(-1.31)	(-2.25)	(0.22)	(1.53)	(-1.68)
Lot Size Squared	0.0000	0.0000	0.0000	0.0000	0.0000
	(-0.38)	(0.71)	(-1.13)	(-1.33)	(0.58)
3 Bedrooms	0.0006	0.0011	-0.0005	-0.0032	0.0100**
	(0.20)	(0.49)	(-0.21)	(-0.32)	(2.35)
4 Bedrooms	0.0014	0.0005	0.0009	-0.0025	0.0067
	(0.39)	(0.19)	(0.34)	(-0.24)	(1.50)
5 Bedrooms	0.0014	0.0012	0.0002	-0.0204*	0.0054
	(0.37)	(0.46)	(0.06)	(-1.76)	(1.14)
6 Bedrooms	0.0041	0.0024	0.0017	-0.0364***	0.0031
	(0.89)	(0.77)	(0.48)	(-2.63)	(0.56)
2 Bathrooms	0.0026	0.0019	0.0009	0.0233***	0.0001
	(1.03)	(1.07)	(0.48)	(3.18)	(0.03)
3 Bathrooms	0.0035	0.0004	0.0033	0.0558***	0.0005
	(1.17)	(0.19)	(1.46)	(6.53)	(0.15)
4+ Bathrooms	0.0006	-0.0011	0.0018	0.0650***	0.0012
	(0.16)	(-0.43)	(0.65)	(6.12)	(0.29)
Finished Basement	0.0017	0.0005	0.0012	0.0179***	-0.0025**
	(1.46)	(0.67)	(1.38)	(5.48)	(-2.00)
Pool	0.0055**	0.0027	0.0030	-0.0012	-0.0008
	(2.16)	(1.53)	(1.54)	(-0.16)	(-0.30)
Garage	-0.0035**	-0.0020**	-0.0017	-0.0001	-0.0004
	(-2.47)	(-2.05)	(-1.51)	(-0.03)	(-0.23)
Carport	-0.0041**	-0.0023	-0.0020	-0.0020	-0.0036
	(-1.97)	(-1.63)	(-1.24)	(-0.33)	(-1.50)
Private Backyard	-0.0002	0.0008	-0.0010	0.0020	0.0004
	(-0.14)	(1.09)	(-1.16)	(0.61)	(0.33)
Sprinkler System	-0.0031	-0.0013	-0.0019	0.0089	-0.0020
	(-1.59)	(-1.00)	(-1.26)	(1.60)	(-0.93)

*Table 7 is continued on the next page

Table 7: Bidding War Correlates (cont.)

Recent Renovation	-0.0027**	-0.0004	-0.0024**	0.0388***	-0.0032**
	(-2.04)	(-0.48)	(-2.36)	(9.93)	(-2.17)
Estate Owned	-0.0061*	-0.0022	-0.0041	-0.0338***	-0.0013
	(-1.85)	(-0.96)	(-1.64)	(-3.65)	(-0.31)
Corporate Relocation	0.0020	0.0016	0.0005	-0.0292***	-0.0016
	(0.58)	(0.68)	(0.19)	(-2.94)	(-0.41)
Historic	-0.0028	-0.0090	0.0061	0.0302	0.0040
	(-0.28)	(-1.31)	(0.79)	(0.89)	(0.31)
Golf Course	-0.0037	-0.0012	-0.0026	-0.0102	-0.0007
	(-1.26)	(-0.61)	(-1.16)	(-1.19)	(-0.23)
Gated Community	-0.0046	-0.0098*	0.0049	0.0432*	-0.0079
	(-0.62)	(-1.90)	(0.85)	(1.95)	(-0.99)
Clubhouse	-0.0035	-0.0046**	0.0008	0.0359***	0.0030
	(-1.19)	(-2.26)	(0.36)	(4.08)	(0.93)
Pond	0.0123**	0.0067*	0.0060	-0.0110	-0.0079
	(2.16)	(1.72)	(1.38)	(-0.67)	(-1.27)
Starter Home	0.0123***	0.0104***	0.0026	-0.0402***	-0.0012
	(2.86)	(3.49)	(0.78)	(-3.35)	(-0.23)
Neighborhood Assoc	-0.0033***	-0.0002	-0.0032***	0.0094***	-0.0021
	(-2.82)	(-0.24)	(-3.58)	(2.71)	(-1.56)
Agent Owned	-0.0051	-0.0014	-0.0040	-0.0019	0.0092*
	(-1.13)	(-0.44)	(-1.16)	(-0.14)	(1.66)
Agent Related	-0.0211**	-0.0091	-0.0131*	0.0372	-0.0112
	(-2.34)	(-1.46)	(-1.90)	(1.37)	(-1.05)
Inventory	-0.0015***	-0.0004***	-0.0011***	-0.0007	-0.0001
	(-7.34)	(-2.94)	(-7.29)	(-1.13)	(-0.24)
Turnover	0.1720***	0.2147***	-0.0378	0.2186*	-0.0526
	(4.37)	(7.92)	(-1.26)	(1.89)	(-1.20)
Winter	0.0113***	0.0058***	0.0058***	0.0405***	-0.0029*
	(7.87)	(5.94)	(5.34)	(9.85)	(-1.78)
Spring	0.0102***	0.0022**	0.0084***	0.0465***	-0.0035**
	(7.02)	(2.20)	(7.53)	(11.07)	(-2.12)
Summer	0.0073***	0.0007	0.0067***	0.0291***	-0.0018
	(4.84)	(0.72)	(5.88)	(6.73)	(-1.04)
Transactions	125,840	125,840	125,840	125,840	44,813

The dependent variable in column 1 is an indicator variable that identifies bidding wars as proxied by *Above List* [TOM ≤ 28]; column 2 is an indicator variable that identifies intentional bidding wars; column 3 is an indicator variable that identifies unintentional bidding wars; column 4 is an indicator variable that identifies underpriced listings - whether or not the listing resulted in a bidding war; and column 5 is an indicator variable that identifies underpriced listings that resulted in a bidding war. Columns 1-4 include all sales transactions from elementary schools that were not affected by redistricting initiatives. Column 5 only includes underpriced listings from elementary school zones that were not affected by redistricting. All specifications include census tract and time fixed effects. Numbers in parentheses are t statistics. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 8: Select summary statistics for the full and matched samples

	Full Sample			Characteristic Match			Nearest Neighbor Match		
	Treatment	Control	t-Stat	Treatment	Control	t-Stat	Treatment	Control	t-Stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment: Above LP									
Transaction Price	197,591	236,124	28.6	198,582	214,166	11.5	198,582	202,002	1.9
List Price (LP)	191,607	246,447	39.1	192,726	222,516	21.5	192,726	209,614	9.4
Time-on-Market	53.3	86.6	34.5	53.8	87.7	32.7	53.8	87.3	27.2
Age	22.5	24.8	10.6	21.9	23.2	5.7	21.9	22.1	0.6
Living Area (Sqft [000s])	2.08	2.34	25.4	2.06	2.09	3.4	2.06	2.04	-1.6
Lot Size (Sqft [000s])	15.89	17.20	8.7	15.70	16.27	3.6	15.70	14.90	-5.0
Bedrooms	3.6	3.8	16.0	3.6	3.5	-7.2	3.6	3.6	-1.2
Full Bathrooms	2.3	2.4	14.8	2.2	2.2	-9.1	2.2	2.2	-1.3
Avg Test Score	0.56	0.64	29.5	0.57	0.61	12.9	0.57	0.57	0.0
Annual Avg Test Score	0.58	0.65	23.3	0.60	0.63	9.3	0.60	0.60	-0.1
Observations	8,078	117,769		7,167	33,154		7,167	7,167	
# Underpriced	3,998	40,815		3,397	-		3,397	-	
% Underpriced	0.49	0.35		0.47	-		0.47	-	
Treatment: Above LP [TOM ≤ 28]									
Transaction Price	210,107	234,410	12.8	213,294	217,111	1.9	213,294	220,881	2.6
List Price (LP)	204,887	244,155	19.8	208,192	225,609	8.4	208,192	229,662	7.3
Time-on-Market	12.7	86.8	54.9	12.6	83.5	52.2	12.6	78.9	48.9
Age	26.8	24.5	-7.6	26.4	24.3	-6.3	26.4	26.5	0.2
Living Area (Sqft [000s])	2.09	2.33	16.7	2.07	2.06	-0.7	2.07	2.06	-0.5
Lot Size (Sqft [000s])	16.07	17.15	5.1	15.89	16.03	0.6	15.89	15.18	-3.1
Bedrooms	3.6	3.8	10.7	3.6	3.5	-10.0	3.6	3.6	-0.7
Full Bathrooms	2.3	2.4	9.4	2.2	2.1	-10.5	2.2	2.2	-0.8
Avg Test Score	0.59	0.63	12.3	0.60	0.62	4.0	0.60	0.60	0.0
Annual Avg Test Score	0.61	0.65	10.5	0.62	0.63	3.4	0.62	0.62	-0.1
Observations	3,935	121,912		3,452	22,798		3,452	3,452	
# Underpriced	2,138	42,675		1,783	-		1,783	-	
% Underpriced	0.54	0.35		0.52	-		0.52	-	

This table reports descriptive statistics for a select group of variables for the non-distressed sales transaction sample and two matched samples. GAMLS is the data source of record for every field except for the living area, lot size, and school test scores. The square feet of living area and lot size were obtained from the CoreLogic tax assessor dataset. The school test scores were obtained from the Georgia Department of Education. The treatment group in the top (bottom) section is *Above LP* transactions (*Above LP [TOM ≤ 28]* transactions). Columns 1-3 display the means and t-statistics for the differences between the means for the treatment and control groups. The control groups in column 2 include every transaction that is not included in the treatment group. The control group in column 5 includes transactions that were not underpriced and match at least one of the treatment records on all of the following criteria: elementary school zone, transaction year, number of bedrooms, and number of bathrooms. The control group in column 8 was created using a one-to-one nearest neighbor matching technique with replacement. The number and percent of observations that were intentionally underpriced in each grouping is displayed below the summary statistics for the two distinct treatments. A house is classified as underpriced if its list price was less than its expected sales price.

Table 9: 2SLS key parameter results

	2000-2014		2000-2006		2007-2014	
	(1)	(2)	(3)	(4)	(5)	(6)
Full Sample						
School Test Score	0.1138***	0.1138***	0.0293***	0.0294***	0.1131***	0.1118***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Above LP [TOM ≤ 28]	-0.0304***		0.0183***		-0.1286***	
	(0.01)		(0.01)		(0.02)	
Above LP [TOM ≤ 42]		-0.0211**		0.0249***		-0.1527***
		(0.01)		(0.01)		(0.02)
Above LP * School Test Score	0.0491***	0.0388***	-0.0028	-0.0065	0.1603***	0.1824***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Number of Observations	125,840	125,840	74,089	74,089	51,751	51,751
Adjusted R-squared	0.86	0.86	0.90	0.90	0.865	0.866
Characteristic Match						
School Test Score	0.0768***	0.0752***	0.0607***	0.0515***	0.0086	0.0217
	(0.01)	(0.01)	(0.00)	(0.01)	(0.03)	(0.03)
Above LP [TOM ≤ 28]	-0.0986***		-0.0612***		-0.2464***	
	(0.01)		(0.01)		(0.03)	
Above LP [TOM ≤ 42]		-0.0771***		-0.0618***		-0.2660***
		(0.01)		(0.01)		(0.03)
Above LP * School Test Score	0.0435***	0.0163	-0.0083	-0.0013	0.2091***	0.2401***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
Number of Observations	26,248	40,319	17,449	28,554	8,799	11,765
Adjusted R-squared	0.93	0.92	0.94	0.93	0.92	0.91
Nearest Neighbor Match						
School Test Score	0.0850***	0.0703***	0.0902***	0.0396**	-0.0796	-0.0244
	(-0.03)	(-0.02)	(-0.02)	(-0.02)	(-0.05)	(-0.04)
Above LP [TOM ≤ 28]	-0.0702***		-0.0544***		-0.2370***	
	(-0.01)		(-0.01)		(-0.03)	
Above LP [TOM ≤ 42]		-0.0609***		-0.0357***		-0.1642***
		(-0.01)		(-0.01)		(-0.02)
Above LP * School Test Score	0.0367**	0.0247*	-0.0060	-0.0066	0.2097***	0.1601***
	(-0.02)	(-0.01)	(-0.01)	(-0.01)	(-0.03)	(-0.03)
Number of Observations	6,904	14,334	4,118	10,312	2,786	4,022
Adjusted R-squared	0.92	0.90	0.95	0.92	0.927	0.904

The dependent variable in every regression is the log of house price. All columns include the following variables: age(^2), square feet living area(^2), lot size(^2), bedrooms, bathrooms, deck/patio, finished basement, fireplace, pool, garage, carport, private backyard, sprinkler system, agent owned, agent related, recent renovation, estate owned, corporate relocation, historic, golf course, gated community, atypical, clubhouse, pond, starter home, neighborhood association, cash, seasonality, inventory, and turnover. Census controls gathered at the block-group level from the 2010 census are also included. The census controls include: median household income, percent white, percent with less than high school degree, percent with an associates degree or higher, poverty rate, and percent of units that are vacant. The annual test score results only include houses located in school attendance zones that were not affected by redistricting during the time period of this study. Census tract and quarterly fixed effects are also included. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 10: Repeat sales specifications

	(1)	(2)	(3)	(4)
School Test Score	0.1165***	0.1164***	0.1171***	0.1174***
	(0.01)	(0.01)	(0.01)	(0.01)
Above LP [TOM ≤ 28]	-0.0424**			
	(0.02)			
Above LP * School Test Score	0.0658***			
	(0.01)			
Intentional		-0.0152**	-0.0381*	-0.0380*
		(0.01)	(0.02)	(0.02)
Unintentional		0.0956***	0.1492***	
		(0.01)	(0.02)	
Intentional * School Test Score			0.0313***	0.0320***
			(0.03)	(0.03)
Unintentional * School Test Score			-0.0785***	
			(0.03)	
House Fixed Effects	Yes	Yes	Yes	Yes
Non-property Characteristics	Yes	Yes	Yes	Yes
Time Fixed Effects	Quarterly	Quarterly	Quarterly	Quarterly
Number of Observations	29,032	29,032	29,032	28,294
Adjusted R-squared	0.97	0.97	0.97	0.97

The dependent variable in the first four columns is the log of house price. Columns 1 to 4 only a subset of houses that had repeat sales. Every column in Table 10 includes house fixed effects to control for the physical characteristics and quality of the house. The following non-property related transaction characteristics are included as controls: agent owned, agent related, cash purchase, recent renovation, estate owned, corporate relocation, inventory, and turnover. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 11: Alternative specifications

	Proxy: Inventory		Proxy: Turnover		Proxy: Avg TOM	
	(1)	(2)	(3)	(4)	(5)	(6)
School Test Score	0.1155***	0.1163***	0.1157***	0.1166***	0.1156***	0.1164***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inventory	0.0040***	0.0041***	0.0040***	0.0040***	0.0039***	0.0040***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Turnover	1.3198***	1.3137***	1.3233***	1.3118***	1.3191***	1.3103***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
School Zone's Average TOM	0.0000	0.0000	0.0000	-0.0001	0.0000	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Above LP [TOM ≤ 28]	0.0516***		0.0388***		0.0748***	
	(0.01)		(0.01)		(0.02)	
Above LP * Proxy	-0.0030*		-0.0803		-0.0005***	
	(0.00)		(0.31)		(0.00)	
Intentional		0.0109		-0.0362**		0.0552***
		(0.02)		(0.02)		(0.02)
Unintentional		0.1056***		0.1219***		0.1004***
		(0.02)		(0.02)		(0.02)
Intentional * Proxy		-0.0050*		0.5283		-0.0010***
		(0.00)		(0.40)		(0.00)
Unintentional * Proxy		-0.0019		-0.6773		-0.0001
		(0.00)		(0.49)		(0.00)
House Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Non-property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Number of Observations	29,032	29,032	29,032	29,032	29,032	29,032
Adjusted R-squared	0.97	0.97	0.97	0.97	0.97	0.97

The dependent variable in all six columns is the log of house price. Columns 1 to 6 only a subset of houses that had repeat sales between 2000-2014. Every column includes house fixed effects to control for the physical characteristics and quality of the house. The following non-property related transaction characteristics are included as controls: agent owned, agent related, cash purchase, recent renovation, estate owned, corporate relocation, inventory, and turnover. The bidding war variables are interacted with inventory in columns 1 and 2, turnover in columns 3 and 4, and the average TOM variable in columns 5 and 6. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Figure 1: Example of Latent Demand for Housing

Figure 2: TOM Kernel Density by Listing Strategy

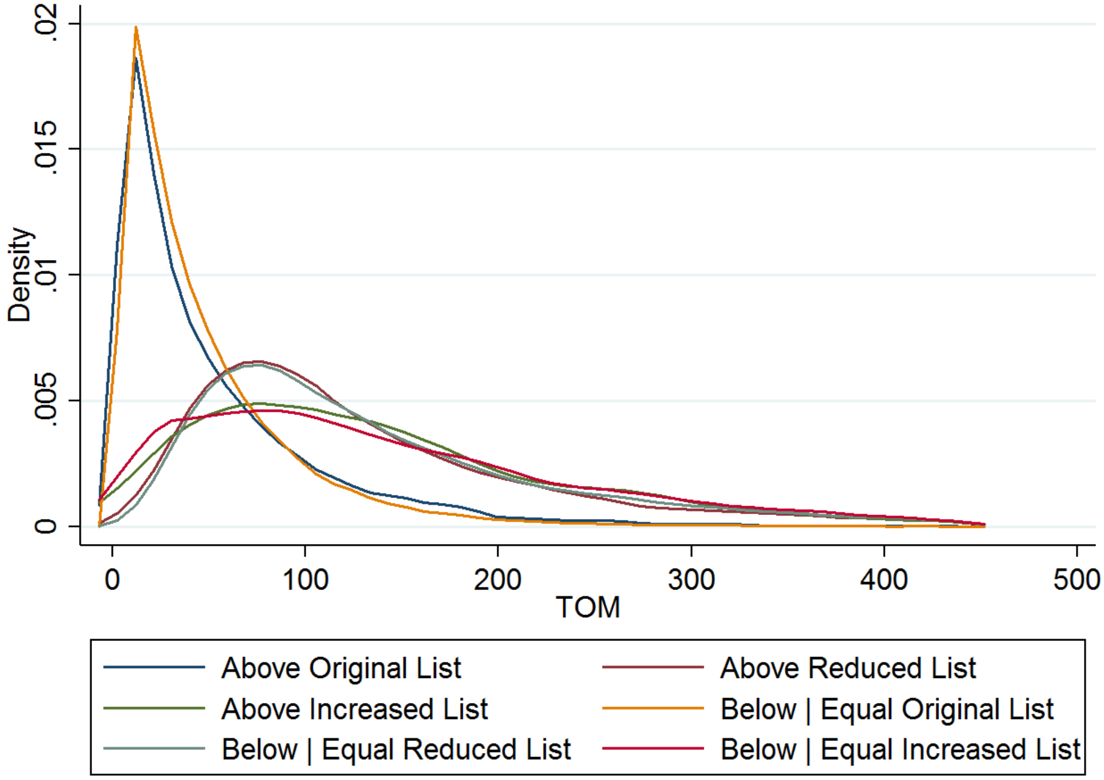


Figure 3: TOM Kernel Density by Listing Strategy (TOM < = 90 days)

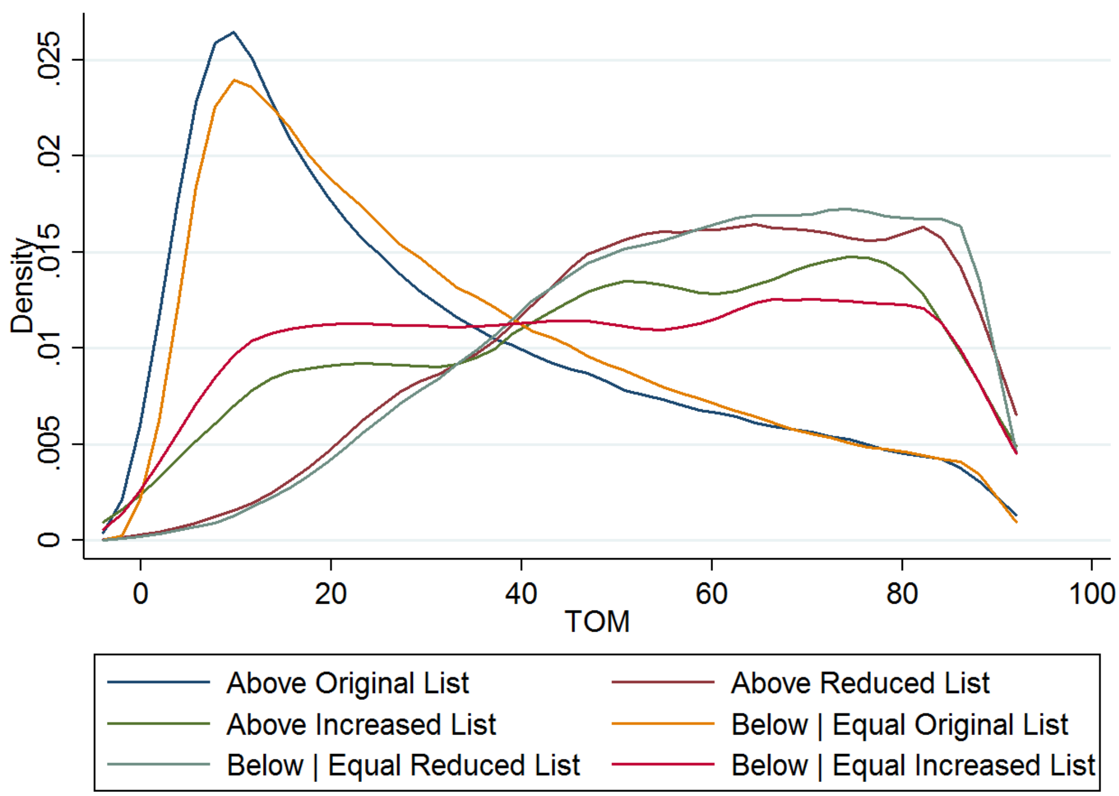
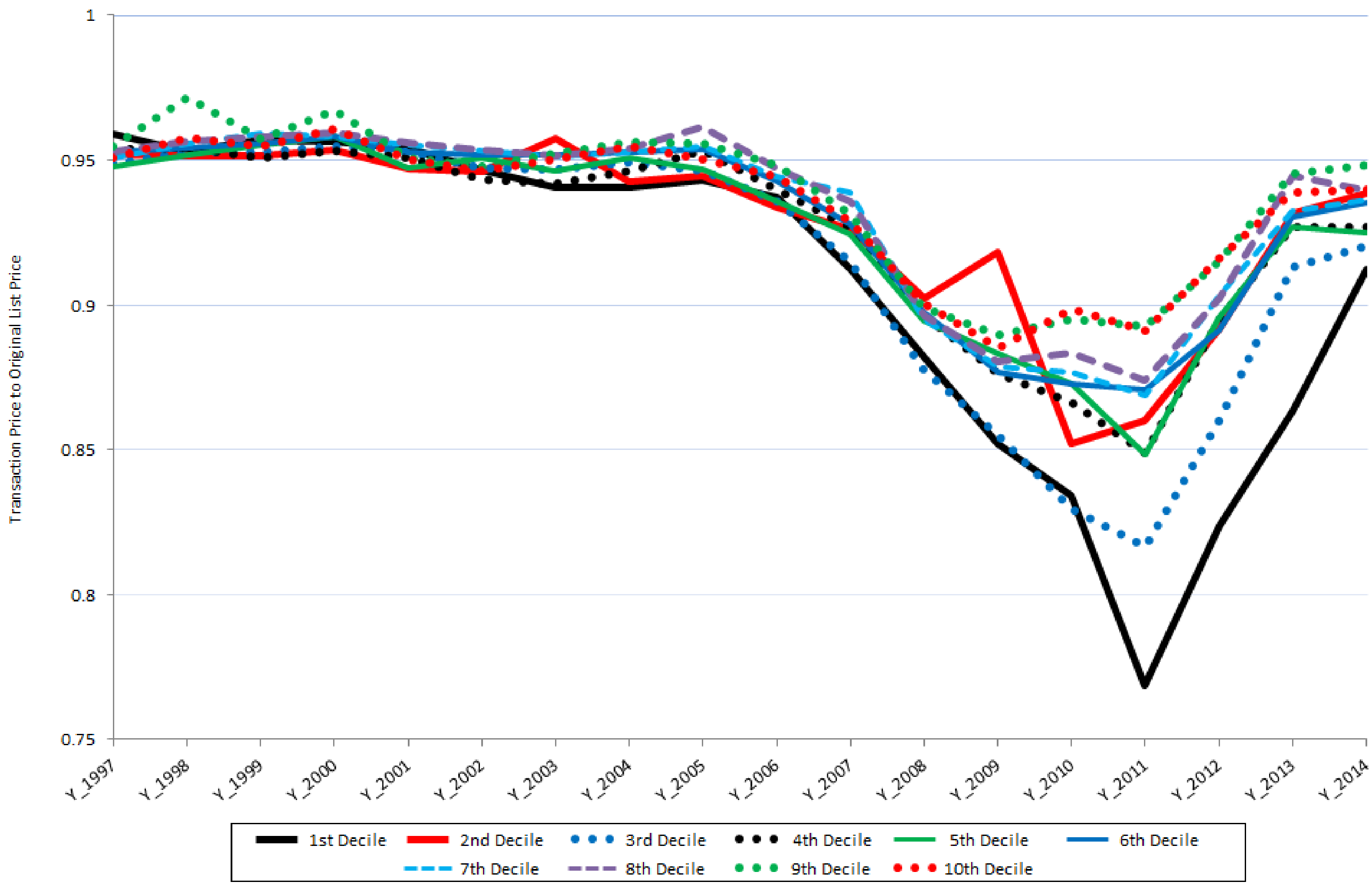


Figure 4: Transaction to Original List Price Ratio by School Quality Decile for "Traditional" Listings



The transaction to original list price ratios were calculated using non-distressed sales in which the property's original listing price exceeded both its expected and actual transaction price. The data has been stratified by the school quality deciles reported in Table 4. The 1st (10th) represents school zones with the lowest (highest) test scores.

Appendix A: Expected Transaction Price

When a homeowner lists their house for sale they can choose either a "traditional" or "bidding war" listing strategy. If the homeowner chooses a bidding war listing strategy, they intentionally underprice their house below their expected transaction price in an attempt to incite a bidding war. However, if the homeowner chooses a traditional listing strategy they set their list price above the expected transaction price. To identify which listing strategy the seller chose I estimate the expected transaction price for each listing when it was listed given the property's physical and location characteristics. To do so, I first estimate a standard hedonic model for all transactions:

$$P_{ijt} = \alpha + \sum_{l=1}^{L} \beta_l X_{jlt} + \varepsilon_{jt} \tag{A1}$$

where P_{ijt} is the log of transaction price for house *i* located in neighborhood j. X_{jlt} represents a vector of L property and location characteristics, β_l represents the corresponding coefficients, α is a constant, and ε_{jt} is the error term. Census tract and quarterly time fixed effects are also included.

The results of estimation process from equation (A1) are displayed in Table A1. The adjusted R-squared for the estimation is .86 and the signs and significance of the variables are all as expected. Using the coefficients, $\widehat{\beta_l}$, from Table A1 - I estimate the expected transaction price, *E(TP)*, *when the property was listed* by updating the quarterly time fixed effect to reflect the date the property was listed instead of when it was sold.

Table A1: Hedonic sales price regression

	2000-2014 (1)
Age	-0.0118***
	(0.00)
Age Squared	0.0001***
	(0.00)
Living Area (Sqft [000s])	0.2866***
	(0.00)
Living Area Squared	-0.0181***
	(0.00)
Lot Size (Sqft [000s])	0.0031***
	(0.00)
Lot Size Squared	-0.0000***
	(0.00)
3 Beds [0, 1]	0.0467***
	(0.00)
4 Beds [0, 1]	0.0630***
	(0.00)
5 Beds [0, 1]	0.0730***
	(0.00)
6 Beds [0, 1]	0.0808***
	(0.00)
2 Baths [0, 1]	0.0747***
	(0.00)
3 Baths [0, 1]	0.1307***
	(0.00)
4+ Baths [0, 1]	0.2789***
	(0.00)
Half Bath [0, 1]	0.0294***
	(0.00)
Finished Basement	0.0442***
	(0.00)
Pool	0.0588***
	(0.00)
Garage	0.0235***
	(0.00)
Carport	0.0193***
	(0.00)
Private Backyard	0.0072***
	(0.00)
Sprinkler System	0.0172***
	(0.00)

*Table A1 is continued on next page

Table A1: Hedonic sales price regression (cont.)

Agent Owned	-0.0010
	(0.00)
Agent Related	0.0056
	(0.01)
Recent Renovation	0.0496***
	(0.00)
Estate Owned	-0.0494***
	(0.00)
Corporate Relocation	-0.0027
	(0.00)
Historic	0.0364***
	(0.01)
Golf Course	0.0094***
	(0.00)
Gated Community	0.1132***
	(0.01)
Club House	0.0683***
	(0.00)
Pond	0.0286***
	(0.01)
Starter Home	-0.0526***
	(0.00)
Neighborhood Assoc.	0.0582***
	(0.00)
Inventory_on	0.0069***
	(0.00)
Turnover	1.6152***
	(0.04)
Average School Test Score	0.1744***
	(0.01)
Winter	0.0080***
	(0.00)
Spring	0.0042***
	(0.00)
Fall	-0.0031**
	(0.00)
Time Fixed Effect	Quarterly
Location Control	Tract
# Observations	214,697
Adjusted R-squared	0.86

The dependent variable in column 1 is log of sales price. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Figure B1: Location of Bidding Wars