Capitalization of the "Shadow Mortgage" and its Implication for Housing Values and Depreciation

Caitlin O'Loughlin*†

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Abstract

This paper examines the effect of the financial condition of local governments on housing values and depreciation of the U.S. housing stock. Housing values bear the burden of municipal fiscal stress reflecting prospective and current homeowners reduced willingness-to-pay for housing. Using panel data from the American Housing Survey from 1984 to 2011, I estimate linear, quantile, and semiparametric varying coefficient (VC) models to examine these effects. The findings from the linear and quantile estimation are compared to the estimation of the VC models, which allow for a nonparametric, smoothed specification of building age. The results suggest that aspects of municipal solvency have differential effects across the distribution of housing values and building age. New, lower priced houses see the largest increases in housing values from larger cash and long-run solvency ratios, which reflect greater spending on infrastructure and other long-run capital investment projects, whereas older, lower priced houses benefit from increases in service-level solvency, suggestive of greater spending on public amenities. Moreover, the results indicate that the housing stock depreciates more slowly in municipalities with larger values of revenue and expenditure per capita, with implied annual depreciation rates ranging from over 0.4 to 0.7 percent.

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*John E. Walker Department of Economics, Clemson University, 417 Sirrine Hall, Clemson, SC, 29634. Email: cnt@g.clemson.edu.

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1 Introduction

Investment in real estate is critical to local governments as many rely on property taxes as a main source of revenue. It is in the best interest of both local governments and homeowners to promote and sustain a thriving real estate market. Since housing is both a consumption and an investment good, households may purchase real estate for different reasons. When deciding to buy, the decision of where to purchase or invest in real estate can be an important one. One may consider the size and attributes of the unit, as well as its location, which reflect the neighborhood characteristics and amenities of the surrounding area such as school quality, access to parks and recreation, and public infrastructure. While the characteristics of the home may be readily apparent, it may be more difficult to assess the financial condition of a city or county. Municipal financial health directly affects the provision of amenities and ultimately impact one's investment over time.

Using a traditional hedonic approach, the willingness-to-pay for certain location amenities such as environmental quality and school quality has been investigated in prior studies. I assert that the financial state of a municipality directly impacts the provision and quality of public goods and services. When a municipality is under fiscal stress, it may decrease the provision or quality of these amenities, resulting in reduced willingness-to-pay for housing. This fiscal stress may also impact the rate of depreciation of the housing stock, thereby eroding households' returns on investment, an issue which has not yet been addressed in the literature. These issues are of increasing importance with numerous municipalities filing for Chapter 9 bankruptcy in recent years including Vallejo, California (CA) in 2008; Harrisburg, Pennsylvania in 2011; Jefferson County, Alabama in 2011; Stockton, CA in 2012; San Bernardino, CA in 2012; Detroit, Michigan in 2013; and Hillview, Kentucky in 2015.

In this paper I investigate the capitalization of municipal fiscal stress in housing values and its impact on depreciation. This capitalization amounts to an additional shadow mortgage on housing. Using panel data from 1984 to 2011, I estimate linear and quantile regression hedonic pricing models, as well as semiparametric varying coefficient (VC) models, for a large and representative sample of owner and renter-occupied properties. While there are different approaches in the literature as to how to predict fiscal stress, I use widely accepted measures of municipal solvency including cash, budgetary, service-level, and long-run.

My findings provide evidence for the shadow mortgage and highlight the differential impact of municipal solvency aspects on housing values. Notably, increases in both cash and long-run solvency measures, suggesting a less financially stable government, negatively impact low-value properties. I find that a ten percent increase in total expenditure per capita leads to an approximate 0.6 percent increase in housing values at the 0.1 quantile, around \$400. By contrast, at the 0.9 quantile, this results in almost a one percent decrease, over \$3,500. Unsurprisingly, higher taxes per capita negatively impact homeowners across the distribution. The ability of a local government to balance its budget is positively valued by homeowners across the distribution of housing values. At the 0.5 quantile, a ten percent increase in total revenue to total expenditure results in a \$1,400 increase in housing values. After accounting for different aspects of municipal solvency, I find that depreciation is lower in areas with higher levels of per capita spending on amenities compared to areas with larger cash or other long-run solvency measures.

The decision to rent or buy a home likely depends on many factors including household income and preferences. Henderson and Ioannides (1986) find that consumers tend to smooth consumption over time, suggesting households that expect lower income in the future (e.g. retirement) are more likely to purchase a home rather than rent. In addition to considering attributes of the home such as number of rooms and floor area, prospective homeowners may also value things such as low crime rates or high school quality. Pope and Pope (2012) investigate the impact of crime on housing values and find that it has a significant and negative effect, reflecting homeowners' willingness-to-avoid. Brasington and Hite (2005) estimate the demand for environmental quality and show that environmental quality and school quality are complement goods, as indicated by a positive cross-elasticity, whereas environmental quality and house size are substitutes. Current and prospective homeowners are responsive to changes in school quality. Hayes and Taylor (1996) find that while location is usually the main driver in residential housing prices, school quality also plays a significant role. Moreover, findings from Thompson (2016) show a decline in housing prices in response to a school district being labeled as fiscally stressed.

Local governments may take on debt by issuing bonds to fund public goods and services such as public works projects or other capital outlays. Bronshtein (2017) finds that governments that expect an increase in the local housing tax base may be more likely to take on debt which was evident in the last recession. This can have negative implications for homeowners with results from MacKay (2014) suggesting an overcapitalization of fiscal debt in home prices. Contributing to municipal debt concerns are rising unfunded pension obligations. Arnott and Meulbroek (2018) discuss the potential impacts of unfunded municipal pension debt and assert that since homes are fixed assets, homeowners will bear the full burden of these obligations over time through lower housing prices. Brinkman et al. (2016) examine determinants of municipal pension funding and find that pension funding choices are fully capitalized in land prices.

In addition to housing and location characteristics, prospective and current homeowners may consider the depreciation rate of housing since it is likely to impact their investment over time. Hulten and Wykoff (1980) define economic depreciation as the "decline in asset price (or shadow price) due to aging." Malpezzi et al. (1987) cite this definition in their estimation of depreciation at the metropolitan statistical area (MSA) level. Leigh (1980) estimates depreciation of the national housing stock to be between 0.2 and 0.4 percent annually. Palmquist (1979) finds that owner-occupied residences depreciate at around 0.8

percent annually, while Randolph (1988a) estimates annual depreciation of 0.6 percent for renter-occupied properties, although he notes that it is not possible to identify depreciation without assuming away vintage effects, or obsolescence of the housing unit over time. Knight and Sirmans (1996) and Wilhelmsson (2008) show that houses with lower levels of maintenance expenditures tend to depreciate faster than those that are relatively more maintained. Francke and van de Minne (2017) find that after 50 years of no maintenance, a structure loses 43 percent of its value on average. For single-family homes, results from Harding et al. (2007) suggest homeowners see little economic gain after controlling for maintenance and home improvements.

Walters (2009) examines whether depreciation rates differ between subsidized and unsubsidized units. He expects subsidized units to depreciate more quickly since their rent only depends on meeting minimum quality standards, but finds no evidence to suggest a significant difference between the two groups. Galbraith (1998) examines filtering as a low-income housing policy and notes that while overall consumption of housing has increased over time, the changes were larger for relatively wealthier households. The location choice of low and high-income households may help to explain this finding. It could be that wealthier households are attracted to amenities, both built and natural, in the city center. Brueckner et al. (1999) argue that this could lead to a Paris-style location pattern with wealthier households concentrating in the city center and households with relatively less means populating the outer arrondissements. Alternatively, the age of the housing stock may explain where high and low-income households choose to live. Brueckner and Rosenthal (2009) find that high-income households tend to locate in areas with a relatively young housing stock. These findings lend support to the idea of downward filtering, or housing trickling down from the wealthiest households to the poorest, until the lowest quality housing drops out of the stock.

The impact of the shadow mortgage on housing values and investment motivates the research question. To my knowledge, no previous studies have empirically analyzed this question using the framework and methodology proposed here. Moreover, the impact of local government fiscal stress on the housing stock is increasingly important in the post-recession climate. This paper expands on the existing literature by examining the differential effect of aspects of the municipal financial condition on housing values and also provides a framework to account for its impact on depreciation.

The rest of the paper is organized as follows. In Section 2, I present a simple theoretical model of bid rent and housing value. I develop the statistical model in Section 3. In Section 4, I describe the data and provide summary statistics. The empirical findings are presented in Section 5. In Section 6, I conclude and summarize the results of the paper as well as describe additional findings and robustness checks.

2 Theoretical Model

I start with a simple theoretical model, adapting from the framework of Rosen (1974) and Hayes and Taylor (1996). I assume that consumers are rational and attempt to maximize their utility, taking the housing stock as given. Consumers earn income y and derive utility from consumption of z, a vector of housing characteristics with prices p, and x, a composite good. Consumers attempt to maximize utility

$$U = U(x, z_1, z_2, \ldots, z_n) \tag{1}$$

subject to their budget constraint

$$y = x + p_1 z_1 + p_2 z_2 + \ldots + p_n z_n, \tag{2}$$

where x is the numeraire good. Therefore, the consumer maximization problem is

$$\mathcal{L} = U(x, z_1, z_2, \ldots, z_n) + \lambda(y - x - p_1 z_1 - p_2 z_2 - \ldots - p_n z_n) \tag{3}$$

with first-order conditions

$$\frac{\partial \mathcal{L}}{\partial x} = \frac{\partial U}{\partial x} - \lambda = 0 \tag{4}$$

and

$$\frac{\partial \mathcal{L}}{\partial z_i} = \frac{\partial U}{\partial z_i} - \lambda p_i = 0 \tag{5}$$

for the i^{th} housing characteristic, $i = 1, \ldots, n$. From (4) and (5), it can be shown that the marginal rate of substitution between good x and z_i is equal to the ratio of prices

$$\frac{U_x}{U_{z_i}} = p_i. \tag{6}$$

The demand equations for x^* and z_i^*, $i = 1, \ldots, n$, can be obtained from (6). Following Henderson (1977), after substituting the demand equations into the utility function, the consumer's indirect utility function is

$$U^*(y - R, z_1, z_2, \ldots, z_n) \tag{7}$$

where R represents total expenditures on housing services. The consumer's bid rent function is therefore consumer's willingness-to-pay for values of z at a given level of U^* and y. After taking the inverse of (7), it can be shown that the consumer's bid rent function is

$$R = R(z_1, z_2, \ldots, z_n \mid y, U^*) \tag{8}$$

where U^* is the level of indirect utility from (7). To estimate a consumer's willingness-to-pay for certain characteristics, partial derivatives of the bid rent function with respect to characteristic z_i can be taken.

The present value of housing services, V, to a potential homebuyer is the discounted sum of after-tax bid rents. Letting τ be the tax rate, i the discount rate, and assuming that housing is an infinitely lived asset, then

$$V = \sum_{t=0}^{\infty}(R - \tau V)e^{-rt} = \frac{R - \tau V}{i} \tag{9}$$

or equivalently,

$$V = \frac{R}{i + \tau}. \tag{10}$$

In equilibrium, the value of housing services equals the highest bid offered by potential consumers. To model the value of housing services, a hedonic pricing function can be estimated containing all characteristics of housing services conferred including observable unit attributes, as well as neighborhood and location amenities such as high-quality schools, highways, and public parks. I posit the revenues and expenditures of municipalities directly fund these public goods and services and the financial state can impact the provision and quality of these goods.

3 Statistical Model

The value of housing services is a function of housing and location specific characteristics. To estimate the marginal effect of each attribute on the response variable, I construct a hedonic model consistent with the proposed theoretical model. Since there is not a renter-equivalent measure of housing value in the data, I specify and estimate a hedonic pricing model for the owner and renter samples separately. My identification strategy consists of two key assumptions: the existence of a national housing market and that the municipal solvency measures accurately reflect the amount and quality of publicly provided amenities.

The first assumption is supported by Linneman (1980) who finds that tests of the national housing market hypotheses cannot be rejected. Moreover, previous studies have utilized this assumption including Chay and Greenstone (2005) who examine the capitalization of air quality in housing values. Identification of the municipal financial state comes through a broad set of observations, with a wide range of solvency measures and fiscal conditions.

Typically, the coefficient on the building age term of the hedonic pricing function is used to estimate depreciation, although this may be misleading if there are nonlinear or interaction effects. To account for these possibilities, I specify an age function

$$h(A_{it}, D_i, F_{it}, S_{ct}) = \sum_{k=1}^{10} \gamma_k a_{it} \mathbb{I}_k(\alpha_{k-1} < a_{it} \leq \alpha_k) + \gamma_{11} a_{it} D_i + \gamma_{12} a_{it} F_{it} + \gamma_{13} a_{it} S_{ct}, \quad (11)$$

where A_{it} is a vector of interactions between the building age of household i at time t, a_{it}, and building age group indicators $\mathbb{I}_k$ following Yoshida (2016), such that α_{k-1} and α_k represent the lower and upper bounds on each age group, respectively. The vector S_{ct} includes the solvency measures for county c at time t, D_i is an indicator for detached housing units, and F_{it} is the floor area in square feet. The age function specification allows depreciation to vary over the life of the structure and also with structure type, floor area, and the municipal financial condition.

To capture the age profile of housing and any potential nonlinear effects, I discretize the first building age term appearing in (11). Moreover, I include an indicator for detached structures since it is likely that they depreciate more slowly than other types of structures. Randolph (1988a) notes that the building age interaction with structure type is especially important because the economics and technology of maintenance behavior is likely to vary across building types. Similarly, depreciation is likely to vary with house size, or floor area, since larger structures tend to be located farther away from the city center where land prices are relatively cheaper. Finally, the interaction between building age and the solvency measure is justified by Breger (1967) who states that depreciation of property may result from either deterioration of the capacity to render service or a decline in the demand for the service rendered.

For the owner-occupied specification, the complete hedonic pricing model is

$$lnV_{it} = \alpha_0 + h(A_{it}, D_i, F_{it}, S_{ct}) + X_{it}\beta_1 + Z_{it}\beta_2 + S_{ct}\beta_3 + \epsilon_{it}, \tag{12}$$

where lnV_{it} is the log of the self-reported housing value for household i at time t. While it is possible that homeowners over or underestimate the value of their home, results from Robins and West (1977) reveal that there is no evidence to suggest this happens systematically. Moreover, Kiel and Zabel (1999) find that self-reported measures yield reliable estimates that accurately reflect both housing and neighborhood characteristics. The vector X_{it} contains observable unit characteristics and household demographics such as the number of rooms, bathrooms, and household size, Z_{it} contains community controls and geographic information including the zone-level average household income and education, and S_{ct} includes the municipal financial state of county c at time t as defined by the cash, budgetary, service, and long-run solvency measures. Since the dependent variable is an individual measure of housing value, as opposed to an aggregate measure, concerns over simultaneity can be avoided.

All solvency measures are for the prior fiscal year since I expect there to be a lag effect in terms of the provision of amenities and services. In this model specification, the marginal effect of the solvency measure on the response variable is a linear function of building age. To obtain a measure of depreciation, I estimate the marginal effect

$$\frac{\partial ln(V_{it})}{\partial h(A_{it}, D_i, F_{it}, S_{ct})}\frac{\partial h(A_{it}, D_i, F_{it}, S_{ct})}{\partial a_{it}}, \tag{13}$$

of building age on housing values evaluated at different percentiles of the solvency measures. As homes age, their value typically decreases over time, although Chinloy (1978) notes that theoretically there is no reason for the depreciation function to be downward sloping.

In addition to the estimation of (12), a similar model, i.e.,

$$lnR_{it} = \gamma_0 + g(A_{it}, D_i, F_{it}, S_{ct}) + X^*_{it}\delta_1 + Z_{it}\delta_2 + S_{ct}\delta_3 + \varepsilon_{it}, \tag{14}$$

is estimated for the renter-occupied sample where lnR_{it} is the log of the annual contract rent of household i at time t. The age function $g(A_{it}, D_i, F_{it}, S_{ct})$ is similar to the one for owner-occupiers in (11). The baseline model for both the owner and renter sample includes the full set of controls, age function, as well as location and year fixed effects, but excludes any of the municipal solvency terms or interactions with these measures.[1]

I estimate (12) and (14) using both ordinary least squares (OLS) and quantile regression. The estimation of the hedonic pricing model via OLS can be severely distorted by outlier observations making quantile regression an attractive approach. Furthermore, it is likely that the marginal effect of municipal solvency differs across the distribution of housing values. Zietz et al. (2008) use quantile regression to estimate a hedonic pricing model to examine the willingness-to-pay for certain housing characteristics. They find that owners of relatively higher-priced homes value certain characteristics such as square footage and number of bathrooms differently than lower priced ones. Moreover, they note that the distribution of age also varies across the different quantiles examined. Zahirovic-Herbert and Chatterjee (2012) find that historic preservation tends to positively impact relatively low-price houses, but the act of preservation may displace low-income residents, leading to a quasi-gentrification effect. By contrast, Zhang (2016) finds that lower valued homes bear more of the negative impact following a major flood.

The quantile regression model for the owner sample, Q, due to Koenker and following

[1]It should be noted that annual property taxes and maintenance costs are omitted from the renter sample estimation since there is no renter equivalent in the data. This is reflected in X^*_{it} and is discussed in section 4.

Greene (2000) can be written as

$$Q(\mathrm{V} \mid \mathbf{Z}, q) = \mathbf{Z}'\beta_{\mathbf{q}} \text{ such that } \Pr(\mathrm{V} \leq \mathbf{Z}'\beta_{\mathbf{q}} \mid \mathbf{Z}) = q,\ 0 < q < 1, \tag{15}$$

where V represents the log of housing value, vector $\mathbf{Z}$ includes the right-hand side of (12) and q represents a given quantile strictly between 0 and 1. Since no assumption is made about the distribution of V $\mid$ $\mathbf{Z}$ or about its conditional variance, this is essentially a semiparametric specification. The estimator, $\mathbf{b}_q$ of β_q for a specific quantile is computed by minimizing the function

$$\begin{aligned} F_n(\beta_q \mid \mathbf{V}, \mathbf{Z}) &= \sum_{i:V_i \geq Z_i'\beta_q}^{n} q \mid V_i - \mathbf{Z_i}'\beta_{\mathbf{q}} \mid + \sum_{i:V_i < Z_i'\beta_q}^{n} (1-q) \mid V_i - \mathbf{Z_i}'\beta_{\mathbf{q}} \mid \\ &= \sum_{i=1}^{n} g(V_i - \mathbf{Z}_i'\beta_q \mid q) \end{aligned} \tag{16}$$

$$g(e_{i,q} \mid q) = \begin{cases} q e_{i,q} & \text{if } e_{i,q} \geq 0 \\ (1-q) e_{i,q} & \text{if } e_{i,q} < 0, \end{cases} \tag{17}$$

and $e_{i,q} = V_i - \mathbf{Z}_i'\beta_q$.[2] To make inference, I bootstrap and cluster the standard errors at the county-level. All models are estimated at the 0.1, 0.25, 0.5, 0.75, and 0.9 quantiles of housing values.

Since I expect the effect of the solvency measures on housing values to vary with building age, I estimate a semiparametric VC model due to Hastie and Tibshirani (1993) as a robustness check for my hedonic pricing models. It is similar to a general additive model in that a single term enters the function nonparametrically, although it permits an interaction between nonparametric and parametric terms. This approach offers several advantages over a standard parametric framework. Specifically, these models relax the assumption of linearity between

[2]The quantile regression model for the owner-occupied sample in (15)–(17) can be easily be modified for the renter sample. See the separate appendix for results from the renter sample estimation.

the predictors and response variables. Wan et al. (2017) apply the VC modeling framework to the estimation of hedonic house prices functions in Hong Kong. They note that VC models reduce modeling bias and also avoid the curse of dimensionality, both advantages over the traditional parametric model.

The VC model specification replaces the parametric building age terms in (11) with smoothed nonparametric versions. The modified building age function for the owner-occupied sample can be represented as

$$\widetilde{h}(a_{it}, D_i, F_{it}, S_{ct}) = f_1(a_{it}) + f_2(a_{it})D_i + f_3(a_{it})F_{it} + f_4(a_{it})S_{ct}, \tag{18}$$

where $f_j(a_{it})$ are the smooth building age functions, $j = 1, \ldots, 4$. The modified building age function $\widetilde{g}(a_{it}, D_i, F_{it}, S_{ct})$ for the renter sample is similar to (18). I adapt (12) and (14) with the modified building age functions for the owner and renter sample estimation, respectively.

4 Data

Data used for estimation are obtained from the American Housing Survey (AHS), U.S. Census of Governments, U.S. Census Bureau, and Bureau of Labor Statistics (BLS). The primary source of data is the AHS. The AHS includes both a national survey and metropolitan survey, with observations in the metropolitan sample being tracked over time. I use the metropolitan sample data which allow me to identify the household county. Unfortunately, not every county is sampled in every survey and therefore the number of years between observations is nonconstant. AHS data include characteristics of the housing unit as well as its occupants and neighborhood. To maximize the number of repeat observations, I use data from 1984 to 2011, a period of 27 years.

Following Rosen (1974), I control for all observable characteristics of the unit, household, and surrounding area which may affect the owner's self-reported value of their home or the annual contract rent that a tenant pays. This includes the number of rooms, number of bathrooms, the floor area of the unit, whether it is a detached or multiunit building, the presence of a working fireplace, and whether it includes a balcony or porch. Since certain features may be more desirable depending on the where the unit is located and furthermore, since there is large regional variation in my sample, I include several interaction effects to account for differences in the inherent value of amenities following Tsoodle and Turner (2008). These include: *air conditioning (ac)* $\times$ *hot*, *fireplace* $\times$ *cold*, and *parking* $\times$ *cold* where *cold* and *hot* are average temperature indicator variables following the AHS definition, *ac* is an indicator if the unit has central air conditioning, *parking* is an indicator for the presence of covered parking, and *fireplace* is an indicator for the existence of a working fireplace. It is plausible that households in areas with colder climates may value attributes such as a fireplace or covered parking more compared to those living in more temperate climates.

To account for variation in the heads of household, I utilize observable characteristics that I expect will influence the self-reported property value including whether the head of household is male, married, college-educated, and older than 65 years. Moreover, I control for household income and differences in observable housing quality. These include indicators for whether the unit has a missing roof, missing walls, broken windows, window bars, whether there have been leaks from the inside or outside in the past 30 days, whether the unit has cracks, and whether there is broken plaster. It should be noted that the wording of the AHS questions changed slightly after 1993 with a new survey format, although it is unlikely to have a significant impact on the results.[3] I also include self-reported measures of satisfaction with the unit and surrounding neighborhood which is included in the AHS. The question asks "On a scale from 1–10, how satisfied are you with the housing unit?" and similarly for the surrounding neighborhood.

[3] See the AHS codebook for further details.

In addition to the quality and satisfaction measures, I also include costs of annual routine maintenance and annual property taxes. Harding et al. (2000) find evidence that suggests homeowners may undermaintain housing if borrowers have limited liability in the case of mortgage default. Unfortunately, there are not equivalent survey questions for renters in the AHS data, and therefore I cannot control for these in the renter model specification. Besides maintenance and property taxes, I control for various geographic attributes, including the zone-level average household size to account for differences between suburban and urban areas.[4] I expect that larger households will tend to live in more suburban areas. I also include the average number of rooms, average household income, the fraction of black households, the fraction of households with a college education, and average building age, all at the zone-level, to capture neighborhood effects.

For the renter sample estimation I exclude all subsidized units (including government owned housing projects or rent-controlled units). These types of properties do not reflect the true market rent and hence, should not be impacted by the "shadow mortgage." Additionally, I only consider occupied units in both the owner and renter samples. The justification for including both owner and renter-occupied units in this analysis is two-fold. Tiebout (1956) states that in regards to location decisions, people vote with their feet, although this effect will not likely be immediate. I include the renter-occupied specification since I expect that the decline in the willingness-to-pay for rental units should similarly be impacted by signs of fiscal stress.

In addition to the housing data from the AHS, I utilize data from the U.S. Census of Governments Annual Survey of State and Local Government Finances. This is an annual survey which assesses the financial state of governments across all levels, although not every government and government type is sampled in each survey.[5] I construct the solvency ratios using data from this survey. To obtain a wide and comprehensive assessment of municipal

[4]The AHS defines a zone as an economically homogenenous area with a population of 100,000 or more.
[5]The full sample of local governments are only surveyed in years ending in a '2' or a '7'.

fiscal health, I employ several different measures. Following the literature, I use measures of cash, budgetary, service-level, and long-run solvency presented in Table 3 following Wang et al. (2007) and later utilized by Anders and Gearhart (2018). These ratios capture the municipal financial condition and can be useful in predicting fiscal stress. Gorina et al. (2018) find that the financial variables most associated with municipal bankruptcies are cash solvency, long-run solvency, and service-level solvency and can be significant in predicting bankruptcies. Alternative measures to predict the likelihood of a bankruptcy filing include a composite fiscal condition score, although the literature is mixed on this approach. McDonald (2017) deems it ineffective and Wang et al. (2007) finds that it is only marginally effective in predicting bankruptcies.

To capture the municipal fiscal state, I include several different measures presented in Table 3. Cash solvency is related to liquidity and demonstrates the ability of a local government to generate funds to pay its current liabilities. To assess the cash solvency, I utilize *Debt-to-Cash* (total debt outstanding to total cash and securities) which captures the ability of a government to balance its budget in the short-run. Smaller values of *Debt-to-Cash* indicate a municipality that is more cash solvent (all else equal). In addition to the cash solvency measure, I include the *Operating Ratio* (total revenue to total expenditures) which captures budgetary solvency. This ratio reflects the ability of a municipality to balance its budget. Increases in this ratio reflect a municipality that is better able to balance their budget, which I expect to have a positive and significant effect on housing values and furthermore, positively reflected in the rate of depreciation of housing. Although, this may be misleading since many local governments are subject to balanced-budget constraints.

I use four measures of service-level solvency including *EperC* (total expenditure to total population), *RperC* (total revenue to total population), *TperC* (total taxes to total population), and *Rev-to-CapOut* (total revenue to total capital outlay). The service-level solvency measures capture the ability of a municipality to provide basic services in the form of local amenities. I expect increases in *EperC* to positively impact housing values and result in lower rates of depreciation, all else equal. Larger values of this measure reflect a municipality with high levels of per capita spending on amenities such as parks and schools. To measure long-run solvency, I include *LTLiability* (total long-term liabilities to total interest on debt), *LTLiabilityperC* (total long-term liabilities to total population), and *Debt-to-Revenue* (total debt outstanding to total revenue). Both *LTLiability* and *LTLiabilityperC* capture current obligations as well as any other obligations that arise upon due date. I expect that increases in these measures will have a negative impact on housing values, as this suggests a government that is less financially stable.

Since houses are non-fungible and largely immobile, housing markets are tied to both the national and local level conditions. To control for local economic conditions, I obtain data from the U.S. Census and BLS. To control for any existing economic trends, I use unemployment data at the county-level. These data are from the BLS Local Area Unemployment Statistics. Note that since the BLS only began reporting unemployment rates at the county-level in 1990, I use the 1980 U.S. Census unemployment rate for observations appearing prior to 1985 and the 1990 value for observations appearing from 1985 to 1989. Furthermore, I control for both population and population change at the county-level using population estimates from the U.S. Census of Governments. This should account for any changes in household sorting over time.

Table 1 presents descriptive statistics by county, MSA, and tenure. Columns 1 and 2 list the county name and the MSA of each municipality in the sample, respectively. The year(s) that each county appear(s) in the sample is (are) listed in column 3. Counties are observed anywhere from one to five times, with 75 percent appearing three or more times in the sample. Columns 4–6 present the sample size by tenure group and list the maximum number of times a given household is observed. Over half of households appear three or more times in the sample. The sample size of owner-occupied properties versus renter-occupied properties varies by county and reflects the tenure breakdown for that location. Maricopa, Arizona has an owner sample of 5,641 households, the largest of any county. San Diego, California has the largest renter sample at 4,454 observations. Detailed descriptions of the housing variables and financial variables appear in Tables 2–3, respectively.

Selective descriptive statistics for the owner sample appear in Table 4. There is considerable variation in self-reported housing values with median and mean housing values of \$149,986 and \$210,406, reflecting a right-skewed distribution. The distribution of building ages is similarly skewed, with a median building age of 30 and a mean of over 34 years. The average number of rooms is seven and slightly over three percent of households reside in trailers. Around 87 percent of households reside in single-family detached houses, compared with just three percent that reside in multiunit structures, or buildings with more than four units. Notably, overall housing satisfaction is relatively high, with a median rating of nine, and an average of 8.5.

There is significant variation in the solvency measures. The first quartile *Debt-to-Cash* observation, a cash solvency measure, is 0.518. A ratio value of less than one may reflect a municipality with a large amount of cash reserves relative to outstanding short-term debt obligations. For the budgetary solvency measure *Operating Ratio*, the mean value is 1.032 which may reflect balanced budget constraints. The ratios with the the largest variation are *LTLiability*, a long-run solvency measure, and *Rev-to-CapOut*, a service-level solvency measure. Both capture long-term capital and infrastructure expenditures and are therefore subject to volatility since municipalities may not invest in these projects at the same rate across time. The first and third quartile of *LTLiability* are 12.931 and 20.315, respectively. For *Rev-to-CapOut*, the median and mean observation are 1,163.672 and 1,507.223, respectively, reflecting a right-skewed distribution. The solvency measure with the least variation is *TperC*, with a standard deviation of 0.540.

5 Empirical Results

The baseline model includes all controls discussed in the data section and presented in Table (2), excluding any solvency measures or interactions with solvency measures. The results from the baseline estimation for the owner sample are presented in Table 5. In column 1 of Table 5, I present results using the traditional approach, including both a linear and quadratic building age term, to capture the possible nonlinear effects of age on housing value. The coefficients on both the linear and quadratic building age terms are significant at one percent and have the expected signs, reflecting the nonlinear effect that building age has on the response variable. The results from the baseline estimation including the building age step function are presented in column 2. The coefficients suggest that the rate of depreciation is higher for relatively newer buildings and then tends to slow as the home ages, similar to findings from Yoshida (2016).

Table 6 shows the results controlling for *Debt-to-Cash*, a cash solvency measure. This measures captures outstanding debt obligations that are due in less than one year and larger values of this ratio suggest a municipality that is less liquid over the short-run. In column 1, results from the linear estimation suggest that a ten percent increase in *Debt-to-Cash* leads to a 0.07 percent decrease in housing values, roughly \$145. In column 2, a ten percent increase in *Debt-to-Cash* leads to a 0.17 percent decrease at the 0.1 quantile of housing values, over \$100. This is compared with a 0.02 increase, approximately \$70, at the 0.9 quantile in column 6. The results indicate that homeowners at the lower end of the distribution have a willingness-to-avoid increases in *Debt-to-Cash*. This seems to suggest that while these households bear the costs from from short-run capital investments such as highway and road improvements, they may not benefit from it. Doucet et al. (2011) discuss this new form of gentrification and suggest that short-run investment spending may be targeted in more affluent areas. While the magnitude of the marginal effect is small, this likely reflects the volatile nature of this solvency measure and understates the true year-to-year change.

I present results examining the impact of *Operating Ratio*, a budgetary solvency measure, in Table 7. Larger values of this measure reflect a local government that is more adept at balancing their budget and suggests greater fiscal health. While the main and interaction term coefficients are insignificant in the linear estimation, both are significant at one percent in the 0.1 and 0.25 quantile estimation in columns 2–3. In column 3, the marginal effect of *Operating Ratio* indicates that a ten percent increase in this measure leads to a 1.1 percent increase in housing values at the 0.25 quantile, over $1,100. The findings imply that increases in budgetary solvency have a positive impact on low-value properties, which reflects the government's ability to cover current or desired service levels. This could signal to households that a municipality may already be in a steady state of amenity provision. It should be noted that in columns 4–6, the marginal effect is also positive for high-value homeowners, but main coefficient term on *Operating Ratio* is not statistically significant at one percent.

To measure the service-level solvency of a municipality, several different measures are utilized. Table 8 presents the results controlling for *EperC*. Larger values of this measure reflect a local government that is better able to provide public amenities. The marginal effect suggests that a ten percent increase in *EperC* leads to over a 0.3 percent increase in the 0.25 quantile of housing values, or roughly $300. García et al. (2010) find a similar positive effect of increases in expenditures on housing values. In column 5, at the 0.75 quantile this leads to a 0.7 percent decrease in housing values, or around $1,800. At the 0.9 quantile, this results in roughly a 0.9 percent decrease, over $3,500. Greater service-level solvency may positively effect housing values at the lower end of the distribution due to the relative lack of privately provided amenities compared with those at the upper end. Nechyba and Walsh (2004) note that fiscal amenities matter and permit high-income households to escape redistributive taxation and improve public good quality.

The results from the estimation controlling for *TperC* are presented in Table 9, another service-level solvency measure. Larger values of *TperC*, suggest a more service-level solvent government. Oates (1969) finds that increases in the property tax rate tends to have a depressing effect on housing values, using the Tiebout sorting hypothesis to explain the finding. The marginal effect of $TperC$ on the response variable is negative across all model estimations. In column 4, a ten percent increase in $TperC$ leads to an approximate 0.4 percent decrease at the 0.5 quantile of housing values, approximately \$700. By contrast, at the 0.9 quantile in column 6, this results in a 0.9 percent decrease in housing values, around \$3,800. These results suggest that "house-rich" homeowners bear a larger burden from increases in this measure, but the effect is uniformly negative across the distribution of housing values.

In Table 10, I examine the impact of *LTLiability*, a long-run solvency measure. Larger values of measure suggest a municipality that is less solvent over the long-run. The marginal effect of *LTLiability* is negative across all model specifications, reflecting the shadow mortgage. At the 0.25 quantile of housing values, a ten percent increase in *LTLiability* leads to a 0.2 percent decrease, around \$200. In column 4, at the 0.5 quantile of housing values, a ten percent increase in *LTLiability* results in a 0.1 percent decrease, or over \$150. While these are relatively small effects, it should be noted that these financial measures are subject to volatility and it would not be unreasonable to see large changes over time. Hence, a ten percent increase is likely understating the true year-to-year change in the measure. Notably, the findings from MacKay (2014) show a 2.5–3.7 percent decrease in housing prices as a result of the negative news coverage regarding municipal debt obligations.

In Table 11, the implied variation in annual depreciation is estimated using the results from the linear estimation of (13) and evaluated at different percentiles of the solvency variables. Notably, the short and long-run solvency measures see the largest variation between the 10 and 90 percentiles. At the 90 percentile the implied depreciation for *Debt-to-Cash* is over 0.7 percent, compared with 0.3 percent at the 10 percentile, for a difference of nearly 0.4 percent annually. For *LTLiability*, the difference in implied annual depreciation between the

10 and 90 percentile is around 0.3 percent annually. Interestingly, higher-levels of service-level solvency tended to have a dampening effect on annual depreciation, with a difference of -0.20 and -0.28 for *TperC* and *EperC*, respectively. These findings indicate the higher levels of spending towards amenities may help slow the rate of depreciation of housing, whereas higher levels of debt, both over the short and long-run, tend to erode housing values more quickly.

Selected results from the estimation of the VC model for the owner sample are presented in Appendix A. They largely confirm the findings from the empirical results of the linear and quantile regressions. Figure 1 of Appendix A suggests that the effect of *Debt-to-Cash* on housing values is positive for relatively new to average-aged buildings, but the relationship is nearly linearly negative. The effect of the *Operating Ratio* is positive across building ages, with wide confidence intervals, and has the strongest positive effect on the oldest structures in the sample. In Figure 3, the effect of *EperC* on housing values is highly nonlinear and largely negative, although there does appear to be a positive impact on housing values for the oldest properties in the sample. For *LTLiability* in Figure 5, the impact of this ratio on housing values is positive for buildings 20 years or younger. For older properties, increases in this measure negatively impact housing values.

In addition to the main model specifications, I include additional owner sample model estimations as well as the full renter sample estimation in the separate appendix. The results for the renter sample estimation are very similar to the empirical findings of the owner sample estimation and suggest the theoretical model is appropriate to use for model predictions. Furthermore, the estimates of implied annual depreciation for the renter-occupied sample remained similar, with less variability, to the estimation using the owner sample. All the models estimated for the owner-occupied specification are similarly estimated for the renter sample, but with the noted differences as discussed in Section 3.

6 Discussion and Conclusion

This paper examines and provides evidence for capitalization of the shadow mortgage. For the average-aged building, increases in cash and long-run solvency measures, suggesting a less-solvent local government, negatively impact housing values. Specifically, a ten percent increase in total debt outstanding to total interest on debt results in an approximate 0.2 decline in housing values at the 0.1 quantile, roughly $100. By contrast, at the 0.9 quantile of housing values, a ten percent increase in this measure leads to a 0.02 percent, or around $70. While these effects are small for the individual homeowner, they can have significant impacts in aggregate. It should also be noted that due to the volatile nature of government investment, on average a ten percent change in these measures likely understates the true year-to-year change.

Unsurprisingly, increases in per capita expenditure positively impact housing values at the lower end of the distribution. A ten percent increase leads to a 0.6 percent increase, nearly $400, at the 0.1 quantile. Surprisingly, the results suggest that at the 0.9 quantile, this results in a 0.9 percent decrease, over $3,500. Notably, Skidmore and Scorsone (2011) find that in times of fiscal stress, municipalities respond by cutting back on recreation spending and capital improvements, as well as other maintenance projects. These findings suggest that local governments should focus on amenity-spending, even in economic downturns, to shield local housing values, especially low-value properties. In regards to taxation, Mieszkowski and Zodrow (1989) discuss two opposing views on the property tax. They consist of the benefit view, suggesting it is effectively a head tax, and the new view which suggests that capital bears the average burden of the tax. While I do not explicitly examine the impact of the property tax, my findings suggest that increases in taxes per capita has a uniformly negative impact on housing values, with high-value properties bearing a larger impact.

Moreover, Brueckner and Helsley (2011) illustrate how the market failures contributing to urban sprawl also impact and contribute to urban blight. They note that excessive suburban development can depress central-city housing and undermine maintenance incentives, leading to deficient levels of central-city investment. The policy implication would suggest shifting populations from the suburbs to city-center with reinvestments, thereby reducing blight leading to a gentrification argument. This is further supported by the estimation of depreciation which finds lower depreciation in areas with high per-capita expenditures, whereas municipalities with large cash and long-run measures have higher depreciation, possibly illustrating the differing impact of the municipal financial state.

While gentrification is highly debated in local communities, Lang (1986) asserts that gentrification may promote municipal fiscal health if it increases the tax base by attracting affluent households. My findings are supported by previous studies including Hilber (2017) who find evidence that public and private investments and also intergovernmental transfers get capitalized into local house prices, especially in areas with strict regulatory and supply constraints. Local governments can benefit select groups by focusing their spending on certain areas as subject to their budgetary allowances. The policy implications of these findings may be useful to address urban issues through focused municipal spending.

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Table 1: Housing Data Sample Statistics

County	MSA	Years	No. owners	No. renters	Max no. obs.
Adams, CO	Denver	86, 90, 95, 04, 11	1,116	454	3
Alameda, CA	San Francisco	85, 89, 93	1,185	1,134	3
Alexandria City, VA	Washington	85, 89, 93, 98, 07	125	224	3
Allegheny, PA	Pittsburgh	86, 90, 95, 04, 11	2,882	1,467	3
Arapahoe, CO	Denver	86, 90, 95, 04, 11	1,579	506	3
Arlington, VA	Washington	85, 89, 93, 98, 07	199	200	3
Ashtabula, OH	Cleveland	04	88	10	1
Baltimore City, MD	Baltimore	87, 91, 98, 07	644	496	2
Baltimore, MD	Baltimore	87, 91, 98, 07	1,197	506	2
Beaver, PA	Pittsburgh	86, 90, 95, 04, 11	478	119	3
Boulder, CO	Denver	86, 90	218	256	2
Brazoria, TX	Houston	87, 91	80	52	2
Broward, FL	Miami	86, 90, 95, 04, 11	1,980	1,075	3
Bucks, PA	Philadelphia	85, 89	298	156	2
Burlington, NJ	Philadelphia	85, 89	162	94	2
Butler, OH	Mansfield	11	195	26	1
Butler, PA	Pittsburgh	95, 04, 11	310	76	3
Camden, NJ	Philadelphia	85, 89	157	99	2
Chambers, TX	Houston	98	10	3	1
Chester, PA	Philadelphia	85, 89	127	95	2
Clark, WA	Seattle	86, 90, 95, 02	910	546	2
Clayton, GA	Atlanta	87, 91, 96, 04, 11	238	190	3
Cobb, GA	Atlanta	87, 91, 96, 04, 11	815	586	2
Collin, TX	Dallas	85, 89, 94, 02, 11	840	381	4
Contra Costa, CA	San Francisco	85, 89, 93	871	648	3
Cook, IL	Chicago	87, 91	931	698	2
Cuyahoga, OH	Cleveland	84, 88, 92, 96, 04, 11	4,608	1,280	3
Dade, FL	Miami	86	277	191	1
Dallas, TX	Dallas	85, 89, 94, 02, 11	3,146	3,382	4
Davis, UT	Salt Lake	84, 88, 92, 98	1,060	411	3
Delaware, PA	Philadelphia	85, 89	235	76	2
Denton, TX	Dallas	85, 89, 94, 02, 11	583	374	4
Denver, CO	Denver	86, 90, 95, 04, 11	1,518	1,318	3
Du Page, IL	Chicago	87, 91	140	111	2
Erie, NY	Buffalo	84, 88, 94, 02, 11	3,822	1,303	4
Fayette, PA	Pittsburgh	86, 90, 04, 11	236	83	2
Frederick, MD	Washington	85, 89, 93, 98, 07	237	77	3
Gloucester, NJ	Philadelphia	85, 89	75	32	2
Gwinnett, GA	Atlanta	87, 91, 96, 04, 11	811	393	3
Hamilton, OH	Cincinnati	86, 90, 98, 11	1,883	729	2
Harford, MD	Baltimore	87, 91, 98, 07	464	94	2
Hillsborough, FL	Tampa	85, 89, 93, 98, 07	1,903	1,396	3
Jackson, MO	Kansas City	86, 90, 95, 02	1,834	1,100	2
Jefferson, AL	Birmingham	84, 88, 92, 98, 11	3,745	2,373	3
Jefferson, MO	Kansas City	87, 91, 96, 04	388	94	2
Kane, IL	Chicago	87, 91	58	34	2
King, WA	Seattle	04, 09	1,700	768	2
Lake, IL	Chicago	87, 91	70	31	2
Livingston, MI	Detroit	85, 89, 93	69	29	2
Lorain, OH	Cleveland	11	160	36	1
Los Angeles, CA	Los Angeles	85, 89, 11	2,927	2,864	2
Macomb, MI	Detroit	85, 89, 93	551	182	3
Maricopa, AZ	Phoenix	85, 89, 94, 02, 11	5,641	4,276	4
Marin, CA	San Francisco	85, 89, 93, 98, 11	600	458	3
McHenry, IL	Chicago	91	25	16	1
Milwaukee, WI	Milwaukee	84, 88, 94, 02, 11	2,656	2,202	4
Monroe, MI	Detroit	85, 89, 93	89	33	3
Monroe, NY	Buffalo	86, 90, 98	2,185	955	2
Montgomery, MD	Washington	85, 89, 93, 98, 07	1,027	395	3
Montgomery, PA	Philadelphia	85, 89	323	166	2
Newport News City, VA	Norfolk	84, 88, 92, 98	550	387	3
Niagara, NY	Buffalo	84, 88, 94, 02, 11	912	416	4
Norfolk City, VA	Norfolk	84, 88, 92	522	522	3

Table 1: Housing Data Sample Statistics — continued

County	MSA	Years	No. owners	No. renters	Max no. obs.
Oakland, MI	Detroit	85, 89, 93	637	562	3
Orange, CA	Anaheim	86, 90, 94, 02, 11	5,418	4,418	4
Palm Beach, FL	Miami	07	173	32	1
Philadelphia, PA	Philadelphia	85, 89	269	221	2
Pierce, WA	Seattle	87, 91, 09	615	525	2
Pinal, AZ	Phoenix	11	72	17	1
Pinellas, FL	Tampa	85, 89, 93, 98, 07	2,142	1,505	3
Portsmouth City, VA	Norfolk	84, 88, 92	282	177	3
Prince Georges, MD	Washington	85, 89, 93, 98, 07	931	411	3
Riverside, CA	San Bernardino	86, 90, 94, 02	2,224	1,618	4
Salt Lake, UT	Salt Lake	84, 88, 92, 98	4,086	2,645	3
San Bernardino, CA	San Bernardino	86, 90, 94, 02	2,228	2,110	4
San Diego, CA	San Diego	91, 94, 02, 11	4,434	4,454	3
San Francisco, CA	San Francisco	85, 89, 93, 98, 11	811	1,722	3
San Mateo, CA	San Francisco	85, 89, 93, 98, 11	1,710	975	3
Snohomish, WA	Olympia	09	55	12	1
St. Louis City, MO	St. Louis	87, 91, 96, 04, 11	453	372	3
St. Louis, MO	St. Louis	87, 91, 96, 04, 11	2,523	801	3
Virginia Beach City, VA	Norfolk	84, 88, 92, 98	1,559	928	3
Washington, DC	Washington	85, 89, 93, 98, 07	302	398	3
Washington, PA	Pittsburgh	86, 90, 95, 04	372	90	2
Waukesha, WI	Milwaukee	84, 88, 94, 02, 11	1,554	375	4
Wayne, MI	Detroit	85, 89, 93	1,309	781	3
Weber, UT	Salt Lake	88, 92, 98	732	353	2
Westmoreland, PA	Pittsburgh	86, 90, 95, 04, 11	1,030	208	3

Table 2: Description of Variables

Variable Name	Variable Description
Dependent Variable	
propvalue	self-reported current market value ($)
annualrent	annual contract rent ($)
Unit Characteristics	
sqfootage	area of unit (1000s of sq ft)
proptax	annual property taxes (owner-sample only) ($)
annualmain	cost of annual maintenance (owner-sample only) ($)
numrooms	number of rooms in unit
age	age of unit at time of observation
numbaths	number of full bathrooms
single	indicator if detached unit
mobile	indicator if mobile home/trailer
large	indicator if located in building with more than four units
centralac	indicator if central ac present
centralheat	indicator if central heat present
fireplace	indicator if working fireplace
balcony	indicator if unit has a porch/balcony
hquality	self-reported housing satisfaction rating
nquality	self-reported nbrhood satisfaction rating
parking	indicator if unit has covered parking
hot	indicator if unit located in county described as "hot" climate (AHS 2011 description)
cold	indicator if unit located in county described as "coldest" climate (AHS 2011 description)
Household Characteristics	
male	indicator if male HOH
married	indicator if married HOH
black	indicator if black HOH
college	indicator if four years of college or more completed by HOH
older	indicator if HOH is 65 years or older
hhincome	total household income ($)
Local-Level Controls	
avgnumper	zone-level average of household size
avgnumrooms	zone-level average number of rooms
avghhincome	zone-level average household income ($)
avgblack	zone-level fraction of black HOHs
avgcollege	zone-level fraction with four years of college or more
avgage	zone-level average age of building
unemprate	county-level unemployment rate
popchg	county-level population change
population	county-level population
Geographic Controls	
state	state (FIPS code)
centralcity	indicator if unit is in central city of MSA
MSA	metropolitan statistical area of unit location
county	county (FIPS code)
zone	socio-economically homogeneous area with 100K population or more

Table 3: Description of Financial Variables & Solvency Measures

Solvency Measure	Description	Financial Ratio	Solvency Type
Debt-to-Cash	Total debt outstanding to total cash and securities	$\frac{\text{Total debt outstanding}}{\text{Total cash and securities}}$	Cash
Operating Ratio	Total revenue to total expenditure	$\frac{\text{Total revenue}}{\text{Total expenditure}}$	Budgetary
Debt-to-Revenue	Total debt outstanding to total revenue	$\frac{\text{Total debt outstanding}}{\text{Total revenue}}$	Long-run
LTLiability	Total debt due within more than one year to total interest on debt	$\frac{\text{Total long-term debt outstanding}}{\text{Total interest on debt}}$	Long-run
LTLiabilityperC	Total debt due within more than one year to total population	$\frac{\text{Total long-term debt outstanding}}{\text{Total population}}$	Long-run
EperC	Total expenditure to total population	$\frac{\text{Total expenditures}}{\text{Total population}}$	Service-level
TperC	Total taxes to total population	$\frac{\text{Total taxes}}{\text{Total population}}$	Service-level
RperC	Total revenue to total population	$\frac{\text{Total revenue}}{\text{Total population}}$	Service-level
Rev-to-CapOut	Total revenue to total expenditure on capital	$\frac{\text{Total revenue}}{\text{Total capital outlay}}$	Service-level

*All financial variables are for prior fiscal year.

Table 4: Selected Descriptive Statistics for Owner Sample

	— Owner Sample —				
Variable	Q1	Median	Mean	Q3	Std. Dev.
Unit & Household					
Building age	17	30	33.712	48	21.294
Number of rooms	5	6	6.576	8	1.717
Number of bathrooms	1	2	1.696	2	0.718
Trailer	0	0	0.032	0	0.175
Fireplace	0	1	0.530	1	0.499
Balcony	1	1	0.897	1	0.303
Central ac	0	1	0.556	1	0.497
Central heat	1	1	0.751	1	0.432
Detached structure	1	1	0.869	1	0.338
Large structure	0	0	0.026	0	0.158
Housing satisfaction	8	9	8.484	10	1.491
Neighborhood satisfaction	7	8	8.140	10	1.796
Missing roof	0	0	0.021	0	0.143
Visible cracks	0	0	0.041	0	0.198
Broken windows	0	0	0.018	0	0.133
Covered parking	1	1	0.840	1	0.367
Housing value ($)	98533.160	149986.400	210406.300	247569.400	215884.900
Log housing value ($)	11.498	11.918	11.917	12.419	0.926
Log square footage	0.262	0.588	0.577	0.875	0.501
Log household income ($)	10.593	11.115	11.024	11.542	0.876
Log population	13.387	13.745	13.782	14.360	0.871
Financial Ratios					
Debt-to-Cash	0.518	0.859	1.089	1.282	1.198
STDebt-to-Cash	0	0	0.051	0.011	0.185
Operating Ratio	0.982	1.031	1.032	1.078	0.106
LT Liability	12.931	15.877	18.663	20.315	24.975
LTLiabilityperC	0.396	0.722	1.275	1.531	1.778
Debt-to-Revenue	0.470	0.797	0.968	1.212	0.744
TperC	0.222	0.319	0.482	0.510	0.540
RperC	0.655	1.102	1.374	1.618	1.321
EperC	0.637	1.084	1.332	1.566	1.228
Rev-to-CapOut	706.854	1163.672	1507.223	1739.885	1458.572

*All dollar values are in 2010 U.S. dollars.

Table 5: Selected Baseline Linear Model Estimates

Dependent Variable: Log housing value	— **Owner Sample** — (1) Linear	(2) Linear
Building Age	-0.0082***	
	(0.0012)	
Building Age^2	5.32×10^{-05}***	
	(1.20×10^{-05})	
Building Age		
$\times$ $\mathbb{I}$(0 - 8 years)		-0.0131***
		(0.0028)
$\times$ $\mathbb{I}$(9 - 17 years)		-0.0073***
		(0.0013)
$\times$ $\mathbb{I}$(18 - 26 years)		-0.0061***
		(0.0009)
$\times$ $\mathbb{I}$(27 - 35 years)		-0.0047***
		(0.0007)
$\times$ $\mathbb{I}$(36 - 44 years)		-0.0036***
		(0.0006)
$\times$ $\mathbb{I}$(45 - 53 years)		-0.0029***
		(0.0005)
$\times$ $\mathbb{I}$(54 - 62 years)		-0.0023***
		(0.0005)
$\times$ $\mathbb{I}$(63 - 71 years)		-0.0024***
		(0.0005)
$\times$ $\mathbb{I}$(72 - 80 years)		-0.0015***
		(0.0005)
$\times$ $\mathbb{I}$(80 years +)		-0.0008
		(0.0006)

This table presents results from the baseline estimation of (12) without controlling for any financial measures. The sample consists of 100,577 observations from 1984 to 2011 and includes 88 counties in total. All models include the full set of controls, year and location fixed effects, and building age is interacted with an indicator if the unit is detached and the floor area of the unit (logged and demeaned). In columns 1–2, the adjusted R-squared values are 0.6021 and 0.6022, respectively. Standard errors are in parentheses and are clustered at the county-level using AHS sample weights. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: Selected Linear and Quantile Model Estimates – Debt-to-Cash (Cash Solvency)

Dependent Variable: Log housing value	— **Owner Sample** — (1) Linear	(2) 0.1 quantile	(3) 0.25 quantile	(4) 0.5 quantile	(5) 0.75 quantile	(6) 0.9 quantile
Log *Debt-to-Cash*	0.0537**	0.0650***	0.0667***	0.0676***	0.0594***	0.0565***
	(0.0206)	(0.0089)	(0.0052)	(0.0051)	(0.0063)	(0.0086)
Building Age						
× Log *Debt-to-Cash*	−0.0018***	−0.0024***	−0.0022***	−0.0020***	−0.0017***	−0.0016***
	(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Building Age						
× 𝕀(0 - 8 years)	−0.0123***	−0.0109***	−0.0099***	−0.0098***	−0.0119***	−0.0118***
	(0.0028)	(0.0023)	(0.0013)	(0.0015)	(0.0016)	(0.0025)
× 𝕀(9 - 17 years)	−0.0070***	−0.0099***	−0.0083***	−0.0075***	−0.0079***	−0.0090***
	(0.0012)	(0.0011)	(0.0006)	(0.0006)	(0.0008)	(0.0010)
× 𝕀(18 - 26 years)	−0.0059***	−0.0093***	−0.0075***	−0.0064***	−0.0061***	−0.0055***
	(0.0009)	(0.0008)	(0.0004)	(0.0004)	(0.0005)	(0.007)
× 𝕀(27 - 35 years)	−0.0046***	−0.0085***	−0.0066***	−0.0053***	−0.0046***	−0.0041***
	(0.0007)	(0.0007)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
× 𝕀(36 - 44 years)	−0.0035***	−0.0084***	−0.0062***	−0.0046***	−0.0037***	−0.0028***
	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
× 𝕀(45 - 53 years)	−0.0030***	−0.0083***	−0.0061***	−0.0042***	−0.0031***	−0.0020***
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× 𝕀(54 - 62 years)	−0.0025***	−0.0084***	−0.0058***	−0.0038***	−0.0024***	−0.0012**
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× 𝕀(63 - 71 years)	−00025***	−0.0085***	−0.0059***	−0.0036***	−0.0020***	−0.0008*
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× 𝕀(72 - 80 years)	−0.0016***	−0.0084***	−0.00054***	−0.0030***	−0.0013***	0.0001
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× 𝕀(80 years +)	−0.0010	−0.0082***	−0.0052***	−0.0025***	−0.0004	0.0008
	(0.0007)	(0.0006)	(0.0004)	(0.0003)	(0.0001)	(0.0002)
Marginal Effect: Log *Debt-to-Cash*						
At Mean(Building Age):	−0.0069	−0.0176	−0.0078	−0.0004	0.0008	0.0017
	(0.0115)	(0.0078)	(0.0042)	(0.0040)	(0.0046)	(0.0066)

This table presents results from the estimation of (12) controlling for cash solvency. The cash solvency measure is Debt-to-Cash (total debt outstanding to total cash and securities). The sample consists of 100,557 observations from 1984 to 2011 and includes 88 counties in total. All models include the full set of controls, year and location fixed effects, and building age is interacted with an indicator if the unit is detached, the floor area of the unit (logged and demeaned), and Debt-to-Cash (logged and demeaned). The marginal effect of log Debt-to-Cash on log property value is estimated at the mean building age. In column 1, the adjusted R-squared value is 0.6033. For the linear specification, standard errors are in parentheses and are clustered at the county-level using AHS sample weights. For the quantile regression estimates, bootstrapped standard errors are in parentheses and are clustered at the county-level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Selected Linear and Quantile Model Estimates – Operating Ratio (Budgetary Solvency)

Dependent Variable:	— **Owner Sample** —					
Log housing value	(1) Linear	(2) 0.1 quantile	(3) 0.25 quantile	(4) 0.5 quantile	(5) 0.75 quantile	(6) 0.9 quantile
Log *Operating Ratio*	0.0245	−0.2204***	−0.1454***	−0.0875***	0.0230	−0.0505
	(0.1359)	(0.0553)	(0.0320)	(0.0285)	(0.0341)	(0.0549)
Building Age						
× Log *Operating Ratio*	0.0040	0.0092***	0.0076***	0.0053***	0.0025***	0.0033**
	(0.0040)	(0.0015)	(0.0008)	(0.0008)	(0.0009)	(0.0014)
Building Age						
× $\mathbb{I}$(0 - 8 years)	−0.0130***	−0.0114***	−0.0111***	−0.0107***	−0.0125***	−0.0123***
	(0.0029)	(0.0023)	(0.0015)	(0.0015)	(0.0016)	(0.0023)
× $\mathbb{I}$(9 - 17 years)	−0.0072***	−0.0100***	−0.0089***	−0.0081***	−0.0085***	−0.0090***
	(0.0013)	(0.0010)	(0.0007)	(0.0007)	(0.0007)	(0.0010)
× $\mathbb{I}$(18 - 26 years)	−0.0060***	−0.0093***	−0.0078***	−0.0069***	−0.0064***	−0.0057***
	(0.0090)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0007)
× $\mathbb{I}$(27 - 35 years)	−0.0046***	−0.0085***	−0.0069***	−0.0058***	−0.0049***	−0.0043***
	(0.0072)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
× $\mathbb{I}$(36 - 44 years)	−0.0035***	−0.0083***	−0.0064***	−0.0049***	−0.0038***	−0.0029***
	(0.0006)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
× $\mathbb{I}$(45 - 53 years)	−0.0028***	−0.0082***	−0.0062***	−0.0045***	−0.0032***	−0.0020***
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
× $\mathbb{I}$(54 - 62 years)	−0.0023***	−0.0083***	−0.0059***	−0.0040***	−0.0024***	−0.0013**
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× $\mathbb{I}$(63 - 71 years)	−0.0024***	−0.0084***	−0.0061***	−0.0040***	−0.0021***	−0.0010*
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× $\mathbb{I}$(72 - 80 years)	−0.0015***	−0.0086***	−0.0055***	−0.0032***	−0.0013***	0.0001
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× $\mathbb{I}$(80 years +)	−0.0007	−0.0078***	−0.0050***	−0.0026***	−0.0004	0.0008
	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
Marginal Effect: Log *Operating Ratio*						
At Mean(Building Age):	0.1595	0.0929	0.1144	0.0933	0.1070	0.0632
	(0.0929)	(0.0437)	(0.0227)	(0.0176)	(0.0216)	(0.0418)

This table presents results from the estimation of (12) controlling for budgetary solvency. The budgetary solvency measure is the Operating Ratio (total revenue to total expenditure). The sample consists of 100,557 observations from 1984 to 2011 and includes 88 counties in total. All models include the full set of controls, year and location fixed effects, and building age is interacted with an indicator if the unit is detached, the floor area of the unit (logged and demeaned), and the Operating Ratio (logged and demeaned). The marginal effect of log Operating Ratio on log property value is estimated at the mean building age. In column 1, the adjusted R-squared value is 0.6024. For the linear specification, standard errors are in parentheses and are clustered at the county-level using AHS sample weights. For the quantile regression estimates, bootstrapped standard errors are in parentheses and are clustered at the county-level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Selected Linear and Quantile Model Estimates – EperC (Service-level Solvency)

Dependent Variable:	— **Owner Sample** —					
Log housing value	(1) Linear	(2) 0.1 quantile	(3) 0.25 quantile	(4) 0.5 quantile	(5) 0.75 quantile	(6) 0.9 quantile
Log *EperC*	−0.0126***	−0.0258	−0.0453**	−0.0827***	−0.1171***	−0.1109***
	(0.0029)	(0.0296)	(0.0186)	(0.0151)	(0.0180)	(0.0259)
Building Age						
× Log *EperC*	−0.0070***	0.0025***	0.0022***	0.0019***	0.0013***	0.0007***
	(0.0012)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Building Age						
× $\mathbb{I}$(0 - 8 years)	−0.0126***	−0.0123***	−0.0113***	−0.0111***	−0.0126***	−0.0144***
	(0.0029)	(0.0021)	(0.0014)	(0.0015)	(0.0018)	(0.0024)
× $\mathbb{I}$(9 - 17 years)	−0.0070***	−0.0104***	−0.0092***	−0.0084***	−0.0085***	−0.0097***
	(0.0012)	(0.0010)	(0.0007)	(0.0007)	(0.0007)	(0.0010)
× $\mathbb{I}$(18 - 26 years)	−0.0058***	−0.0095***	−0.0082***	−0.0072***	−0.0065***	−0.0063***
	(0.0008)	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)
× $\mathbb{I}$(27 - 35 years)	−0.0043***	−0.0085***	−0.0072***	−0.0059***	−0.0050***	−0.0047***
	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
× $\mathbb{I}$(36 - 44 years)	−0.0032***	−0.0083***	−0.0066***	−0.0050***	−0.0040***	−0.0034***
	(0.0006)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
× $\mathbb{I}$(45 - 53 years)	−0.0025***	−0.0083***	−0.0065***	−0.0046***	−0.0033***	−0.0025***
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
× $\mathbb{I}$(54 - 62 years)	−0.0021***	−0.0083***	−0.0063***	−0.0042***	−0.0026***	−0.0017***
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
× $\mathbb{I}$(63 - 71 years)	−0.0021***	−0.0086***	−0.0065***	−0.0042***	−0.0023***	−0.0013**
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× $\mathbb{I}$(72 - 80 years)	−0.0015***	−0.0089***	−0.0063***	−0.0038***	−0.0017***	−0.0004
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
× $\mathbb{I}$(80 years +)	−0.0009	−0.0086***	−0.0060***	−0.0032***	−0.0010***	0.0002***
	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
Marginal Effect:						
Log *EperC*						
At Mean(Building Age):	−0.0592	0.0609	0.0313	0.0196	−0.0714	−0.0859
	(0.0665)	(0.0288)	(0.0179)	(0.0149)	(0.0174)	(0.0242)

This table presents results from the estimation of (12) controlling for service-level solvency. The service-level solvency measure is EperC (total expenditure to population). The sample consists of 100,577 observations from 1984 to 2011 and includes 88 counties in total. All models include the full set of controls, year and location fixed effects, and building age is interacted with an indicator if the unit is detached, the floor area of the unit (logged and demeaned), and the EperC (logged and demeaned). The marginal effect of log EperC on log property value is estimated at the mean building age. In column 1, the adjusted R-squared value is 0.6028. For the linear specification, standard errors are in parentheses and are clustered at the county-level using AHS sample weights. For the quantile regression estimates, bootstrapped standard errors are in parentheses and are clustered at the county-level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9: Selected Linear and Quantile Model Estimates – TperC (Service-level Solvency)

Dependent Variable:	— **Owner Sample** —					
Log housing value	(1) Linear	(2) 0.1 quantile	(3) 0.25 quantile	(4) 0.5 quantile	(5) 0.75 quantile	(6) 0.9 quantile
Log *TperC*	−0.0790	−0.0739***	−0.0923***	−0.0904***	−0.0969***	−0.1046***
	(0.0520)	(0.0215)	(0.0125)	(0.0098)	(0.0144)	(0.0231)
Building Age						
× Log *TperC*	0.0012**	0.0019***	0.0016***	0.0014***	0.0010***	0.0004*
	(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Building Age						
× $\mathbb{I}$(0 - 8 years)	−0.0127***	−0.0112***	−0.0111***	−0.0110***	−0.0122***	−0.0137***
	(0.0029)	(0.0022)	(0.0014)	(0.0015)	(0.0016)	(0.0023)
× $\mathbb{I}$(9 - 17 years)	−0.0072***	−0.0099***	−0.0093***	−0.0086***	−0.0087***	−0.0096***
	(0.0012)	(0.0010)	(0.0007)	(0.0006)	(0.0007)	(0.0010)
× $\mathbb{I}$(18 - 26 years)	−0.0059***	−0.0092***	−0.0083***	−0.0074***	−0.0066***	−0.0062***
	(0.0008)	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)
× $\mathbb{I}$(27 - 35 years)	−0.0045***	−0.0083***	−0.0073***	−0.0060***	−0.0051***	−0.0046***
	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
× $\mathbb{I}$(36 - 44 years)	−0.0033***	−0.0082***	−0.0068***	−0.0052***	−0.0040***	−0.0032***
	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
× $\mathbb{I}$(45 - 53 years)	−0.0026***	−0.0081***	−0.0066***	−0.0047***	−0.0034***	−0.0023***
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
× $\mathbb{I}$(54 - 62 years)	−0.0022***	−0.0082***	−0.0063***	−0.0043***	−0.0027***	−0.0015***
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× $\mathbb{I}$(63 - 71 years)	−0.0022***	−0.0085***	−0.0065***	−0.0043***	−0.0024***	−0.0011**
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× $\mathbb{I}$(72 - 80 years)	−0.0016***	−0.0088***	−0.0063***	−0.0039***	−0.0018***	−0.0003
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× $\mathbb{I}$(80 years +)	−0.0008	−0.0082***	−0.0058***	−0.0032***	−0.0009**	0.0005
	(0.0006)	(0.0007)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Marginal Effect:						
Log *TperC*						
At Mean(Building Age):	−0.0377	−0.0102	−0.0373	−0.0440	−0.0642	−0.0920
	(0.0478)	(0.0201)	(0.0115)	(0.0093)	(0.0143)	(0.0233)

This table presents results from the estimation of (12) controlling for service-level solvency. The service-level solvency measure is TperC (total taxes to population). The sample consists of 100,557 observations from 1984 to 2011 and includes 88 counties in total. All models include the full set of controls, year and location fixed effects, and building age is interacted with an indicator if the unit is detached, the floor area of the unit (logged and demeaned), and TperC (logged and demeaned). The marginal effect of log TperC on log property value is estimated at the mean building age. In column 1, the adjusted R-squared value is 0.6026. For the linear specification, standard errors are in parentheses and are clustered at the county-level using AHS sample weights. For the quantile regression estimates, bootstrapped standard errors are in parentheses and are clustered at the county-level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 10: Selected Linear and Quantile Model Estimates – LTLiability (Long-run Solvency)

Dependent Variable:			— **Owner Sample** —			
Log housing value	(1) Linear	(2) 0.1 quantile	(3) 0.25 quantile	(4) 0.5 quantile	(5) 0.75 quantile	(6) 0.9 quantile
Log *LTLiability*	0.0847**	0.0886***	0.0876***	0.1063***	0.1079***	0.1036***
	(0.0009)	(0.0151)	(0.0102)	(0.0089)	(0.0106)	(0.0158)
Building Age						
× Log *LTLiability*	−0.0029***	−0.0031***	−0.0032***	−0.0034***	−0.0032***	−0.0029***
	(0.0009)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Building Age						
× 𝕀(0 - 8 years)	−0.0132***	−0.0115***	−0.0126***	−0.0110***	−0.0129***	−0.0132***
	(0.0028)	(0.0024)	(0.0015)	(0.0014)	(0.0015)	(0.0022)
× 𝕀(9 - 17 years)	−0.0074***	−0.0102***	−0.0095***	−0.0081***	−0.0086***	−0.0096***
	(0.0012)	(0.0011)	(0.0007)	(0.0006)	(0.0007)	(0.0010)
× 𝕀(18 - 26 years)	−0.0061***	−0.0093***	−0.0083***	−0.0069***	−0.0065***	−0.0060***
	(0.0009)	(0.0008)	(0.0005)	(0.0004)	(0.0005)	(0.0007)
× 𝕀(27 - 35 years)	−0.0047***	−0.0085***	−0.0072***	−0.0056***	−0.0050***	−0.0044***
	(0.0007)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
× 𝕀(36 - 44 years)	−0.0036***	−0.0083***	−0.0066***	−0.0048***	−0.0039***	−0.0031***
	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0006)
× 𝕀(45 - 53 years)	−0.0028***	−0.0081***	−0.0063***	−0.0041***	−0.0032***	−0.0021***
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
× 𝕀(54 - 62 years)	−0.0023***	−0.0081***	−0.0059***	−0.0036***	−0.0025***	−0.0012**
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
× 𝕀(63 - 71 years)	−0.0024***	−0.0083***	−0.0061***	−0.0037***	−0.0023***	−0.0009*
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× 𝕀(72 - 80 years)	−0.0015***	−0.0085***	−0.0055***	−0.0030***	−0.0013***	0.0002
	(0.0005)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0005)
× 𝕀(80 years +)	−0.0004	−0.0074***	−0.0047***	−0.0018***	0.0000	0.0011**
	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0004)	(0.0005)
Marginal Effect:						
Log *LTLiability*						
At Mean(Building Age):	−0.0146	−0.0177	−0.0222	−0.0102	−0.0022	0.0033
	(0.0261)	(0.0103)	(0.0033)	(0.0056)	(0.0067)	(0.0193)

This table presents results from the estimation of (12) controlling for long-run solvency. The long-run solvency measure is LTLiability (total long-term debt outstanding to total interest on debt). The sample consists of 100,557 observations from 1984 to 2011 and includes 88 counties in total. All models include the full set of controls, year and location fixed effects, and building age is interacted with an indicator if the unit is detached, the floor area of the unit (logged and demeaned), and the LTLiability (logged and demeaned). The marginal effect of log LTLiability on log property value is estimated at the mean building age. In column 1, the adjusted R-squared value is 0.6029. For the linear specification, standard errors are in parentheses and are clustered at the county-level using AHS sample weights. For the quantile regression estimates, bootstrapped standard errors are in parentheses and are clustered at the county-level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

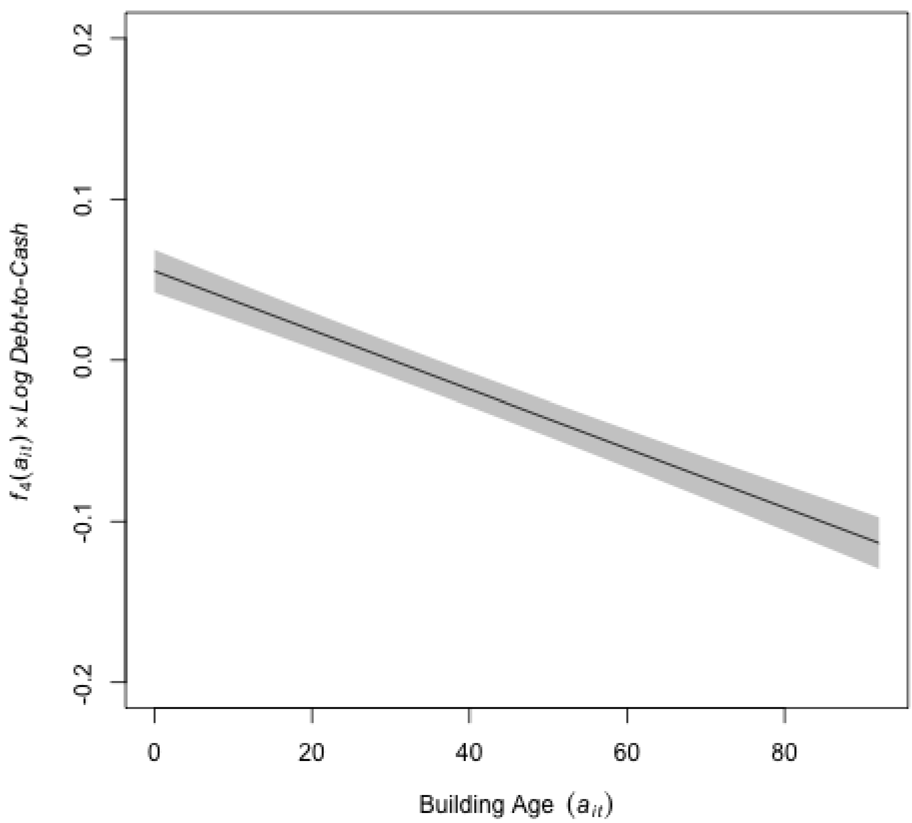
Table 11: Variation in Implied Annual Depreciation – Linear Model

	— **Owner Sample** —					
	(1) 10 percentile	(2) 25 percentile	(3) 50 percentile	(4) 75 percentile	(5) 90 percentile	(6) 90 − 10 percentile
Log *Debt-to-Cash*	0.3332	0.4974	0.5865	0.6557	0.7291	0.3959
	(0.0011)	(0.0009)	(0.0008)	(0.0008)	(0.0009)	
Log *Operating Ratio*	0.6497	0.6162	0.5939	0.5738	0.5413	−0.1084
	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0011)	
Log *EperC*	0.7410	0.6851	0.5826	0.5235	0.4635	−0.2775
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	
Log *TperC*	0.6734	0.6577	0.6099	0.5579	0.4713	−0.2021
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	
Log *LTLiability*	0.4634	0.5262	0.5992	0.6724	0.7355	0.2721
	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0009)	

This table presents results from the estimation of (13) for each linear model in Tables 6–10, respectively, examining the marginal effect of building age at different percentiles of the solvency variable of interest. The presented values are annual depreciation rates in percentages (with negative values being appreciation). The difference in implied annual depreciation between the 90 and 10 percentile of each solvency variable is presented in column 6. Robust standard errors in parentheses.

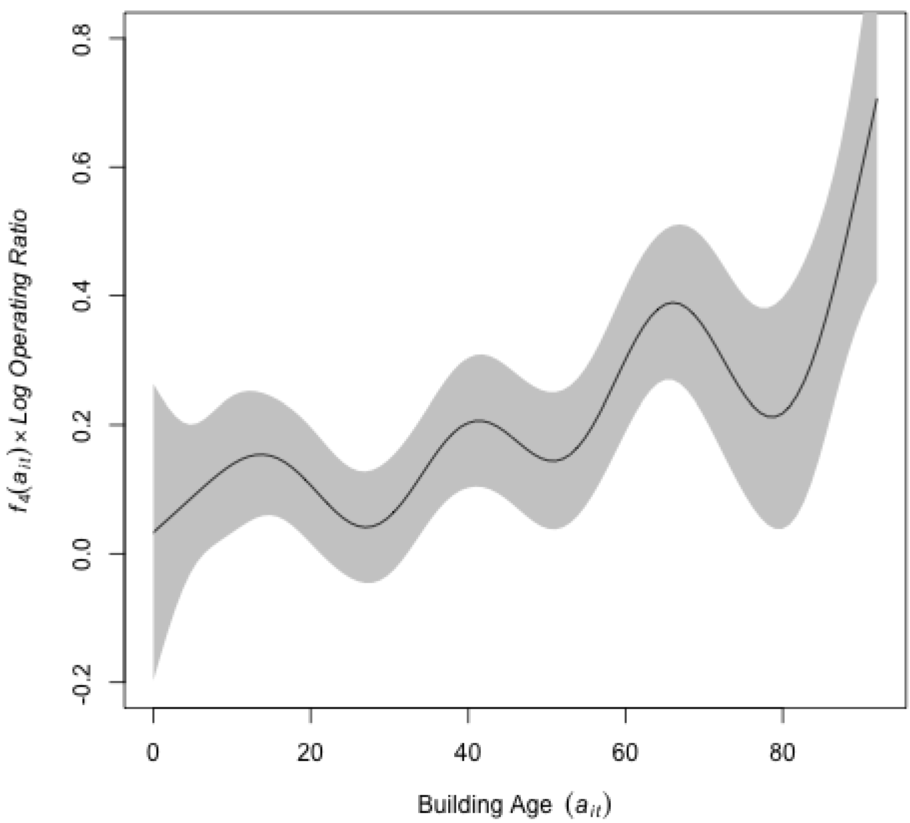
A Nonparametric Estimation

Figure 1: Nonparametric Building Age Interaction with Debt-to-Cash



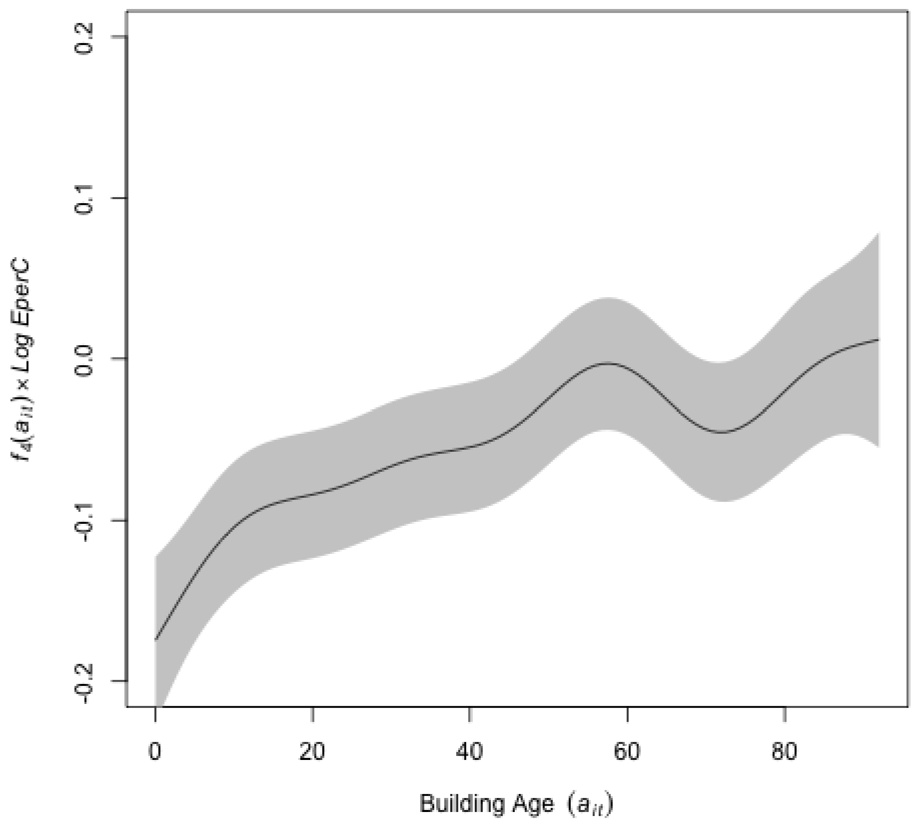
This figure presents results from the estimation of (18) controlling for Debt-to-Cash (total debt outstanding to total cash and securities) with 95% point-wise confidence interval. Building age is estimated nonparametrically using a thin plate spline and interacted with Debt-to-Cash (logged and demeaned), an indicator if the unit is detached, and the floor area (logged and demeaned). All smooth terms are significant at 1% with p-values approximately less than 0.001.

Figure 2: Nonparametric Building Age Interaction with the Operating Ratio



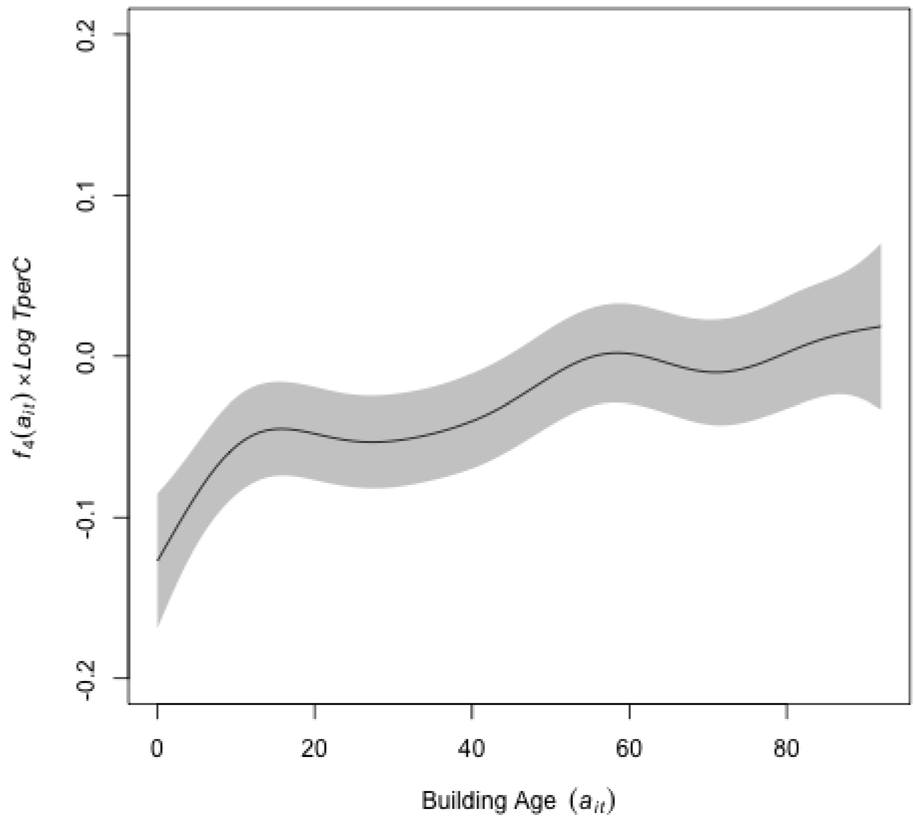
This figure presents results from the estimation of (18) controlling for Operating Ratio (total revenue to total expenditure) with 95% point-wise confidence interval. Building age is estimated nonparametrically using a thin plate spline and interacted with the Operating Ratio (logged and demeaned), an indicator if the unit is detached, and the floor area (logged and demeaned). All smooth terms are significant at 1% with p-values approximately less than 0.001. Note the scale change from other figures.

Figure 3: Nonparametric Building Age Interaction with EperC



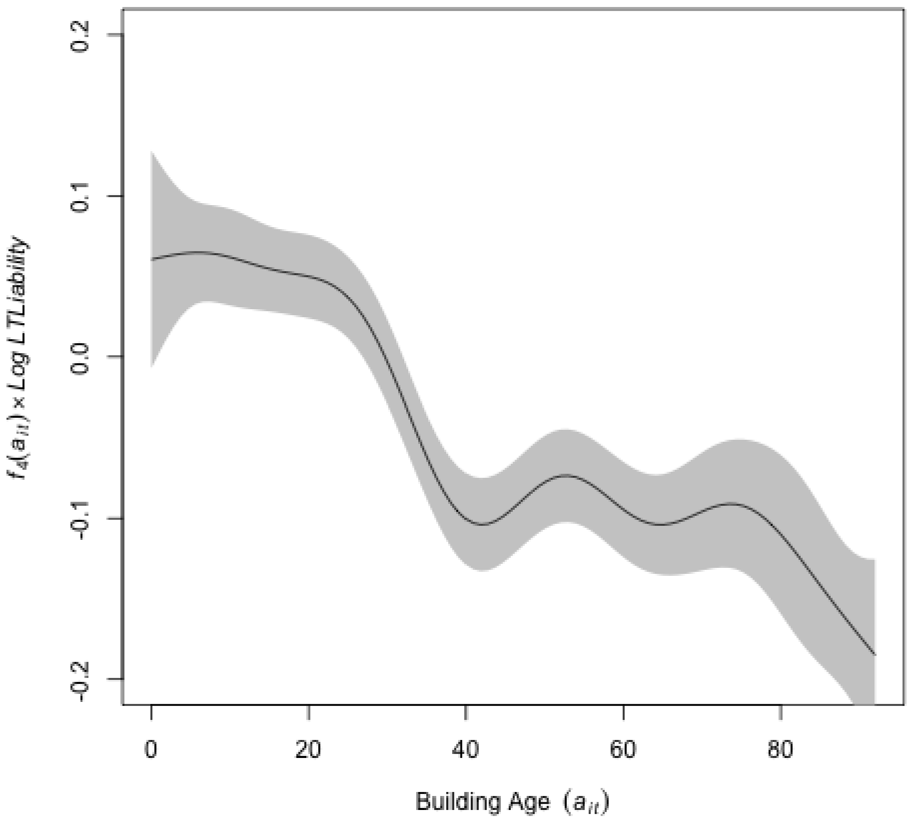
This figure presents results from the estimation of (18) controlling for EperC (total expenditure to total population) with 95% point-wise confidence interval. Building age is estimated nonparametrically using a thin plate spline and interacted with the EperC (logged and demeaned), an indicator if the unit is detached, and the floor area (logged and demeaned). All smooth terms are significant at 1% with p-values approximately less than 0.001.

Figure 4: Nonparametric Building Age Interaction with TperC



This figure presents results from the estimation of (18) controlling for TperC (total revenue to total population) with 95% point-wise confidence interval. Building age is estimated nonparametrically using a thin plate spline and interacted with the TperC (logged and demeaned), an indicator if the unit is detached, and the floor area (logged and demeaned). All smooth terms are significant at 1% with p-values approximately less than 0.001.

Figure 5: Nonparametric Building Age Interaction with LTLiability



This figure presents results from the estimation of (18) controlling for LTLiability (total long-term debt outstanding to total interest on debt) with 95% point-wise confidence interval. Building age is estimated nonparametrically using a thin plate spline and interacted with the LTLIability (logged and demeaned), an indicator if the unit is detached, and the floor area (logged and demeaned). All smooth terms are significant at 1% with p-values approximately less than 0.001.