

No-Arbitrage Valuation of Residential Real Estate: *Evidence from Rent-to-Own Contracts* *

Robert A. Jarrow[†] Yildiray Yildirim[‡]

December 25, 2025

Abstract

We propose a no arbitrage valuation framework for illiquid residential real estate that complements hedonic and machine learning automated valuation models by providing a consistent pricing kernel for claims written on housing. Building on the theory of nontraded assets, we decompose each property's value into a component spanned by a traded residential REIT index and the default free term structure, priced under a risk neutral measure, and a residual idiosyncratic component valued under the physical measure. Mortgage default enters as a reduced form adjustment reflecting market wide expectations of distressed resale, yielding a closed form default adjusted house value. We calibrate the model using 674,629 Georgia MLS transactions from 2007 to 2019 and validate it on 926 homes acquired by Home Partners of America. Applied to rent to own contracts, the embedded purchase option averages about 13 percent of property value. A 5 percent annual eviction hazard reduces option values by about one tenth and raises the share of never exercised contracts from 69 percent to 82 percent, illustrating how termination risk limits conversion.

JEL Classification: G12, G21, R31

Keywords: Residential real estate; Non-traded assets; No-arbitrage valuation; Rent-to-own contracts; Option pricing; Default risk; Eviction risk

*We thank Sheridan Titman, Brent Ambrose, Chester Spatt, Fabrice Tourre, and Joshua Coven for helpful comments. We also thank seminar participants at Baruch College, the National University of Singapore, and conference participants at the 2025 International Risk Management Conference and the 2025 Risk Sciences Annual Conference (Nanyang Technological University) for valuable feedback. Preston Wong and Eun Kyu Lee provided excellent research assistance with data collection and preparation. We gratefully acknowledge the Steven L. Newman Real Estate Institute for generously providing access to the property transaction data.

[†]Samuel Curtis Johnson Graduate School of Management, Cornell University, Ithaca, New York, USA; email: robertjarrow@cornell.edu

[‡]Zicklin School of Business, Baruch College, The City University of New York, New York, NY, USA; email: yildiray.yildirim@baruch.cuny.edu

1 Introduction

Rent-to-own contracts embed purchase options worth roughly 13 percent of property value, about 38,000 dollars for the average home, yet fewer than 20 percent of tenants ultimately convert to ownership. This large wedge between theoretical option value and realized outcomes is consistent with Blackstone’s 2025 decision to wind down its 2 billion dollar Home Partners of America program and highlights a broader challenge in housing markets: valuing illiquid residential real estate with embedded options and distressed resale risk. This paper develops a no-arbitrage valuation framework that directly addresses this challenge.

Residential real estate accounts for a large share of household wealth and plays a central role in both the macroeconomy and the financial system. Yet individual houses trade infrequently, are highly heterogeneous, and are commonly exposed to distressed resale through mortgage-related liquidation risk. These features make it difficult to apply standard arbitrage pricing tools, which presume liquid underlyings and continuous trading. At the same time, institutional investors increasingly hold single family rentals (e.g., [Coven, 2025](#)) and structured housing contracts, such as rent-to-own programs, that embed nontrivial option value and termination risk. A valuation framework that can handle both illiquidity and embedded options in housing is therefore important for asset managers, lenders, and policymakers.

The workhorse approach for valuing houses is the hedonic regression, often operationalized as an automated valuation model (AVM) that regresses sale prices on property characteristics, neighborhood fixed effects, and sometimes macro controls ([Rosen, 1974](#); [Malpezzi, 1999](#)). These models are highly useful for mass appraisal but are inherently reduced form. In practice, distressed resale risk typically enters only through foreclosure indicators or delinquency proxies (e.g., [Campbell, Giglio and Pathak, 2011](#); [Clauret and Daneshvary, 2009](#); [Pennington-Cross, 2006](#)). Hedonic AVMs also rely on observed transactions in relatively liquid submarkets and are not designed to price option-based claims written on housing. In thin markets, where comparable sales are limited, distressed, or

outdated, hedonic AVMs can produce large and systematic errors (Malpezzi, 1999; Clapp and Wang, 2006). These models are also sensitive to outliers and segmentation across neighborhoods and property types (Rousseeuw and Leroy, 1987; Knight, Dombrow and Sirmans, 1995; Bourassa, Hoesli and Sun, 2006). Because hedonic AVMs do not deliver a traded pricing kernel, they cannot be used directly to value embedded options in contracts such as lease options, shared equity agreements, or rent-to-own programs.

A natural question is what our framework provides that a flexible hedonic regression augmented with a REIT factor cannot. The answer lies not in the house-value equation itself, but in the existence of a pricing measure that can be applied consistently to contingent claims. Hedonic AVMs, however sophisticated, explain transaction prices conditional on observables. They do not specify how the stochastic discount factor evolves, nor how unspanned idiosyncratic risk should be treated in derivative pricing. In this sense, hedonic models explain prices, while our framework delivers valuation.

Related work in financial economics uses option pricing tools to value development, abandonment, or prepayment decisions (e.g., Black and Scholes, 1973; Titman, 1985; Grenadier, 1996; Cunningham, 2006). This literature emphasizes the real options dimension of real estate investment and mortgage contracts (e.g., Plaut, 1991; Campbell and Cocco, 2015), but typically assumes a traded underlying, frictionless markets, or abstracts from incomplete markets and the sporadic trading of residential properties. More broadly, evidence shows that property returns load on both market-level and idiosyncratic factors and are only partially integrated with standard risk factors (Geltner, 1989; Ling and Naranjo, 1997; Favilukis, Ludvigson and Van Nieuwerburgh, 2017). Despite these advances, the literature lacks a tractable no-arbitrage framework that treats residential properties as illiquid and nontraded assets, explicitly incorporates distressed resale risk, and delivers a pricing kernel that can be used for contracts written on houses.

This paper develops and implements such a no-arbitrage valuation framework for illiquid residential real estate with distressed resale risk associated with mortgage default. Build-

ing on [Jarrow \(2023\)](#)'s theory of nontraded assets, we treat houses as illiquid claims whose values are anchored to a traded residential REIT market while allowing for property-specific heterogeneity and market-wide exposure to liquidation risk. Under mild assumptions, this structure yields a closed-form expression for a default-adjusted market value that reflects equilibrium expectations of distressed resale at the market level, rather than the financing choice of a particular owner. The resulting value both organizes MLS transaction prices and serves as the underlying state variable for pricing structured housing contracts such as rent-to-own programs. While our empirical application focuses on residential housing, the framework applies more broadly to the valuation of illiquid real assets with embedded options and default risk.

Intuitively, the framework is a disciplined extension of comparable sales valuation. Practitioners start with comps and adjust for observable differences in characteristics and location. We retain that logic through a comparables-based normalization that anchors each property to the relevant local price level, but we additionally anchor the systematic component of housing risk to a traded residential REIT index. Because the REIT index is traded, its systematic component is priced under a risk-neutral measure associated with the traded submarket, while residual local variation is treated under the physical measure as unspanned risk. This distinction is immaterial for point valuation, but essential for pricing contracts whose payoffs depend on the timing and risk exposure of future house values.

We proxy the systematic component of housing returns using the FTSE Nareit US Residential REIT Index, a liquid residential rental benchmark. This approach parallels valuation practice in private equity and corporate finance, where public comparables are used to infer the systematic risk exposure of illiquid or nontraded firms ([Damodaran, 2012](#)). The market component is priced under the risk-neutral measure, while the idiosyncratic component is treated under the statistical measure and does not earn a systematic risk premium.

Our contribution is primarily methodological and lies in asset pricing with an appli-

cation to residential real estate. We make three main contributions. First, on the theory side, we adapt the no-arbitrage framework for nontraded assets to residential housing and derive a closed form default-adjusted market value. The framework treats a liquid residential REIT index and the term structure of bonds as the traded part of the market, prices the residual house component under the physical measure, and incorporates distressed resale risk through a Cox process with a recovery parameter. The resulting valuation formula separates the systematic component of a property's value from its idiosyncratic and default components and can be used to price both the house itself and contingent claims written on it.

Second, we calibrate the model using 674,629 Georgia MLS transactions between 2007 and 2019. For each sale, we construct a comparables-based normalization factor that maps the REIT index to the relevant local price level, and then estimate the model parameters by nonlinear least squares with an unbiasedness constraint. The calibrated model explains about two thirds of the variance in prices in sample, retains meaningful explanatory power out of sample, and produces economically sensible loadings on property characteristics and macro variables. The estimated recovery rate is around 60 percent, implying distressed sale discounts of roughly 40 percent, and the default intensity parameters tie liquidation risk to the level of forward rates. Comparisons with a standard hedonic regression and the Zillow Home Value Index show that a parsimonious no-arbitrage structure can match much of the predictive performance of reduced form AVMs while remaining suitable for derivative pricing.

Third, we apply the calibrated valuation function as a pricing engine for rent-to-own contracts. In our setup, the tenant's purchase right is an American style call option on the default-adjusted market value, and eviction acts as a termination event that eliminates the option. Applying the model to a large set of Georgia properties, we find that the embedded purchase option is worth roughly 13 percent of property value on average, even when tenants pay no explicit option premium. Introducing a baseline annual eviction hazard rate

of 5 percent reduces option values by about one tenth and raises the share of contracts that are never exercised from 69 percent to 82 percent. We validate the framework on a subsample of approximately 900 Georgia properties acquired by Home Partners of America and find similar option values and eviction sensitivities, suggesting that the model generalizes well from the full MLS universe to an institutional rent-to-own portfolio. These results are model based counterfactuals rather than an evaluation of any specific program, but they illustrate how strike schedules and eviction policies shape the value and exercise of purchase options in structured housing contracts.

Related work falls into three strands. Hedonic pricing models and their machine learning extensions regress house prices on property characteristics and neighborhood indicators, but typically treat default and illiquidity only implicitly ([Rosen, 1974](#); [Malpezzi, 1999](#); [Case and Shiller, 1989](#); [Bekkerman, McMillen and Oleson, 2019](#)). Option-based real estate models use continuous time methods to value development, demolition, and mortgage-related options, but generally assume a traded underlying or abstract from incomplete markets and sporadic trading ([Titman, 1985](#); [Grenadier, 1996](#); [Plaut, 1991](#); [Campbell and Cocco, 2015](#)). A separate literature on credit risk and nontraded assets studies defaultable claims and incomplete markets in other settings (e.g., [Jarrow, 2023](#)). Our contribution is to integrate insights from these strands into a tractable valuation framework for illiquid housing assets that anchors prices to a traded residential REIT index, incorporates distressed resale risk, and delivers a pricing kernel for contracts written on nontraded residential real estate.

The remainder of the paper is organized as follows. Section [2](#) reviews the related literature on housing valuation and rent-to-own contracts. Section [3](#) lays out the theoretical framework and derives the default-adjusted market value. Section [4](#) describes the data, estimation strategy, and main empirical results, including robustness checks and comparisons to hedonic benchmarks. Section [5](#) applies the model to institutional rent-to-own contracts and examines how eviction risk affects embedded option values, fair lease payments, and conversion incentives. Section [6](#) concludes with implications for investors and housing

policy.

2 Literature Review

A large literature studies residential real estate valuation using both hedonic methods and tools from financial economics. Early hedonic models trace back to [Rosen \(1974\)](#), who formalizes house prices as the sum of implicit prices for observable characteristics under competitive market assumptions. This framework underlies most automated valuation models used in practice. Subsequent work extends hedonic regressions to incorporate spatial structure, neighborhood effects, and broader market indicators ([Malpezzi, 1999](#); [Case and Shiller, 1989](#)). These approaches deliver strong predictive performance for transaction prices and are well suited to mass appraisal in liquid markets.

Despite their success, hedonic valuation methods remain fundamentally reduced form. Empirical refinements emphasize spatial autocorrelation and boundary definitions ([Dubin, 1998](#); [Clapp and Wang, 2006](#)), durable housing stocks and local decline ([Glaeser and Gyourko, 2005](#)), and robustness to outliers and segmentation across submarkets ([Knight, Dombrow and Sirmans, 1995](#); [Bourassa, Hoesli and Sun, 2006](#)). More recent machine learning extensions further improve predictive accuracy by capturing nonlinear interactions among characteristics ([Antipov and Pokryshevskaya, 2012](#); [Glaeser et al., 2020](#); [Bekkerman, McMillen and Oleson, 2019](#)). However, these models continue to rely on observed transactions and do not deliver a pricing kernel. As a result, they are not designed to value default exposed claims or contracts written on housing, particularly in illiquid or thinly traded markets.

A separate strand of the literature applies option pricing techniques to real estate valuation. Building on [Black and Scholes \(1973\)](#), [Titman \(1985\)](#) shows that land prices embed real options related to development timing, while [Grenadier \(1996\)](#) and [Cunningham \(2006\)](#) analyze investment and redevelopment decisions under uncertainty. These models highlight the importance of option like features in real estate assets and mortgage contracts

([Plaut, 1991](#); [Campbell and Cocco, 2015](#)), but typically assume a traded underlying asset or abstract from incomplete markets and infrequent trading. Consequently, they do not provide a direct valuation framework for owner occupied or institutionally held residential properties that trade sporadically and are subject to default and distressed resale.

Complementary evidence from asset pricing shows that real estate returns load on both market level and idiosyncratic factors. [Geltner \(1989\)](#) demonstrates that appraisal based indices understate volatility, while [Ling and Naranjo \(1997\)](#) document partial integration of property returns with aggregate risk factors. [Favilukis, Ludvigson and Van Nieuwerburgh \(2017\)](#) further show that credit constraints and limited risk sharing amplify local price dispersion. These findings motivate valuation frameworks that distinguish systematic risk from property specific variation, but existing approaches do not integrate this decomposition into a no-arbitrage pricing kernel for residential housing.

Our paper also relates to the literature on credit risk and nontraded assets. [Jarrow \(2023\)](#) develops a general no-arbitrage framework for valuing nontraded assets by decomposing payoffs into a component spanned by traded securities and a residual idiosyncratic component priced under the physical measure. While this framework is general, it has not been implemented for residential real estate or calibrated to large scale transaction data in a way that incorporates mortgage default and distressed resale.

This paper brings these strands together in a unified valuation framework for residential housing. We anchor property values to a traded residential REIT index and the term structure of interest rates, explicitly incorporate mortgage default through a Cox process with recovery, and treat the residual house level component under the physical measure. The resulting pricing kernel accommodates illiquidity, default risk, and infrequent trading and can be applied directly to the valuation of rent-to-own and related housing contracts.

3 The Model Structure

Intuitively, our approach decomposes each property’s value into a market-traded component, spanned by a residential REIT index and default-free bonds, and a residual idiosyncratic component that is not traded and therefore does not carry a systematic risk premium. The traded component is valued under a risk-neutral measure $\mathbb{Q}^s$, while the idiosyncratic component is evaluated under the physical measure $\mathbb{P}$. This section formalizes that decomposition at a high level, shows how mortgage default is incorporated via a Cox process, and states the closed-form expression for the model-implied value $V_{t,i}$ used in estimation. Technical details and proofs are collected in the Online Appendix.

We build on the no-arbitrage pricing framework for non-traded assets presented in [Jarrow \(2023\)](#). In that setting, the key insight is to decompose any illiquid asset’s terminal payoff into (i) a portion that can be replicated using traded securities (such as a suitable real estate index), and (ii) a residual hedging error that is purely idiosyncratic. Provided this hedging error is purely idiosyncratic, hence carrying no systematic risk premium, its arbitrage-free value is zero under all equivalent martingale measures. Consequently, the unique no-arbitrage price is obtained by taking the appropriate risk-neutral expectation of the first, replicable term alone.

This two-part decomposition is conceptually similar to how corporate finance practitioners value illiquid private firms by referencing publicly traded comparables. In those settings, the value of a private firm is typically estimated by decomposing its risk into systematic (market-correlated) and idiosyncratic (firm-specific) components, with the former inferred from a comparable public firm’s beta (see [Damodaran, 2012](#)). In our framework, the REIT index plays the role of this public benchmark, enabling tractable valuation of real estate assets that do not trade continuously. Specifically, this role of the REIT index is analogous to that of the S&P 500 or sector-specific indices in private firm valuation, where market returns are used to identify replicable risk components and estimate exposure (beta) for non-traded firms.

Comps-Based Intuition and a Simple Example It is useful to clarify how our approach relates to standard comparable-sales valuation. In practice, residential valuation almost always begins with comps: recent sales of similar properties are adjusted for observable differences in size, age, location, and amenities. Hedonic regressions formalize this logic by estimating average adjustment factors across many transactions.

Our framework retains this comps-based foundation, but extends it along two dimensions that hedonic methods do not address. First, it separates the portion of house value that comoves with aggregate housing markets from the portion that is purely local and idiosyncratic. Second, it provides a pricing kernel that can be applied consistently to contingent claims written on housing.

To see the connection, consider a simple example. Suppose a property in a given ZIP code last sold at time s , and that nearby comparable homes traded at similar prices. A standard comps approach would scale that historical price forward using local appreciation rates inferred from recent sales. In our framework, this scaling is accomplished by anchoring the property to a traded residential REIT index, which captures the systematic component of housing market movements. The normalization factor $a_{s,i}$ plays the role of a location-specific comp adjustment, mapping the REIT index to the local price level of the property.

The key distinction is that the REIT index is a traded asset. This allows the systematic component of housing value to be priced under a risk-neutral measure, exactly as in standard asset pricing. The residual difference between the property's value and the REIT-implied component is treated as idiosyncratic risk and evaluated under the physical measure, consistent with its diversifiable nature.

In this sense, our approach can be viewed as a hybrid between comps-based valuation and contingent-claims analysis. Hedonic models adjust comps using statistical averages but do not specify how risk is priced. Our framework uses comps to pin down the local price level, while the traded REIT index provides the pricing kernel needed to value default exposure and option-like features. This distinction is immaterial for point valuation of homes,

but becomes essential when pricing contracts such as rent-to-own agreements, where payoff timing and risk exposure depend on the evolution of house values.

Operationally, our framework works in three steps. First, we decompose each property's value into a market-replicable component, spanned by a traded residential REIT index and default-free bonds and priced under the risk-neutral measure $\mathbb{Q}^s$, and an idiosyncratic component, which is treated under the statistical (physical) measure $\mathbb{P}$. Second, we introduce mortgage default on the owner side via a Cox process, so that liquidation values and distressed-sale discounts enter the no-arbitrage price through the recovery rate φ and intensity parameters (π_0, π_1) . Third, we add the present value of rental (or occupancy) cash flows to obtain a closed-form expression for $V_{t,i}$ that can be estimated from transaction data and then used as the underlying state variable in pricing rent-to-own contracts. This separation between traded, non-traded, and default components clarifies how our application extends [Jarrow \(2023\)](#) to the residential real estate setting and prepares the ground for the empirical specification in Section 4.

This three-step decomposition—REIT-based systematic value, idiosyncratic component, and default-adjusted cash flows—makes the model straightforward to embed in portfolio-level valuation or contract-design tools.

Non-traded RRE as a priced asset

We model the traded market using a residential REIT index and the term structure of default-free zero-coupon bonds. Let S_t denote the time- t price of the REIT index, and let $p(t, T)$ be the time- t price of a default-free zero-coupon bond maturing at T , with money-market account $B_t = \exp\left(\int_0^t r_s ds\right)$. The REIT pays a continuous dividend yield δ , which we assume is reinvested, so the cumulative gains process is $S_t^* := S_t e^{\delta t}$. As usual, absence of arbitrage in the REIT–bond submarket implies existence of a risk-neutral measure $\mathbb{Q}^s$ under which discounted traded prices are martingales. The formal construction is given in the Online Appendix.

Let $\mathcal{F}_T^s$ denote the information generated at horizon T by the traded REIT and bond prices, and let X_T be any payoff that depends only on these traded assets (for example a portfolio of REITs and bonds). Restricted-market completeness implies that X_T can be replicated and hence valued by

$$X_t = \mathbb{E}^{\mathbb{Q}^s} \left(\frac{X_T}{B_T} \middle| \mathcal{F}_t \right) B_t. \quad (1)$$

Now consider the terminal value $V_{T,i}$ of a particular residential property i at some fixed horizon T . Following [Jarrow \(2023\)](#), we decompose it into a part spanned by the traded assets and a residual component:

$$V_{T,i} = \underbrace{\mathbb{E}^{\mathbb{P}}[V_{T,i} | \mathcal{F}_T^s]}_{\text{replicable component}} + \underbrace{(V_{T,i} - \mathbb{E}^{\mathbb{P}}[V_{T,i} | \mathcal{F}_T^s])}_{\text{hedging error}}. \quad (2)$$

The first term is $\mathcal{F}_T^s$ -measurable and can be replicated using the REIT and bonds; the second term is the hedging error.

The central assumption is that the hedging error in (2) is purely idiosyncratic, i.e., diversifiable and not priced for systematic risk. Under this condition, [Jarrow \(2023\)](#) shows that the no-arbitrage value of property i at time t is obtained by first taking the physical conditional expectation with respect to the traded-information set and then discounting under $\mathbb{Q}^s$:

$$V_{t,i} = \mathbb{E}^{\mathbb{Q}^s} \left(\mathbb{E}^{\mathbb{P}} \left(\frac{V_{T,i}}{B_T} \middle| \mathcal{F}_T^s \right) \middle| \mathcal{F}_t \right) B_t. \quad (3)$$

Similarly, the time- t value of any derivative written on $V_{t,i}$ with payoff $g(V_{\tau,i})$ at some $\tau \in [t, T]$ is

$$C_t = \mathbb{E}^{\mathbb{Q}^s} \left(\mathbb{E}^{\mathbb{P}} \left(\frac{g(V_{\tau,i})}{B_{\tau}} \middle| \mathcal{F}_{\tau}^s \right) \middle| \mathcal{F}_t \right) B_t. \quad (4)$$

Expressions (3)–(4) are the key pricing relationships we take to the data. The full martingale-based derivation and measure-theoretic setup are provided in the Online Appendix.

3.1 Parametric valuation without default

To implement (3) empirically, we impose a tractable parametric structure on the future sale value and occupancy benefits of each property. Fix a selling horizon T years ahead and consider property i .

We assume that the owner derives a stream of cash flows $c_{t,i} \geq 0$, corresponding to either explicit rent or the implicit rental benefit of living in the home, at dates $t = 1, \dots, T$. These cash flows are treated as $\mathcal{F}_t^s$ -measurable, i.e., driven by traded market conditions and property characteristics observed at time 0.

We add two assumptions to facilitate the empirical analysis:

ASSUMPTION 1 (*the RRE's time- T selling value*). For all $t + T \in [0, \mathbb{T}]$,

$$V_{t+T,i} = \frac{V_{s,i}^{comp}}{S_s} S_{t+T} \mu_T e^{\Theta_T \cdot X_{0,i}},$$

where $V_{s,i}^{comp}$ is the value of a set of comparables to property i at some date $s < t$, and $\mu_T e^{\Theta_T \cdot X_{0,i}} \geq 0$ captures the idiosyncratic component of the property's value. Here μ_T and Θ_T are parameters that depend on the selling horizon T , and $X_{0,i}$ is a vector of time-0 property characteristics (e.g., square footage, ZIP code). The factor $a_{s,i} := V_{s,i}^{comp} / S_s$ normalizes the REIT index to the level of the local housing market for property i at time s .

ASSUMPTION 2 (*cash flows*). For all $t \in [0, \mathbb{T}]$,

$$\mathbb{E}^{\mathbb{P}}(c_{t,i} | \mathcal{F}_t^s) = e^{v \cdot G_0} c_i,$$

where $c_i \geq 0$ is a property-specific constant and $v \cdot G_0$ is an index of macroeconomic covariates at time 0 that affect rental cash flows.

The key limitation of the condition $\mu_T e^{\Theta_T \cdot X_{0,i}}$ in Assumption 1 is that the idiosyncratic component of the RRE's value is treated as a deterministic function of the holding horizon and property characteristics. Similarly for the conditional expected value of the RRE's cash

flows in Assumption 2. This deterministic specification represents a deliberate trade-off between tractability and richness. In reality, property-specific values are subject to stochastic shocks over the holding period (e.g., local development, school redistricting). Since American option values are strictly increasing in the volatility of the underlying asset, ignoring idiosyncratic volatility implies that our model-derived option premiums likely understate the true economic value of the contract. Our estimates should therefore be interpreted as a baseline valuation; incorporating stochastic idiosyncratic variance would only increase the theoretical value of the tenant's purchase option.

Using Assumptions 1 and 2 inside (3), and exploiting the fact that the cumulative-dividend REIT price $S_t^* = S_t e^{\delta t}$ and bond prices are Q^s -martingales, we obtain the valuation formula

$$V_{t,i} = a_{s,i} S_t e^{-\delta T} \mu_T e^{\Theta_T \cdot X_{0,i}} + e^{v \cdot G_0} c_i \sum_{k=1}^T p(t, t+k), \quad (5)$$

where $a_{s,i} := V_{s,i}^{comp} / S_s$ for $s < t$. The short derivation is given in the Online Appendix.

Expression (5) has a simple interpretation: the value of property i equals: (i) the value of the REIT, $S_t e^{-\delta T}$, scaled by a comparables-based exposure $a_{s,i}$ and an idiosyncratic factor $\mu_T e^{\Theta_T \cdot X_{0,i}}$, plus (ii) the present value of the property's cash flows over the horizon $[t, t+T]$.

The exposure parameter $a_{s,i}$ is held fixed over the relevant horizon. Econometrically, this can be interpreted as a property-specific "REIT beta" that scales the traded index to the level of the local housing market for property i and time s . Allowing $a_{s,i}$ to vary deterministically or stochastically over time would require additional instruments or stronger identification assumptions and is difficult to discipline with the limited number of transactions per property. We therefore interpret $a_{s,i}$ as a long-run average exposure to aggregate housing risk. Time variation in local demand shifters and amenities is absorbed by the idiosyncratic component and by the ZIP code and time fixed effects in the empirical implementation.

Note that the REIT index price process already embeds a dividend yield δ . The consumption benefit from occupancy is instead captured by the model's cash-flow component, the second term in expression (5).

Discussion. In practice, housing markets are highly local and no single traded index can span all systematic risk in residential real estate. Our use of a broad residential REIT index should therefore be interpreted as a parsimonious approximation to the component of RRE risk that can be hedged through liquid securities. Any residual discrepancy between observed transaction prices and model-implied values is treated as unspanned, and hence priced under the physical measure as idiosyncratic risk.

3.2 Including Home Owner Default

Economically, mortgage financing affects valuation through its impact on the distribution of future sale prices. If the borrower defaults before the planned sale date, the property is liquidated at a distressed (recovery) value; if the borrower remains current, it is sold at full market value. In our reduced-form setup this is captured by a Cox default intensity process, which shifts probability mass from the non-distressed payoff to the distressed payoff but does not introduce a separate, owner-specific pricing kernel.

This section therefore models the situation in which typical homebuyers finance their purchase with a mortgage and face the possibility of default¹. The default risk is incorporated as a property-level state variable, summarized by ϕ_t , rather than as a characteristic of a particular seller. Conceptually, ϕ_t should be interpreted as the average default intensity relevant for the segment of the housing market in which the property trades (e.g., ZIP code-by-time), not as an idiosyncratic function of the current owner's balance sheet.

Formally, we treat homeowner default as the first jump time of a Cox process whose intensity is driven by observable state variables, including the term structure of interest rates. Let $f(t, u)$ denote the instantaneous forward rate at time t for maturity u . We assume:

¹A natural direction for future work is to link MLS transactions to lien and mortgage records in order to test whether, controlling for property and neighborhood characteristics, houses owned with a mortgage trade at different prices from those owned free and clear. Such an exercise would provide a direct empirical test of the default-risk channel emphasized by our model and would complement the foreclosure-discount evidence in [Campbell, Giglio and Pathak \(2011\)](#).

ASSUMPTION 3 (*Default intensity under $\mathbb{Q}$*). For $t \leq u \leq t + T$,

$$\phi_u = \pi_0 + \pi_1 f(t, u).$$

Thus the default intensity depends on the time- t forward rate for $u \in [t, t + T]$, allowing homeowner defaults to be correlated with the level of interest rates. In the empirical implementation, the continuous-time integral $\int_t^{t+T} f(t, u) du$ is approximated by the monthly sum $\sum_{k=1}^T f(t, t + k)$ using the fitted instantaneous forward rates from the FRED forward-rate curve.

If default occurs before T , the property is sold at a distressed recovery value proportional to the non-distressed selling price. Let $\varphi \in (0, 1)$ denote the recovery rate, so that the loss-given-default (LGD) is $1 - \varphi$. Under the above assumptions, and using the same specification for the idiosyncratic component as in (5), the arbitrage-free value of property i at time t can be written as

$$\begin{aligned} V_{t,i}^{\text{model}} = & \underbrace{(1 - \varphi) \mu_T \cdot a_{s,i} \cdot S_t \cdot e^{-\delta T} \cdot e^{\Theta_T \cdot X_{0,i}} \cdot e^{-\pi_0 T - \pi_1 \int_t^{t+T} f(t,u) du}}_{\text{Survival value: Adjusted Selling Price}} \\ & + \underbrace{\varphi \mu_T \cdot a_{s,i} \cdot S_t \cdot e^{-\delta T} \cdot e^{\Theta_T \cdot X_{0,i}}}_{\text{Recovery (Liquidation) Value}} \\ & + \underbrace{e^{\nu \cdot G_0} \cdot c_i \cdot \sum_{s=1}^T p(t, t + s)}_{\text{Present Value of Cash Flow Component}}, \end{aligned} \tag{6}$$

where again $a_{s,i} := V_{s,i}^{\text{comp}} / S_s$ for $s < t$. The derivation from the Cox-process specification to (6) is provided in the Online Appendix.

Expression (6) is the central object used in our empirical work. The parameters (φ, π_0, π_1) should be interpreted as reduced-form pricing adjustments summarizing the joint effect of default risk and distressed-sale discounts on transaction values, not as structural borrower-level hazard rates.

Although some transactions involve cash purchases, the default component in our

model should be interpreted as a reduced-form pricing adjustment that reflects market-wide expectations of distressed resale risk typical for a given location and time, rather than the financing choice of a particular buyer. Even cash transactions are priced in equilibrium against comparables and expected future market conditions, which embed the likelihood and severity of distressed sales.

Interpretation. In a frictionless Walrasian setting, the fundamental value of an asset does not depend on the identity of the current owner. Our framework is consistent with this principle: the stochastic discount factor is pinned down by the traded REIT–bond submarket, and homeowner default appears only through its impact on the distribution of resale prices. We do not claim that two otherwise identical houses sell at different prices solely because one seller is more levered than another. Instead, the default intensity ϕ_t proxies for the aggregate likelihood that the property will be sold under distressed conditions (foreclosure, short sale, forced sale) given typical financing arrangements in that local market. The model price $V_{t,i}$ should thus be viewed as a reduced-form, no-arbitrage value that embeds the possibility of distressed liquidation, rather than as the outcome of bilateral search or Nash bargaining between a specific buyer and a specific seller.

4 Empirical Analysis

There are three steps in estimating $V_{t,i}$. Throughout this section, we interpret $V_{t,i}$ as a model-implied, shadow no-arbitrage value that rationalizes the observed MLS closing price of property i at time t . The sample includes both regular and distressed transactions, which we do not separately identify. Instead, default intensity and recovery parameters are estimated in a reduced-form manner so that the model can accommodate forced sales and foreclosure discounts through the distribution of cash flows, even though such events are relatively infrequent. Accordingly, the model-implied values should be interpreted as equilibrium

prices reflecting average financing and default conditions within each local market segment, rather than as asking prices arising from particular bilateral negotiations.

The estimation proceeds in three steps. First, we select the selling horizon T . For the main results, we set $T = 10$, but empirical investigation indicates that $T = 5$ has little impact on the results.² Second, we estimate the normalization factor $a_{s,i}$ based on a set of comparables. Third, we estimate the parameter vector $\Theta = (\mu_T, \Theta_T, \varphi, \pi_0, \pi_1)$.

4.1 Estimating the Normalization Factor

The key quantity determining the normalization factor $a_{s,i}$ at time s for property i is the value of a set of comparable sales, $V_{s,i}^{\text{comp}}$. As described in Section 3, the model decomposes each property's value into a systematic component, captured by a traded REIT index and priced under the risk-neutral measure, and an idiosyncratic component, evaluated under the physical measure. While the REIT-linked component captures broad market movements, the idiosyncratic component must be inferred from local transaction data. The normalization factor $a_{s,i}$ anchors the model-implied value to this local price level.

To construct $V_{s,i}^{\text{comp}}$, we use a comparables-based procedure. For each property, we identify nearby and similar recently sold properties and compute $V_{s,i}^{\text{comp}}$ as the average sale price from this set. We now describe the criteria used to define comparables and the similarity metric used to rank them.

Comparable Filtering. For each property in the dataset, we construct a pool of potential comparables by imposing four restrictions. First, a comparable must lie within a 5-mile radius of the target property's ZIP code centroid. Second, it must match the target's number of bedrooms and bathrooms, pool availability, garage status, and property type. Third, it must have sold within the past 183 days (approximately six months). Fourth, if the target

²This reflects the slow-moving nature of real estate markets. Once the primary drivers of house price dynamics (e.g., property characteristics and macroeconomic variables) are captured, subdividing the time horizon further (from 5 to 10 years) yields only a marginal improvement in fit. Moreover, key property characteristics and broader macro trends do not vary rapidly enough to warrant finer temporal granularity.

has non-missing values for age, square footage, or lot size, we retain only properties with corresponding non-missing attributes.

These restrictions ensure that the potential comparables closely resemble the target property in location, timing, and basic structural characteristics. The 5-mile radius reflects a trade-off between spatial precision and the need to retain a sufficiently large comparison set, particularly in lower-density or peri-urban areas. This procedure mirrors standard appraisal practice, where comparable sales are used to extract localized price information not captured by market-wide indices such as REITs.

Similarity Score. For each potential comparable j to target property i , we compute a similarity score

$$s_{ij} = \prod_{m \in \{\text{date, age, sqft, lot, dist}\}} \left(1 + \frac{|d_{m,ij}|}{\tau_m} \right),$$

where $d_{m,ij}$ denotes the difference between properties i and j along dimension m . The tolerances are

$$\tau_{\text{date}} = 183 \text{ days}, \quad \tau_{\text{age}} = 10 \text{ years}, \quad \tau_{\text{sqft}} = 0.25 \times \text{sqft}_i,$$

$$\tau_{\text{lot}} = 0.25 \times \text{lot}_i, \quad \tau_{\text{dist}} = 5 \text{ miles}.$$

A lower score indicates a closer match. We rank all potential comparables by s_{ij} in ascending order and retain the ten most similar properties.

Selecting Top Comparables. The selected comparables and their sale prices define $V_{s,i}^{\text{comp}}$. The normalization factor is then computed as

$$a_{s,i} = \frac{V_{s,i}^{\text{comp}}}{S_s},$$

where S_s is the REIT index level at time s . This normalization ensures consistency between the traded REIT-based valuation and local transaction data.

Although this individualized procedure is computationally demanding due to the scale of the dataset, it substantially improves the relevance of the comparable set and enhances the accuracy of the normalization factor, thereby improving the overall reliability of the model's empirical implementation.

4.2 Calibrating Strategy

Given potential noise in the data and model misspecification, we calibrate the parameter vector

$$\Theta = (\mu_T, \Theta_T, v, \pi_0, \pi_1, \varphi)$$

by pooling all transactions in the training sample and minimizing a weighted nonlinear least squares criterion. Let $V_{t,i}^{\text{model}}(\Theta)$ denote the model-implied value for property i at sale date t , and define the log-transformed observed sale price as

$$y_{t,i} = \log(1 + \text{closeprice}_{t,i}).$$

The estimation problem is

$$\min_{\Theta} \frac{1}{2} \sum_{t,i} w_{t,i} \left[y_{t,i} - \log(1 + V_{t,i}^{\text{model}}(\Theta)) \right]^2$$

subject to an unbiasedness constraint requiring the weighted average model value to match the weighted average observed price:

$$\sum_{t,i} w_{t,i} (e^{y_{t,i}} - V_{t,i}^{\text{model}}(\Theta)) = 0.$$

This constraint eliminates systematic over- or under-pricing in the pooled cross section.

Standard errors reported in Tables 2 and 3 are computed from the inverse of the observed Hessian of the nonlinear least squares objective at the optimum and are therefore robust to heteroskedasticity in the residuals.

where

- $y_{t,i} = \log(\text{closeprice}_{t,i} + 1)$ denotes the observed log-transformed sale price of property i at time t .³
- w_i is a property-specific weight defined as

$$w_i = \min\left\{1 + \beta \ln\left(1 + \frac{\text{closeprice}_{t,i}}{\text{pivot}}\right), w_{\max}\right\},$$

with $\beta = 0.5$, $\text{pivot} = 300,000$, and $w_{\max} = 2$.

We employ weighted least squares to account for the well-documented heteroskedasticity in housing transaction prices, whereby higher-priced properties tend to exhibit larger absolute pricing errors. The weighting scheme increases gradually with price and is capped to prevent extreme observations from dominating the estimation. This approach balances efficiency and robustness across the full price distribution, from modest homes to high-end properties.

All specifications include month-of-sale and ZIP-code fixed effects. Month fixed effects absorb seasonal patterns in housing demand, while ZIP fixed effects capture persistent location-specific amenities and neighborhood quality. Macroeconomic variables enter through the vector G_t and vary at the monthly frequency; they are identified from time-series variation rather than from cross-sectional differences within a given month.

In summary, the calibration combines property-specific characteristics, market-wide economic factors, and REIT-linked components within a unified no-arbitrage structure. Property characteristics enter under the physical measure and capture idiosyncratic variation in housing values, while the traded REIT index prices the systematic component under

³Given the scale of transaction prices, $\ln(V_{t,i}(\Theta)) \approx \ln(1 + V_{t,i}(\Theta))$ is an excellent approximation.

the risk-neutral measure. The property-level variables include the number of bedrooms and bathrooms, square footage, property age, pool availability, and indicators for property condition, along with month-of-sale and ZIP-code fixed effects that absorb seasonal patterns and persistent location-specific amenities.

In addition, the model incorporates market-wide variables that proxy for broader economic conditions affecting housing demand and financing. These include the Consumer Price Index, mortgage rate spreads, the unemployment rate, the VIX, housing starts, and delinquency rates on single-family residential mortgages. Together, these variables allow the model to account for macroeconomic conditions that influence expected cash flows and default risk in residential real estate markets.

Together, these property-level and market-wide variables support a hybrid valuation framework that integrates a no-arbitrage pricing structure with cross-sectional econometric estimation, allowing the model to capture both systematic and idiosyncratic drivers of residential property values, as well as their interaction with default risk.

4.3 Data

This section describes the data sets used in the empirical investigation. The data source CoreLogic maintains two Georgia-based Multiple Listing Services (MLS): FMLS (First Multiple Listing Service) and SAV (Savannah MLS). FMLS, one of the state's oldest and most widely used MLSs, primarily covers the metro Atlanta region and North Georgia, whereas SAV is a more specialized MLS serving the Coastal Georgia (Savannah) area. Because SAV's coverage is significantly smaller, this study draws on data from the Georgia First Multiple Listing Service (MLS), encompassing 674,629 residential property transactions recorded between January 6, 2007, and December 30, 2019.

The property-level data capture a wide range of intrinsic characteristics, including square footage, number of bedrooms and bathrooms, age, pool availability, and property condition (e.g., resale, new construction, fixer upper). To reflect broader economic conditions

that influence the real estate market, the dataset also integrates indicators from FRED (Federal Reserve Economic Data) and Zillow, including the Consumer Price Index (CPI), mortgage spreads, the unemployment rate, the VIX (Market Volatility Index), and housing starts. In addition, the dataset includes the final sale price (closeprice), month of sale, and ZIP code for each transaction, enabling both seasonal and location-specific fixed effects to be incorporated in the analysis.

These variables proxy for key market-wide drivers of housing demand and financing conditions. Interest rate effects enter both directly, through mortgage spreads, and indirectly through the term-structure variables used in the Cox default intensity, as well as through housing starts and delinquency rates. Unfortunately, we do not have consistent tract- or ZIP-level measures of household income for the full sample period. As a result, income growth is captured indirectly through macroeconomic controls and location fixed effects, rather than through explicit local income series.

We include month and ZIP code fixed effects in all specifications to absorb seasonality and broad neighborhood-level differences in amenities and local market conditions. However, as emphasized by [Abbott and Klaiber \(2011\)](#), fixed effects defined over relatively large spatial units, such as counties or ZIP codes, may not fully eliminate omitted-variable bias when capitalization occurs at finer spatial scales (e.g., census tracts or subdivisions). While finer-scale controls would be ideal, consistent census tract identifiers are not available in our MLS dataset. Consequently, the use of ZIP-level fixed effects represents a pragmatic compromise between spatial resolution and data coverage, and some localized unobserved heterogeneity may remain.

We employ a time-based split of the dataset into training (in-sample) and testing (out-of-sample) sets, allocating approximately 80% of the data to training and 20% to testing. The training set spans January 16, 2007 to March 30, 2018 (335,145 transactions), and the testing set extends from March 30, 2018 to December 30, 2019 (83,643 transactions). To ensure sufficient representation in both sets, we require each ZIP code to have at least 30 transactions in both

the training and testing periods; this filter yields 139 ZIP codes and enhances the robustness of the analysis.

The rent estimate for the i^{th} RRE, denoted c_i , is designed to capture rental costs based on observable property characteristics. While the rent estimation algorithm is computationally efficient, it is relatively parsimonious and introduces some measurement error. The algorithm uses rental observations within a 5-mile radius of the target property and relies primarily on the number of bedrooms to predict rent. This choice reflects the limited availability of rental observations, which precludes the use of more detailed variables such as square footage or lot size without substantially reducing the sample. Attempts to incorporate richer features (e.g., latitude/longitude or square footage) reduced the estimable rental sample by over 90% due to missingness and sparsity, so we adopt the more robust bedroom-only specification within a 5-mile radius.

Alternative rent estimation methods, such as the Zillow Observed Rent Index (ZORI) at the ZIP code or county level, were considered but rejected due to their limited temporal coverage (ZORI data begin in 2015) and the lack of granularity for single-family homes, as ZORI is primarily available for multifamily properties or at the national level. Despite its limitations, the rent estimation algorithm provides a transparent and tractable way to impute rental cash flows in the absence of more complete lease-level data.

We acknowledge that the rental imputation algorithm, based on bedroom counts within a 5-mile radius, is a parsimonious proxy necessitated by data limitations. While this approach introduces property-level measurement error, the large scale of the sample (674,629 transactions) ensures that idiosyncratic estimation errors largely cancel out in the aggregate calibration. Moreover, standard errors-in-variables logic suggests that measurement noise in rental estimates would typically bias option value estimates toward zero (attenuation bias). Consequently, the estimated embedded option value of approximately 13.4% should be interpreted as a conservative lower bound relative to a setting with perfect rental foresight.

The model incorporates additional financial and economic factors to enhance predictive

accuracy. The dividend yield of the REIT (Real Estate Investment Trust) index captures the income-generating component of real estate investments, while the recovery rate φ (with haircut $1 - \varphi$) adjusts property values for default-related liquidation risk. Forward rates obtained from FRED’s monthly fitted instantaneous forward rate curve are used to estimate the default intensity parameters π_0 and π_1 introduced in the pricing model.

In addition, the model incorporates a market-traded pricing kernel via the FTSE Nareit US Residential REIT Index. This index tracks publicly traded REITs focusing on residential properties, including single-family rentals and multifamily complexes, and provides a continuously traded benchmark for the systematic component of residential real estate values. Monthly index levels are obtained from *S&P Global* spanning 2006 to 2024, ensuring overlap with the 2007–2019 MLS sample. Unlike statistical house price benchmarks (e.g., Case-Shiller or ZHVI), this REIT index is investable and supports no-arbitrage valuation, making it integral to the decomposition framework developed in Section 3.

While we proxy for systematic housing risk using the FTSE Nareit US Residential REIT Index, we do not claim that a single traded index spans all local housing shocks. In the model, the REIT captures the common traded factor, while residual local risk is treated as idiosyncratic and priced under the physical measure rather than loaded onto an additional systematic factor.

Prior to estimation, extensive data cleaning and preprocessing were performed to ensure reliability and consistency. This process involved removing properties with missing or inconsistent data, such as listings with zero bedrooms or bathrooms or those labeled “To Be Built” or “Under Construction.” The sample is restricted to homes priced below \$4 million, with non-residential and incomplete listings removed. Very low-price transactions (e.g., \$1 placeholders or distressed resales) are retained because they appear in MLS data and reflect realistic distressed market conditions, consistent with the model’s treatment of default risk. Extreme price values are winsorized to mitigate the influence of outliers, and dummy variables are created for categorical features (e.g., property condition, ZIP code, month of

sale) to incorporate fixed effects.

Foreclosure and short-sale transactions are not explicitly identified or removed from the data. Consequently, the estimated recovery parameter φ should not be interpreted as the realized recovery rate on a specific foreclosed home. Instead, it represents a reduced-form pricing object that aggregates the market-wide expectation of distress. For valuation purposes, this effective recovery rate captures the expected exposure of a housing portfolio to liquidation risk, rather than the binary legal status of an individual deed.

4.4 Results and Robustness

The results from the estimation support the ability of the model to predict real estate prices. By construction, the model incorporates both a REIT-index-based systematic component and a property-specific component, allowing us to test its performance across a wide range of market and property conditions. The robustness of the model is evident in the in-sample and out-of-sample performance, as reflected by the R^2 values of 0.6431 and 0.2331, respectively (Table 2). The model's ability to explain 64.31% of the variance in property prices in the training set indicates its effectiveness in accounting for both micro-level property characteristics and macroeconomic conditions, though the lower out-of-sample R^2 suggests some challenges in generalization.

Although an in-sample R^2 of 0.6431 is below the 0.775 achieved by a standard OLS hedonic regression, this partly reflects our focus on a parsimonious, option-theoretic structure that incorporates default risk and illiquidity, as well as the use of robust weighting to limit the influence of extreme observations. More importantly, the model maintains nontrivial out-of-sample explanatory power.

It is important to emphasize that our out-of-sample statistics are *conditional* on the realized paths of the macroeconomic variables (CPI, unemployment, delinquency rates, housing starts, etc.) over the testing period. When we roll the model forward, we feed in the actual observed macro series for those dates. In a truly ex ante forecasting exercise, these

variables would need to be predicted, so the reported out-of-sample R^2 should be interpreted as an upper bound on predictive performance rather than a guarantee of real-time accuracy.

A related concern is that our out-of-sample R^2 for individual property prices is lower than what a standard hedonic regression achieves in-sample. This reflects a deliberate trade-off. For option pricing, what matters is correct specification of the *distribution* of future property values, not point prediction of individual transactions. Two pieces of evidence suggest the model is well-specified for its intended purpose. First, the out-of-sample correlation with the Zillow Home Value Index is 0.87 (Figure 3), indicating that the model tracks aggregate market dynamics accurately even on unseen data. Second, the model predicts that approximately 11% of HPA contracts would become exercisable under standard 3% strike escalation, closely matching the sub-20% conversion rate reported for the actual program. These validation checks suggest that the model captures the economically relevant features of housing risk, even if idiosyncratic transaction-level noise reduces point-prediction R^2 .

In terms of the importance of various covariates, the condition of a property plays a significant role in valuation, as reflected by the coefficients for the condition dummy variables. Newly constructed properties ($\Theta_{\text{New Construction}}$) command the highest premium, with a 48.08% increase in value compared to the baseline category (Fixer Upper). This premium reflects the appeal of modern construction, updated building codes, and the absence of wear and tear. Resale properties (Θ_{Resale}) also exhibit a substantial premium (28.83%), as they are typically well-maintained and move-in ready. Updated or remodeled properties ($\Theta_{\text{Updated/Remodeled}}$) show a 35.06% premium, indicating that buyers are willing to pay more for homes that have been recently renovated or modernized. These results underscore the importance of property condition in real estate valuation, with buyers placing a premium on newer or well-maintained homes.

Table 2 presents the estimated coefficients for the property-specific and market-wide variables. A positive and statistically significant coefficient on square footage (Θ_{sqft}) confirms that larger homes command higher prices, with an approximately 26.80% increase in value

for every unit increase in log square footage. However, the number of bedrooms (Θ_{beds}) has a negative coefficient, suggesting that inefficient layouts with excessive small bedrooms may reduce desirability. The number of bathrooms (Θ_{baths}) contributes positively to home values, reinforcing the idea that increased functionality enhances marketability. Similarly, properties with pools (Θ_{pool}) tend to sell at a 4.64% premium, reflecting buyer preferences for leisure amenities. Lot size also exhibits a positive impact (Θ_{acres}), with larger lots commanding a premium of approximately 5.86% for each unit increase in log acreage.

Macroeconomic factors also significantly influence real estate prices via their impact on the present value of rental income (the cash flows over $[0, T]$). The positive coefficient on CPI (v_{cpi}) suggests that inflation increases housing prices, potentially reflecting higher construction and maintenance costs that raise replacement value, as well as purchasing power adjustments. Interestingly, the unemployment rate (v_{unemp}) has a positive effect, contrary to traditional expectations. This may reflect countercyclical monetary policy responses during periods of high unemployment, which could lead to lower interest rates and increased housing demand. The VIX (v_{vix}) indicates that higher market volatility is associated with downward pressure on real estate prices, likely reflecting increased economic uncertainty. Housing starts (v_{houst}) have a positive effect on prices, suggesting that increased construction activity may signal market confidence. Delinquency rates (v_{delin}) show a strong negative association with prices, confirming that higher default risk in the mortgage market depresses housing values. These macro coefficients enter through the physical measure in our model, modifying the expected present value of idiosyncratic cash flows.

Table 2 also reports the default-risk parameters, which indicate that credit conditions affect pricing in a reduced-form manner. The estimated recovery rate $\varphi = 0.5967$ is consistent with distressed properties trading at large discounts, on the order of 40% on average, relative to non-distressed sales with similar characteristics. The small but statistically significant baseline intensity $\pi_0 = 0.0051$ and its dependence on the term structure ($\pi_1 = 0.0101$) imply that the default-adjustment term is sensitive to the level of interest rates. Because we do

not separately identify physical default probabilities from risk premia, these parameters should be interpreted as reduced-form adjustments that summarize the joint effect of default risk and foreclosure discounts on observed prices, rather than as structural hazard rates for individual borrowers.

In summary, the estimation results align well with economic theory, underscoring both the importance of individual property characteristics and the influence of broader market conditions. At the micro level, larger homes, newer or well-maintained properties, and amenities like pools command significant price premiums, reflecting standard hedonic pricing principles that buyers pay more for enhanced utility and quality. At the macro level, the positive coefficient on CPI suggests that inflation pushes housing prices higher, reflecting both rising construction and maintenance costs and increased demand for inflation-hedging assets. The positive relationship between housing prices and unemployment diverges from standard expectations, but may reflect countercyclical monetary policy: during downturns, lower interest rates and accommodative credit conditions can stimulate housing demand despite weaker labor markets. Meanwhile, factors such as delinquency rates capture the risk environment in mortgage markets: when delinquency rates are higher, buyers and lenders may impose risk premiums, influencing observed sale prices. Together, these results demonstrate that the model's no-arbitrage structure, grounded in both traded and non-traded components, captures the multifaceted economic reality of the residential real estate market.

At the same time, we do not interpret the estimated macroeconomic coefficients as structural causal effects. They are reduced-form parameters that summarize partial correlations conditional on the other covariates in the model. Signs that differ from simple comparative-statics intuition (for example, the positive coefficient on unemployment in some specifications) likely reflect omitted variables, policy responses, or sample composition rather than true causal relationships. We therefore treat these estimates as economically informative but avoid strong causal claims.

Figure 4 translates the full-model coefficients in Table 2 into percentage effects on house values. The figure highlights the substantial premiums associated with property condition: new construction commands the largest premium at roughly 62% above the fixer-upper baseline, followed by updated/remodeled properties (about 42%) and resale properties (about 33%). Among property features, the addition of a bathroom has a more substantial positive impact (approximately 13%) than an increase in square footage (about 2.6% for a 10% increase) or the presence of a pool (around 5%). Notably, adding a bedroom has a slight negative effect (about -1.4%), supporting the earlier interpretation that floor plans with many small bedrooms may reduce overall property desirability.

On the macroeconomic side, the recovery rate φ has one of the largest impacts. Since the haircut (LGD) equals $1 - \varphi$, the estimated $\varphi \approx 0.60$ implies a distressed-sale discount of roughly 40%, meaning that distressed properties sell at substantially lower values relative to comparable non-distressed homes. The CPI shows a moderate positive effect (6.1% for a 1% increase), while delinquency rates have a sizeable negative effect (approximately -24%), consistent with distress spillovers into local housing markets. Overall, the figure illustrates the model's flexibility in capturing both continuous and discontinuous value drivers, including condition, amenities, and macro-level volatility.

Interpretation and limitations These results show that the calibrated no-arbitrage model can account for a large share of cross-sectional price variation in our Georgia MLS sample while delivering an economically interpretable decomposition into systematic, idiosyncratic, and default components. However, the parameters should be viewed as reduced-form: we do not separately identify physical default probabilities from default risk premia, nor do we claim that the macro coefficients represent structural causal effects. Moreover, the results are specific to Georgia's housing market over the sample period and may not directly generalize to other regions or periods without re-calibration.

4.4.1 Robustness Test

This section reports the results from two robustness tests. First, we re-estimated the model setting the market covariates $G_0 = 0$. As shown in Table 2 (the full model) and Table 3 (the $G_0 = 0$ specification), omitting macroeconomic covariates leads to only relatively modest changes in the property-specific coefficients, but a noticeable drop in overall model fit. For instance, the coefficient on square footage (0.2680 vs. 0.2666) and the baseline default intensity (π_0) both shift only slightly, suggesting that macro variables help absorb some of the variation in price. This is consistent with the model’s structure, where G_0 enters through the physical measure and improves valuation by capturing macro shocks not spanned by the traded REIT component. Nevertheless, removing broader market signals such as CPI, unemployment, and the VIX decreases the in-sample R^2 from 0.6431 to 0.6396 and the out-of-sample R^2 from 0.2331 to 0.1974, confirming that macro conditions do refine predictive accuracy, particularly for out-of-sample generalization.

As an additional robustness test, we compared our weighted sum of squared estimation to estimating an Ordinary Least Squares (OLS) baseline model. Table 4 further highlights the differences between estimation approaches. The OLS model achieves an R^2 value of 0.775, which differs from the robust model’s 0.6431. While the OLS R^2 appears higher, this likely reflects in-sample overfitting and greater sensitivity to noise and outliers, rather than superior out-of-sample performance. Unlike our weighted estimator, the OLS specification does not correct for heteroskedasticity, which is well-documented in real estate markets, nor is it derived from a no-arbitrage framework. The OLS coefficient estimates are broadly similar to those from our primary specification but exhibit some differences—for instance, the coefficient for lot size is notably higher in the OLS model (0.1276 vs. 0.0586), suggesting that the weighted approach may better control for heterogeneity in property characteristics.

Our objective is therefore not to outperform OLS or black-box AVMs on pure predictive fit, but to show that a parsimonious, no-arbitrage-consistent valuation model can match a substantial fraction of price variation while enabling derivative-style pricing of contracts

such as rent-to-own options.

Figure 3 illustrates the strong alignment between the model's predicted prices and the Zillow Home Value Index (ZHVI) in both the training (left) and test (right) datasets. On the x-axis, the log-transformed ZHVI values increase, while the y-axis shows the mean predicted sale price (in millions of dollars). The red regression line with its confidence band highlights the positive relationship between the two series. In the training set (left plot), the correlation of 0.84 indicates a robust in-sample fit, showing that the model effectively captures variations in ZHVI. Notably, in the test set (right plot), the correlation increases to 0.87, reflecting an ability to track the ZHVI index out-of-sample. This strong correlation—especially out-of-sample—demonstrates the model's capacity to capture broad market trends in residential property values through the interaction of its systematic (REIT-based) and macroeconomic components. The close clustering of data points around the regression line further confirms that the model tracks broad market trends—measured by the ZHVI—quite closely even on unseen data. These high correlation values underscore the model's ability to mirror macro-level home price movements as represented by ZHVI in both the training and test periods, despite the more modest R^2 values observed in the property-level predictions.

Figure 2 provides additional diagnostic insight into model performance through a series of plots comparing observed versus predicted values, residuals, and their distributions for both in-sample and out-of-sample datasets. The scatter plots reveal the relationship between observed and predicted values, while the residual plots help identify potential patterns or biases in the errors. The histograms and QQ plots of residuals assess the normality of the error distribution, which is important for inference. These diagnostics confirm the model's overall fit while highlighting areas where predictive accuracy varies across the price distribution.

Despite its strong performance, the model has certain limitations that warrant further investigation. For example, while the inclusion of ZIP code fixed effects helps account for location-specific variations, the model does not explicitly capture neighborhood-level factors such as school quality or crime rates, which could further enhance predictive accuracy. Ad-

ditionally, the more substantial gap between in-sample and out-of-sample performance suggests potential overfitting or time-varying relationships that future research could address through alternative specifications or additional covariates. Future work might also explore nonlinear modeling extensions, richer spatial granularity, or time-varying macro sensitivities to further enhance out-of-sample performance under changing economic conditions. Exploring the inclusion of additional macroeconomic indicators or alternative weighting schemes could provide further insights into the dynamics of real estate pricing under different market conditions.

5 Valuing the Rent-to-Own Contract

The valuation framework developed in this paper provides a natural foundation for pricing structured housing contracts with embedded optionality. Our primary application is to institutional rent-to-own (RTO) contracts such as Blackstone’s Home Partners of America (HPA) “Choice Lease” program, where we show that embedded purchase options are worth roughly 13.4% of property value on average and that eviction policies materially erode this value.

Tenants pay a refundable security deposit equal to two months’ rent—there is no upfront option fee and no rent premium—and rents are set at or slightly below prevailing market levels for qualifying households (typically those earning up to 80% of Area Median Income).⁴ In return, tenants receive a free, unconditional right—but not the obligation—to purchase the home at a predetermined price that escalates annually by 3–5% above HPA’s acquisition cost plus closing and turnover expenses. If a tenant defaults on rent or breaches the lease, HPA may terminate occupancy and evict the tenant, forfeiting only the security deposit and extinguishing the purchase option.

Our goal is not to strictly replicate HPA’s realized cash flows or conversion rates, given

⁴See <https://www.prnewswire.com/news-releases/home-partners-of-america-launches-first-of-its-kind-choice-lease-program-with-initial.html> for details.

the absence of comprehensive tenant-level data. Instead, we seek to show how a calibrated no-arbitrage model can be used as a design tool for analyzing and optimizing stylized rent-to-own contracts.

HPA's key contract terms can be summarized as follows.⁵ Tenants sign an initial 12-month lease that automatically renews annually for up to 60 months, creating a five-year option window during which they hold a zero-cost, nontransferable right to purchase the home at a predetermined strike price. Rents escalate at a fixed annual rate of approximately 3.75 percent, providing predictable and transparent adjustments over the lease term. Tenants pay rent at or slightly below prevailing market rates; none of the rent is credited toward purchase, and there are no down-payment credits or rent-to-equity conversions. The purchase price is disclosed at move-in and escalates annually. For example, if HPA's all-in acquisition cost is \$300,000, the Year 1 strike is \$300,000, the Year 2 strike is \$300,000 multiplied by 1.03, and subsequent strikes increase at the same rate. Because only about 20 percent of tenants ultimately exercise, HPA collects full market rent from the majority of occupants. When tenants do not convert, or are evicted, the home is resold or re-leased at prevailing market value, allowing the institution to offer the purchase option without charging an explicit up-front fee.

In practice, only about 20 percent of HPA tenants convert to homeowners within the five-year term.⁶ Among those who do convert, roughly 75 percent exercise in months 49–60, when the gap between market value and the escalated strike price tends to be greatest. Very few tenants exercise in Years 1–2, reflecting the time required to qualify for mortgage financing or accumulate savings for closing costs.

Related institutional rent-to-own programs share the same basic structure but differ in how the embedded option is funded. Divvy Homes converts approximately 25 percent of monthly payments into equity credits that accumulate toward a down payment, with unused

⁵See <https://www.moodys.com/web/en/us/insights/resources/lease-to-purchase-how-build-homeownership.pdf>.

⁶See <https://research.contrary.com/company/divvy-homes> and <https://techequity.us/wp-content/uploads/2022/11/Rent-to-Own-the-American-Dream.pdf>.

credits forfeited if the tenant does not purchase. Landis Technologies emphasizes financial coaching; tenants pay a small reservation fee, rent at or slightly below market rates, and direct 20–30 percent of monthly rent into a supervised savings account. ZeroDown requires a refundable membership fee and allows tenants to switch homes once, with purchase prices locked in for the first three years. Pathway Homes offers a longer option window of up to ten years, with the purchase price escalating annually according to a regional house price index such as the FHFA series.

Despite these institutional differences, rent-to-own contracts share a common economic structure. Each embeds an implicit option price at time $t = 0$, which may take the form of an upfront deposit, a membership or administrative fee, or a rent premium. If the tenant does not exercise, this payment or accrual is forfeited; if the option is exercised, it offsets the purchase price, mirroring the payoff of an American-style call option. In addition, virtually all institutional rent-to-own contracts include a termination clause under which default or eviction extinguishes the embedded purchase right.

Our framework provides an arbitrage-free method for valuing rent-to-own contracts with the home as a sporadically traded asset (see expression 4). The decomposition into market-driven components (proxied by REITs) and idiosyncratic components is particularly well-suited because it captures both systematic risk and localized variation. To value this rent-to-own contract, recall that the residential real estate price evolves across time t as

$$V_{t,i} = \left((1 - \varphi) \alpha \beta_t + \varphi \alpha \right) S_t + e^{v G_0} c_i \sum_{s=1}^T p(t, t+s), \quad (7)$$

where

$$\alpha := \mu_T(a_{s,i}) e^{-\delta T} e^{\Theta_T X_{0,i}} \quad \text{and} \quad \beta_t := \exp\left(-\pi_0 T - \pi_1 \int_t^{t+T} f(t, u) du\right).$$

Equations (7)–(12) therefore turn the house-value model into a pricing engine: for any given property and set of contract parameters (strike path, horizon, eviction hazard), the framework delivers the American-style option value and the fair lease payment that makes

the contract zero-value under risk-neutral pricing.

To incorporate eviction as a “default event,” we introduce a hazard rate λ capturing the probability that the tenant fails to pay rent or otherwise breaches lease terms and is evicted before the contract’s natural maturity. Should such a default occur at time $\tau < \tau_{\max}$, the rent-to-own contract terminates early and the embedded purchase option becomes worthless. Accordingly, any expected payoff calculations must be adjusted by the probability that the tenant survives (i.e., is not evicted) through each potential exercise date.

Consistent with evidence that eviction risk is economically significant in institutional single-family rental portfolios, we adopt a baseline annual eviction probability of approximately 5% as a transparent reduced-form calibration rather than an estimated parameter; the framework can easily be used to explore alternative hazard rates.⁷

The embedded call option in a rent-to-own contract has the following terms:

- K_j = predetermined purchase price in year j (strike price),
- τ = option expiration (maximum contract length, typically 5 years),
- t_j = potential exercise dates (end of each lease year) for $j = 1, \dots, \tau$.

The call option’s time 0 value, considering the American exercise feature, is

$$C(V_{0,i}, \{K_j\}_{j=1}^\tau, \tau) = \sup_{k \in \{t_1, \dots, t_\tau\}} \mathbb{E}^\mathbb{Q} \left[|V_{k,i} - K_k|^+ / B_k \right], \quad (8)$$

where $|x|^+ = \max(x, 0)$. Here, k is a stopping time that represents the optimal exercise time chosen from the set of discrete exercise dates $\{t_1, \dots, t_\tau\}$. Using expression (4), this becomes

$$C(V_{0,i}, \{K_j\}_{j=1}^\tau, \tau) = \sup_{k \in \{t_1, \dots, t_\tau\}} \mathbb{E}^\mathbb{Q} \left[\left[\gamma_k S_k + e^{v G_0} c_i \sum_{s=1}^T p(k, k+s) - K_k \right]^+ / B_k \right], \quad (9)$$

where $\gamma_t := (1 - \varphi) \alpha \beta_t + \varphi \alpha$.

⁷See, for example, (Raymond et al., 2016) and data summarized by the Princeton Eviction Lab, which document that eviction and forced-move activity in large institutional rental portfolios is economically meaningful. We emphasize that the 5% figure is a pricing calibration, not a structural estimate of physical eviction probabilities.

Proof. Expression (4) simplifies because the randomness in $V_{t+k_i, i}$ is generated by $p(k, k + s)$, $f(k, k + s)$, and S_k for $s = 1, \dots, T$. All of these random variables are $\mathcal{F}_k^s$ -measurable. Hence, the conditional expectation in expression (4) involving $\mathbb{P}$ simplifies as written. $\square$

The consumer is long this option and short the lease payments l_i per year over the life of the contract. Consequently, for a given lease payment l_i , the value of the rent-to-own (RTO) contract at time 0 to the consumer is

$$RTO_0 = C(V_{0,i}, \{K_j\}_{j=1}^\tau, \tau) - l_i \sum_{u=t_1}^{k^*} p(0, u), \quad (10)$$

where k^* is the optimal exercise time obtained from solving expression (9). The fair lease payment l_i sets this contract's value to zero, i.e.

$$l_i = \frac{C(V_{0,i}, \{K_j\}_{j=1}^\tau, \tau)}{\sum_{u=t_1}^{k^*} p(0, u)}. \quad (11)$$

When default and eviction⁸ are introduced, each potential payoff $|V_{k,i} - K_k|^+$ at exercise date t_k must be multiplied by the probability that the tenant has *not* been evicted by time t_k . In continuous time, this is modeled with a survival function

$$S(t) = \exp\left(-\int_0^t \lambda(u) du\right),$$

where $\lambda(u)$ is the risk-neutral eviction hazard rate. Here, $\lambda(u)$ denotes the *risk-neutral* eviction intensity under the measure $\mathbb{Q}^s$, so $S(t)$ represents the risk-neutral survival probability that the contract has not been terminated by time t .

If $\tau_e < t_k$, i.e., eviction occurs prior to t_k , the payoff is zero. Consequently, the value

⁸This eviction risk is the counterparty risk involved in the transaction from the perspective of the seller.

formula in (9) becomes

$$C_{\text{with eviction}}(V_{0,i}) = \sup_{k \in \{t_1, \dots, t_\tau\}} \mathbb{E}^{\mathbb{Q}^s} \left[\mathbf{1}_{\{\tau_e > t_k\}} \cdot \frac{|V_{k,i} - K_k|^+}{B_k} \right]. \quad (12)$$

The net effect is a reduction in the expected payoff by the probability of early default.

To estimate this fair lease payment, we make the following simplifications. First, we assume that the REIT index satisfies a geometric Brownian motion, given by

$$dS_t = (\kappa_t - \delta) S_t dt + \sigma S_t dW(t),$$

where κ_t is a stochastic drift, $\delta \geq 0$ is the constant dividend yield, and $\sigma > 0$ is the REIT's constant volatility. Here, W is a standard Brownian motion under $\mathbb{P}$ with $W(0) = 0$, and W is $\mathbb{F}$ -adapted. Under the risk-neutral measure $\mathbb{Q}^s$, the evolution satisfies

$$dS_t = (r_t - \delta) S_t dt + \sigma S_t d\tilde{W}(t),$$

where $\tilde{W}$ is a standard Brownian motion under $\mathbb{Q}^s$. Second, to simplify the computation, as an approximation we assume that forward rates are constant over the life of the contract, so that $p(0, u) = p(t, t + u)$ and $f(0, u) = f(t, u)$, with $r_0 = f(0, 0) = r_t$ for all t .

Hence, the fair lease payment l_i accounting for eviction risk is given by

$$l_i = \frac{\sup_{k \in \{t_1, \dots, t_\tau\}} \mathbb{E}^{\mathbb{Q}^s} \left[|S_k - K_k^*|^+ e^{-r_0 k} \right] \times \mathbb{Q}^s(\tau_e > k)}{\sum_{u=t_1}^{k^*} p(0, u)},$$

where:

- $\mathbb{Q}^s(\tau_e > k) = \mathbb{E}^{\mathbb{Q}^s} \left[e^{-\int_0^k \lambda_s ds} \right]$ is the survival probability,
- $K_k^* = \frac{e^{\nu G_0} c_i \sum_{s=1}^T e^{-r_0 s} + K_k}{(1 - \varphi) \alpha e^{-\pi_0 T - \pi_1 \int_0^T f(0, u) du} + \varphi \alpha}$ (strike adjustment),

- $\alpha := \mu_T(a_{s,i}) e^{-\delta T} e^{\Theta_T X_{0,i}},$
- λ_s follows a Cox process (Section 3.1.2).

The strike must be adjusted because the underlying value $V_{k,i}$ already embeds the discounted value of future occupancy (rental) benefits. Using the contractual strike K_k alone would therefore double-count these cash flows in the option payoff. The adjusted strike K_k^* adds back the present value of the occupancy component so that the exercise payoff $|V_{k,i} - K_k^*|^+$ reflects only the incremental value of purchasing rather than renting at the exercise date t_k .

Including eviction risk in the calculation lowers the expected value of the embedded call to the seller, because there is a nonzero probability that the tenant’s default leads to contract termination before the option can be exercised. Thus, any up-front or monthly “option premium” in rent must be adjusted accordingly to reflect the likelihood of early termination.

5.1 Full-Sample Counterfactual Analysis

Rent-to-own (RTO) contracts offer potential homebuyers the opportunity to lease a property while holding an option to purchase it at a predetermined price within a specified timeframe, typically addressing affordability and credit-accessibility constraints. In this section we evaluate the economics of a standardized RTO contract as if it were available for every property in the Georgia housing market. This is explicitly a *counterfactual* exercise: in reality only a small share of properties participate in institutional RTO programs.

Within the CoreLogic MLS data, we identify approximately 926 properties that were acquired by institutional rent-to-own operators such as Home Partners of America (HPA). For the main results below, however, we apply the RTO contract valuation to the full sample of 415,411 properties as a benchmark. This allows us to ask how such contracts would perform if they were broadly available across heterogeneous properties and geographies, rather than limited to the relatively small set of observed institutional acquisitions.

This full-sample benchmark serves two purposes. First, it provides a normative yardstick by quantifying the distribution of option values, fair lease payments, and conversion incentives across properties with different characteristics and market conditions. Second, it offers a simulation platform for evaluating potential program expansion useful for policy-makers, housing nonprofits, and institutional investors.

5.1.1 Contract Structure and Pricing Methodology

The rent-to-own contracts are structured as 5-year arrangements with annual exercise opportunities. The strike prices escalate by 3% annually on a compound basis, such that the Year 5 strike price equals approximately 15.93% above the initial purchase value. The 3% annual escalation rate mirrors the contractual design of programs such as HPA and lies close to long-run nominal house price appreciation in many U.S. metropolitan areas. Mechanically, higher escalation rates make the option less likely to finish in the money, lowering the embedded option value and the fair lease premium, whereas lower escalation rates have the opposite effect. Thus, our baseline results should be interpreted as conditional on an institutionally realistic, “moderate” indexation schedule.

We compute the option value for each property using a binomial lattice framework that incorporates property-specific fundamentals and macroeconomic market conditions. While the rent-to-own contract is executed with a tenant rather than a mortgaged homeowner, we retain property values that reflect seller-side mortgage default and liquidation risk. This is because $V_{0,i}$ represents the market-clearing price an institutional owner would pay to acquire the home, accounting for illiquidity and possible resale under distress.

Tenant-side default (i.e., eviction) is modeled separately as an option knock-out hazard, so the Cox process for homeowner default affects only the underlying property value $V_{0,i}$, while the eviction hazard affects only the probability that the tenant survives to exercise the option. This two-tier structure ensures that our valuation reflects both market-wide ownership risk and contract-specific occupancy risk. This ensures the embedded option is

priced relative to already risk-adjusted valuations, avoiding double-counting the impact of tenant default. The inputs include a fixed REIT volatility of 21%. This volatility estimate corresponds to the annualized standard deviation of monthly total-return changes in the FTSE Nareit US Residential REIT Index over the 2007–2019 sample period, and the default intensity is governed by a Cox process with the recovery rate $\varphi = 0.5967$ (implying a 40% haircut). The lease payment is calculated to fairly amortize the embedded option value over the holding horizon.

The option value is computed for each property, representing the monetary worth of the tenant’s right to purchase at a predetermined strike price. Fair monthly lease payments are then derived by amortizing this option value over the expected contract duration, such that the contract is actuarially fair to both parties under risk-neutral pricing assumptions.

5.1.2 Economic Metrics Summary

Table 5 summarizes key financial metrics derived from the rent-to-own contract valuation, presented separately for the no-eviction benchmark (Panel A) and the scenario incorporating a 5% eviction probability (Panel B). The underlying sample includes 415,411 properties in both Panel A and Panel B.

Under the no-eviction assumption, the average option value embedded in the contract is \$38,762—roughly 13.43% of the property value—while the median monthly lease payment is \$567.52. This reflects the economic worth of deferring a purchase decision while retaining the flexibility to buy at a predetermined strike price. The amortized lease payments imply an annual yield of 4.50% relative to property value, indicating that tenants pay a modest premium for this optionality.

Because eviction risk reduces the probability that the tenant survives to exercise the purchase option, the expected option payoff declines. As a result, the actuarially fair lease payment—the payment that amortizes the embedded option value over the life of the contract—must also decrease when eviction risk is introduced. Intuitively, when the option is

less likely to be realized, the tenant does not need to pay as much through the lease stream to compensate the landlord for granting the option.

Once eviction risk is introduced (Panel B), both the option value and the monthly payment decrease: the average option value drops to \$35,103, and the median lease payment declines to \$460.05. This reduction is intuitive: eviction acts as a “knock-out” risk, cutting off a tenant’s ability to exercise the option if lease obligations are breached. Landlords must adjust pricing downward to compensate for the possibility that the contract terminates before the option matures. Consequently, the lease becomes cheaper, but the embedded optionality is diminished.

From a practical standpoint, this reduction in lease payments under eviction may seem beneficial for affordability, but it also reflects the contract’s weakened ability to build equity. In markets where tenants are budget-constrained, lower monthly payments may be attractive, but they come with a higher probability of the option becoming worthless. This is consistent with real-world RTO outcomes: tenants often prioritize near-term cash flow over long-term value realization, especially when job instability or medical costs increase the risk of eviction. Thus, even a modest hazard rate introduces an implicit trade-off between affordability and wealth-building potential.

The price-to-rent ratio, which reflects the number of years of rent required to match the property price, rises from 35.07 to 42.07 under eviction (see Figure 8). Formally, the price-to-rent ratio is defined as

$$\text{Price-to-Rent} = \frac{\text{Property Value}}{12 \times c_i},$$

where c_i is the imputed monthly rent. This increase occurs because eviction reduces expected lease income, making properties appear more expensive relative to rent. Importantly, the total cost difference between the rent-to-own contract and immediate purchase decreases from 7.67% to 4.70% (see Figure 9), suggesting that eviction risk reduces the premium

tenants pay, though at the cost of diminished option value and lower conversion probability.

From the landlord's perspective, the pricing shift under eviction reflects rational risk management. If a portion of tenants are expected to default before exercising, the landlord can afford to lower lease payments because they recover value through early termination and re-lease opportunities. In this sense, RTO contracts behave like hybrid rental instruments with embedded options, where the lease stream is the primary source of return and the purchase conversion is a lower-probability windfall. This dynamic is especially relevant in institutional portfolios, where scale and turnover efficiency mitigate the losses from occasional tenant walkaways or evictions.

These results highlight a key economic trade-off: the RTO contract creates real financial value through flexibility and time-delayed capital commitment, but its benefits are partially eroded by the risk of non-completion. When eviction is possible, tenants face a smaller expected payoff, and landlords must reprice accordingly. Moreover, these findings reveal a gap between the theoretical option value and the tenant's ability to benefit from it in practice. Even though the contract embeds substantial financial value, many tenants may not realize that value due to eviction, credit denial, or life shocks. This highlights the importance of thoughtful program design: unless RTO contracts are supported by stronger protections and accessibility mechanisms, they may deliver optionality without equity.

5.1.3 Conversion Strength and Exercise Timing

Figure 6 shows how eviction risk affects the optimal exercise timing across properties. Under the no-eviction scenario (Panel A), 287,466 properties (69.2%) remain unexercised (Year 0), with the remaining 30.8% exercising across different years: 9.5% in Year 1, 9.9% in Year 2, 1.4% in Year 3, and 10.0% at maturity (Year 5). When a 5% annual eviction probability is incorporated (Panel B), 341,277 (82.2%) remain unexercised, with 5.5% exercising in Year 1, 2.3% in Year 2, and 10.0% at Year 5. This reflects that eviction risk increases the share of never-exercised properties and reduces intermediate-year exercises.

In our model, tenants are permitted to exercise their purchase option at any time before contract maturity, reflecting the American-style nature of the rent-to-own agreement. The distribution of exercise years in Figure 6 primarily reflects which contracts become sufficiently in-the-money to warrant exercise at all. This pattern emerges from our standard parameters, including a modest 3% annual strike price growth.

To isolate the theoretical question of optimal exercise timing independent of in-the-money status, we conducted a specialized analysis of HPA contracts shown in Figure 1. Under the standard 3% annual strike growth, 88.9% of these contracts never become exercisable. However, when we artificially boost the strike growth rate to an extreme 26–29% annually to simulate a market boom, we observe a revealing pattern: those contracts that do become exercisable (11.1%) exercise only at Year 5, with none exercising in Years 1–4.

These results emerge endogenously from the option’s structure: as an American-style call on a cash flow-paying asset (opportunity cost = rental payments), its time value typically exceeds the cost of waiting when strike price growth is reasonably contained relative to interest rates.

That said, our model likely understates the real-world complexity of tenant decision-making. In practice, many tenants do not remain in the home for the full 5-year term. Programs like HPA report conversion rates below 20%, and many tenants exit early, whether voluntarily or due to eviction. This suggests that while Year 5 may be theoretically optimal for exercisable options, actual tenant behavior is influenced by credit constraints, income shocks, and timing risks that our model doesn’t fully capture.

5.1.4 Cost-Benefit and Price-to-Rent Comparison

Figures 8 and 9 provide complementary views on the financial implications of rent-to-own contracts. The price-to-rent ratio indicates how many years of rent would be needed to match the home’s value. Under the no-eviction benchmark, the median price-to-rent ratio is 35.07, rising to 42.07 when a 5% eviction risk is incorporated. This upward shift reflects a decline

in expected lease income: eviction truncates some lease streams, so even if property values stay the same, the present value of rent declines—making the price appear relatively higher.

The total cost difference metric compares the net present value of all payments under a rent-to-own contract to the cost of immediate purchase. The median cost difference decreases from 7.67% with no eviction to 4.70% with eviction, reflecting the lower lease payments required when eviction risk is present. Both distributions show a tall bar at 0%, indicating that approximately 69.2% (no eviction) and 82.2% (with eviction) of contracts are never exercised—so rent-to-own is cost-neutral versus purchase for these properties.

The distributions in both figures exhibit long right tails, indicating that some tenants face very high premiums for choosing rent-to-own. These cases often reflect properties with low rental yield or high option value relative to the strike price path. However, the persistence of a wide interquartile range also highlights how sensitive rent-to-own economics are to location-specific rent dynamics and property characteristics.

5.1.5 Interest Rate Sensitivity

Figure 7 illustrates how key contract metrics respond to changes in the risk-free interest rate and asset volatility under a 5% eviction assumption. Several important economic patterns emerge.

First, as interest rates rise, the value of the embedded purchase option increases—both in absolute terms and as a percentage of the property price. Panel A shows option value rising from about \$23,000 at 15% volatility to \$68,000 at 35%, while Panel C shows option value climbing from about \$40,000 at a 2% risk-free rate to \$53,700 at 6%. This may seem counterintuitive at first, since higher discount rates reduce the present value of future payoffs. However, in an American-style option framework, rising interest rates also reduce the present value of the strike price, effectively making it “cheaper” in discounted terms. This increases the relative attractiveness of waiting to exercise, thereby enhancing the option’s time value.

Second, lease payments increase with interest rates. For a given option value, higher

interest rates require steeper monthly amortization to fairly compensate the landlord. Panel B shows the implied annual yield rising from roughly 3.9% to 11.6% as volatility increases, while Panel D displays the implied yield versus the risk-free rate, rising from approximately 6.8% to 9.6%. This sharp sensitivity implies that RTO contracts may become substantially less affordable in high-rate environments—even if the option value itself is increasing.

Third, the asymmetry between tenant and landlord exposure becomes more pronounced as rates rise. Tenants face higher monthly obligations, which can increase financial strain and raise eviction risk. Landlords, meanwhile, face higher opportunity costs of capital, and thus demand higher lease payments to remain indifferent. In equilibrium, this creates pressure on contract viability: many tenants may be priced out before they can realize the option's upside.

This analysis underscores the sensitivity of rent-to-own contracts to macroeconomic conditions. Unlike a traditional mortgage where the rate is fixed, lease terms must adjust to keep the contract actuarially fair. In a rising-rate environment, landlords must charge more to cover the same economic exposure—potentially squeezing out the very households RTO programs are designed to serve. Conversely, in low-rate periods, RTO may offer particularly attractive entry paths into ownership, both for tenants and for landlords seeking to monetize appreciation.

5.2 Empirical Validation: Home Partners of America Contracts

We identified approximately 926 properties in the CoreLogic MLS data that were acquired by institutional rent-to-own operators, such as Home Partners of America (HPA). While the current analysis applies our valuation framework to the entire Georgia MLS dataset as a counterfactual, this identified subset enables a direct validation on observed rent-to-own transactions.

Table 6 presents a focused analysis of these 926 properties. Under the no-eviction scenario (Panel A), these HPA properties show higher average values: option value of

\$45,696 (13.06% of property value) compared to \$38,762 (13.43%) for the full sample, and monthly lease payments of \$1,245 versus \$1,030 for the broader market. The higher absolute values reflect the fact that HPA properties have higher average values (\$351,061 versus \$296,971).

When eviction risk is introduced (Panel B), HPA contracts follow similar patterns to the broader market: option values decrease to \$41,422 (11.83% of property value) and monthly lease payments drop to \$818. The price-to-rent ratio increases from 37.06 to 44.35, and the total cost difference decreases from 6.62% to 4.02%, consistent with the eviction risk reducing the premium tenants pay while also reducing option value.

These results suggest that institutional operators like HPA tend to select properties with higher values and potentially better risk-return characteristics, but the fundamental economics of eviction risk apply similarly across both institutional and broader market samples.

5.3 Policy and Contract Design Implications

Our findings carry important implications for the design of rent-to-own (RTO) contracts and their potential role in housing policy. First, the analysis highlights that RTO structures embed real economic value for tenants, but this value is highly contingent on contract completion. Eviction risk acts as a critical “knock-out” hazard: once triggered, the tenant forfeits all accumulated option value, sharply reducing both expected payoffs and conversion incentives (see Figures 6, 8, and 9). As our results show, even a modest eviction probability materially reduces the expected payoff, lease pricing, and conversion strength. Therefore, efforts to make RTO contracts more inclusive must begin by minimizing pre-exercise risk exposure. From an affordability perspective, these results imply that access to homeownership through rent-to-own contracts depends less on headline rent levels and more on contract features that preserve option value and reduce the likelihood of early termination.

Second, policy interventions could focus on strengthening the structural features that

promote successful conversion. These include grace periods for missed rent payments, clearer resolution processes for maintenance disputes, and credit support mechanisms to help tenants qualify for financing before the option expires. Flattening the strike price schedule or offering partial credit for lease payments toward purchase may also help align tenant incentives with conversion outcomes. Without such features, RTO contracts risk becoming high-cost rental products with limited ownership transition.

Third, the variability in cost-benefit outcomes across properties suggests that RTO should be viewed as a targeted, not universal, tool. Our model identifies a wide range of total cost differentials and price-to-rent ratios—some of which may be economically unattractive under standard contract terms. This heterogeneity calls for location-specific design, especially when public resources or affordable housing policy are involved. RTO contracts may be most effective when focused on transitional households—those with rising credit profiles, income volatility, or short-term liquidity constraints.

Finally, institutional experience underscores the need for more realistic modeling. In February 2025, Blackstone announced it would wind down Home Partners of America, citing persistently low conversion rates and high eviction-related turnover.⁹ This real-world outcome reinforces our emphasis on eviction as a core economic risk.

HPA's failure suggests a fundamental *valuation misalignment*: the embedded purchase option was theoretically valuable (approx. 13%), but the eviction barrier acted as a pricing friction that prevented tenants from realizing that value. Consequently, the provider bore the volatility risk and operational carry of the option structure without capturing the benefit of the exercise (conversion), leading to unsustainable churn.

To translate these findings into practical design guidance, our results point to several contract features that materially affect realized outcomes. First, although tenants optimally delay exercise until the final year in the model, real world attrition occurs much earlier. Introducing strike price discounts for early purchase, flattening escalation schedules, or

⁹<https://www.credaily.com/briefs/blackstone-shuts-down-home-partners-single-family-rental-arm/>

offering partial rent credits could encourage earlier exercise and reduce dropout. Second, because eviction eliminates all accumulated option value, even modest protections such as grace periods for late payments or hardship clauses can meaningfully improve survival rates and increase realized conversions.

Third, lease terms should be better aligned with mortgage readiness. Many tenants exit not because they lack intent to purchase, but because they fail to qualify for financing before the option expires. Contracts that integrate credit counseling, pre-qualification checkpoints, and rent-to-credit reporting may help bridge this final gap to ownership. Fourth, the economic value of the purchase right should be made transparent. Clear disclosure of the strike schedule, option mechanics, and the cost of flexibility can improve financial literacy and allow tenants to make more informed choices. Finally, rent-to-own programs are most effective when targeted to the right properties and households. Our results suggest focusing on homes with favorable price-to-rent ratios and tenants with upward financial trajectories, rather than applying a uniform contract structure across heterogeneous markets (see Figure 8 and Table 5).

Overall, these findings suggest that rent-to-own contracts can expand access to ownership for a subset of households when contract features preserve option value and limit early termination risk. By contrast, poorly designed contracts are unlikely to improve affordability and may instead amplify financial fragility through high attrition and low conversion.

6 Conclusion

This paper proposes a structural, no-arbitrage valuation framework for residential real estate and shows how it can be used to price rent-to-own (RTO) contracts. The framework is designed to complement, rather than replace, hedonic and machine-learning AVMs: given property-level characteristics and imputed rents, it provides a theoretically coherent mapping from house values to derivative-style contract prices. By modeling the purchase right as

an American-style call on a default-adjusted house value and treating eviction as a knock-out hazard, we quantify the embedded economic value of RTO structures and the trade-offs they pose for tenants and landlords.

Beyond its application to RTO, the model represents a broader advancement in residential real estate (RRE) valuation. It captures nonlinear pricing dynamics by integrating property-specific characteristics with macroeconomic drivers, including a REIT-based index and the term structure of interest rates. By embedding stochastic default risk through a Cox process and incorporating a liquidation discount, the framework can be used to value both individual properties and real options on real estate, making it useful for distressed asset analysis, portfolio risk modeling, and policy simulations.

Empirically, we apply the model to a large sample of Georgia MLS properties. We find that the average embedded option value exceeds \$38,762 (13.43% of property value), and that tenants consistently benefit from deferring exercise to Year 5, an outcome that emerges endogenously from the economic structure, not from contractual restrictions. Once eviction risk is introduced, even at modest levels, option values fall, lease payments decline, and fewer contracts offer strong conversion incentives. These results show that the flexibility RTO contracts provide is structurally valuable but vulnerable to tenant instability.

We also test the model on a subsample of 926 properties acquired by Home Partners of America (HPA), providing an empirical application to an actual institutional RTO portfolio. HPA-selected homes exhibit higher average values, lease payments, and option premia than the full sample, but respond similarly to eviction risk, suggesting that the model's mechanisms generalize across institutional and broader market segments.

These findings help explain the gap between theoretical and real-world outcomes. In our model, tenants are assumed to remain in the lease through Year 5 unless evicted; non-evicted tenants can purchase at any time and optimally delay exercise to maturity, while some may rationally choose not to exercise if the option is out-of-the-money at expiration. In reality, voluntary early exits, credit denials, liquidity shocks, and other frictions can lead

tenants to exit before maturity or fail to close despite having a valuable option. Programs like HPA's Choice Lease, which reportedly experienced low conversion rates and high turnover before being discontinued in 2025,¹⁰ offer a clear illustration. Our model highlights one consistent mechanism: eviction and early exit risk act as a barrier that destroys option value for tenants, while leaving the provider exposed to asset volatility and operational risk.

The broader policy implication is that RTO contracts can expand access to ownership only if tenant continuity is protected. Flattened strike prices, eviction grace periods, partial rent credits, and supportive features like financial coaching can help preserve option value for tenants and boost conversion rates. At scale, our model supports AVMs, scenario analysis, and stress testing for investors and agencies, providing a foundation for next-generation RRE valuation tools.

Our results reveal both the promise and pitfalls of structured housing contracts. Well-structured RTO programs have the potential to bridge gaps in housing affordability by enabling renters without mortgage eligibility to build wealth and pursue homeownership. However, eviction risk and aggressive strike price schedules can severely reduce the actual economic benefit for tenants. These findings suggest that policymakers and housing organizations should focus on safer, more equitable RTO designs that truly promote affordability and social mobility, especially for underserved renters.

Several limitations suggest directions for future research. Our implementation relies on a reduced form eviction hazard, a parsimonious rent imputation algorithm, and ZIP code fixed effects, and does not explicitly model borrower balance sheets or lender behavior. Integrating neighborhood level risk factors such as school quality, climate exposure, or gentrification trajectories, and linking MLS transactions to mortgage and credit data, would expand the model's ability to simulate equity building outcomes across diverse geographies and populations.

In conclusion, our framework offers a rigorous and extensible foundation for valu-

¹⁰See, for example, <https://www.credaily.com/briefs/blackstone-shuts-down-home-partners-single-family-rental-arm/>.

ing RTO and other hybrid real estate contracts, with strong relevance to housing policy, institutional finance, and household welfare. By tying a traded REIT-based pricing kernel to heterogeneous, illiquid properties and to contract-level default and eviction risk, the model provides a practical toolkit for designing and evaluating housing contracts in today's evolving residential real estate landscape.

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Online Appendix: Model Details

Roadmap. This appendix collects the formal market setup and proofs underlying the pricing relationships in Section 3. Section A1 constructs the REIT–bond submarket and shows how restricted-market completeness delivers the valuation formula for traded payoffs in equation (1). Section A2 applies Jarrow (2023) to decompose non-traded residential real estate (RRE) payoffs into replicable and idiosyncratic components, yielding the pricing equation for non-traded assets and derivatives in equations (2)–(4). Section A3 derives the closed-form expression for RRE values without default risk in equation (5) under Assumptions 1–2. Section A4 introduces the Cox default intensity and provides the derivation of the default-adjusted valuation formula (6).

A1 Market structure and restricted completeness

We work on a complete filtered probability space $(\Omega, \mathcal{F}, \mathbb{P} := (\mathcal{F}_t)_{t \in [0, T]}, \mathbb{P})$ satisfying the usual conditions, with $\mathcal{F} = \mathcal{F}_T$ and $\mathbb{P}$ the statistical (physical) probability measure.

Traded in the market over $[0, T]$ are a residential REIT index, an entire term structure of default-free zero-coupon bonds, and a collection of RREs indexed by $i = 1, \dots, I$. The markets for the REIT, bonds, and RREs are assumed to be *competitive* and *frictionless*. Competitive means that traders act as price takers; frictionless means there are no transaction costs or trading constraints. The REIT and bonds are assumed to trade continuously, while RREs trade only sporadically.

Let S_t denote the REIT’s time- t market price, assumed to be an $\mathbb{P}$ -adapted semimartingale. In our empirical implementation, S_t corresponds to the FTSE Nareit US Residential REIT Index, which provides liquid exposure to systematic returns in the multifamily and residential housing sectors. The REIT pays dividends, which without loss of generality are assumed to be continuously reinvested in the index (see Jarrow (2021)). The cumulative

gains process (REIT price plus accumulated dividends) is $S_t^* := S_t e^{\delta t}$, where $\delta \geq 0$ is the constant dividend yield per unit time.

We denote the time- t value of a default-free zero-coupon bond maturing at T by $p(t, T)$ for $0 \leq t \leq T \leq \mathbb{T}$, and assume $p(t, T) > 0$ and $\mathbb{F}$ -adapted for all $T \in [0, \mathbb{T}]$. The money-market account is

$$B_t = e^{\int_0^t r_s ds},$$

where r_s is the default-free spot rate of interest, assumed $\mathbb{F}$ -adapted.

Let $\mathbb{F}^s = (\mathcal{F}_t^s)_{0 \leq t \leq \mathbb{T}}$ denote the filtration generated by $(S_t, p(t, T))$ for all $T \in [0, \mathbb{T}]$. We assume $\mathbb{F}^s \subset \mathbb{F}$ and $\mathbb{F}^s \neq \mathbb{F}$, so that residential properties contain additional randomness not spanned by the REIT and bonds.

Let $V_{t,i}$ be the time- t value of the i^{th} RRE, and let $\mathbb{F}^\xi = (\mathcal{F}_t^\xi)_{0 \leq t \leq \mathbb{T}}$ be the filtration generated by $\{V_{t,i} : i = 1, \dots, I\}$. This filtration captures randomness in RREs that is orthogonal to $\mathbb{F}^s$. We assume that the overall filtration factorizes as $\mathbb{F} = \mathbb{F}^\xi \vee \mathbb{F}^s$.

We impose absence of arbitrage (NFLVR) and no dominance for the joint market of REIT, bonds, and RREs (see [Jarrow \(2021\)](#)). By the first fundamental theorem of asset pricing, there exists at least one equivalent martingale measure $\mathbb{Q}$ on $(\Omega, \mathcal{F})$ such that the discounted price processes

$$\frac{S_t^*}{B_t}, \quad \frac{p(t, T)}{B_t} \text{ for all } T \in [0, \mathbb{T}], \quad \frac{V_{t,i}}{B_t} \text{ for all } i$$

are $\mathbb{Q}$ -martingales with respect to $\mathbb{F}$.

Because RREs trade only sporadically and $\mathbb{F}^s \neq \mathbb{F}$, the full market is incomplete and the martingale measure $\mathbb{Q}$ is not unique. However, we assume that the *restricted* market consisting only of the REIT and default-free bonds is complete with respect to the traded information $\mathbb{F}^s$.

Assumption (Restricted-market completeness). The market consisting only of the REIT and default-free bonds is complete with respect to $\mathbb{F}^s$. Formally, for any time $T \in [0, \mathbb{T}]$ and

any $\mathcal{F}_T^s$ -measurable payoff X_T that is integrable under an equivalent martingale measure, there exists an admissible self-financing trading strategy using only the REIT and bonds that replicates X_T , whose value process is a martingale with respect to the martingale measure.

Under this assumption, the restricted market admits a unique martingale measure $\mathbb{Q}^s$, which coincides with the restriction of any global martingale measure $\mathbb{Q}$ to the traded-information σ -field $\mathcal{F}_T^s$: $\mathbb{Q}^s := \mathbb{Q} |_{\mathcal{F}_T^s}$. By the second fundamental theorem of asset pricing, the time- t value of any $\mathcal{F}_T^s$ -measurable payoff X_T is then uniquely given by equation (1), which we repeat here for convenience:

$$X_t = \mathbb{E}^{\mathbb{Q}^s} \left(\frac{X_T}{B_T} \middle| \mathcal{F}_t \right) B_t.$$

This restricted completeness mirrors public-private firm valuation, where completeness within the traded market enables identification of replicable risk components even when the illiquid asset itself does not trade continuously.

A2 Non-traded RRE pricing and derivatives

We now apply [Jarrow \(2023\)](#) to the non-traded RRE. Consider the $\mathcal{F}_T$ -measurable payoff $V_{T,i}$ of the i^{th} RRE at horizon T . Decompose it as in equation (2):

$$V_{T,i} = \underbrace{\mathbb{E}^{\mathbb{P}}[V_{T,i} | \mathcal{F}_T^s]}_{\text{replicable component}} + \underbrace{(V_{T,i} - \mathbb{E}^{\mathbb{P}}[V_{T,i} | \mathcal{F}_T^s])}_{\text{hedging error}}.$$

The first term is $\mathcal{F}_T^s$ -measurable and, by restricted-market completeness, can be replicated using REITs and bonds and valued according to equation (1). The second term represents the (unspanned) hedging error. We assume that this hedging error is idiosyncratic risk which, by definition, is not priced for systematic risk and carries zero value under any equivalent martingale measure that agrees with $\mathbb{Q}^s$ on the traded filtration.

Under this assumption, [Jarow \(2023\)](#) shows that the time- t arbitrage-free value for the i^{th} RRE satisfies equation (3):

$$V_{t,i} = \mathbb{E}^{\mathbb{Q}^s} \left(\mathbb{E}^{\mathbb{P}} \left(\frac{V_{T,i}}{B_T} \middle| \mathcal{F}_T^s \right) \middle| \mathcal{F}_t \right) B_t.$$

Similarly, for any Borel-measurable and integrable payoff $g(V_{\tau,i})$ at $\tau \in [t, T]$, the derivative value C_t is given by equation (4):

$$C_t = \mathbb{E}^{\mathbb{Q}^s} \left(\mathbb{E}^{\mathbb{P}} \left(\frac{g(V_{\tau,i})}{B_{\tau}} \middle| \mathcal{F}_{\tau}^s \right) \middle| \mathcal{F}_t \right) B_t.$$

These expressions are the starting point for the parametric specification used in the empirical analysis.

A3 Derivation of the valuation formula without default

This section provides the short derivation of expression (5) under Assumptions 1–2.

Fix a selling horizon T for the i^{th} RRE and assume the cash-flow and terminal-value specifications in Assumptions 1–2. Using Assumption 1, we write the terminal selling value as

$$V_{t+T,i} = a_{s,i} S_{t+T} \mu_T e^{\Theta_T \cdot X_{0,i}}, \quad a_{s,i} := \frac{V_{s,i}^{\text{comp}}}{S_s}.$$

Using Assumption 2, the conditional expected cash flows satisfy

$$\mathbb{E}^{\mathbb{P}}(c_{t,i} | \mathcal{F}_t^s) = e^{\nu \cdot G_0} c_i \quad \text{for } t = 1, \dots, T.$$

Applying (3) with these specifications, and using the facts that the cumulative-dividend

process $S_t^* = S_t e^{\delta t}$ and the discounted bond prices are $\mathbb{Q}^s$ -martingales, we obtain

$$\begin{aligned} V_{t,i} &= \mathbb{E}^{\mathbb{Q}^s} \left(\mathbb{E}^{\mathbb{P}} \left(a_{s,i} \frac{S_{t+T}}{B_{t+T}} \mu_T e^{\Theta_T \cdot X_{0,i}} \middle| \mathcal{F}_{t+T}^s \right) \middle| \mathcal{F}_t \right) B_t \\ &\quad + \mathbb{E}^{\mathbb{Q}^s} \left(\sum_{k=1}^T \frac{e^{v \cdot G_0} c_i}{B_{t+k}} \middle| \mathcal{F}_t \right) B_t. \end{aligned}$$

By $\mathbb{Q}^s$ -martingale pricing, this simplifies to

$$V_{t,i} = a_{s,i} S_t e^{-\delta T} \mu_T e^{\Theta_T \cdot X_{0,i}} + e^{v \cdot G_0} c_i \sum_{k=1}^T p(t, t+k),$$

which is exactly expression (5) in the main text.

A4 Homeowner default and derivation of equation (6)

We now provide the formal Cox-process setup and derivation leading to the default-adjusted valuation formula (6).

Let $\Gamma_t = (\Gamma_1(t), \dots, \Gamma_n(t))' \in \mathbb{R}^n$ be a collection of state variables describing the property and macroeconomic environment at time t , and let $\mathbb{F}^\Gamma = (\mathcal{F}_t^\Gamma)_{0 \leq t \leq T}$ be the filtration they generate. We assume $\mathcal{F}_t^\Gamma \subset \mathcal{F}_t^s$ and that S_t and B_t are included in Γ_t .

Let $\tilde{\phi} : [0, T] \times \mathbb{R}^n \rightarrow [0, \infty)$ be a measurable function and define the (physical) intensity process $\tilde{\phi}_t = \tilde{\phi}_t(\Gamma_t) \geq 0$ with $\int_0^T \tilde{\phi}_t(\Gamma_t) dt < \infty$ almost surely. Let $N_{t,i} \in \{0, 1, 2, \dots\}$ with $N_{0,i} = 0$ be a Cox process conditional on $\mathcal{F}_T^\Gamma$ with intensity $\tilde{\phi}_t(\Gamma_t)$. This intensity represents the i^{th} homeowner's default intensity; since we do not observe borrower characteristics, we assume it does not depend on i .

The default time $\tau_i \in [0, T]$ is defined as the stopping time

$$\tau_i \equiv \inf \{t > 0 : N_{t,i} = 1\}.$$

Conditional on the information generated by Γ_t over $[0, T]$, the Cox process behaves like a standard Poisson process, so in particular

$$\mathbb{P}(\tau_i > T | \mathcal{F}_T^\Gamma \vee \mathcal{F}_t) = e^{-\int_t^T \tilde{\phi}_u du}$$

and

$$\mathbb{P}(\tau_i > T | \mathcal{F}_t) = \mathbb{E}^\mathbb{P} \left[e^{-\int_t^T \tilde{\phi}_u du} | \mathcal{F}_t \right].$$

Under an equivalent martingale measure $\mathbb{Q}$, we define the risk-neutral intensity ϕ_t via $\phi_t = \tilde{\phi}_t \kappa_t$, where $\kappa_t(\omega) \geq 0$ is a predictable process such that $\int_0^T \phi_t(\Gamma_t) \kappa_t dt < \infty$ almost surely. The process κ_t represents a default jump risk premium. As in the main text, we impose Assumption 3,

$$\phi_u = \pi_0 + \pi_1 f(t, u), \quad t \leq u \leq t + T,$$

so that the intensity is affine in the forward rate curve.

If default has not occurred by time T , the property sells at the full, non-distressed selling value $a_{s,i} S_T e^{\xi_{T,i}}$, where $\xi_{T,i} = \ln(\mu_T e^{\Theta_T X_{0,i}})$. If the owner has defaulted by T , the property is sold at the recovery value $\varphi a_{s,i} S_T e^{\xi_{T,i}}$. Thus the terminal payoff is

$$V_{T,i} = 1_{\{\tau_i > T\}} a_{s,i} S_T e^{\xi_{T,i}} + \varphi 1_{\{\tau_i \leq T\}} a_{s,i} S_T e^{\xi_{T,i}}.$$

Including cash flows, the arbitrage-free value of the RRE at time t is

$$\begin{aligned} V_{t,i} = & \mathbb{E}^{\mathbb{Q}^s} \left(\frac{\mathbb{E}^\mathbb{P} \left(1_{\{\tau_i > t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}} | \mathcal{F}_{t+T}^s \right)}{B_{t+T}} | \mathcal{F}_t \right) B_t \\ & + \varphi \mathbb{E}^{\mathbb{Q}^s} \left(\frac{\mathbb{E}^\mathbb{P} \left(1_{\{\tau_i \leq t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}} | \mathcal{F}_{t+T}^s \right)}{B_{t+T}} | \mathcal{F}_t \right) B_t \\ & + \mathbb{E}^{\mathbb{Q}^s} \left(\sum_{k=1}^T \frac{c_i}{B_{t+k}} | \mathcal{F}_t \right) B_t. \end{aligned}$$

For simplicity we assume that default does not affect the present value of the cash flows from the RRE, which is a reasonable approximation in our setting.

Under the maintained assumptions we can simplify the first expectation as follows. Using measurability and conditioning first on $\mathcal{F}_T^\Gamma \vee \mathcal{F}_t$, we have

$$\begin{aligned}
& \mathbb{E}^{\mathbb{Q}^s} \left(\frac{\mathbb{E}^{\mathbb{P}} \left(1_{\{\tau_i > t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}} \middle| \mathcal{F}_{t+T}^s \right)}{B_{t+T}} \middle| \mathcal{F}_t \right) B_t \\
&= \mathbb{E}^{\mathbb{Q}^s} \left(\frac{1_{\{\tau_i > t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}}}{B_{t+T}} \middle| \mathcal{F}_t \right) B_t \\
&= \mathbb{E}^{\mathbb{Q}^s} \left(\mathbb{E}^{\mathbb{Q}^s} \left(\frac{1_{\{\tau_i > t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}}}{B_{t+T}} \middle| \mathcal{F}_T^\Gamma \vee \mathcal{F}_t \right) \middle| \mathcal{F}_t \right) B_t \\
&= \mathbb{E}^{\mathbb{Q}^s} \left(\frac{a_{s,i} S_{t+T} e^{\xi_{t+T,i}}}{B_{t+T}} \mathbb{E}^{\mathbb{Q}^s} \left(1_{\{\tau_i > t+T\}} \middle| \mathcal{F}_T^\Gamma \right) \middle| \mathcal{F}_t \right) B_t \\
&= \mathbb{E}^{\mathbb{Q}^s} \left(\frac{a_{s,i} S_{t+T} e^{\xi_{t+T,i}}}{B_{t+T}} e^{-\int_t^{t+T} \phi_u du} \middle| \mathcal{F}_t \right) B_t.
\end{aligned}$$

With deterministic intensity given by Assumption 3, the survival factor can be taken outside the inner expectation, yielding

$$\mathbb{E}^{\mathbb{Q}^s} \left(\frac{a_{s,i} S_{t+T} e^{\xi_{t+T,i}}}{B_{t+T}} \middle| \mathcal{F}_t \right) B_t e^{-\int_t^{t+T} \phi_u du}.$$

Using the same martingale arguments as in Section A3, this equals

$$a_{s,i} S_t e^{-\delta T} \mu_T e^{\Theta_T \cdot X_{0,i}} e^{-\pi_0 T - \pi_1 \int_t^{t+T} f(t,u) du}.$$

Next, note that $1 - 1_{\{\tau_i > t+T\}} = 1_{\{\tau_i \leq t+T\}}$, so

$$\begin{aligned} & \mathbb{E}^{\mathbb{Q}^s} \left(\frac{\mathbb{E}^{\mathbb{P}} \left(1_{\{\tau_i \leq t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}} \mid \mathcal{F}_{t+T}^s \right)}{B_{t+T}} \mid \mathcal{F}_t \right) B_t \\ &= \mathbb{E}^{\mathbb{Q}^s} \left(\frac{\mathbb{E}^{\mathbb{P}} \left(a_{s,i} S_{t+T} e^{\xi_{t+T,i}} \mid \mathcal{F}_{t+T}^s \right)}{B_{t+T}} \mid \mathcal{F}_t \right) B_t \\ &\quad - \mathbb{E}^{\mathbb{Q}^s} \left(\frac{\mathbb{E}^{\mathbb{P}} \left(1_{\{\tau_i > t+T\}} a_{s,i} S_{t+T} e^{\xi_{t+T,i}} \mid \mathcal{F}_{t+T}^s \right)}{B_{t+T}} \mid \mathcal{F}_t \right) B_t. \end{aligned}$$

The first expectation on the right-hand side equals $a_{s,i} S_t e^{-\delta T} \mu_T e^{\Theta_T \cdot X_{0,i}}$ by the same argument as in the no-default case. Combining the pieces and multiplying by the recovery rate φ yields the second line of equation (6). Adding the cash-flow component from Assumption 2 then completes the derivation of expression (6) in the main text.

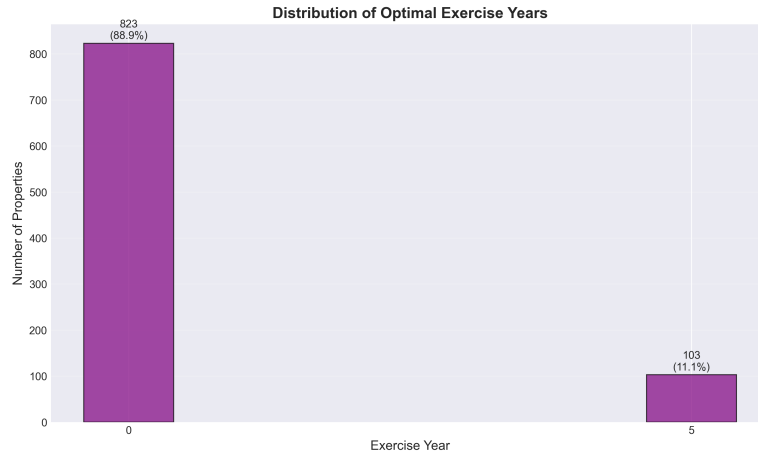


Figure 1: Distribution of Optimal Exercise Years for HPA-Only Contracts

Note: This histogram shows optimal exercise timing for HPA-only contracts under an inflated strike-growth assumption. In all other figures, we escalate the strike at a standard 3 % annual home-price appreciation—under that baseline, 823 contracts (88.9 %) never become in-the-money within five years (Year 0). Here, to isolate the small subset that would optimally defer exercise, we boost the strike's growth rate to an extreme 26–29 % per annum—simulating a market boom—which results in 103 contracts (11.1 %) exercising only at Year 5.

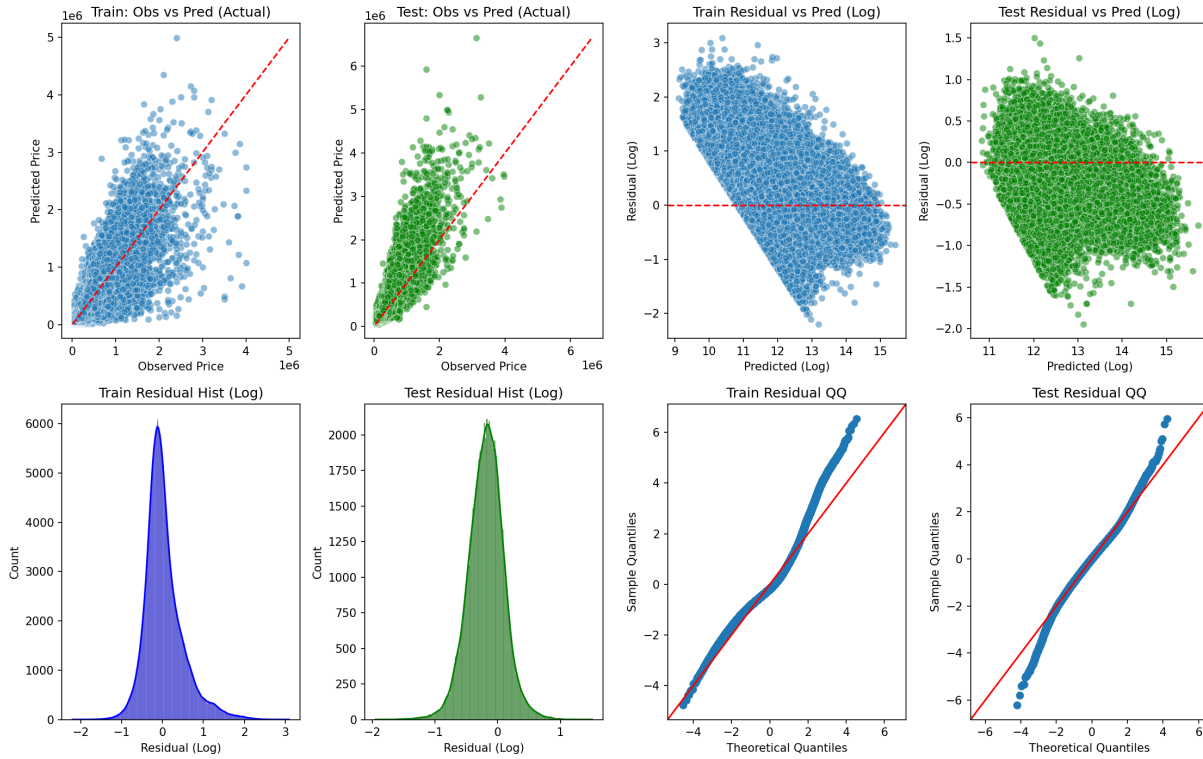


Figure 2: Diagnostic Plots

Note: This figure illustrates the diagnostic plots for the model, comparing observed versus predicted values, residuals, and their distributions for both the in-sample (training) and out-of-sample (testing) sets. The dataset was split based on time, with the training set covering the period from January 16, 2007 to March 30, 2018 (335145 rows), and the testing set covering March 30, 2018 to December 30, 2019 (83643 rows). A minimum of 30 transactions per ZIP code was required in both the training and testing sets, resulting in 139 ZIPs meeting this threshold. Model performance metrics are reported as RMSE (123,957.91 for in-sample vs. 200,477.00 for out-of-sample), R^2 (0.6431 vs. 0.2331), and MAPE (32.70% vs. 32.42%). The diagnostic plots include scatter plots of observed versus predicted values, residual plots, histograms of residuals, and QQ plots to assess the normality of residuals. These plots provide insights into the model's accuracy, bias, and residual distribution, ensuring that the model performs well across different price ranges and market conditions, both in-sample and out-of-sample.

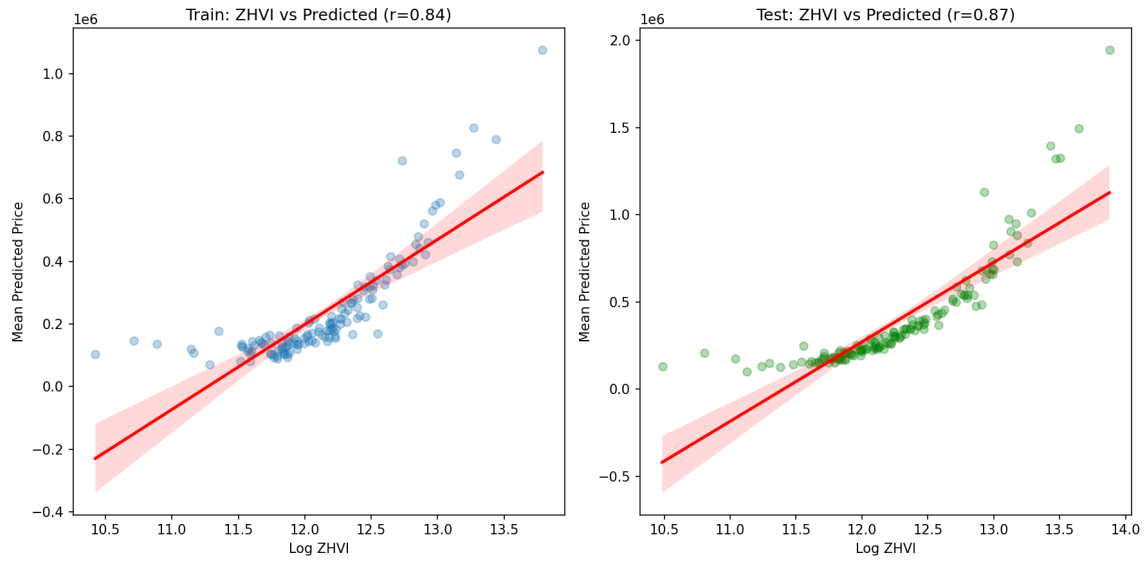


Figure 3: Zillow House Price vs Mean Model Predicted Prices in Zip code

Note: Scatter plots comparing log(ZHVI) on the x-axis against the model's mean predicted price on the y-axis, for the training set (left) and testing set (right). The model's predictions align closely with ZHVI in both phases, reflected by strong correlations of 0.84 (training) and 0.87 (testing).

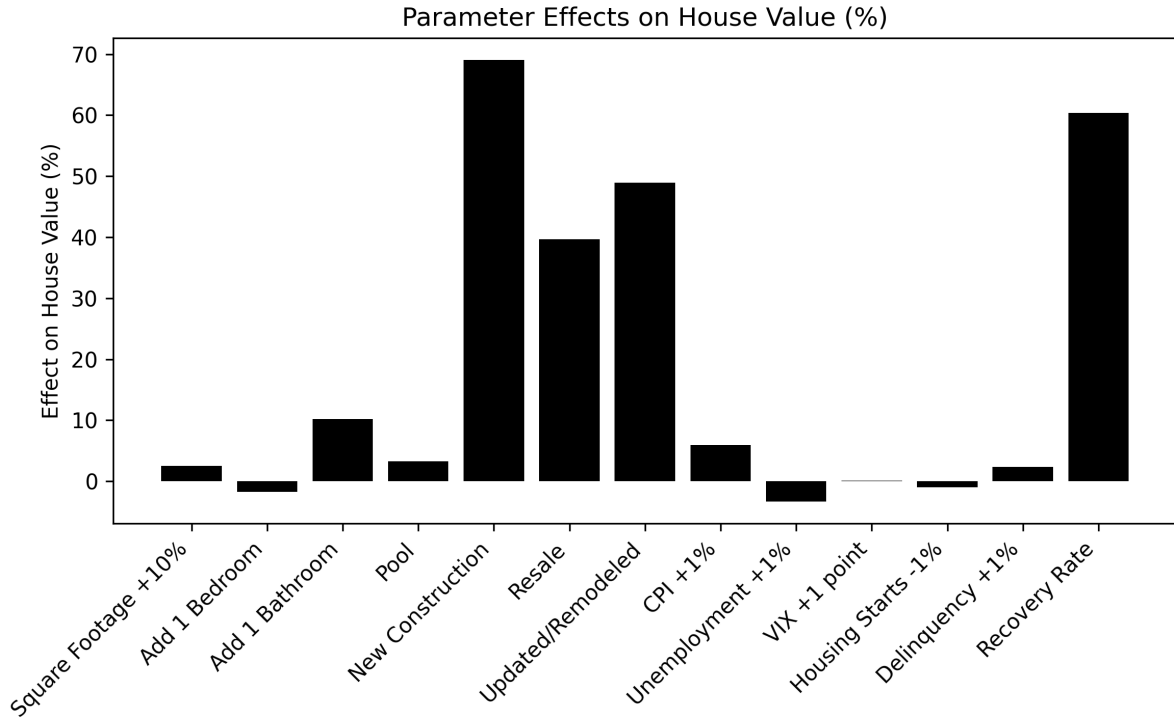
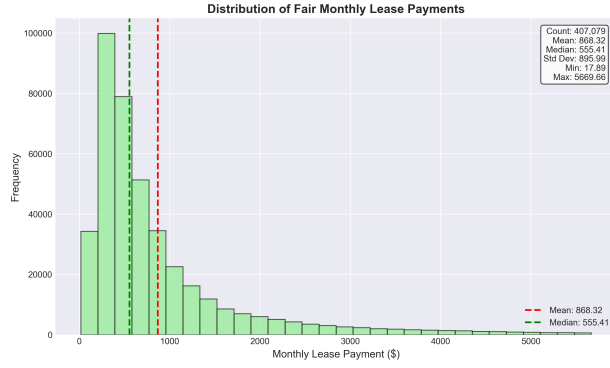
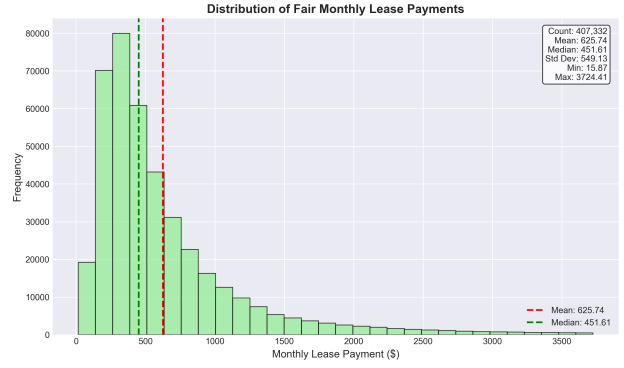


Figure 4: Parameter Effects on House Value (%)

Note: This figure illustrates the percentage effects of various property characteristics and macroeconomic factors on house values based on the full model estimates in Table 2. The effects for continuous variables (Square Footage, CPI, Unemployment, VIX, Housing Starts, Delinquency) represent the impact of a 1% increase, while effects for discrete variables (Bedrooms, Bathrooms, Pool, property conditions) represent the impact of adding one unit or the presence of the feature. The Recovery Rate shows the effect of the recovery parameter φ (haircut $1 - \varphi$) on property values. New Construction, Updated/Remodeled properties, and Resale homes show substantial premiums compared to the baseline Fixer Upper category, while macroeconomic factors demonstrate varying levels of influence on housing values.



(a) Panel A: No Eviction



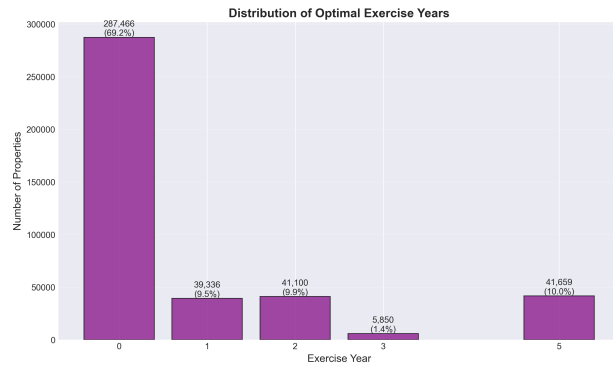
(b) Panel B: With Eviction Risk

Figure 5: Distribution of Fair Monthly Lease Payments

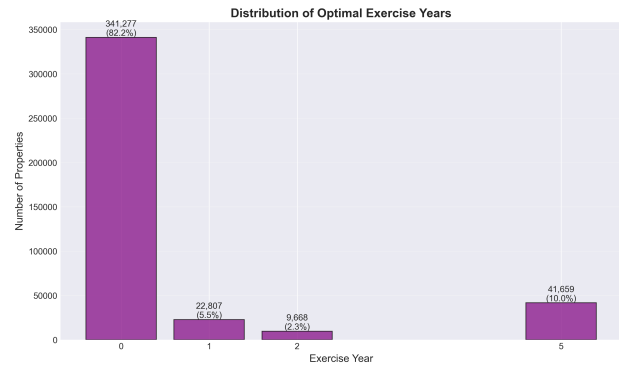
Panel A (No Eviction): $N = 407,079$; mean = \$868.32; median = \$555.41; SD = \$895.99; min = \$17.89; max = \$5,669.66.

Panel B (5% annual eviction risk): $N = 407,332$; mean = \$625.74; median = \$451.61; SD = \$549.13; min = \$15.87; max = \$3,724.41.

Notes: Introducing eviction risk shifts the distribution downward—both the average and the median fair lease fall, and the right tail is truncated relative to the no-eviction case. These patterns match the summary statistics in Table 5 (median falls from about \$568 $\rightarrow$ \$460 when a 5% annual eviction hazard is assumed). Figure 5 shows that introducing a 5% *annual* eviction hazard shifts the entire distribution of fair monthly lease payments *downward*. Both the mean and the median fall (median $\approx$ \$568 $\rightarrow$ \$460; see Table 5), and the right tail becomes noticeably thinner. Intuitively, eviction reduces the expected option payoff, so the actuarially fair lease that amortizes that option must also be lower.



(a) Panel A: No Eviction



(b) Panel B: With Eviction Risk

Figure 6: Distribution of Optimal Exercise Years

Note: "Year 0" indicates properties that are never exercised over the five-year option window. In Panel A (no eviction risk, N=415,411), 287,466 properties (69.2 %) remain unexercised (Year 0), 39,336 (9.5 %) exercise in Year 1, 41,100 (9.9 %) in Year 2, 5,850 (1.4 %) in Year 3, and 41,659 (10.0 %) at maturity (Year 5). In Panel B (5 % annual eviction risk, N=415,411), 341,277 (82.2 %) remain unexercised, 22,807 (5.5 %) at Year 1, 9,668 (2.3 %) at Year 2, and 41,659 (10.0 %) at Year 5. Introducing eviction risk increases the share of never-exercised properties and reduces intermediate-year exercises, while the proportion exercising at maturity remains constant.

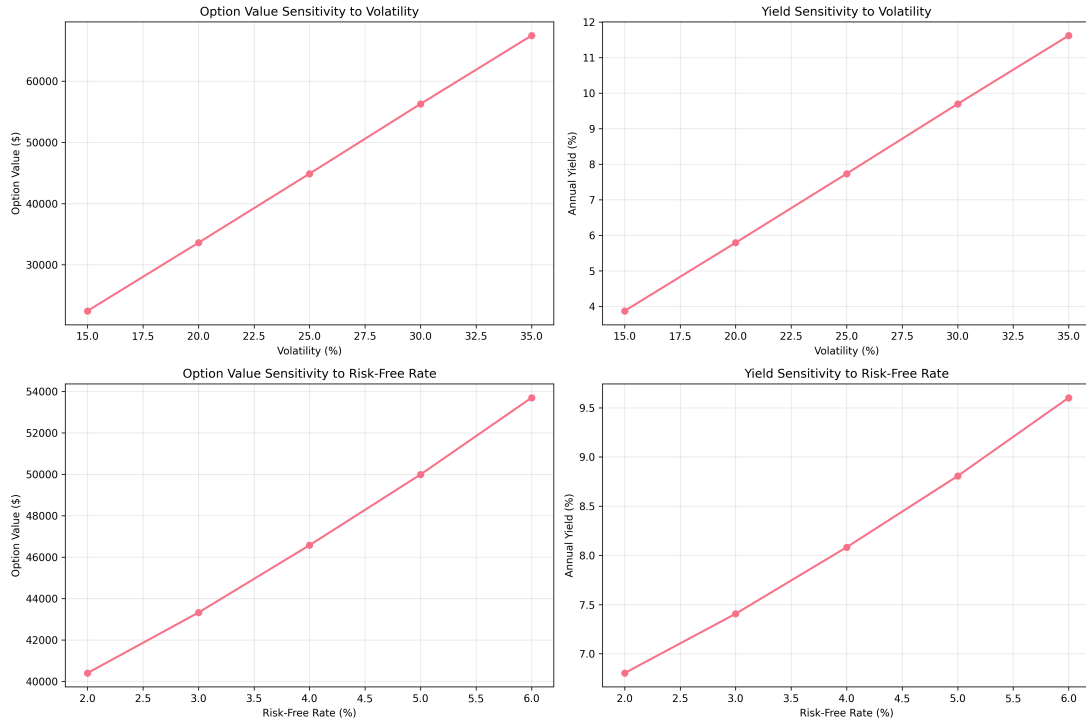
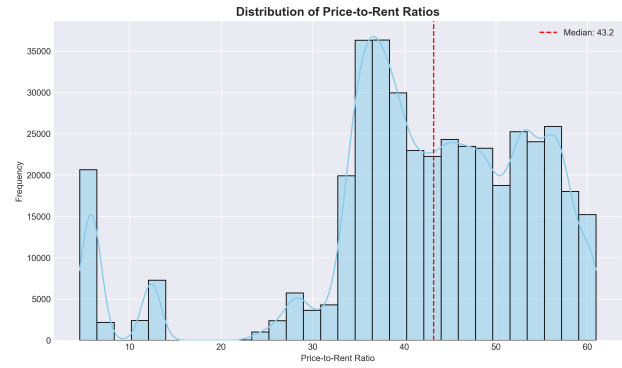


Figure 7: rent-to-own Option Sensitivity Analysis (with 5% Eviction Risk)

Note: All panels assume a 5% annual eviction probability. Panel A (top-left) shows option value rising from about \$23,000 at 15% volatility to \$68,000 at 35%, reflecting greater upside optionality under higher price uncertainty. Panel B (top-right) plots the implied annual yield versus volatility, increasing from roughly 3.9% to 11.6% over the same range. Panel C (bottom-left) shows option value climbing from about \$40,000 at a 2% risk-free rate to \$53,700 at 6%, as higher discount rates raise the present value of the lease-to-buy option. Panel D (bottom-right) displays the implied yield versus the risk-free rate, rising from approximately 6.8% to 9.6%. Together, these panels demonstrate that under eviction risk, both higher volatility and higher interest rates boost the option's value and the required lease yield.



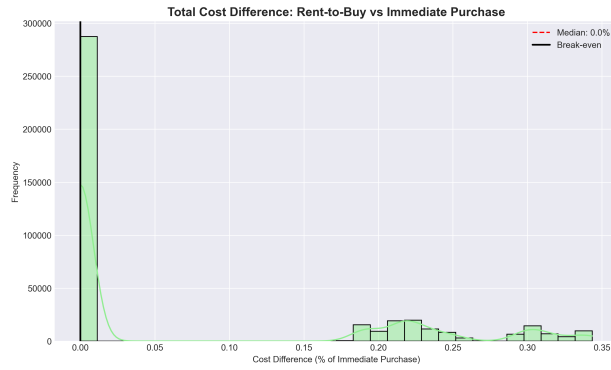
(a) Panel A: No Eviction



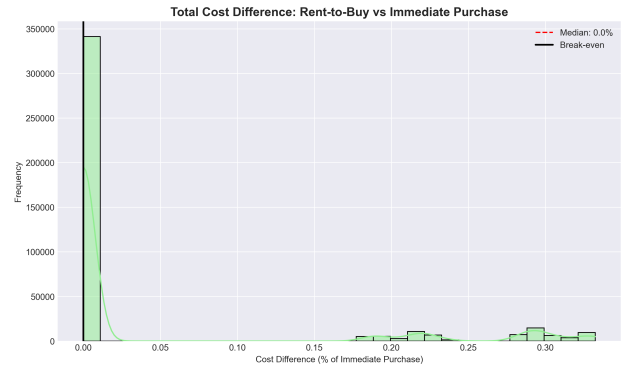
(b) Panel B: With 5% Eviction Risk

Figure 8: Distribution of Price-to-Rent Ratios

*Note: Panel A plots the histogram (with density curve) of price-to-rent ratios assuming tenants never face eviction ($N = 407,332$; median = 38.43). Panel B shows the distribution when a 5% annual eviction risk is imposed ($N = 407,079$; median = 43.19). Each vertical dashed line marks the panel's median. Both distributions are right-skewed, indicating substantial heterogeneity in rental yields. Introducing eviction risk **raises** the median price-to-rent ratio, because eviction reduces expected lease income; as a result, properties appear more expensive relative to rent, making renting relatively more attractive than buying.*



(a) Panel A: No Eviction



(b) Panel B: With 5% Eviction Risk

Figure 9: Total Cost Difference: Rent-to-Buy vs. Immediate Purchase

*Note: Panel A plots the distribution of total cost differences (as a percentage of purchase price) when tenants never face eviction ($N = 415,411$). The tall bar at 0% indicates that 69.2% of contracts are never exercised, making rent-to-own cost-neutral relative to immediate purchase. Panel B shows the distribution when a 5% annual eviction risk is introduced ($N = 415,411$). In this case, the spike at 0% becomes even larger (82.2%), because more tenants lose the option before maturity and therefore never incur an exercise-related premium. Among exercised contracts, the right tail remains, but represents a smaller share of the overall distribution. Overall, eviction risk **increases** the mass at zero and **reduces** the expected cost differential between rent-to-own and purchase.*

Table 1: Data Summary (After Basic Filters)

	Close Price	Square Feet	Lot Size Acres	Age	Bedrooms	Total Bathroom
count	674,629.00	674,629.00	282,174.00	674,629.00	674,629.00	674,629.00
mean	276,554.68	2,106.41	5.92	26.97	3.57	2.74
std	233,804.69	1,516.96	303.49	22.24	1.04	1.02
min	1.00	0.00	0.00	0.00	0.00	0.00
25%	140,000.00	1,348.00	0.17	11.00	3.00	2.00
50%	223,500.00	1,948.00	0.30	21.00	3.00	2.50
75%	346,000.00	2,749.00	0.49	38.00	4.00	3.00
max	20,000,000.00	455,200.00	81,145.00	219.00	8.00	22.00

Note: This table presents descriptive statistics for Georgia residential properties after applying basic filters including property type selection, and removal of outliers. The dataset contains 674,629 properties.

Table 2: Parameter Estimates (Full Model)

Parameter	Estimate	Std. Error	p-value
Property-Specific Coefficients (Θ)			
Intercept (θ_0)	7.3737	0.7107	0.000
Bedrooms (Θ_{beds})	-0.0140	0.0014	0.000
Square Footage (Θ_{sqft})	0.2680	0.0277	0.000
Bathrooms (Θ_{baths})	0.1268	0.0128	0.000
Lot Size (Θ_{acres})	0.0586	0.0058	0.000
Pool (Θ_{pool})	0.0464	0.0046	0.000
New Construction ($\Theta_{\text{New Construction}}$)	0.4808	0.0488	0.000
Resale (Θ_{Resale})	0.2883	0.0286	0.000
Updated/Remodeled ($\Theta_{\text{Updated/Remodeled}}$)	0.3506	0.0345	0.000
Market-Wide Coefficients (v)			
CPI (v_{cpi})	0.0584	0.0057	0.000
Unemployment Rate (v_{unemp})	0.1309	0.0130	0.000
VIX (v_{vix})	-0.0019	0.0002	0.000
Delinquency Rates (v_{delin})	-0.2409	0.0249	0.000
Housing Starts (v_{houst})	0.0248	0.0025	0.000
Default Parameters			
π_0	0.0051	0.0005	0.000
π_1	0.0101	0.0010	0.000
φ	0.5967	0.0584	0.000
Fixed Effects			
Month Fixed Effects		Yes	
ZIP Code Fixed Effects		Yes	

Note: This table presents parameter estimates from the full model including property-specific coefficients (Θ_T), market-wide variables (v), and default-related parameters (π_0, π_1, φ). The in-sample (training) fit is characterized by an R^2 of 0.6431 and RMSE of 123,957.91, while the out-of-sample (testing) fit has an R^2 of 0.2331 and RMSE of 200,477.00. Month and ZIP code fixed effects are included to account for seasonal and location-specific factors. Standard errors and p-values are reported for each parameter. Here, φ denotes the recovery rate in liquidation; the corresponding haircut (loss-given-default) is $1 - \varphi$.

Table 3: Parameter Estimates ($G = 0$)

Parameter	Estimate	Std. Error	p-value
Property-Specific Coefficients (Θ)			
Intercept (θ_0)	7.0351	0.6780	0.000
Square Footage (Θ_{sqft})	0.2666	0.0256	0.000
Bedrooms (Θ_{beds})	-0.0140	0.0014	0.000
Bathrooms (Θ_{baths})	0.1270	0.0134	0.000
Pool (Θ_{pool})	0.0463	0.0046	0.000
New Construction ($\Theta_{\text{New Construction}}$)	0.4819	0.0493	0.000
Resale (Θ_{Resale})	0.2939	0.0296	0.000
Updated/Remodeled ($\Theta_{\text{Updated/Remodeled}}$)	0.3502	0.0369	0.000
Default Parameters			
π_0	0.0050	0.0005	0.000
π_1	0.0100	0.0010	0.000
φ	0.5676	0.0563	0.000
Fixed Effects			
Month Fixed Effects		Yes	
ZIP Code Fixed Effects		Yes	

Note: This table presents parameter estimates from the model excluding market-wide variables ($G_0 = 0$). Property-specific coefficients (Θ_T) and default-related parameters (π_0, π_1, φ) are shown. The in-sample (training) fit is characterized by an R^2 of 0.6396 and RMSE of 124,564.42, while the out-of-sample (testing) fit has an R^2 of 0.1974 and RMSE of 205,090.51. Month and ZIP code fixed effects are included to account for seasonal and location-specific factors. Standard errors and p-values are reported for each parameter. Here, φ denotes the recovery rate in liquidation; the corresponding haircut (loss-given-default) is $1 - \varphi$.

Table 4: OLS Regression Results

Variables	Coefficient	Std. Error
Intercept	12.3859***	0.0128
Bedrooms	-0.0129***	0.0009
Square Footage (Log)	0.2709***	0.0010
Bathrooms	0.1231***	0.0010
Lot Size (Acres, Log)	0.1276***	0.0033
Pool (Yes=1)	0.0507***	0.0006
New Construction	0.5047***	0.0042
Resale	0.2675***	0.0036
Updated/Remodeled	0.3780***	0.0043
Month Fixed Effects	Yes	
ZIP Code Fixed Effects	Yes	
N	335,145	
R^2	0.775	
Adjusted R^2	0.775	

Note: Significance levels: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. This table reports the results from a standard OLS (Ordinary Least Squares) regression on the same training data. Month and ZIP code fixed effects are included but not reported in the coefficient block.

Table 5: Economic Metrics Summary

Panel A: No Eviction								
Metric	Count	Mean	Std Dev	Min	25%	Median	75%	Max
Option Value (\$)	415 411	38 762.00	33 698.62	1 084.90	18 517.88	29 126.99	47 896.20	894 248.20
Option Value (% of Price)	415 411	13.43	2.62	8.87	11.08	13.13	15.34	22.01
Monthly Lease Payment (\$)	415 411	1 029.90	1 546.73	17.89	336.24	567.52	1 056.57	57 377.54
Annual Lease Percentage (%)	415 411	4.50	4.59	1.67	2.16	2.60	3.26	23.19
Price-to-Rent Ratio	415 411	35.07	14.57	4.31	30.71	38.43	46.21	59.73
Total Cost Difference (%)	415 411	7.67	11.83	0.00	0.00	0.00	20.39	38.32
Property Value (\$)	415 411	296 971.13	263 161.63	50 000.00	140 013.02	224 047.75	365 663.16	6 661 355.44

Panel B: 5% Eviction Risk								
Metric	Count	Mean	Std Dev	Min	25%	Median	75%	Max
Option Value (\$)	415 411	35 102.82	30 772.59	962.39	16 627.67	26 321.28	43 329.44	834 228.70
Option Value (% of Price)	415 411	12.15	2.58	8.13	9.85	11.65	14.04	20.85
Monthly Lease Payment (\$)	415 411	731.18	997.77	15.87	283.78	460.05	791.88	49 462.88
Annual Lease Percentage (%)	415 411	3.28	3.58	1.54	1.92	2.32	2.75	21.97
Price-to-Rent Ratio	415 411	42.07	12.99	4.55	36.41	43.19	51.96	65.14
Total Cost Difference (%)	415 411	4.70	10.30	0.00	0.00	0.00	0.00	37.08
Property Value (\$)	415 411	296 971.13	263 161.63	9 001.92	140 013.02	224 047.75	365 663.16	6 661 355.44

Note: This table summarizes key economic metrics for 415,411 valid contracts in Panel A (No Eviction) and Panel B (5% eviction risk). Option Value is the dollar worth of the purchase option, shown also as a percentage of property value. Monthly Lease Payment and Annual Lease Percentage amortize the option over expected tenure. Price-to-Rent Ratio indicates how many years of rent equal the purchase price. Total Cost Difference measures the percentage premium of rent-to-own over immediate purchase. Property Value reports the underlying home price distribution. For Panel B, a 5% annual eviction probability is assumed.

Table 6: HPA Contracts: Economic Metrics Summary

Panel A: No Eviction								
Metric	Count	Mean	Std Dev	Min	25%	Median	75%	Max
Option Value (\$)	926	45 696.28	20 779.78	13 121.27	29 987.39	40 316.96	56 962.46	130 501.19
Option Value (% of Price)	926	13.06	2.37	9.15	10.86	13.02	15.00	20.08
Monthly Lease Payment (\$)	926	1 244.63	1 573.40	216.76	501.85	687.75	1 070.86	11 047.19
Annual Lease Percentage (%)	926	4.19	4.46	1.75	2.11	2.54	2.92	20.72
Price-to-Rent Ratio	926	37.06	14.01	4.83	34.26	39.35	47.34	57.30
Total Cost Difference (%)	926	6.62	11.24	0.00	0.00	0.00	18.74	34.82
Property Value (\$)	926	351 060.84	147 406.14	108 198.46	243 115.26	308 264.86	433 199.16	981 960.25

Panel B: 5% Eviction Risk								
Metric	Count	Mean	Std Dev	Min	25%	Median	75%	Max
Option Value (\$)	926	41 422.35	19 245.33	11 642.20	27 042.34	36 491.91	51 943.63	123 679.38
Option Value (% of Price)	926	11.83	2.35	8.34	9.65	11.54	13.76	19.03
Monthly Lease Payment (\$)	926	818.13	958.32	192.33	438.71	599.12	857.60	10 469.71
Annual Lease Percentage (%)	926	2.81	2.85	1.59	1.88	2.25	2.66	19.64
Price-to-Rent Ratio	926	44.35	11.19	5.09	37.56	44.47	53.11	62.87
Total Cost Difference (%)	926	4.02	9.78	0.00	0.00	0.00	0.00	33.78
Property Value (\$)	926	351 060.84	147 406.14	108 198.46	243 115.26	308 264.86	433 199.16	981 960.25

Note: Panel A (No Eviction) and Panel B (5% Eviction Risk) each summarize 926 HPA contracts. Under no eviction, option values, lease payments, and cost differences are higher on average, whereas introducing eviction risk reduces those metrics—particularly lowering mean option value by about 9% and median lease payments by roughly 13%.