Rationality and exuberance in land prices and the supply of new housing

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ABSTRACT

We estimate a mixed logit model of new housing construction decisions from a panel of land parcels zoned single family residential in LA County during 1988-2012. The probability of construction depends on expectations about post-construction house and land prices, on the cost of construction, city-year specific fixed effects, and on random shocks. The long run price elasticity of housing supply is derived from the annual construction elasticity. Reservation prices for investing in land exceed market prices by 4% in the 2000-2007 boom, trailing them by 3.5% during the subsequent crash years. Exuberance during the boom is indicated by decreased sensitivity to prices and costs and increased sensitivity to random shocks. A measure of entropy climbs to between 20%-30% of investors' reservation price for land during house price booms, but begins to recede prior to the peak.

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1. Introduction

We introduce a new approach to estimating housing supply which is microeconomic and micro-econometric. We model an individual land developer's decision to construct housing under uncertainty, together with the choice of structural density at which to construct. Our approach combines the intensive and extensive margins of land development, studied separately in the extant literature reviewed briefly below. The market's responsiveness along either margin is obtained by aggregating over the micro decisions of land developers. We use discrete choice theory to formulate our model. We first describe a binary logit model which we then extend to a mixed logit to more fully capture the uncertainties faced by the land developer.

Previous econometric studies of housing supply can be sorted into two complementary groups. One group has focused on the intensive margin of the production of housing services, the other group on the extensive margin of housing stock expansion. The first group has normally relied on micro data to estimate the relative weights of land and non-land inputs in a housing production function. The approach is traceable to the model of urban structure by Muth (1969) and the early work is surveyed by McDonald (1981). A difficulty with this approach has been the absence of reliable data on land prices and on the quantity of housing services. But in a recent contribution, Epple, Gordon and Sieg (2010) showed how to use nonparametric methods to treat housing services and prices as latent variables.

The second group of studies employs an aggregative approach to measure housing market responsiveness in the extensive margin. In Topel and Rosen (1988) and DiPasquale and Wheaton (1994), a time series of national housing stocks is related to average housing prices, the latter study taking extra care to identify demand and supply schedules. Meyer and Somerville (2000) show that if changes in housing stocks are related to changes in the levels of housing prices instead, then doing so gives lower but more reasonable estimates of the construction and supply elasticity. They motivate their empirical model by the stylized theory in Capozza and Helsley (1989) who showed that under perfect foresight land prices are *ceteris paribus* higher in a faster growing market.

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Green, Malpezzi and Mayo (2005) examined the variation of supply responsiveness at the metropolitan level arguing that the price elasticity of housing supply is higher in fast growing, less land use regulated and smaller metropolitan areas. Using similar theory and long term aggregated data, Saiz (2010) showed that the supply elasticity can be lower due to geographic limitations on land available for development and due to regulations on land use.

Our mixed logit model is estimated using a long term panel data of land parcels zoned for single family housing spanning the period 1988-2012 in Los Angeles County. During this time span the housing and land markets underwent important cyclical fluctuations. The data reveals wide heterogeneity in housing and land prices, even within a relatively limited geography. A logical consequence of this heterogeneity is that investors in developable land find it difficult to observe current prices for their land parcels and to forecast land and housing prices forward. Nevertheless, they must do so because they face non-negligible lags between the time of the construction decision and the sale of the completed housing. Therefore, the formation of price expectations impacts the decision of whether and at what structural density to construct, and this becomes the central focus of our model.

We model rational expectations about future profits by treating the uncertainty in land and house prices that naturally arise in a forward looking setting and cannot be ignored. We estimate the investor's reservation price for holding onto a land investment. We decompose this reservation price into a systematic component explained by rational profit calculations based on expected prices and costs under uncertainty, and a seemingly irrational part, a measure of *entropy* driven by shocks to profits that appear in the model as white noise. We show that during periods of irrational exuberance in housing, such as from 2000 to 2007, or during the earlier savings and loan crisis cycle, the entropy component of investors' reservation prices for land rose to between 20%-30% from negligible levels in normal periods. But entropy receded sharply before prices peaked. This suggests that land investors were "smart investors" selling ahead of the marginal housing consumers who acted like "ordinary investors" caught with unsustainable mortgages.[2] In our model, during price booms or bubbles, investors' reservation prices for land ran ahead of market prices by 4%, and during price crashes trailed by about 3.5%, although over the entire period from 1988-2012 rational expectations appeared to be holding on average. Our model shows that a 1%

[2] The terms "ordinary" and "smart" investors are borrowed from Shiller (2014).

excess of reservation land prices over market prices during a year, results in a 1.12% increase in the market price of land in the next year, but has no significant impact on next year's house prices.

Our microeconomic model yields a clear path from the housing price elasticity of new construction on each land parcel to the short term aggregate and long term aggregate price elasticity of the housing stock. Our housing stock elasticity increases as the time horizon into the future lengthens, approaching infinite elasticity asymptotically over time. This clears up considerable ambiguity in the literature about the relationship between construction and the long run stock elasticity. We show that during the temporally heterogeneous time span from 1988 to 2012, the annual construction elasticity in LA County varied between 1 and 18 with a mean of 4.04 while the annual stock elasticity varied between almost zero and 0.045 with a mean of 0.026. We are able to calculate the long run stock elasticity for a time horizon of any length by compounding the effect of either a changing-in-time or a constant-in-time annual stock elasticity. Such a long run stock elasticity measures the percent by which the aggregate stock of housing over a period would be larger had housing prices been one percent higher than their actual values in each year. The long run stock elasticity that we estimate occurred over our 1988-2012 study period is 0.63, similar to the estimate by Saiz (2010) for the entire LA metropolitan area over 1970-2000.

In our model, investing in land for possible future development can be interpreted as investing in a call option, as is implicit in Capozza and Helsley (1990) who treated systemic uncertainty in income in a growing housing market. We present the concept in a different way, focusing on the idiosyncratic uncertainties in the expectations of individual investors in land. Investment in developable land is leveraged by the ratio of the price of the housing to be built to the current market price of the underlying land. Fluctuations in housing prices that are driven by exogenous demand or supply shocks are transmitted to land prices, magnified by the leverage ratio. Here, we present the concept in simple terms.

To see the role of the leverage ratio, we note first that the land price, $L,$ is the residual after subtracting the construction cost from the house price P per square foot of floor, f is the structural density (floor area to land area ratio) and k is the construction cost per square foot of floor. Differentiating $L = Pf - kf$ with respect to L, P, f, k, then dividing through by L and multiplying by fP / fP, and ignoring any change in f by setting $df = 0$, we get:

$$\frac{dL}{L} = \left(\frac{dP}{P} - \left(\frac{k}{fP} \right) \frac{dk}{k} \right) \left(\frac{fP}{L} \right).$$

The leverage ratio is $fP/L > 1$. Suppose that dP/P is a random rate of change in the expected housing price and *dk/k* in the rate of change of construction cost. As construction costs normally fluctuate a lot less than prices, we set $dk/k = 0$ to get the simpler expression

$$\frac{dL}{L} = \left(\frac{dP}{P} \right) \left(\frac{fP}{L} \right),$$

which shows that a random fluctuation in the expected housing price gets multiplied by the leverage ratio to get the corresponding random fluctuation in the expected land price.

The decision to construct is to exercise a non-expiring call option to build housing on the land. The developer has bought the land in the past, perhaps years before the date in which construction occurs. As the date of probable construction approaches, the expected land value (the call option's value) rises. Expected land price rises because of fluctuations in population or in income growth, or in better transportation increase the demand for housing at locations not heretofore developed, or due to idiosyncratic shocks. The developer can exit at any time by selling the call option at the current land price, or can choose to keep the land asset (postponing the sale of the land or the exercise of the call option). The call option's strike price is the construction cost which, unlike strike prices on common stocks, could be rising or falling. Exercising the call option is preferable to selling it when the underlying security (in this case the housing to be constructed) is worth more than the current land price (current value of the option) plus the current cost of construction. Land parcels that are nearing their anticipated construction dates are in-the-money call options, their leverage ratios are lower, making their prices less volatile and are therefore perceived as less risky investments than are parcels unlikely to be constructed on soon. The latter are out-of-the-money call options with higher leverage ratios and more volatile land prices. At any point in time, construction decisions occur for those parcels the investors of which expect higher post-construction housing prices relative to land prices. These expectations combine a mix of rationality and exuberance and, as noted earlier, our model separately identifies and measures the two.

The paper is organized as follows. In section 2 we review the data we work with and summarize the temporal behavior of key variables in the data. In section 3, we model developers' expectations of future land and housing prices and the structural density of construction. In section 4 we present the discrete choice model, specializing to a mixed logit model. Section 5 then derives formulas for the elasticity of new construction and of housing stock by time horizon. Section 6 describes our estimation procedure, and section 7 discusses our benchmark results and several modifications. We conclude in section 8.

2. Data

Our data are from the property records for Los Angeles County in 2012. In our sample, the County is represented by 85 cities (LA being the biggest) and all unincorporated parts comprise an 86th geographic area.[3] The observations are separately titled land parcels zoned for single family housing development and are either undeveloped at the start of 1988, or are houses built earlier. If, during 1988-2012, a parcel was subdivided into separately titled parcels, then the subdivisions appear in the data as separate parcels from 2012 back to 1988. Merged parcels also appear as single parcels, from 2012 back to 1988. The data contains the sales year and sale value for parcels with single family housing and for undeveloped land parcels. We work with the last sale value which is the most reliable. For land parcels that were constructed on, we have the year of construction and the amount of floor space built. All our variables are in nominal dollars.

[FIGURE 1 ABOUT HERE]

The six panels of Figure 1 illustrate the time path of relevant variables over 1988-2012. To the 12 years from 1988-1999 we refer as the *S & L Crisis and Recovery.* The middle 8 years from 2000 through 2007 saw a huge spike in housing prices and, following Robert Shiller (2005), we call it the period of *Irrational Exuberance.* To the last five years from the house price top in 2008 we refer as the *Mortgage Crisis and Recovery*. In the panels of Figure 1 the period of irrational exuberance is shaded.

Panel (a) of Figure 1 shows the Case-Shiller index of housing price for the Los Angeles MSA, derived from repeat sales of houses (see Case and Shiller,1989), juxtaposed against our yearly average house sales prices. The fit of these two series is remarkably close. The average of the sale price of a house divided by its floor area, more than tripled from 1988 to the end of 2007, then crashing by 41% to 2009. The average of the sales price of an undeveloped land parcel in panel (b), increased 8.11 times from 1988 to 2012, but included a big correction of 53% from 2002 to 2005, ahead of the crisis, followed by a steep recovery, increasing 160% from 2005 to 2012.

[3] The property records from 1988-2008 are from SCAG (Southern California Association of Governments). We supplemented these with records from Dataquick© for 2008 through 2012. These two are mutually consistent, include the same attributes and are from the same publicly available assessment data. Pre 1988 data is not reliable due to many missing observations.

Notably, from panel (b) during the period of irrational exuberance, house sales prices increased 2.35 times, but land sales prices made a huge fluctuation with essentially no net change.

Panel (c) shows that the number of house sales increased six fold from the 1990 bottom to the 2006 peak, corrected sharply to the 2008 bottom, recovering to the 2007 peak by 2012. New construction in panel (c), fell steeply from 1989 to 1994 in the savings and loans crisis, increased steadily to 2006, collapsing during the mortgage crisis. From panel (d), undeveloped land sales followed a similar pattern peaking in 2004, earlier than house sales, then recovering sharply from the 2008 bottom. Panel (e) shows the average structural density of newly constructed homes: the ratio of the floor area to the area of the lot, known as FAR. It increased by 38% from 0.26 in 1988 to 0.36 in 2004, subsequently declining back to 0.26. Construction costs in panel (f) are computed from the RSMeans Building Construction Cost Data handbooks (1988-2012) by scaling the construction cost of low-rise buildings by the Los Angeles City index. From 1988 to the peak in 2009, construction cost increased by 99.3%. Meanwhile, the one year seasonally unadjusted T-bill rate had a huge downward trend with cyclical fluctuations. Figure 2 shows the geographic distribution of the undeveloped land parcels at the start of1988 and 2012. These are evenly distributed throughout the County both north and south of the mountain ranges.

[FIGURE 2 ABOUT HERE]

3. Modeling expected land values, housing values and floor area

We refer to agents who own land parcels interchangeably as developers or investors. To model the developer's decision of whether to construct housing or not, we need to impute the agent's expectations concerning a currently undeveloped parcel. We use superscript *nd* for a land parcel *i* in the "not developed" state, and *d*, "developed", for a parcel *i* with existing or prospective housing. In our data, the vast majority of houses that are built, sell within one year of construction.[4] We assume a one-year lag, since from the data we cannot specify a shorter lag, and two years is unrealistic for most single family housing. A developer of land parcel *i* who contemplates construction in year t followed by sale in $t+1$ must anticipate the following. *First*, what will be the

[4] The Census (https://www.census.gov/construction/nrs/new_vs_existing.html) reports that 25% of houses are sold on completion, the rest are evenly split as "not yet started" and "under construction." The National Association of Home Builders reports that construction takes 7 months on average, and 8 months from permit issuance to completion in the West Coast (http://eyeonhousing.org/2013/10/how-long-does-it-take-to-build-a-house/).

market value, $V_{i,t+1}^{nd}$, of the land parcel, should construction be foregone in year t ? *Second,* if housing is built in year t, what should be its structural density (FAR), f_{it}? *Third*, what would be the market value, $V_{i,t+1}^{d}$, of the housing at the chosen FAR?

We estimate regressions to impute these investor expectations to any land parcel by year:

$$\log\left(V_{it}^{nd}\right) = \mathbf{a}^{nd}\mathbf{X}_{it} + \alpha\log\left(A_i\right) + \theta_{it}^{nd}. \tag{1a}$$

$$\log\left(V_{it}^{d}\right) = \mathbf{a}^{d}\mathbf{X}_{it} + \beta\log\left(H_i\right) + \gamma\log\left(A_i\right) + \theta_{it}^{d}, \tag{1b}$$

$$\log\left(f_{it}\right) = \mathbf{a}^{f}\mathbf{X}_{it} + \theta_{it}^{f}. \tag{1c}$$

Housing prices vary spatially due to the landscape of natural amenities and of public goods and services, and they vary over time due to national, regional and local factors influencing the demand for or supply of single family housing. To control for such spatiotemporal variation, our independent exogenous variables $\mathbf{X}_{it}$ include 85 city-specific fixed effects and 24 year-specific fixed effects. By picking up the influences of the city- and year-specific unobserved variables, the fixed effects reduce or eliminate the correlation among the regression error terms and take care of endogeneity problems. The $\mathbf{X}_{it}$ also include geographic location by using geocoding methods to measure shortest distances for each parcel: to downtown LA which is also the region's largest job center; to the nearest job sub-center in the region;[5] to the nearest highway; and to the Pacific coastline. The regressions include a land parcel's area or lot size, A_i, and – for built parcels –, H_i, the floor space or housing size.

A well-understood unique aspect of housing markets is that when housing sells, sales value is observed but the value of the land included in house value is not; when land sells, its value is observed but the value of a house and the FAR that might be built on it cannot be; most housing constructed sells within a year or two, but the land on which construction occurred could have been purchased years ago and its current value is not observed. Because of these reasons each of the three regressions were estimated by Ordinary Least Squares (OLS) from separate samples all consisting of observations in 1988-2012, using the last recorded sales values for (1a) and (1b), and the FAR in the year of construction for (1c). For (1a) we used the sales of 13,903 undeveloped

[5] Subcenter definitions for the LA region are from Arnott and Ban (2010) http://vcpa.ucr.edu/Papers.html

land parcels, 3,504 of them in the City of LA The observations for (1b) are the 610,440 houses sold in the County, 179,040 of them in the City of LA. For the FAR regression (1c) the sample consists of 137,275 parcels on which houses were constructed, 17,584 in the City of LA.

[TABLE 1 ABOUT HERE]

The regressions' results are shown in Table 1. FAR decreases with each of the distances. House and land parcel sales values decrease with distance to downtown LA confirming that the market values accessibility to the biggest jobs center. But downtown LA has only about 4-5% of metropolitan area jobs in 2000. Hence distance from downtown LA is not very powerful. Land value decreases about four times as fast as house value because at any location land is normally scarcer than is floor space: the supply of floor space at a dear location can be increased by building at higher FAR, whereas the land quantity at the same location cannot be increased. In the case of distance to the nearest job sub-center we find that house prices decrease with such distance, but the variable was insignificant for land value and was dropped from that regression. Both values decrease with distance from the Pacific coastline, reflecting the amenity value attributed to proximity to the coast. Both values increase with distance from the nearest highway, reflecting the nuisance effects of highway congestion, pollution and noise. All independent variables in Table 1 are significant at 1% or better. The elasticity of land value with respect to lot size is 0.37 (α in (1a)). House value elasticity with respect to floor space is 0.7 (β in (1b)) and 0.17 with respect to lot size (γ in (1b)).

To impute land value, house value and FAR to an undeveloped parcel in any year, the regressions are transformed by taking the exponential of both sides. Then define $\xi_{it}^{j} \equiv e^{\theta_{it}^{j}}$ for regression $j = nd, d, f$. Residuals θ_{it}^{j} are assumed i.i.d.-normal with zero mean and variance ν^{j}. Then ξ_{it}^{j} are lognormal with $E\left[\xi_{it}^{j}\right] = e^{\nu^{j}/2}$ and $\operatorname{var}\left(\xi_{it}^{j}\right) = e^{\nu^{j}}\left(e^{\nu^{j}} - 1\right)$. First, FAR is imputed to any undeveloped land parcel. From (1c):

$$f_{it}\left(\xi_{it}^{f}\right) = \exp\left(\mathbf{a}^{f}\mathbf{X}_{it}\right)\xi_{it}^{f}, \tag{2a}$$

$$\overline{f}_{it} \equiv E\left[f_{it}\left(\xi_{it}^{f}\right)\right] = \exp\left(\mathbf{a}^{f}\mathbf{X}_{it} + \frac{\nu^{f}}{2}\right). \tag{2b}$$

Floor space on the parcel to be constructed in year *t* is then $H_{it} = \overline{f}_{it}A_{i}$. House values are imputed from (1b) to any parcel to which floor space has been imputed:

$$V_{it}^{d}\left(\xi_{it}^{d}\right)=A_i^{\gamma}H_i^{\beta}\exp\left(\mathbf{a}^{d}\mathbf{X}_{it}\right)\xi_{it}^{d}, \tag{3a}$$

$$\bar{V}_{it}^{d}=E\left[V_{it}^{d}\left(\xi_{it}^{d}\right)\right]=A_i^{\gamma}H_i^{\beta}\exp\left(\mathbf{a}^{d}\mathbf{X}_{it}+\frac{v^{d}}{2}\right). \tag{3b}$$

The developer can determine a profit maximizing floor space from (3b) that should be built on parcel *i* in year *t*. Profit from constructing H_{it} square feet of floor space in year *t* would be:

$$A_i^{\gamma}\exp\left(\mathbf{a}^{d}\mathbf{X}_{it}+\frac{v^{d}}{2}\right)H_{it}^{\beta}-k_tH_{it}, \tag{4}$$

where k_t is the unit construction cost. The profit maximizing floor space and FAR would be:

$$H_{it}^{*}=\left(\frac{\beta A_i^{\gamma}\exp\left(\mathbf{a}^{d}\mathbf{X}_{it}+\frac{v^{d}}{2}\right)}{k_t}\right)^{\frac{1}{1-\beta}}, \quad f_{it}^{*}=\frac{H_{it}^{*}}{A_i}. \tag{5}$$

The profit-maximizing FAR, which we calculated for each parcel that underwent construction, has a substantially higher median and mean than the data FAR or the regression-imputed FAR. This is explained by large-lot zoning and building regulations which favor lower FAR, or by the need felt by developers to conform to the established FAR of the neighborhood. Both factors cause a departure from unconstrained profit maximization. In the absence of the regulations and the need to conform, developers might build multiple family housing approaching the profit maximizing FAR levels. We use the regression-imputed FAR to model developer choices of structural density.

For an undeveloped land parcel, value in year *t* is imputed by:

$$V_{it}^{nd}\left(\xi_{it}^{nd}\right)=A_i^{\alpha}\exp\left(\mathbf{a}^{nd}\mathbf{X}_{it}\right)\xi_{it}^{nd}, \tag{6a}$$

$$\bar{V}_{it}^{nd}\equiv E\left[V_{it}^{nd}\left(\xi_{it}^{nd}\right)\right]=A_i^{\alpha}\exp\left(\mathbf{a}^{nd}\mathbf{X}_{it}+\frac{v^{nd}}{2}\right). \tag{6b}$$

The price of the parcel per square foot of the land is then $L_{it}\left(\xi_{it}^{nd}\right)\equiv\frac{V_{it}^{nd}\left(\xi_{it}^{nd}\right)}{A_i}$ and, on average, $\bar{L}_{it}\equiv\frac{\bar{V}_{it}^{nd}}{A_i}$. The unit floor price of the prospective housing is $P_{it}\left(\xi_{it}^{d}\right)\equiv\frac{V_{it}^{d}\left(\xi_{it}^{d}\right)}{\bar{f}_{it}A_i}$ and, on average, $\bar{P}_{it}\equiv\frac{\bar{V}_{it}^{d}}{A_i\bar{f}_{it}}$. Thus, $\bar{P}_{it},\bar{L}_{it},\bar{f}_{it}$, are imputations of house price, land price and FAR based on observed characteristics, and $P_{it}\left(\xi_{it}^{d}\right)$, $L_{it}\left(\xi_{it}^{nd}\right)$, $f_{it}\left(\xi_{it}^{f}\right)$, include deviations due to unobserved effects. Observed effects are modeled by the transformed regressions, parcel-specific deviations by the ξ_{it}^{j}, $j = nd, d, f$.

4. The decision to construct

Each year, a rational investor compares the present value economic profit of constructing and not constructing on a parcel of land and chooses the more profitable action. Such a discrete choice model was proposed by Anas and Arnott (1991). If the choice is to forego construction in year *t*, the parcel remains in the *nd* state and at the start of year *t*+1, it is valued at $L_{i,t+1}\left(\xi_{i,t+1}^{nd}\right)$ *per unit of land*; but if constructed on, the floor space and the underlying land in the year *t*+1 would be valued at $P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)$ *per unit of floor space*. Economic profits *per unit of the parcel's land* at the start of any year *t* are specified as $\Pi_{it}^{nd} = \pi_{it}^{nd} - L_{it}\left(\tilde{\xi}_{it}^{nd}\right) + u_{it}^{nd}$, $\Pi_{it}^{d} = \pi_{it}^{d} - L_{it}\left(\tilde{\xi}_{it}^{nd}\right) + u_{it}^{d}$, where

$$\pi_{it}^{nd} = \frac{L_{i,t+1}\left(\xi_{i,t+1}^{nd}\right)}{1 + r_t + \rho}, \tag{7a}$$

$$\pi_{it}^{d} = \frac{\left(P_{i,t+1}\left(\xi_{i,t+1}^{d}\right) - k_t\right) f_{it}\left(\xi_{it}^{f}\right)}{1 + r_t + \rho} + \mathbb{C}_{c(i)t}. \tag{7b}$$

The investor discounts future cash flows at a *risk-adjusted normal rate of return* $r_t + \rho$, where r_t is a risk-free one-year T-bill rate and ρ is a time-invariant risk-premium appropriate to single family housing development. In section 7 we will discuss how the risk premium ρ is determined and what role it plays in our estimation results. Recall that in (7b) k_t is the cost of construction per unit of floor space. $\mathbb{C}_{c(i)t} = \mathbb{C}_{ct}$ for all $i \in c$ are any unobserved but systematic non-financial costs of developing a unit amount of land in year *t* for a parcel *i* located in city *c*. The notation $c(i)$ refers to the city in which a parcel *i* is located. u_{it}^{nd}, u_{it}^{d} are two unobserved random profit shocks drawn from a distribution each year, for each parcel *i*. $L_{it}\left(\tilde{\xi}_{it}^{nd}\right)$ is the current market price of the land, based on $\tilde{\xi}_{it}^{nd}$ which was determined by looking forward in the previous period *t*-1.

Suppose that a developer knows $\boldsymbol{\xi}_{it} = \left(\xi^{nd}_{it+1}, \xi^{d}_{it+1}, \xi^{f}_{it}\right)$ for his parcel. Then π^{nd}_{it} is the discounted profit based on systematic factors if the year-ahead land price is $L_{i,t+1}\left(\xi^{nd}_{i,t+1}\right)$ and the developer chooses *nd*. π^{d}_{it} is the discounted profit based on systematic profit factors if the year-ahead housing price is $P_{i,t+1}\left(\xi^{d}_{i,t+1}\right)$ and the developer chooses *d* and builds FAR $f_{it}\left(\xi^{f}_{it}\right)$. In contrast to the $\boldsymbol{\xi}_{it}$, the developer does not, at the start of year *t*, know the idiosyncratic random profit shocks $\mathbf{u}_{it} = \left(u^{nd}_{it}, u^{d}_{it}\right)$. We assume that these are revealed to the developer later during year *t* and, at such time, the decision to construct is made. If the π^{nd}_{it} and π^{d}_{it} are well-specified, then $\mathbf{u}_{it} = \left(u^{nd}_{it}, u^{d}_{it}\right)$ are white noise (Train (2009)). We assume, that $\mathbf{u}_{it}$ and $\boldsymbol{\xi}_{it}$ are uncorrelated, that is $\operatorname{cov}\left(u^{s}_{it}, \xi^{\ell}_{it}\right) = 0$ for $\forall s = nd, d$ and $\forall \ell = nd, d, f$.

Once the idiosyncratic shocks are revealed, the developer constructs if $\Pi^{d}_{it} - \Pi^{nd}_{it} \geq 0$. If $\Pi^{d}_{it} - \Pi^{nd}_{it} < 0$, then construction is foregone and the binary decision process repeats again in year $t+1$ when new systematic profits are imputed by the developer and a new pair of idiosyncratic random profit shocks $\mathbf{u}_{it} = \left(u^{nd}_{it}, u^{d}_{it}\right)$ is realized. The probability the investor of parcel i will construct in year t, conditional on $\boldsymbol{\xi}_{it} \equiv \left(\xi^{nd}_{i,t+1}, \xi^{d}_{i,t+1}, \xi^{f}_{it}\right)$ is:[6]

$$Q^{d}_{it} = Prob\left[\Pi^{d}_{it} - \Pi^{nd}_{it} \geq 0\right] = Prob\left[\pi^{d}_{it} - \pi^{nd}_{it} \geq u^{nd}_{it} - u^{d}_{it}\right]. \tag{8}$$

Only differences matter in this binary comparison. $L_{it}\left(\tilde{\xi}^{nd}_{it}\right)$, subtracted in (7a) and (7b) is the market opportunity cost of the land at the start of year *t*. In a perfectly functioning land market, prior to the revelation of the idiosyncratic random profit shocks, the investor-developer can walk away from the year-*t* decision to construct or not, by selling the land and recovering this opportunity cost. But once the construction decision is engaged, then $L_{it}\left(\tilde{\xi}^{nd}_{it}\right)$ becomes a sunk opportunity cost. In a competitive market, the developer values the land investment at the reservation price $\hat{L}_{it}$, the highest price the developer would bid at the start of year *t*, if he were to

[6] To avoid notational clutter, we hereafter suppress the dependence of π^{d}_{it} and π^{nd}_{it} on $\boldsymbol{\xi}_{it}$.

buy the land anew. Hence, $\hat{L}_{it}$ is the value of the land that would leave the investor with zero expected economic profit:

$$E\left[\max\left(\pi_{it}^{nd}+u_{it}^{nd},\ \pi_{it}^{d}+u_{it}^{d}\right)\right]-\hat{L}_{it}=0. \tag{9}$$

[FIGURE 3 ABOUT HERE]

Figure 3 shows the decision tree of the developer-investor. At the top level of the tree the decision shown is that at the start of year. If $\hat{L}_{it} < L_{it}\left(\tilde{\xi}_{it}^{nd}\right)$, then the developer is better off to sell the parcel. If $\hat{L}_{it} \geq L_{it}\left(\tilde{\xi}_{it}^{nd}\right)$ then there is an expected arbitrage opportunity to buy the parcel at the market price $L_{it}\left(\tilde{\xi}_{it}^{nd}\right)$ and reap excess profits by engaging the decision to construct or not. In the decision tree's second level, the developer has learned the draw of the idiosyncratic shocks $\mathbf{u}_{it}=\left(u_{it}^{nd},u_{it}^{d}\right)$ and decides whether to construct or not.

We will now discuss two special cases of the discrete choice model for the construct-or-not decision: the *binary logit* and our *mixed binary logit*.

4.1 Binary logit and its properties

The *binary logit model* is derived by assuming that the idiosyncratic random profit shocks $\mathbf{u}_{it}=\left(u_{it}^{nd},u_{it}^{d}\right)$ are revealed in year *t* as two independent draws from the same extreme value type I (Gumbel) distribution with variance σ_{ut}^{2}, or dispersion parameter $\lambda_t=\left(\pi/\sqrt{6}\right)/\sigma_{ut}\geq 0$ (McFadden, 1974; Train, 2009). Then equation (8), conditional on $\boldsymbol{\xi}_{it}$, gives:

$$Q_{it}^{d}=\frac{\exp\lambda_t\pi_{it}^{d}}{\exp\lambda_t\pi_{it}^{d}+\exp\lambda_t\pi_{it}^{nd}}=\frac{\exp\lambda_t\left(\pi_{it}^{d}-\pi_{it}^{nd}\right)}{1+\exp\lambda_t\left(\pi_{it}^{d}-\pi_{it}^{nd}\right)},\ \ Q_{it}^{nd}=1-Q_{it}^{d}. \tag{10}$$

The probability function given by (10) is a sigmoid curve confined between zero and one, asymptotic to zero from above as $\pi_{it}^{d}-\pi_{it}^{nd}\to-\infty$ and to one from below as $\pi_{it}^{d}-\pi_{it}^{nd}\to+\infty$ and $Q_{it}^{d}=0.5$ when $\pi_{it}^{d}-\pi_{it}^{nd}=0$. Three properties of the binary logit model are important to note in our context:

(i) *Homogeneity of degree zero of the construction probability*: economists treat the housing production function as constant returns to scale (e.g. Epple et al., 2010). This assumption to which we adhere, allows us to model housing production on a unit-sized land parcel. Formal support for this assumption is in part A of the Appendix, where we prove that the binary logit construction probability (10) is homogeneous of degree zero in the parcel's land area A_i. Then the parcel's expected land area that would be constructed on is $A_i Q_{it}^d$, and the expected floor space that will be constructed is $A_i Q_{it}^d f_{it}$. Both are homogeneous of degree one in A_i.

(ii) *Idiosyncratic heterogeneity and choice elasticity*: note how the construction probability (10) changes with the dispersion parameter. Suppose that $\sigma_{ut} \to +\infty$ and hence $\lambda_t \cong 0.$ The idiosyncratic random profit shocks then swamp the systematic profit factors and $Q_{it}^d \simeq 0.5.$ Hence investors become insensitive to prices and randomize between constructing and not constructing, appearing economically irrational. At the other extreme, as $\sigma_{ut} \to 0$, then $\lambda_t \to +\infty$. In this case, the idiosyncratic random profit shocks become negligibly small and the choice with the higher profit based on the systematic factors alone has a probability of nearly one. To see how λ_t controls the elasticity, let $\eta_{\pi_{it}^d}$ denote the elasticity of Q_{it}^d with respect to π_{it}^d. From (10):

$$\frac{\partial Q_{it}^d}{\partial \pi_{it}^d} = \lambda_t Q_{it}^d \left(1 - Q_{it}^d\right) > 0 \text{ and } \eta_{\pi_{it}^d} = \lambda_t \pi_{it}^d \left(1 - Q_{it}^d\right) > 0. \tag{11}$$

(iii) *Expected profit in advance of the decision to build and the reservation price for land*: Conditional on a draw of the vector $\boldsymbol{\xi}_{it}$, the binary logit calculus gives a closed form expression for (9) the expected maximized profit of the investor in advance of the idiosyncratic shocks. If the investor knows $\boldsymbol{\xi}_{it}$, and has rational expectations about the idiosyncratic shocks, under the logit calculus the expected maximized profit at the start of year *t* is:

$$E\left[\max\left(\Pi_{it}^{nd}, \Pi_{it}^{d}\right)\right] = \frac{1}{\lambda_t} \ln\left(\exp \lambda_t \pi_{it}^d + \exp \lambda_t \pi_{it}^{nd}\right).^7 \tag{12a}$$

Then, from (9), the investor's reservation price for the land is (see part B of Appendix):

$$\hat{L}_{it} = \underbrace{\frac{1}{\lambda_t} \ln\left(\exp \lambda_t \pi_{it}^d + \exp \lambda_t \pi_{it}^{nd}\right)}_{Reservation\ price} = \underbrace{\pi_{it}^{nd} Q_{it}^{nd} + \pi_{it}^d Q_{it}^d}_{Systematic\ return} - \underbrace{\frac{Q_{it}^d \ln Q_{it}^d + Q_{it}^{nd} \ln Q_{it}^{nd}}{\lambda_t}}_{\substack{Random\ return\ due\ idiosyncratic \\ profit\ shocks\ (entropy)}}. \tag{12b}$$

[7] Small and Rosen (1981) derived the consumer surplus by integrating the consumer's logit choice probability when the marginal utility of income is constant, that is by integrating the expected demand. The probability function given by (10) is the expected supply function of the land developer. Hence, in our case, (12a) is the corresponding expression, the producer surplus of the land developer.

On the right side, the first term gives the part of the reservation price, $\hat{L}_{it}\left(\boldsymbol{\xi}_{it}\right)$, that depends on the the expected value of the systematic profits, while the second term is the additional expected value from the idiosyncratic random profit shocks u_{it}^{d}, u_{it}^{nd} when they are, as yet, unknown to the developer. This second term is the mean measure of information (or entropy) in the binary choice probability (Theil, 1967). It is normalized by the dispersion parameter of the logit model. By differentiation of (12a), using (12b), we can also see that the reservation price on land tends to infinity monotonically:

$$\frac{\partial \hat{L}_{it}}{\partial \lambda_t} = \frac{1}{\lambda_t}\left[\pi_{it}^{nd} Q_{it}^{nd} + \pi_{it}^{d} Q_{it}^{d} - \frac{1}{\lambda_t}\ln\left(\exp \lambda_t \pi_{it}^{d} + \exp \lambda_t \pi_{it}^{nd}\right)\right] = \frac{Q_{it}^{d} \ln Q_{it}^{d} + Q_{it}^{nd} \ln Q_{it}^{nd}}{\lambda_t^{\,2}} < 0. \qquad (13)$$

The entropy tends to $\ln\left(1/2\right)$ and, hence, the right side of (13) tends to infinity as $\lambda_t \to 0$. More volatility in the idiosyncratic random profit shocks (smaller λ_t) increase the expected maximum return and therefore the reservation price that would be bid for land.

4.2 Mixed binary logit

Our *mixed binary logit model* is a generalization of the logit in which $\boldsymbol{\xi}_{it} \equiv \left(\xi_{i,t+1}^{nd}, \xi_{i,t+1}^{d}, \xi_{it}^{f}\right)$ is treated as a random vector.[8] Then the choice probability and the reservation price are obtained by integrating over the joint distribution of $\boldsymbol{\xi}_{it}$. One interpretation of our mixed logit is that, at the beginning of year *t*, but before the idiosyncratic random profit shocks become known, the investor of parcel *i* does not yet know exactly what FAR to build or next year's housing and land prices, but knows only their joint distribution. A second interpretation is that even if $\boldsymbol{\xi}_{it}$ are known to the investor-developers, the econometrician who cannot observe this knowledge, can only infer the expected value of a developer's construction probability and the developer's reservation price for the land. These two interpretations cannot be distinguished econometrically, so it is immaterial whether the mixed logit is descriptive of the behavior of the developer under uncertainty or descriptive of the econometrician's limited ability to observe the developer.

[8] Train (2009) provides a lucid exposition of the mixed logit. McFadden and Train (2000) explain that any random utility model can be approximated by a mixed logit, hence mixed logit is more general than probit. Berry, Levinsohn, and Pakes (1995) treated income, which entered the utility function nonlinearly, as being randomly distributed in their mixed logit models. We treat the developers' year-ahead expected prices as being randomly distributed.

In our mixed logit model $\boldsymbol{\xi}_{it}$ is a random draw from a time-invariant multivariate lognormal distribution $G\left(\boldsymbol{\xi}\middle|\boldsymbol{\Sigma}_{\xi}\right)$. Then, the mixed logit choice probability which we denote as $\breve{Q}_{it}^{d}$ is:

$$\breve{Q}_{it}^{d} = \int_{\xi} Q_{it}^{d} \mathbf{d}G\left(\boldsymbol{\xi}\middle|\boldsymbol{\Sigma}_{\xi}\right). \tag{14}$$

The reservation price for holding on to the land is:

$$\hat{L}_{it} = \int_{\xi} \hat{L}_{it}\left(\boldsymbol{\xi}_{it}\right) \mathbf{d}G\left(\boldsymbol{\xi}\middle|\boldsymbol{\Sigma}_{\xi}\right). \tag{15}$$

To see how closely reservation prices agree with market prices, we need to compare $\hat{L}_{it}$ from (15) with the imputed land price from the land value regression, calculated as:

$$\bar{L}_{it} = \int_{\xi} L_{it}\left(\xi_{it}^{nd}\right) \mathbf{d}G\left(\boldsymbol{\xi}\middle|\boldsymbol{\Sigma}_{\xi}\right). \tag{16}$$

We use lot areas to calculate weighted averages $\hat{L}_{t} = \sum_{\forall i \in B(t)} \frac{A_i \hat{L}_{it}}{\sum_{\forall k \in B(t)} A_k}$ and $\bar{L}_{t} = \sum_{\forall i \in B(t)} \frac{A_i \bar{L}_{it}}{\sum_{\forall k \in B(t)} A_k}$ where $B(t)$ is the set of parcels constructed on during *t*. Then, $\frac{\hat{L}_t - \bar{L}_t}{\bar{L}_t} > 0 \; (< 0)$ is the rate by which the land reservation price of investors that choose to construct in year *t* exceeds or falls below the market price of land. Since the model calculates reservation prices by assuming a risk-adjusted normal rate of return of $r_t + \rho$, a positive $\frac{\hat{L}_t - \bar{L}_t}{\bar{L}_t}$ also measures the excess economic return that investors can expect to capture by trading land parcels in year *t*.

5. Construction and stock elasticity

In the binary logit model, the elasticity of the probability of construction on parcel *i* with respect to the year-ahead house price is: [9]

$$\eta_{Qit} \equiv \frac{\partial Q_{it}^{d} / \partial P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)}{Q_{it}^{d} / P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)} = \lambda_t \frac{P_{i,t+1}\left(\xi_{i,t+1}^{d}\right) f_{it}\left(\xi_{i,t}^{f}\right)}{1 + r_t + \rho}\left(1 - Q_{it}^{d}\right). \tag{17}$$

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[9] From (11), using the chain rule of differentiation, since π_{it}^{d} is a function of $P_{i,t+1}^{d}$.

And in the case of the mixed binary logit, the elasticity of the construction probability $\breve{Q}_{it}^{d}$ with respect to the expected price $\overline{P}_{i,t+1}$, recalling from section 2 that $P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)=\frac{\overline{P}_{i,t+1}}{e^{\nu^{d}/2}}\ \xi_{i,t+1}^{d}$, is

$$\breve{\eta}_{Qit}\equiv\frac{\partial\breve{Q}_{it}^{d}}{\partial\overline{P}_{i,t+1}}\frac{\overline{P}_{i,t+1}}{\breve{Q}_{it}^{d}}=\frac{1}{\breve{Q}_{it}^{d}}\int_{\xi}\lambda_{t}\frac{P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)f_{it}\left(\xi_{it}^{f}\right)}{1+r_{t}+\rho}Q_{it}^{d}\left(1-Q_{it}^{d}\right)\mathbf{d}G\left(\boldsymbol{\xi}\middle|\boldsymbol{\Sigma}_{\xi}\right).\quad(18)$$

[10]

Construction is an annual flow of floor space. The stock of housing grows by the accumulation of the annual construction flow. Let S_t be the aggregate stock of housing in the beginning of year *t*, then the stock expected at time $t+1$ is S_t plus the expected floor space that would be added by construction during year *t* on parcels that are undeveloped at the start *t*. Recall that A_i is the lot area of parcel *i*, and f_{it} is the FAR of the construction on parcel i in year t. Then, $E\left[A_i f_{it}\left(\xi_{it}^{f}\right)\breve{Q}_{it}^{d}\right]=A_i E\left[f_{it}\left(\xi_{it}^{f}\right)\right]\breve{Q}_{it}^{d}=A_i\overline{f}_{it}\breve{Q}_{it}^{d}$ is the expected floor space on parcel *i* in year t. Let $U(t)$ be the set of parcels undeveloped at the start of *t* then the expected stock adjusts forward by:

$$S_{t+1}=S_{t}+\sum_{\forall i\in U(t)}A_i\overline{f}_{it}\breve{Q}_{it}^{d}\ .\quad(19)$$

The price elasticity of the aggregate stock may then be defined as the expected expansion of that stock by construction on undeveloped parcels when all floor prices rise proportionally. Writing prices as $\hat{P}_{i,t+1}\left(\xi_{i,t+1}^{d}\right)=\kappa P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)$, where κ is the constant of proportionality, the stock elasticity in year *t* is $\breve{\eta}_{St}\equiv\left.\frac{dS_{t+1}/d\kappa}{S_{t+1}/\kappa}\right|_{\kappa=1}$:

$$\breve{\eta}_{St}=\frac{\sum_{\forall i\in U(t)}A_i\overline{f}_{it}\int_{\xi}\lambda_{t}\frac{P_{i,t+1}\left(\xi_{i,t+1}^{d}\right)f_{it}\left(\xi_{it}^{f}\right)}{1+r_{t}+\rho}Q_{it}^{d}\left(1-Q_{it}^{d}\right)\mathbf{d}G\left(\boldsymbol{\xi}\middle|\boldsymbol{\Sigma}_{\xi}\right)}{S_{t}+\sum_{\forall i\in U(t)}A_i\overline{f}_{it}\breve{Q}_{it}^{d}}=\frac{\sum_{\forall i\in U(t)}A_i\overline{f}_{it}\breve{Q}_{it}^{d}\breve{\eta}_{Qit}}{S_{t+1}},\quad(20)$$

by noting that the integral in the numerator is $\breve{Q}_{it}^{d}\breve{\eta}_{Qit}$ .This micro-based aggregate stock elasticity reveals an important feature. To see this, we define weights w_{it} on expected floor spaces:

[10] The elasticity with respect to the land price, the construction cost and the interest rate are similarly calculated.

$$w_{it} \equiv \frac{A_i \bar{f}_{it} \breve{Q}_{it}^d}{\sum_{\forall \ell \in U(t)} A_\ell \bar{f}_{\ell t} \breve{Q}_{\ell t}^d}. \tag{21}$$

Suppose tentatively that the stock S_t , in the beginning of the period is negligibly small. Then, using (19) in the denominator (20) with $S_t \cong 0$, the stock elasticity collapses to the weighted average value of the construction elasticity over all the parcels:

$$\breve{\eta}_{S,t+1}\Big|_{S_t \cong 0} \cong \sum_{\forall i \in U(t)} w_{it} \breve{\eta}_{Qit}. \tag{22}$$

But if, S_t , the stock inherited from the past is bigger, the stock elasticity becomes increasingly smaller diverging from the weighted average construction elasticity. This reveals that there is an initial-condition-bias in the computation of the stock elasticity in the conventional literature. *Ceteris paribus*, for larger markets with higher inherited stocks, the stock elasticity would be lower than for markets with a smaller inherited stock even though the construction elasticity under current economic conditions were the same. That is, new construction but not the entire stock can be explained by current economic conditions.

There is yet another way of writing the annual stock elasticity (20):

$$\breve{\eta}_{S,t+1} = \left(\sum_{\forall i \in U(t)} w_{it} \breve{\eta}_{Qit} \right) \left(\frac{S_{t+1} - S_t}{S_{t+1}} \right). \tag{23}$$

To see this, we plug into (23) the weights, w_{it} , from (21) and $S_{t+1} - S_t$ from (19) and cancel terms to see that we get the right side of (20). From (23), the stock elasticity for any year is the weighted average of the parcel-specific construction elasticity values for the previous year multiplied with the fraction of the year t+1 stock that was added in the previous year. Thus, the annual stock elasticity increases with higher weighted average construction elasticity, but this effect can be much weakened if stock growth is low for reasons other than the construction elasticity.

We define the long run stock elasticity (LRSE) over any period $t \to T$ as the percent increase in stock over the period when prices in each year during that period are set one percent higher than they were. This LRSE is then calculated by compounding the effect of the annual stock elasticity over $t \to T$:

$$\eta_{t \to T}^{LRSE} = 100 \times \left\{ \prod_{\tau = t}^{T} \left(1 + \frac{\breve{\eta}_{S\tau}}{100} \right) - 1 \right\} \tag{24}$$

Consider the special case where the annual stock elasticity is $\breve{\eta}_S$, constant over time. The long run elasticity over a time span of Δ years is:

$$\eta_{\Delta}^{LRSE} = 100 \times \left\{ \left(1 + \frac{\breve{\eta}_S}{100}\right)^{\Delta} - 1 \right\}. \tag{25}$$

$\lim_{\Delta \to \infty} \eta_{\Delta}^{LRSE} = +\infty$, and the supply becomes infinitely house price elastic asymptotically over time.

6. Estimation procedure

The data for the mixed logit estimation takes the form of a panel with attrition. For any year *t*, the set $U(t)$ includes all the undeveloped parcels at the start of *t*. During *t*, construction occurs on a set of parcels $B(t) \subset U(t)$ which are removed from $U(t)$ to get $U(t+1)$ .The data starts with 165,243 parcels in *U*(1988) and 14,667 of these transition into *B*(1988), so in 1989 there are 150,576 parcels available for construction and so on. At the end of 2011, 19,450 parcels remain in *U*(2011) of which 426 became constructed on in that year. Pooling the parcels in the sets available for construction in the beginning of each year, we get 1,832,640 observations.

Let Φ denote a vector that contains the dispersion parameter λ_t for each year and the constant $\mathbb{C}_{ct}$ for each city-year combination. Let y_{it} be a categorical variable equal to one if single family housing is constructed on a parcel $i \in B(t) \subset U(t)$ in year t or zero otherwise. Before we can estimate Φ we must specify $\boldsymbol{\Sigma}_{\xi}$, the variance-covariance matrix of $G\left(\boldsymbol{\xi} \middle| \boldsymbol{\Sigma}_{\xi}\right)$. Recall that $\xi_{it} = e^{\theta_{it}}$ and that, therefore, since θ_{it} are normally distributed, ξ_{it} are log-normally distributed. Then $\boldsymbol{\Sigma}_{\xi}$ implied by $\boldsymbol{\Sigma}_{\theta}$. The diagonal elements of $\boldsymbol{\Sigma}_{\theta}$ are the squares of the standard errors of the regressions reported in Table 1. For our benchmark mixed logit model, we assume that the covariance elements of $\boldsymbol{\Sigma}_{\theta}$ (and, hence, of $\boldsymbol{\Sigma}_{\xi}$) are zero. But some covariance may exist in $\boldsymbol{\Sigma}_{\theta}$ if, for example, a variable that is highly correlated with the land value residual is also highly correlated with the house value or the FAR residuals. Suppose that for any two of the three regressions j, k, $(j \neq k)$, a pair of in $\boldsymbol{\Sigma}_{\theta}$ are ν^j, ν^k and the corresponding covariance is $\nu^{j,k}$. Then $\operatorname{cov}\left(\xi_{it}^j, \xi_{it}^k\right) = e^{\left(\frac{\nu^j + \nu^k}{2}\right)}\left(e^{\nu^{j,k}} - 1\right)$. In section 7, after obtaining the benchmark model with zero covariance terms, we will re-estimate it by inferring the three covariance terms $\nu^{j,k}$ from a subsample of parcels.

Given $G\left(\xi \middle| \Sigma_{\xi}\right)$, the Partial Maximum Simulated Likelihood Estimator (PMSLE) of Φ is denoted by $\hat{\Phi}$ and is obtained by maximizing the simulated log-likelihood function

$$\hat{\Phi} = argmax\, SLL_t = \sum_{\forall c} \sum_{\forall i \in c \cap U(t)} y_{it} log \breve{Q}_{it}^{d} + \left(1 - y_{it}\right) log\left(1 - \breve{Q}_{it}^{d}\right). \tag{26}$$

$\hat{\Phi}$ is consistent and asymptotically normal even if the idiosyncratic random profit shocks u_{it}^{nd} and u_{it}^{d}, which are assumed to be independent of each other in any year t, are arbitrarily serially correlated over the years. The existence of any such serial correlation only requires that the standard errors of $\widehat{\Phi}$ be adjusted by using the robust asymptotic variance matrix estimator. In a panel data setting, the Conditional Maximum Simulated Likelihood Estimator (CMSLE) requires us to model the multivariate distribution of the decision vector $y_{i1}, y_{i2}, \dots, y_{iT}$, given the explanatory variables. In that case we would have to specify a complete inter-temporal covariance matrix for the idiosyncratic shocks $u_{it}^{nd}, u_{it}^{d}, t = 1,2, \dots, T$. Specifying and estimating such a covariance matrix in the presence of serial correlation is not only computationally difficult, but it would also make our results statistically less robust. Seemingly, ignoring serial correlation would make statistical inference meaningless. The PMSLE is a simpler estimator which takes care of any arbitrary serial correlation by just requiring us to adjust the asymptotic variance estimator. This is completely analogous to the linear regression model in the presence of serial correlation.[11]

The city-year constants, $\mathbb{C}_{ct}$, ensure that none of our explanatory variables are endogenous and so $\widehat{\Phi}$ is a consistent estimator of Φ. The city-year constants capture unobservable effects like quality of a school district and/or local zoning regulations which are likely to be correlated with our explanatory variables. Thus, including the constants ensures that our explanatory variables are independent of the error terms. Our sample spans 85 cities (plus one unincorporated area) and 24 years[12], hence we must estimate 1955 city-year constants. Estimating so many constants using a gradient based numerical optimization procedure is infeasible. The problem is solved by employing the BLP procedure (Berry (1994) and Berry, Levinsohn, Pakes (1995)) to calibrate

[11] See Woolridge (2010), pages 401-412, for partial likelihood methods in a panel data setting. Berry, Levinsohn, and Pakes (1995), pages 862-863, deal with serial correlation in their panel data set similarly. Instead of specifying a serial correlation structure, they use a covariance matrix estimator that yields standard errors robust to arbitrary serial correlation.

[12] We did not use the last year 2012, since investors in the model look one year ahead. The regression constants for 2013 are not available. Hence, 2013 prices expected by 2012 investors cannot be forecast.

these constants which are found so that the model's predicted land development matches the land development observed in the data for each city-year combination.

The PMSL estimation steps are as follows:

Step 0: We guess the value of $\boldsymbol{\lambda} = \left(\lambda_1, ..., \lambda_T\right)$

Step 1: We guess $\mathbb{C}_{ct}; \forall(c,t)$.

Step 2: For each parcel and year, that is each it, we sample the additive multivariate normal $\boldsymbol{\theta}_{it} = \left(\theta_{it}^{nd}, \theta_{it}^{d}, \theta_{it}^{f}\right)$, and then take their exponentials to generate the multiplicative lognormally distributed $\boldsymbol{\xi}_{it} = \left(\xi_{i,t+1}^{nd}, \xi_{i,t+1}^{d}, \xi_{it}^{f}\right)$.

Step 3: Given the draw of all $\boldsymbol{\xi}_{it}$ we impute house values, land values and FARs to each parcel *i* in year *t* using the procedure discussed in section 2;

Step 4: Using equation (10) we calculate the binary logit probability Q_{it}^{d} for the draw $\boldsymbol{\xi}_{it}$;

Step 5: We repeat steps 2-4 one hundred times and average the results of the one hundred logit probabilities Q_{it}^{d} to get an estimate of the mixed logit probability $\breve{Q}_{it}^{d}$ given by equation (14), an unbiased and asymptotically efficient estimator of the true choice probability;[13]

Step 6: (BLP *procedure*): A_i is the land area of parcel *i*. Given λ_t for each year *t*, adjust the city-year constants, $\mathbb{C}_{ct}$, where *r* is the iteration counter, so that $\mathbb{C}_{ct}^{r+1} = \mathbb{C}_{ct}^{r} + log\left(\frac{\sum_{i\in c\cap U(t)} A_i y_{it}}{\sum_{i\in c\cap U(t)} A_i\, {}^{r}\breve{Q}_{it}^{d}}\right)$ $\forall(c,t)$. Note that the numerator inside the parenthesis is the land in city *c* that becomes developed in year *t* in the data. The denominator is the land that becomes developed as predicted by the model. We update $\mathbb{C}_{ct}^{r}$ in step 1 and repeat steps 2 to step 6, until at some iteration $r = R$: $\left|\sum_{i\in c\cap U(t)} A_i\left(y_{it} - {}^{R}\breve{Q}_{it}^{d}\right)\right| < tol$ where *tol* is an appropriately small tolerance. Hence observed and predicted city land shares are matched as required by the BLP procedure, and consequently $\mathbb{C}_{ct}^{R+1} = \mathbb{C}_{ct}^{R}$.

[13] We verified that doubling the number of draws to 200 leaves the results unchanged.

Step 7: (*Maximizing likelihood*): Given $\mathbb{C}_{ct} = \mathbb{C}_{ct}^{R}$ for t, we adjust λ_t according to a numerical optimization procedure[14] which maximizes the simulated log-likelihood function.

Step 8: Given the λ_t found in step 7 we return to step 0 and we continue the loop of step 0 to step 8 until the value of λ_t converges to within a small tolerance.

7. Results: the benchmark model and its variations

In our benchmark model, for which we will now report detailed results, the parameter λ_t is separately estimated for each year; the risk-premium is set as $\rho = 0.07$; and the covariance terms in Σ_ξ are ignored. We will, however, modify the benchmark model in three ways; (i) by making λ constant over time, and by making it uniform within each of the three historical periods; (ii) by including the covariance terms in Σ_ξ; and (iii) by seeing how the risk-premium ρ affects the λ estimates. The benchmark model's results are shown in Figures 4, 5 and 6, in column three of Table 2 and in the top third of Table 3.

[FIGURES 4, 5, 6 ABOUT HERE]

[TABLES 2, 3 ABOUT HERE]

7.1 The benchmark model

As the house price bubble heated up investor decisions to construct got driven more by the idiosyncratic random profit shocks than by the price and cost-based systematic factors. This is seen from panel (a) of Figure 4 which shows that the variance of the shocks estimated in the benchmark model sharply surged (λ sharply dropped) during housing price booms, and then fell severely (λ rose), starting ahead of the housing price busts. The panel shows that these turning points occurred both during the Savings and Loans Crisis period as well as in the beginning of the recent Mortgage Crisis period. We will return to this issue below.

The non-financial costs $\mathbb{C}_{ct}$ in panel (b) of Figure 4, calibrated as the BLP constants, are negatively valued, measuring the effect of city-year specific non-financial impediments to construction. For each year, the average value of the constants across the 85 cities is displayed.

[14] R implements the robust inverse parabolic method of Brent (1973) which does not require derivatives. If the inverse parabolic method gives a new implausible guess, the algorithm switches to a golden section search.

These impediments amounted to no more than \$7 or \$8 per square foot of land prior to 2007 but increased sharply to \$25 during the house price bust, then rebounded back just as sharply. The non-financial costs are consistently somewhat higher for the City of Los Angeles than for the suburban areas of the County. Quigley and Rafael (2005) provided evidence that city-specific regulatory impediments affect the cost of housing in California, where cities have significant powers over zoning and land use. Our non-financial costs are intended to capture these city-specific effects, while their trends over time reflect the aversion to develop land during years of crashing housing prices.

Panel (c) of Figure 4 shows how much the annual construction and stock elasticity varied in 1988-2012. The construction elasticity varied between 1 and 18, while the stock elasticity ranged between just above zero and 0.045. A huge spike in construction elasticity occurred after house prices bottomed following the mortgage crisis. At that point new construction reached a point of sharp sensitivity to house price increases, because entropy had already receded (as we shall see shortly from panel (f) of Figure 5). The annual stock elasticity peaked in 2005 and then fell dramatically as new construction dried up. Panel (d) of Figure 4 illustrates that the year-by-year stock growth predicted by the model tracks closely the path of actual stock growth throughout the 24-year period.

Figure 5 includes additional crucial insights. First, panels (a) and (b) provide a visual of how closely, predicted reservation prices for land from equation (15) track the market prices of land from equation (16). Importantly, they show that while housing prices per unit of land area bubbled up dramatically in the Irrational Exuberance period, land prices did climb too, but corrected back to the 2000 level, before the peak in house prices. Panel (c) of Figure 5 shows that land price changes displayed higher year-to-year volatility than did house prices, but remained relatively subdued. That is also reflected in what happened in 2000-2007, when from panel (b) of Figure 1 we can see that land sale prices in 2000-2007 made a huge round trip. Land prices barely increased over 2000-2007. But consumers of housing and those speculating in housing units got swept away by the exuberance as house prices per unit of land more than doubled This is suggestive that smarter investors in land remained more restrained and rational than the ordinary investors buying houses.[15] Panel (d) of Figure 5 provides another way of seeing the difference in exuberance

[15] Geanakoplos (2009), Haughwout et al. (2011) and Duca, Muellbauer and Murphy (2011) have argued that the crisis was caused by the effects of the extensive and loose use of mortgages and collateral on the demand-side.

between house buyers and land investors: the ratio of housing price to land price or the economic leverage ratio, discussed in the Introduction, doubled during the period of irrational exuberance.

Panel (e) of Figure 5 illustrates how the percentage excess returns perceived by investors, that is $\frac{\hat{L}_t - \bar{L}_t}{\bar{L}_t} \times 100$, fluctuated around a mean of 0.05% over the entire period from 1988-2012, while panel (f) of Figure 5 shows that during the bubble-like periods, entropy climbed to over 20% of the investors' reservation prices for land, before it started receding again. This happened in 1988 prior to the savings and loan crisis, when entropy reached nearly 30% of the investor reservation price, then sharply receding before house prices peaked. It happened again, in 2004-2006 prior to the mortgage crisis when entropy eked above 20%, then sharply receding just before the 2007 peak year in house prices. That the peak in entropy was reached before price peak is yet another indication that investors in land became aware of the limits to their exuberant expectations before house prices reached top levels. Then, just as investors began to reign in the irrational part of their expectations, the housing price bubble reached its bursting point trapping ordinary housing consumers.

7.2 Less variation in λ over time

In the benchmark model, λ_t is separately estimated for each year. The result of this model and its variations are shown in Table 2. Table 3 shows two modifications of the variation of λ over time that depart from the benchmark model. In the second model in Table 3, λ is estimated to be different for each of the three historical periods, but remains uniform for the years within each period. Hence, a single λ is estimated for each period by pooling the years of that period. In the third model in Table 3, λ is assumed to remain constant over the entire 24 year period and is estimated by pooling all of the years. Panel (a) of Figure 4 juxtaposes the λ values of the three variations.

All three models compared in Table 3 predict that during the period of irrational exuberance, investors' reservation land prices ran ahead of market land prices implying an excess return of about 4 percentage points, while during the mortgage crisis and recovery period all three models predict that reservation prices were about 3.5 percentage points below market prices. Thus, in an environment of strongly rising prices, exuberance (or animal spirits) was causing expectations to run ahead of the market, with the opposite occurring when prices were falling sharply. A remaining question is how the exuberance or pessimism in a particular year correlated with actual land price and housing price change in the subsequent year. To discover this we regressed $\frac{\bar{L}_{t+1} - \bar{L}_t}{\bar{L}_t}$ and $\frac{\bar{P}_{t+1} - \bar{P}_t}{\bar{P}_t}$ against $\frac{\hat{L}_t - \bar{L}_t}{\bar{L}_t}$. Calculating elasticity from the regression slope coefficients we find that a 1% excess in the land's reservation price over the land's market price, causes a 1.12% increase in the market price of land in the following year and this effect is highly significant statistically. In contrast, the corresponding effect on housing prices is 0.37% but not statistically significant. This makes sense, since investors would be buyers of land when their expectations are exuberant and sellers of land when they are pessimistic, hence driving land prices up and down accordingly. Nevertheless, forward causality is hard to argue if high expectations in a year are driven by investors' being able to perceive that prices will be rising in the subsequent year (backward causality). Either way, our model shows that there is a strong link between expectations and actual changes in the price of land. And the fact that land investors' expectations had no significant impact on forward housing prices suggests that the land and housing markets were decoupled during the bubble year. Although we are not aware of work in the extant literature that investigates the efficiency of the land market, the seminal work of Case and Shiller (1989) showed that the market for existing houses may not be efficient.

With respect to the construction and stock elasticity shown in Table 3, the year-by-year-λ and 3-period-λ models are in close agreement and predict a similar long run stock elasticity over each sub-period or the entire period of 1988-2012, from equation (24). The early studies of the housing supply elasticity, surveyed by Blackley (1999) and Di Pasquale (1999), used reduced form equations that could not clearly distinguish between demand and supply. Such studies consistently yielded estimates of the long run supply elasticity above one, and as high as 4. Among the more recent work, using their national macro model, Mayer and Somerville (2000) distinguished between construction and supply elasticity, using changes in the price level, rather than the level of prices. They estimated the former at about 6 in the ballpark of our estimates and the annual supply elasticity at 0.08 about three times higher than ours. The difference is explainable by our equation (20). LA County being larger than the average county in the nation, the denominator of (20) is lower for the average county, hence a similar construction elasticity in LA and other places would result in a higher stock elasticity for the nation. Our stock elasticity also agrees with the 30-

year supply elasticity for the LA metropolitan area estimated by the macro model of Saiz (2010) who studies the period 1970-2000.

Our equation (25) brings some clarity to the issue of how elastic housing supply is in the long run, an issue that has been debated in the literature since the 1960s. The answer crucially depends on how long the long run is. The annual elasticity of 0.026 of the benchmark, if it were to remain constant, would compound to 2.63 after 100 years. More precisely what this means is that if, over a century, housing prices each year were 1% higher than their actual values, *and keeping all else constant*, then at the end of the century the stock would be only 2.63% bigger.

Finally, the other annual elasticity estimates of the construction probability, averaged over the period 1988-2012, are as follows. The elasticity with respect to the year-ahead land price is -0.95 or a bit less, in absolute value, than one fourth the elasticity with respect to the year-ahead house price; -0.0075 with respect to the risk-free interest rate; and -2.294 with respect to the unit construction cost.

7.3 Sensitivity to the risk premium ρ

Figure 6 shows how the maximum likelihood estimate of λ changes depending on the value of the risk premium ρ when it is varied in the wide range of zero to seventeen percentage points above the one-year T-bill rate. For each value of ρ, the λ on the vertical axis is the simple average of the λ_t estimated for each of the 24 years. Note from the figure that as the risk premium rises from zero to seventeen percent, the excess returns above the risk-adjusted normal rate of return predicted by the model fall from about +8% to -8% per year while the λ changes mildly from 0.17 to 0.22. This range of λ affects other results of the estimated model only marginally as shown in Table 2. There is, therefore, a great deal of latitude in deciding which value of the risk premium, ρ, to adopt without much consequence on the model's results. For example, when $\rho = 0.07$ developers expect nearly zero percent excess return per year over their risk-adjusted discount rate. This suggests that expectations over the 24 years are in line with the performance of actual prices in the market. This supports the hypothesis of rational expectations in a competitive setting in the long run. But, as we saw before, this does not hold in each sub-period. Based on the above estimations with various values of ρ, we decided to settle on $\rho = 0.07$ for the benchmark risk premium.

Geltner et al. (2013) provide insightful information on the issue of the returns actually expected by real estate developers. In pages 776-777 of their book, they report on a survey of developers of small to midscale multifamily housing projects in Boston circa 2005, who were asked what internal rates of return they would require to enter various phases of such projects. In an environment of about a 4% risk-free interest rate, developers reported that they would require 8.3% for stabilized properties, 9.3% for properties with lease-up risk, 17.8% in the construction phase and 37.8% in the earlier and more speculative land assembly phase. Netting out the risk-free rate, this suggests a risk premium that declines from 33.7% to 4.3% over the life of a real estate development project. On page 250 they cite another survey in which developers of apartments reported a total return expectation of 8.78%-10.98%, implying risk premiums between 4.68 and 6.98%. Glaeser, Gyourko and Saiz (2008) assumed a profit margin for homebuilders of 17% and net profit margin of 9-11% depending on overhead structure implying, in our case, risk premiums of 4.9 to 6.9%, again after netting out our 4.1% risk-free rate.[16]

In his Nobel lecture, Shiller (2014) suggested that the long term risk premium for stock investing could be set in such a way that a constant risk-free rate plus ρ equal the long term average return of the stock market. To adapting this to our setting, we can use our land prices. The average annual nominal land price growth rate from all land parcel sales in our data was 15% per year during 1988-2012. Netting out the average one-year T-bill rate of 4.10% over the same period we get a risk premium of 10.9%. This is higher than the 7% risk premium of our benchmark model but within the range that we examine. From Figure 6, we can see that with this higher risk premium, expected excess returns for our land investors would be closer to -4% than to the almost zero percent of our benchmark model. Other results change very little.

7.4 Adding covariance

To estimate the covariance terms in $\mathbf{\Sigma}_{\xi}$, we need a common sample of parcels for which land value, house value and FAR observations are available. To form such a sample we isolated the parcels that sold in an undeveloped state, subsequently got housing constructed on them and then sold again with the constructed house. There are only 5,421 such parcels for which the time between the sale after construction and the sale before construction is recorded and the time

[16] Other evidence about profits achieved by homebuilders comes from the 2014 surveys of the NAHB (National Association of Home Builders). Gross profit margins ranged from 22% of revenue in 2006 to 12% in 2012, or 28.2% to 13.6% on costs. To be consistent with zero excess returns, the risk premia would have to be 24.1% to 9.5% after netting out a risk-free rate of 4.1%.

between them does not exceed two years. To estimate $\mathbf{\Sigma}_{\xi}$, we fixed the coefficients of (1a)-(1c), except the city and year constants, to the values of those coefficients that we obtained from the OLS estimation of each regression with the larger samples (Table 1). Then, the Seemingly Unrelated Regressions procedure was run on the common sample to estimate the city and year constants together with the covariance terms of the residuals across the three regressions. The covariance values we found are: $Cov\left(\theta_{it}^{nd}, \theta_{it}^{d}\right) = 0.17$, $Cov\left(\theta_{it}^{d}, \theta_{it}^{f}\right) = 0.05$, $Cov\left(\theta_{it}^{nd}, \theta_{it}^{f}\right) = 0.23$.

Column 6 of Table 2 includes the effect on the results of the benchmark model when these estimated covariance terms are included in $\mathbf{\Sigma}_{\xi}$. Even though the average value of λ doubled from the benchmark case, the construction elasticity increased by only 50%, while the annual stock elasticity decreased by only about 10%. The expected excess returns increased from nearly 0% to +3.05%, which means that a somewhat higher risk premium ρ would be required to get near zero percent excess returns over 1988-2014. This model then is not too different from our benchmark case. We also experimented with other perturbations of the covariance structure but all of these had similarly marginal impact on the benchmark model. From these results it is safe to conclude that imposing a diagonal variance-covariance matrix in the benchmark case is reasonable.

7.5 Binary logit model

We also estimated the binary logit model (last column of Table 2). To estimate this model, the FAR, house price and land price imputations were all set at their average values $\overline{f}_{it}$, $\overline{P}_{it}$, $\overline{L}_{it}$, since the logit does not permit stochastic treatment of the variables that appear in the systematic portion of profit. The dispersion parameter λ of the idiosyncratic shocks is different each year, varies between 0.0015 and 0.04, and on average $\lambda = 0.004$. This turns out to be unacceptably low implying a very high standard deviation of the idiosyncratic shocks of $\sigma_u = \left(\pi / \sqrt{6}\right) / \overline{\lambda} \simeq \$320$ per square foot of land, that is about 5-6 times the average market price of land, and about ten times the highest value found in the case of the mixed logit models. Expected excess returns predicted by the model, are about 126% per year.

Why does the logit model perform so poorly? The reason is that the model attributes all of the heterogeneity among developers to the idiosyncratic random profit shocks the dispersion of which is measured by λ, ignoring the fact that there is substantial uncertainty in how developers estimate the future prices of the land they hold, or of the houses they would build, and the floor area they would construct. The mixed logit model, as we saw, corrects this bias, by shifting the major part of the uncertainty away from the idiosyncratic random profit shocks, placing it on the developers' expectations of year-ahead prices and the FAR.[17] Therefore, not surprisingly, the mixed logit is an attractive model of land developer behavior since anticipations of future values and FARs are key in the land development process.

8. Conclusions

Economists have been pre-occupied with their relatively incomplete understanding of housing supply compared to their understanding of housing demand. But the recent housing bubble and subsequent crash have refocused attention on demand side issues, especially on the role of financial leverage and collateral, particularly during periods of exuberance. So the pendulum may now swing the other way seeking to better understand behavior on the demand side. Our results indicate that idiosyncratic uncertainties and deviations from rational expectations among land investors increased on the upside when housing prices were sharply rising, and on the downside when housing prices were sharply falling. Yet, through the prism of our model, we quantified several indications that land investors appear to have remained much more rational during the bubble than were consumers of housing.

Recently Geanakoplos et al. (2012) presented a microscopic agent-based model of housing consumers' bounded rational behavior in the presence of systemic risk. Improved understanding of housing market dynamics would come about by synthesizing complex microscopic models of the demand side with models of the supply side such as ours, in order to microsimulate the interaction of the two sides of the market to study price formation. The econometrics of discrete choice that we employed here to explain the behavior of land investors can also be used to explain mortgage choice, the decision to default or not and other aspects of the demand side.

Appendix

A. Homogeneity of the logit model

Lemma: *Suppose that profit maximization is expressed on a whole parcel basis rather than on a per unit area basis. Then,* Q_{it}^{d} *, the logit choice probability given by* (10)*, remains unchanged. Hence,* (10) *is homogeneous of degree zero in parcel size,* A_i.

[17] Revelt and Train (1998), reach a similar conclusion in their use of the mixed logit to model consumer choice of household appliances.

Proof: We use abbreviated notation by suppressing the ξ_{it}. Scaling the profits by parcel size, A_i, profits per parcel become:

(i) $A_i\Pi_{it}^{nd} = \frac{A_i L_{i,t+1}}{1+r_t+\rho} + A_i u_{it}^{nd} - A_i L_{it}$;

(ii) $A_i\Pi_{it}^{d} = \frac{A_i\left(P_{i,t+1}-c_t\right)f_{it}}{1+r_t+\rho} + A_i\mathbb{C}_{c(i)t} + A_i u_{it}^{d} - A_i L_{it}$.

Then, $\operatorname{var}\left(A_i u_{it}^{nd}\right) = A_i^2 \operatorname{var}\left(u_{it}^{nd}\right) = A_i^2\sigma_{ut}$ and $\operatorname{var}\left(A_i u_{it}^{d}\right) = A_i^2 \operatorname{var}\left(u_{it}^{d}\right) = A_i^2\sigma_{ut}$. The dispersion parameter of the scaled model for parcel *i*, therefore, is:

(iii) $\lambda_{it} = \frac{\pi/\sqrt{6}}{A_i\sigma_{ut}} = \frac{\lambda_t}{A_i}$, where λ_t is the dispersion parameter of the model before scaling.

Applying the scaling (i) and (ii) and the λ_{it} given by (iii) to the logit probability (10) we see that it is not changed by the scaling. QED

B. Derivation of (12b)

We write the two probabilities as:

$$Q_{it}^{d} = \frac{\exp\lambda_t\pi_{it}^{d}}{\exp\lambda\pi_{it}^{nd} + \exp\lambda_t\pi_{it}^{d}}, \quad Q_{it}^{nd} = \frac{\exp\lambda_t\pi_{it}^{nd}}{\exp\lambda\pi_{it}^{nd} + \exp\lambda_t\pi_{it}^{d}}.$$

Now take the log of both sides of each of these two equations above and divide through by λ_t.

$$\frac{1}{\lambda_t}\ln Q_{it}^{d} = \pi_{it}^{d} - \frac{1}{\lambda_t}\left(\exp\lambda\pi_{it}^{nd} + \exp\lambda_t\pi_{it}^{d}\right),$$
$$\frac{1}{\lambda_t}\ln Q_{it}^{nd} = \pi_{it}^{nd} - \frac{1}{\lambda_t}\left(\exp\lambda\pi_{it}^{nd} + \exp\lambda_t\pi_{it}^{d}\right).$$

Next, we multiply the first of the above by Q_{it}^{d} and the second by Q_{it}^{nd}. Then, adding the two resulting equations and apply $Q_{it}^{d} + Q_{it}^{nd} = 1$, to get (12b). QED

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<table>
<tr><td colspan="2"></td><td>1</td><td>2</td><td>3</td></tr>
<tr><td rowspan="6">Independent variables</td><td></td><td>LAND VALUE</td><td>HOUSE VALUE</td><td>FLOOR AREA RATIO</td></tr>
<tr><td>Dependent variable</td><td>$\ln\left(V^{nd}\right)$</td><td>$\ln\left(V^{d}\right)$</td><td>$\ln\left(f\right)$</td></tr>
<tr><td>Sample</td><td>Land parcels sold 1988-2012</td><td>Houses sold 1988-2012</td><td>Houses built 1988-2012</td></tr>
<tr><td>Size of sample</td><td>13,903</td><td>610,440</td><td>137,275</td></tr>
<tr><td>Number of year constants</td><td>24</td><td>24</td><td>24</td></tr>
<tr><td>Number of city constants</td><td>80</td><td>85</td><td>85</td></tr>
<tr><td>CBD</td><td>Shortest Distance to Downtown L.A.</td><td>-0.04
(0.0035)</td><td>-0.01
(0.0001)</td><td>-0.01
(0.0004)</td></tr>
<tr><td>JSC</td><td>Shortest Distance to Nearest Job Sub-center</td><td>---</td><td>-0.01
(0.0001)</td><td>-0.01
(0.0005)</td></tr>
<tr><td>ROAD</td><td>Shortest Distance to Major Road</td><td>+0.06
(0.0054)</td><td>+0.01
(0.0004)</td><td>-0.009
(0.0008)</td></tr>
<tr><td>COAST</td><td>Shortest Distance to Coastline</td><td>-0.03
(0.0026)</td><td>-0.004
(0.0001)</td><td>-0.003
(0.0004)</td></tr>
<tr><td>log (H)</td><td>log(Floor Space)</td><td>---</td><td>+0.70
(0.0011)</td><td>---</td></tr>
<tr><td>log (A)</td><td>log(Lot Size)</td><td>+0.37
(0.0093)</td><td>+0.17
(0.0011)</td><td>---</td></tr>
<tr><td rowspan="2"></td><td>R^2</td><td>0.41</td><td>0.80</td><td>0.24</td></tr>
<tr><td>Standard error of regression $\left(\sqrt{v^j}\right)$</td><td>1.26</td><td>0.28</td><td>0.37</td></tr>
</table>

TABLE 1

The land value, house value and FAR regressions
(Standard errors in parenthesis)

NOTE: All estimated coefficients are significant at 1% or better.

	Mixed logit models [a]					Benchmark mixed logit with covariance [b]	Binary logit model [c]
	Higher risk premium		Benchmark model	Lower risk premium			
Risk premium, above one year T-bill rate $(\rho \times 100)$	17%	10%	7%	5%	0%	7%	7%
Results							
Average value of yearly λ	0.21	0.20	0.18	0.18	017	0.39	0.004
Range of yearly λ	0.01-0.83	0.04-0.82	0.04-0.67	0.04-0.67	0.01-0.68	0.04-0.99	0.001-0.04
Expected excess returns [d] (average of annual)	-6.80%	-2.70%	0.05%	1.73%	7.7%	3.05%	125.76%
Construction elasticity [e] (average of annual)	4.20	4.30	4.04	4.11	4.14	6.10	0.24
Stock elasticity [f] (average of annual)	0.0262	0.0269	0.0262	0.0270	0.0266	0.0244	0.0013
Long run stock elasticity(24 yrs) [g]	0.631	0.648	0.631	0.650	0.640	0.587	0.0312
Log likelihood [h]	-487,412	-487,321	-487,086	-487,137	-487,021	-490,584	-497,603

TABLE 2

The benchmark mixed logit model and variations of it

NOTES: [a] (i) For each model, the panel data consist of 1,832,640 observations, comprised of 165,243 parcels that are initially undeveloped in 1988 and which appear as observations until they are developed. At the end of 2011, 19,450 parcels remain undeveloped; (ii) each model is estimated with 100 independent draws to sample FAR, house price and land price for each parcel and year, the results being unchanged with 200 repetitions; (iii) $\Sigma_{\boldsymbol{\theta}}$ is diagonal with $\nu^{nd} = 1.59, \nu^{d} = 0.08, \nu^{f} = 0.14$;

[b] Covariance terms $\nu^{nd,d} = 0.17, \nu^{nd,f} = 0.23, \nu^{d,f} = 0.05$ are included in $\Sigma_{\boldsymbol{\theta}}$;

[c] The logit was estimated by imputing all house and land prices and FARs from the regressions, ignoring deviations from the regression line;

[d] $E_t\left[\left(\hat{L}_t - \overline{L}_t\right) / \overline{L}_t\right] \times 100$, based on equations (15) and (16);

[e] Reported as the average over the years of the simple average of the construction elasticity of each parcel for each year;

[f] Calculated for each year from equation (20) or (23), then reported as the average value over the years;

[g] From equation (24).

[h] Sum of the log likelihoods over all the years.

	1988-2012	*S & L crisis and recovery* 1988-1999	*Irrational exuberance* 2000-2007	*Mortgage crisis and recovery* 2008-2012
Year-by-year-λ model				
Idiosyncratic dispersion, λ (standard error)	0.18 (0.0005)	0.19 (0.0005)	0.07 (0.0001)	0.36 (0.0009)
Expected excess return [a]	0.05%	-1.49%	3.91%	-3.65%
Construction elasticity [b]	4.04	2.99	2.98	9.29
Annual stock elasticity [c]	0.026	0.031	0.029	0.004
Long run stock elasticity [d]	0.63	0.37	0.23	0.03
Three-period-λ model				
Idiosyncratic dispersion, λ (standard error)	---	0.18 (0.0001)	0.05 (0.00002)	0.26 (0.0004)
Expected excess return [a]	0.46%	-2.67%	4.44%	-3.65%
Construction elasticity [b]	3.47	3.03	2.52	6.70
Annual stock elasticity [c]	0.027	0.036	0.025	0.004
Long run stock elasticity [d]	0.66	0.38	0.20	0.03
Constant-λ model				
Idiosyncratic dispersion, λ (standard error)	0.07 (0.000008)	0.07 (0.000008)	0.07 (0.000008)	0.07 (0.000008)
Expected excess return [a]	0.60%	-0.17%	3.62%	-3.10%
Construction elasticity [b]	2.20	1.43	3.28	2.33
Annual stock elasticity [c]	0.019	0.015	0.033	0.002
Long run stock elasticity [d]	0.46	0.16	0.26	0.01

TABLE 3

The year-by-year-λ (benchmark), 3-period-λ and constant-λ models

NOTES: All models estimated with $\rho = 0.07$; All λ estimates are statistically significant at the 1% level or better; In the 3-period-λ and year-by-year-λ models, the λ, the standard errors in parentheses, the expected excess returns, the construction elasticity and the stock elasticity are reported as the averages over the relevant years;

[a] $E_t\left[\left(\hat{L}_t - \overline{L}_t\right)/\overline{L}_t\right]\times 100$, based on eq. (15) and (16);

[b] Reported as the average over the relevant years of the simple average of the construction elasticity of each parcel for each year;

[c] From equation (20) or (23), then reported as the average value over the years;

[d] From equation (24).

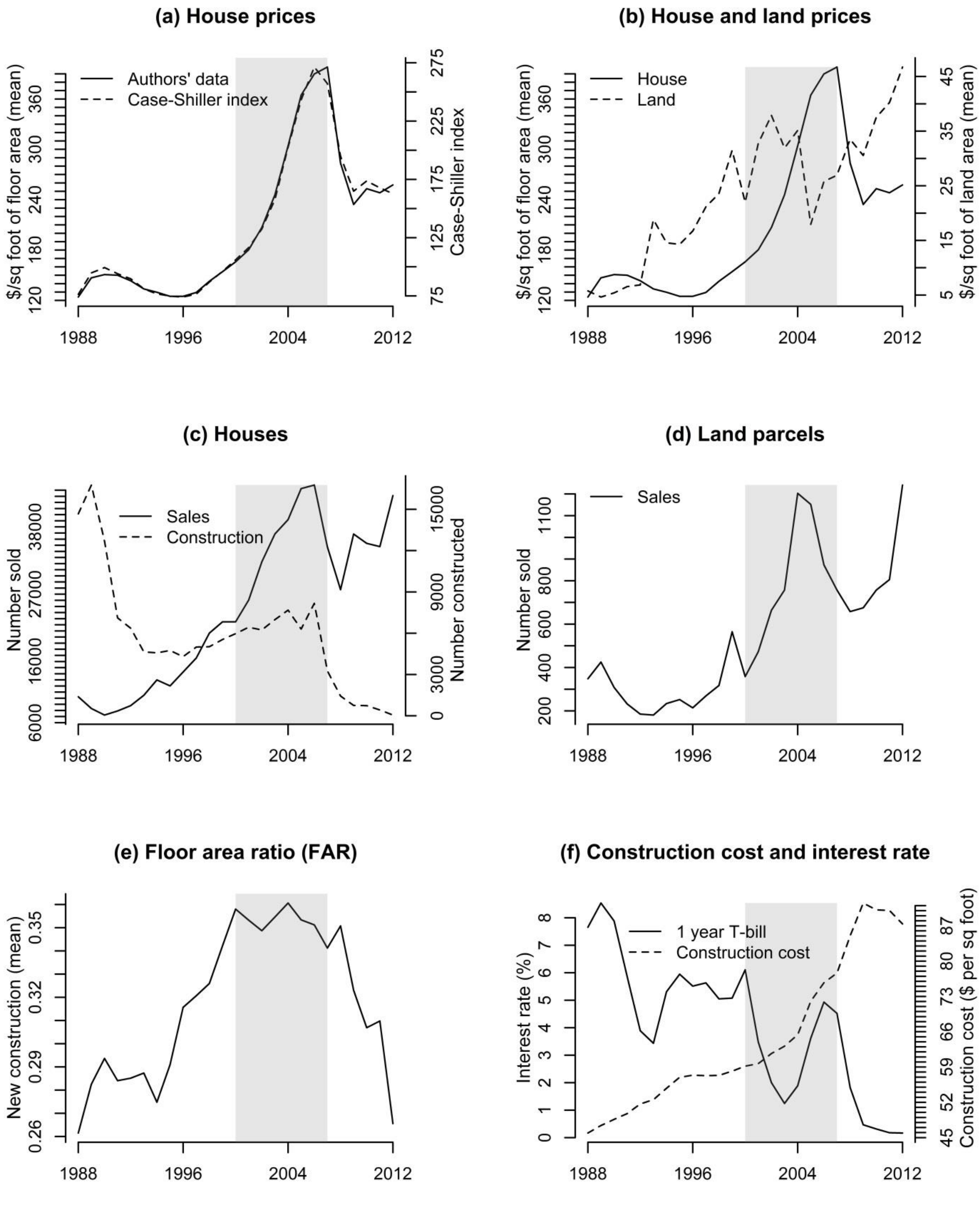

FIGURE 1
Los Angeles County, 1988-2012

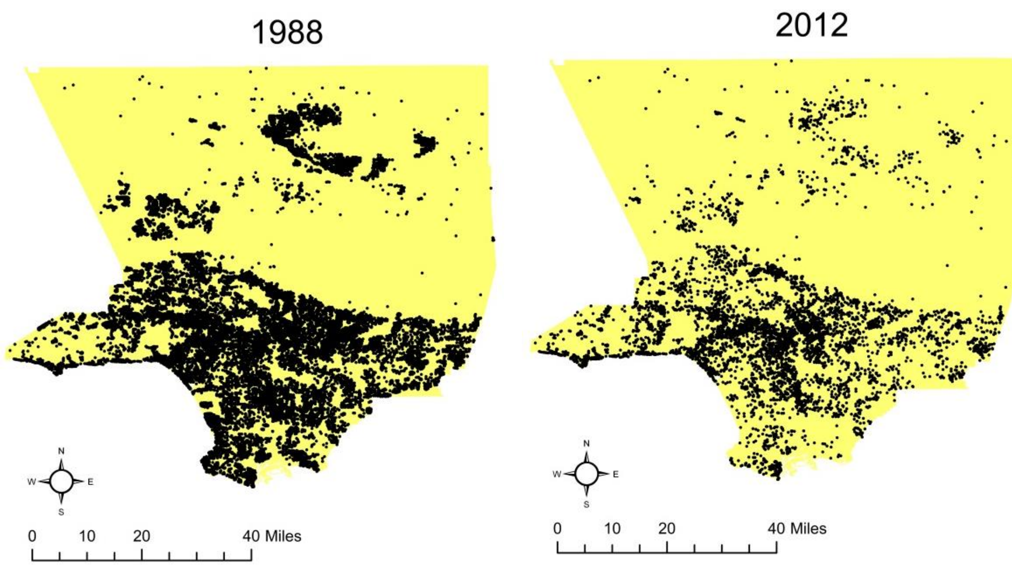

FIGURE 2
Undeveloped parcels, LA County

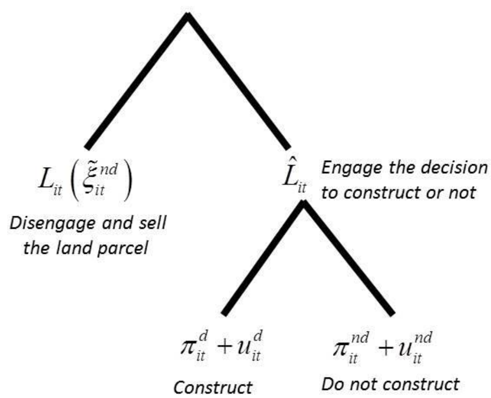

FIGURE 3
Decision tree of investor-developer

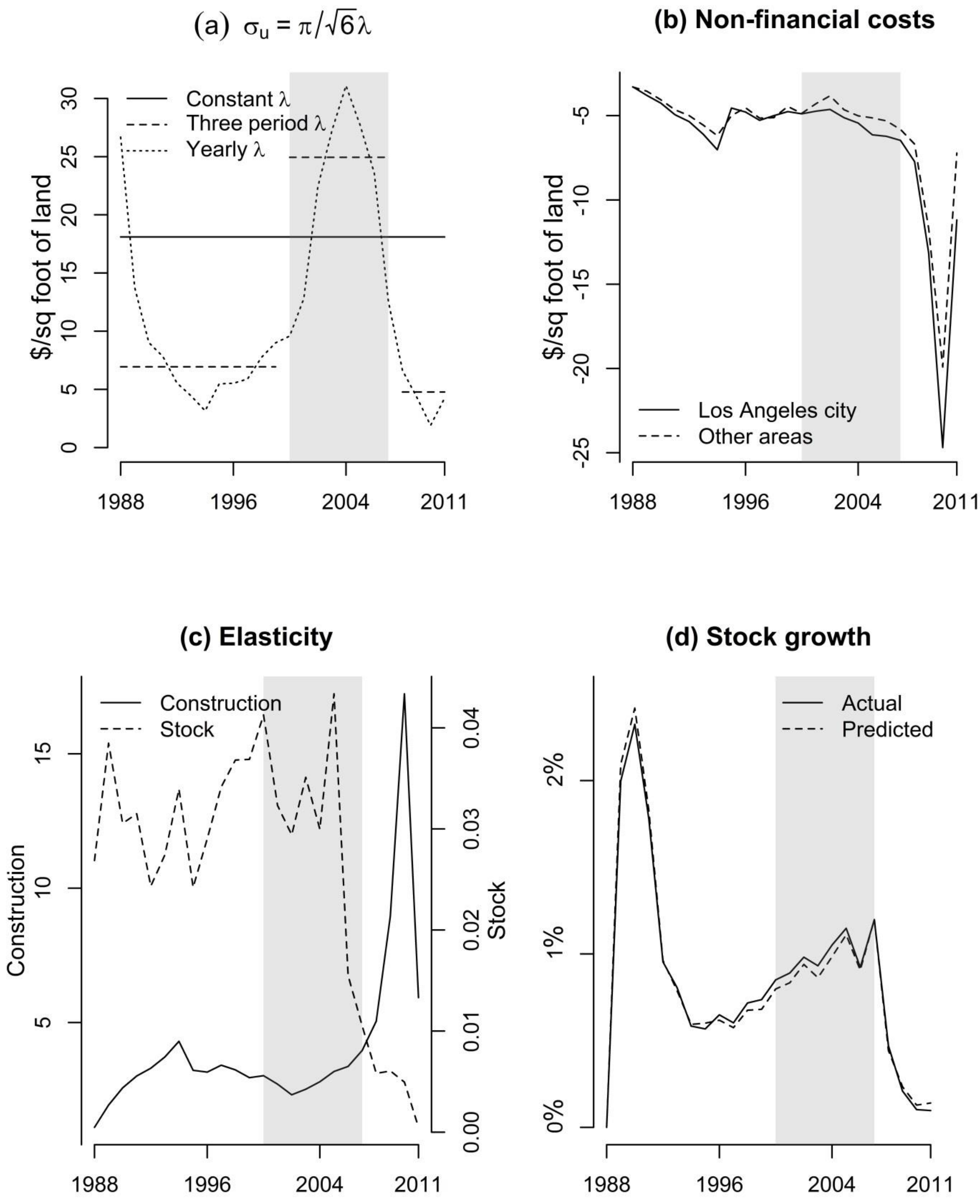

FIGURE 4
Estimates, elasticity and stock growth in the benchmark model

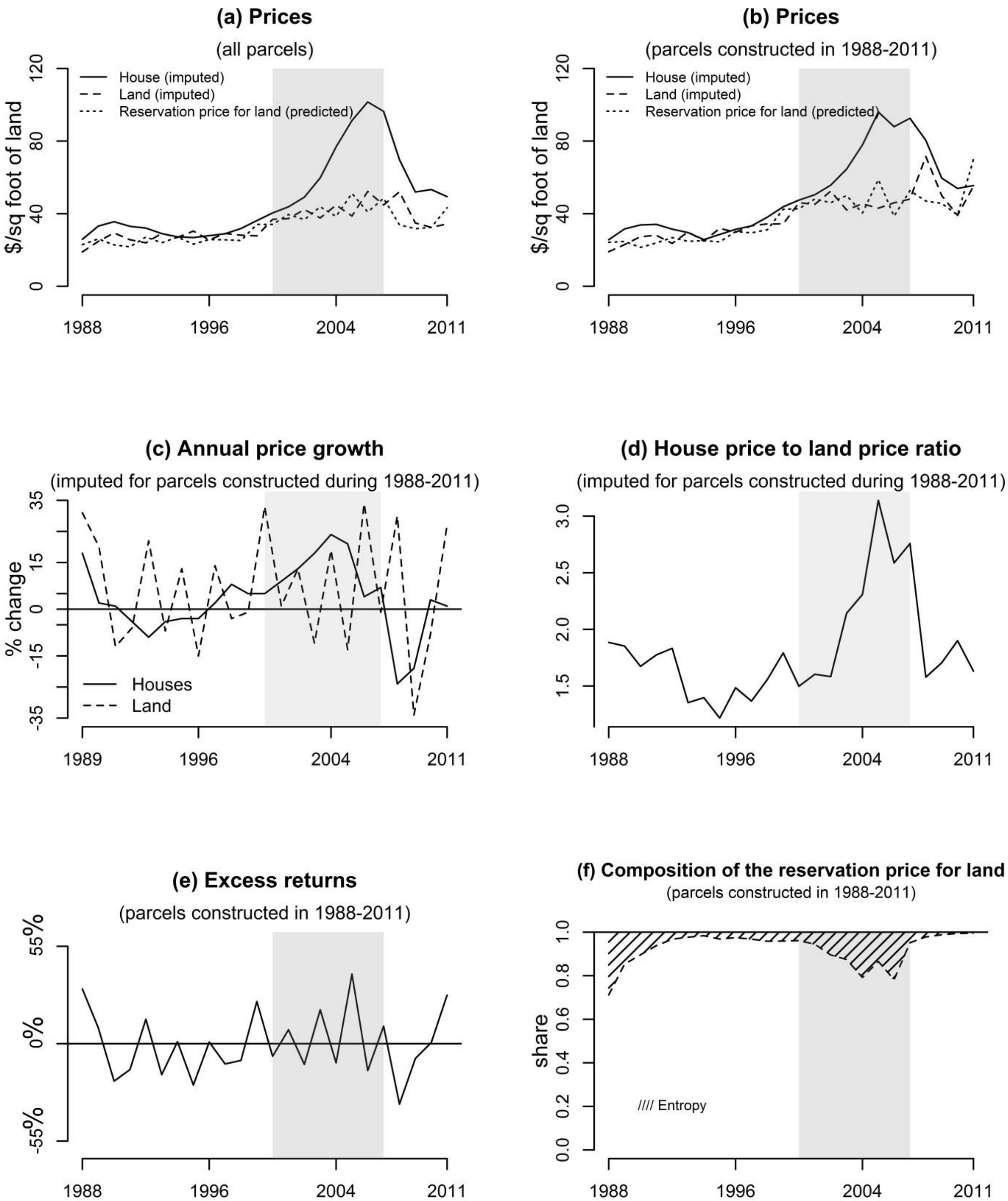

FIGURE 5
Predicted prices and returns in the benchmark model

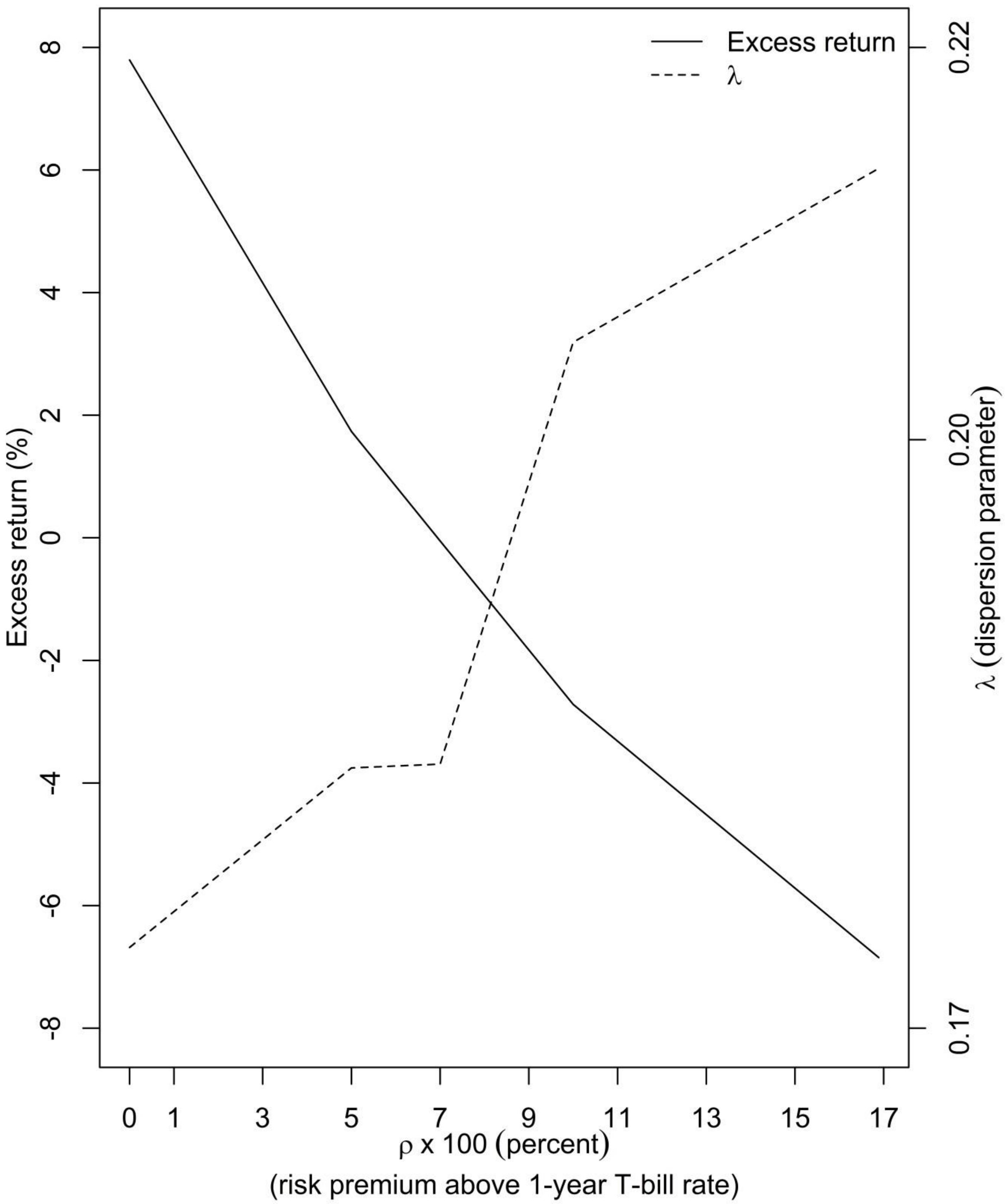

FIGURE 6

Effect of ρ on λ and predicted excess returns