

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

Alex Anas (\*) and Debarshi Indra (\*\*)

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### **ABSTRACT**

We estimate a mixed logit model of new housing construction decisions under uncertainty from a panel of land parcels zoned single family residential in LA County. Our study period from 1988 to 2012 includes the savings and loans and the recent mortgage crises. The probability of construction depends on stochastic expectation of post-construction prices, on the cost of construction, on fixed effects reflecting geographic and regulatory impediments to development, and on noisy perceptions of the payoffs of constructing or not. 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 6.21% in the 2000-2007 boom, trailing them by 2.06% during the subsequent crash years. Exuberance during the boom is indicated by higher sensitivity to noise and lower to price. A measure of entropy that reflects the sensitivity to noise climbs to 16%-38% of investors' reservation price for land during price booms, but begins to recede prior to the peak.

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(\*) Corresponding author: State University of New York at Buffalo, Amherst, New York 14260.  
[alex.anas@verizon.net](mailto:alex.anas@verizon.net); 716-645-8663

(\*\*) Center for Sustainable Suburban Development, School of Public Policy, University of California at Riverside 92521

# Rationality and exuberance in land prices and the supply of new housing<sup>1</sup>

Alex Anas and Debarshi Indra

## 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 and the structural density at which to construct under uncertainty about post-construction prices, and noisy perception of the payoff of developing or not. We use discrete choice theory to formulate our model. We first describe a binary logit model to treat the effect of the noisy payoffs, and then extend it to a mixed logit to more fully capture the uncertainty in the land investor expectations of year-ahead prices. The market's responsiveness is obtained by aggregating over the micro decisions of land developers.

Our approach combines the intensive and extensive margins of land development, studied separately in the extant literature. One group of studies 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. Mayer and Somerville (2000) show that if changes in housing stocks are related to changes in the levels of housing prices

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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. 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 land use regulations.

In contrast to the aggregative models, theoretical microeconomic models of land development under rational expectations assume that all rents on buildings grow with random motion around a well-defined exponential trend. They also assume that all land investors are homogeneous and have identical expectations about the future. In such an idealized environment, it is plausible that investors in land can see deep into the future and act confidently with rational expectations. Using such a framework, Capozza and Helsley (1990) model when in the future it is optimal for the land to be developed; and Capozza and Li (2002) examine at what structural density it is optimal to develop the land.

Our long term panel data of land parcels zoned for single family housing spanning the period 1988-2012 in Los Angeles County, presents a reality that is far more complex than that assumed in the theoretical models. During this long time span the housing and land markets underwent enormous fluctuations that could not have been foreseen. These fluctuations were associated with the savings and loan crisis that had repercussions into the early nineties, and more recently with the housing bubble followed by the mortgage crisis. In addition to these highly non-stationary or bubble-like temporal fluctuations, the data also reveals wide heterogeneity in housing and land prices, even within the relatively limited geography of the County. A plausible consequence of all this spatiotemporal inhomogeneity is that investors in developable land cannot reliably forecast the future price of their land or the future price of the prospective housing they would build, except perhaps by looking forward for relatively short periods, and even then only imperfectly.

Almost all housing construction of single family housing takes a year or less from permit issuance to completion.<sup>2</sup> We assume that investors contemplating construction must forecast the year ahead market price of their land and the year ahead market price of the prospective housing. Price forecasts are made with stochastic expectations about the year-ahead prices; and additionally decisions to construct or not are subject to noisy perceptions of their payoffs. If the decision is to not construct, then the decision repeats again next year with updated price forecasts and new noisy perceptions of the payoffs for the next year ahead. Investors have a reservation price for holding onto a land investment each year, given that they might construct on it. We decompose this reservation price into a systematic component explained by rational profit calculations based on expected prices under uncertainty, and a measure of *entropy* driven by the noise in the payoffs of constructing and not constructing. 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 16%-38% 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.<sup>3</sup> In our model, during the 2000-2007 price boom, investors' reservation prices for land ran ahead of market prices by 6.2%, and trailed by about 2.06% during the subsequent price crash, although over the entire period from 1988-2012 rational expectations appeared to be holding on average. Our model shows that a 1% excess of reservation land prices over market prices during a year, results in a 1.11% increase in the market price of land in the next year, but has no significant impact on next year's house prices.

Our microeconomic approach yields a clear path from the housing price elasticity of new construction on each land parcel to the short term 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 over time. This clears up the 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

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<sup>2</sup> The Census reports that 25% of houses are sold on completion, the rest evenly split as "not yet started" and "under construction." (U.S. Census, 2015). The National Association of Home Builders (2013) reports that construction takes 7 months on average, and in the West Coast, 8 months from permit issuance to completion.

<sup>3</sup> The terms "ordinary" and "smart" investors are borrowed from Shiller (2014).

elasticity in LA County varied between 2 and 4 with a mean of 2.89 while the annual stock elasticity varied between almost zero and 0.053 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.

The existing literature on local housing supply finds that local land use regulations and local geographic features can significantly affect local housing supply by hindering land development for residential purposes. In addition, as Saiz (2010) points out, the home voter hypothesis of Fischel (2001) argues that areas with initially high land values have stricter land use regulations, since incumbent residents in such areas seek to protect their investments. In California, in particular, cities have strong powers in regulating land use as documented by Quigley and Raphael (2005). These observations suggest that in the choice model we need to model the effects of land use regulations as non-financial costs borne by developers. To ensure identification of our parameters in such an environment we employ the BLP or Berry, Lehvinsohn, and Pakes (2005) approach and estimate city-year fixed effects which we hope capture the effects of local land use regulations on the decision to construct. We find that these fixed effects do measure a cost to developers, and are have a positive and statistically significant relationship to land sales values. We also show that the costs measured by the BLP constants are higher in the City of LA as compared to the average values over the rest of the County, for each year during the period 1988-2010. These findings confirm Fischel's hypothesis and imply more stringent land-use regulations in the City than in the rest of the County and in the cities of the County with higher land values.

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 year-ahead land and housing prices and we model the structural density of new construction. In section 4 we present the discrete choice model of the decision to construct and its properties, specializing to a mixed logit model. Section 5 derives the elasticity of new

construction and of housing stock by time horizon. Section 6 describes the estimation procedure, and in section 7 our benchmark results and its variations are discussed. We conclude in section 8.

## 2. Data

Our data are from the property records for Los Angeles County in 2012.<sup>4</sup> In our sample, the County is represented by 85 cities (LA being the biggest) and all unincorporated parts comprise an 86<sup>th</sup> geographic area. 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 or if parcels were merged, then the subdivisions or the merged parcel appear in the data as separate 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 if such parcels sold during 1988-2012. 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 temporal structure of the 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

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<sup>4</sup> 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 property assessments. Pre 1988 data are not reliable due to many missing observations.

to 2012. Notably, from panel (b) during the period of irrational exuberance, house sales prices increased 2.39 times, but land sales prices made a big fluctuation with essentially no net change.

Panel (c) shows that the number of houses sold 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 33% from 0.27 in 1988 to 0.36 in 2004, subsequently declining to 0.30. Construction costs in panel (f) are computed from the RSMMeans 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 doubled. 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 of 1988 and 2012. These are evenly distributed throughout the County both north and south of the mountain ranges.

[FIGURE 2 ABOUT HERE]

### 3. Modeling profit expectations

We refer to agents who own land parcels interchangeably as developers or investors. In the next section, we will model such investors' decisions under uncertainty, of whether to construct housing or not on a parcel that is undeveloped in the beginning of any year  $t$ . In order to do so, we first need to model the developer's year-ahead profit expectations from the currently undeveloped land parcel. We use superscript  $nd$  for a land parcel  $i$  that will remain in the "not developed" state, and  $d$ , "developed", for a parcel  $i$  that will become developed with prospective housing on it. In our data, the vast majority of houses that are built, sell within one year of construction. We assume a one-year lag between construction and sale, since from the data we cannot specify a shorter lag, and two years is unrealistically long for most single family housing.

A developer of land parcel  $i$  who contemplates construction in year  $t$  followed by sale in year  $t+1$  knows the probability distribution of the market price of land that will hold should he not build (the  $nd$  state), and the probability distribution of the market price of the floor space for his parcel in year  $t+1$  should he build (the  $d$  state), conditional on building a particular FAR in

year  $t$ . We will estimate the probability distributions of the year-ahead land and floor prices. From the year-ahead prices and the FAR of the housing planned to be constructed in year  $t$ , the developer calculates the expected economic profits of the developed and undeveloped states in year  $t$ . The prospective FAR that a developer would build on his parcel may be known to the developer, but it is not perfectly observed by the econometrician. Therefore, we also treat the prospective FAR as having a probability distribution which we will estimate. The investor discounts future cash flows at a *risk-adjusted normal rate of return*  $r_t + \rho$ , where  $r_t$  is the risk-free one-year T-bill rate in year  $t$  and  $\rho$  is a time-invariant risk-premium appropriate to single family housing development.

We specify the state-dependent economic profits *per unit of the parcel's land* at the start of year  $t$  as follows:

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

$$\Pi_{it}^d = \frac{(P_{i,t+1} - k_t) f_{it}}{1+r_t+\rho} - L_{it} + \mathbb{C}_{c(i)t} + u_{it}^d. \quad (1b)$$

$L_{it}$  is the known market price of the parcel's land in year  $t$ , hence also its current market opportunity cost.  $k_t$  is the cost of construction per unit floor space in year  $t$  (exclusive of land costs). The year-ahead prices of the land and the housing floor space, and the FAR that would be built on parcel  $i$  in year  $t$  are given by the functions  $L_{i,t+1} \equiv L(\mathbf{Z}_{i,t+1}, \xi_{i,t+1}^{nd})$ ,  $P_{i,t+1} \equiv P(\mathbf{Z}_{i,t+1}, \xi_{i,t+1}^d)$  and  $f_{it} \equiv f(\mathbf{Z}_{it}, \xi_{it}^f)$  respectively. These depend on current observable parcel characteristics  $\mathbf{Z}_{it}$  and on the random variable  $\xi_{it}^f$  for the FAR; and on  $\mathbf{Z}_{i,t+1}$  and the random variables  $\xi_{i,t+1}^{nd}, \xi_{i,t+1}^d$  for the year-ahead land and housing prices. The additive terms  $u_{it}^{nd}$  in (1a) and  $\mathbb{C}_{c(i)t} + u_{it}^d$  in (1b) measure non-financial costs or benefits that depend on unobserved factors.  $\mathbb{C}_{c(i)t}$  is the systematic non-financial cost or benefit of developing parcel  $i$  in year  $t$  that will be modeled as a fixed-effect that varies by year and the city  $c(i)$  in which the parcel  $i$  is located; and  $u_{it}^{nd}, u_{it}^d$  are state-dependent random effects or noisy profit shocks that vary idiosyncratically among the parcels each year according to a distribution that we will specify. We will refer to these as noisy



idiosyncratic profit shocks (NIPS, hereafter). We aim to model  $L(\bullet), P(\bullet), f(\bullet)$  and the  $\mathbb{C}_{c(i)t}$  in such a way that the  $u_{it}^{nd}, u_{it}^d$ , the NIPS, can be considered as white noise.

We focus on how  $L(\mathbf{Z}_{i,t+1}, \xi_{i,t+1}^{nd})$ ,  $P(\mathbf{Z}_{i,t+1}, \xi_{i,t+1}^d)$  and  $f(\mathbf{Z}_{it}, \xi_{it}^f)$  are imputed from estimates based on the available data, while in the next section will focus on how the fixed and random non-financial effects are modeled. The data includes  $V_{it}^d$ , the recorded sales values of houses that sold;  $V_{it}^{nd}$  is the recorded sales values of land parcels that sold; and  $f_{it}$ , is the FAR of constructed houses,. The attribute vector will be  $\mathbf{Z}_{it} = (\mathbf{X}_{it}, A_i, H_i)$ , where  $A_i$  is the parcel's land area (or lot size), and  $H_i$  is the observed or prospective floor space on it, and  $\mathbf{X}_{it}$  is a vector of other attributes. From such data, three regressions are estimated with residuals  $\theta_{it}^{nd}, \theta_{it}^d, \theta_{it}^f$ .

$$\log(V_{it}^{nd}) = \mathbf{a}^{nd} \mathbf{X}_{it} + \alpha \log(A_i) + \theta_{it}^{nd}. \quad (2a)$$

$$\log(V_{it}^d) = \mathbf{a}^d \mathbf{X}_{it} + \beta \log(H_i) + \gamma \log(A_i) + \theta_{it}^d, \quad (2b)$$

$$\log(f_{it}) = \mathbf{a}^f \mathbf{X}_{it} + \theta_{it}^f. \quad (2c)$$

House values 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, these 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;<sup>5</sup> to the nearest highway; and to the Pacific coastline. For undeveloped parcels, the regression (2a) includes a land parcel's area or lot size,  $A_i$ , and – for built parcels – regression (2b) includes  $A_i$  and  $H_i$ , the floor space.

The regressions (2a)-(2c) were estimated by Ordinary Least Squares (OLS) from separate samples all consisting of observations in 1988-2012, using the last recorded sales values for (2a)

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

and (2b), and the FAR in the year of construction for (2c). For (2a) there are sales of 13,903 undeveloped land parcels, 3,504 of them in the City of LA. For such parcels,  $V_{it}^{nd}$ , the land sales value is recorded in the data but  $V_{it}^d$ , and the FAR do not exist. The observations for (2b) are the 610,440 houses sold in the County, 179,040 of them in the City of LA. For such parcels,  $V_{it}^d$ , the house value and the FAR are recorded in the data, but the land value is not observed. For the FAR regression (2c) the sample consists of 124,134 parcels on which houses were constructed, 18,067 in the City of LA. For these parcels the data gives  $f_{it}$ , the FAR, but not  $V_{it}^{nd}$  and  $V_{it}^d$ . There is a much smaller sample of observations for which the date and sale price of the land, the date of the subsequent construction on the land, and the date and price of the sale of the constructed house are all recorded in the data and are within an interval of two years. Using this smaller sample to jointly estimate (2a)-(2c) by the Seemingly Unrelated Regressions (SUR) procedure gives unreliable results for the three regressions because of the small sample size. In section 7.4, we will report on a simplified SUR procedure that we use on this smaller sample to infer the off-diagonals of the variance-covariance matrix  $\Sigma_{\theta}$ . The diagonal elements of  $\Sigma_{\theta}$  are inferred as the squares of the standard errors of the separately estimated OLS regressions. These OLS results including the standard errors regressions are shown in Table 1.

**[TABLE 1 ABOUT HERE]**

The FAR decreases with each of the distances.<sup>6</sup> 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, because the supply of floor space at a dear location can be increased by building at a 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

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<sup>6</sup> The California Coastal Commission, created in the 1970s, regulates development within a mile of the coast. In a variation of the regressions of Table 1, we specified distance to the coast as  $\delta_1$  (ONE) COAST +  $\delta_2$  (1-ONE) COAST, (ONE =1 if COAST <1, ONE=0 otherwise). All results and the  $R^2$  estimates are essentially unchanged, but the FAR increases slightly for COAST <1. The commissioners likely exercise their control more strictly closer to the coastline, which explains the lower FAR near the coast. We are grateful to David Brownstone who helped us interpret this result.

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 ( $\alpha$  in (2a)). House value elasticity with respect to floor space is 0.7 ( $\beta$  in (2b)) and 0.17 with respect to lot size ( $\gamma$  in (2b)).

The regressions (2a)-(2c) are used to impute year-ahead land value, house value and FAR to an undeveloped parcel in any year. To do so we must transform the regressions by taking the exponential of both sides. We define  $\xi_{it}^j \equiv e^{\theta_{it}^j}$  for regression  $j = nd, d, f$ . Because the additive residuals  $\theta_{it}^j$  are assumed i.i.d.-normal with zero mean and variance  $v^j$ , the multiplicative residuals  $\xi_{it}^j$  of the transformed regressions are lognormal with  $E[\xi_{it}^j] = e^{v^j/2}$  and  $\text{var}(\xi_{it}^j) = e^{v^j} (e^{v^j} - 1)$ . FAR is imputed to any undeveloped land parcel by transforming (2c):

$$f_{it} = \exp(\mathbf{a}^f \mathbf{X}_{it}) \xi_{it}^f, \quad (3a)$$

$$\bar{f}_{it} \equiv E[f_{it}] = \exp\left(\mathbf{a}^f \mathbf{X}_{it} + \frac{v^f}{2}\right). \quad (3b)$$

Floor space on the parcel to be constructed in year  $t$  is then  $H_{it} = \bar{f}_{it} A_i$ . House values are imputed from (2b) to any parcel to which floor space has been imputed:

$$V_{it}^d = A_i^\gamma H_i^\beta \exp(\mathbf{a}^d \mathbf{X}_{it}) \xi_{it}^d, \quad (4a)$$

$$\bar{V}_{it}^d = E[V_{it}^d] = A_i^\gamma H_i^\beta \exp\left(\mathbf{a}^d \mathbf{X}_{it} + \frac{v^d}{2}\right). \quad (4b)$$

The developer can determine a profit maximizing floor space from (4b) that should be built on parcel  $i$  in year  $t$ . The profit from constructing  $H_{it}$  square feet of floor space in year  $t$  would be:

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

Then, the profit maximizing floor space and FAR would be:

$$H_{it}^* = \left( \frac{\beta A_i^\gamma \exp\left(\mathbf{a}^d \mathbf{X}_{it} + \frac{v^d}{2}\right)}{k_t} \right)^{\frac{1}{1-\beta}}, \quad f_{it}^* = \frac{H_{it}^*}{A_i}. \quad (6)$$

$f_{it}^*$ , calculated for each parcel that underwent construction, had a substantially higher median and mean than the data FAR or the regression-imputed FAR from (3b). This is explained by 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 zoning regulations and the need to conform, developers might build multiple family housing approaching profit maximizing FAR levels. But given the realities of regulation and conformity, we use the regression-imputed FAR from (3a) in the profit equation (1b).

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

$$V_{it}^{nd} = A_i^\alpha \exp(\mathbf{a}^{nd} \mathbf{X}_{it}) \xi_{it}^{nd}, \quad (7a)$$

$$\bar{V}_{it}^{nd} \equiv E[V_{it}^{nd}] = A_i^\alpha \exp\left(\mathbf{a}^{nd} \mathbf{X}_{it} + \frac{v^{nd}}{2}\right). \quad (7b)$$

The price of the parcel per square foot of the land is then imputed by  $L_{it} \equiv \frac{V_{it}^{nd}}{A_i}$  and, on average,

$\bar{L}_{it} \equiv \frac{\bar{V}_{it}^{nd}}{A_i}$ . The unit floor price of the prospective housing is imputed by  $P_{it} \equiv \frac{V_{it}^d}{f_{it} A_i}$  and, on

average, by  $\bar{P}_{it} \equiv \frac{\bar{V}_{it}^d}{A_i f_{it}}$ . Thus,  $\bar{P}_{it}, \bar{L}_{it}, \bar{f}_{it}$ , are imputations of mean house price, land price and

FAR based on the characteristics  $\mathbf{Z}_{it} = (\mathbf{X}_{it}, A_i, H_i)$ , and the uncertainty measured by the

variances of the random effects  $v^{nd}, v^d, v^f$ ;  $P_{it}, L_{it}, f_{it}$ , are stochastic imputations that are

generated by sampling the random effects  $\xi_{it}^j, j = nd, d, f$ .

#### 4. The decision to construct

Suppose that a developer faces no uncertainty in year-ahead prices and the FAR to construct. Such a developer knows  $\xi_{it} = (\xi_{it+1}^{nd}, \xi_{it+1}^d, \xi_{it}^f)$  for his parcel. The developer would still

be subject to the uncertainty caused by the idiosyncratic noise in profits  $\mathbf{u}_{it} = (u_{it}^{nd}, u_{it}^d)$ . We assume that these are revealed to the developer later during year  $t$  and, at such time, the decision to construct is made. If construction does not occur in year  $t$ , the parcel remains in the  $nd$  state and at the start of the next year,  $t+1$ , it is priced at  $L_{i,t+1} = L(\mathbf{Z}_{i,t+1}, \xi_{i,t+1}^{nd})$  per unit of land; alternatively the developer builds FAR of  $f(\mathbf{Z}_{it}, \xi_{it}^f)$ , and the floor space in year  $t+1$  is priced at  $P_{i,t+1} = P(\mathbf{Z}_{i,t+1}, \xi_{i,t+1}^d)$ . We define  $\pi_{it}^{nd} = \frac{L_{i,t+1}}{1+r_t+\rho}$  and  $\pi_{it}^d = \frac{(P_{i,t+1} - k_t)f_{it}}{1+r_t+\rho} + \mathbb{C}_{it}^d$  to abbreviate the expressions (1a), (1b). Each year, a rational investor compares the present value economic profit of constructing,  $\Pi_{it}^d = \pi_{it}^d - L_{it} + u_{it}^d$  given by (1a) and not constructing,  $\Pi_{it}^{nd} = \pi_{it}^{nd} - L_{it} + u_{it}^{nd}$  given by (1b) and chooses the more profitable of the two actions. If the  $\pi_{it}^{nd}$  and  $\pi_{it}^d$  are well-specified, then NIPS  $\mathbf{u}_{it} = (u_{it}^{nd}, u_{it}^d)$  are indeed white noise (see Train (2009)). Therefore, we assume, that  $\mathbf{u}_{it}$  and  $\xi_{it}$  are uncorrelated, that is  $\text{cov}(u_{it}^s, \xi_{it}^\ell) = 0$  for  $\forall s = nd, d$  and  $\forall \ell = nd, d, f$ .

Once the NIPS are revealed, the developer constructs if  $\Pi_{it}^d - \Pi_{it}^{nd} \geq 0$ . Otherwise, construction is foregone and the binary decision process repeats again in year  $t+1$  when a new pair of noisy shocks  $\mathbf{u}_{it} = (u_{it}^{nd}, u_{it}^d)$  occur. The probability the investor of parcel  $i$  will construct in year  $t$ , conditional on  $\xi_{it} \equiv (\xi_{i,t+1}^{nd}, \xi_{i,t+1}^d, \xi_{it}^f)$  is then:

$$Q_{it}^d = \text{Prob}[\Pi_{it}^d - \Pi_{it}^{nd} \geq 0] = \text{Prob}[\pi_{it}^d - \pi_{it}^{nd} \geq u_{it}^{nd} - u_{it}^d]. \quad (8)$$

Only differences matter in this binary comparison. Hence,  $L_{it}$ , the market price of land in the current year which was subtracted in (1a) and (1b), does not affect the decision to construct. 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 if the land is not sold, the construction decision must be engaged, and then  $L_{it}$  becomes a sunk opportunity cost.

In a competitive market, a developer values the land investment at the reservation price  $\hat{L}_{it}$ , the highest price to bid at the start of year  $t$ , if he were to buy the land anew. Hence,  $\hat{L}_{it}$  is the

price of the land that would leave zero expected economic profit to the investor operating under uncertainty about the NIPS:

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

In a perfectly functioning land market,  $L_{it} = \hat{L}_{it}$  would hold for each undeveloped land parcel and year, before the NIPS are revealed. This would be a perfect vindication of the rational expectations hypothesis. Instead, our model allows  $L_{it}$ , the market price, and  $\hat{L}_{it}$ , the reservation price to differ on each parcel. Hence, arbitrage opportunities exist. If  $\hat{L}_{it} < L_{it}$ , the developer is better off to sell the parcel. If  $\hat{L}_{it} \geq L_{it}$  then a developer is better off to keep (or buy) the parcel at the market price  $L_{it}$  and reap excess expected profits by engaging the decision to construct or not when the NIPS are revealed.

We will now discuss two special cases of a 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  $\mathbf{u}_{it} = (u_{it}^{nd}, u_{it}^d)$  are two independent draws from the same type I extreme value distribution with variance  $\sigma_{ut}^2$ , or dispersion parameter  $\lambda_t = (\pi / \sqrt{6}) / \sigma_{ut} \geq 0$  (McFadden, 1974; Train, 2009).

Then the construction probability, given by equation (8) and conditional on  $\xi_{it}$ , becomes:

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

The probability function given by (10) is a sigmoid curve confined between zero and one, asymptotic to zero from above as  $\pi_{it}^d - \pi_{it}^{nd} \rightarrow -\infty$  and to one from below as  $\pi_{it}^d - \pi_{it}^{nd} \rightarrow +\infty$  and  $Q_{it}^d = 0.5$  when  $\pi_{it}^d - \pi_{it}^{nd} = 0$ .

Three properties of binary logit 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. Muth (1969), Epple et al., 2010). This

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<sup>7</sup> Such a discrete choice model was proposed by Anas and Arnott (1991).

assumption to which we also adhered in the foregoing, allowed 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 parcels 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  $\sigma_{ut} \rightarrow +\infty$  and hence  $\lambda_t \cong 0$ . The noisy idiosyncratic profit shocks then swamp the systematic profit factors and  $Q_{it}^d \cong 0.5$ . Hence investors become insensitive to prices and randomize between constructing and not constructing, appearing economically irrational. At the other extreme, as  $\sigma_{ut} \rightarrow 0$ , then  $\lambda_t \rightarrow +\infty$ . In this case, the noisy idiosyncratic 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  $\lambda_t$  controls the elasticity, let  $\eta_{\pi_{it}^d}$  denote the elasticity of  $Q_{it}^d$  with respect to  $\pi_{it}^d$ . From (10):

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

(iii) *Expected profit in advance of the decision to build and the reservation price for land*:

Conditional on a draw of the vector  $\xi_{it}$ , 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  $\xi_{it}$ , and has rational expectations about the idiosyncratic shocks, under the logit calculus the expected maximized profit at the start of year  $t$  is:

$$E \left[ \max \left( \Pi_{it}^{nd}, \Pi_{it}^d \right) \right] = \frac{1}{\lambda_t} \ln \left( \exp \lambda_t \pi_{it}^d + \exp \lambda_t \pi_{it}^{nd} \right).^8 \quad (12a)$$

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

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<sup>8</sup> 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.

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

On the right side, the first term gives the part of the reservation price,  $\hat{L}_{it}$ , that depends on the the expected value of the systematic profits, while the second term is the additional expected value from the NIPS when they are, as yet, unknown to the developer. This second term is the mean measure of expected 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:

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

The entropy tends to  $\ln(1/2)$  and, hence, the right side of (13) tends to infinity as  $\lambda_t \rightarrow 0$ . More volatility in the noisy idiosyncratic profit shocks (smaller  $\lambda_t$ ) 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  $\xi_{it} \equiv (\xi_{i,t+1}^{nd}, \xi_{i,t+1}^d, \xi_{it}^f)$  is treated as a random vector.<sup>9</sup> Then the choice probability and the reservation price are obtained by integrating (10) and (12b) over the joint distribution of  $\xi_{it}$ . One interpretation of our mixed logit is that, at the beginning of year  $t$ , but before the NIPS 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  $\xi_{it}$  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

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<sup>9</sup> 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.



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.

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

$$\tilde{Q}_{it}^d = \int_{\xi} Q_{it}^d \mathbf{d}G(\xi|\Sigma_\xi). \quad (14)$$

The reservation price for holding on to the land is:

$$\hat{L}_{it} = \int_{\xi} \hat{L}_{it}(\xi_{it}) \mathbf{d}G(\xi|\Sigma_\xi). \quad (15)$$

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:

$$\bar{L}_{it} = \int_{\xi} L_{it}(\xi_{it}^{nd}) \mathbf{d}G(\xi|\Sigma_\xi). \quad (16)$$

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:<sup>10</sup>

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

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<sup>10</sup> From (11), using the chain rule of differentiation, since  $\pi_{it}^d$  is a function of  $P_{i,t+1}^d$ .

And in the case of the mixed binary logit, the elasticity of the construction probability  $\tilde{Q}_{it}^d$  with respect to expected price  $\bar{P}_{i,t+1}$ , recalling that  $P_{i,t+1} = \frac{\bar{P}_{i,t+1}}{e^{\nu^d/2}} \xi_{i,t+1}^d$ , is:

$$\tilde{\eta}_{Q_{it}} \equiv \frac{\partial \tilde{Q}_{it}^d}{\partial \bar{P}_{i,t+1}} \frac{\bar{P}_{i,t+1}}{\tilde{Q}_{it}^d} = \frac{1}{\tilde{Q}_{it}^d} \int_{\xi} \lambda_t \frac{P_{i,t+1} f_{it}}{1+r_t+\rho} Q_{it}^d (1-Q_{it}^d) \mathbf{d}G(\xi|\Sigma_{\xi}).^{11} \quad (18)$$

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,  $E[A_i f_{it} \tilde{Q}_{it}^d] = A_i E[f_{it}] \tilde{Q}_{it}^d = A_i \bar{f}_{it} \tilde{Q}_{it}^d$  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:

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

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  $\hat{P}_{i,t+1} = \kappa P_{i,t+1}$ , where  $\kappa$  is the constant of proportionality, the stock elasticity in year  $t$  is

$$\tilde{\eta}_{S_t} \equiv \left. \frac{dS_{t+1}/d\kappa}{S_{t+1}/\kappa} \right|_{\kappa=1} : \quad \tilde{\eta}_{S_t} = \frac{\sum_{\forall i \in U(t)} A_i \bar{f}_{it} \int_{\xi} \lambda_t \frac{P_{i,t+1} f_{it}}{1+r_t+\rho} Q_{it}^d (1-Q_{it}^d) \mathbf{d}G(\xi|\Sigma_{\xi})}{S_t + \sum_{\forall i \in U(t)} A_i \bar{f}_{it} \tilde{Q}_{it}^d} = \frac{\sum_{\forall i \in U(t)} A_i \bar{f}_{it} \tilde{Q}_{it}^d \tilde{\eta}_{Q_{it}}}{S_{t+1}}, \quad (20)$$

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

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

<sup>11</sup> The elasticity with respect to the land price, the construction cost and the interest rate are similarly calculated.

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:

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

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):

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

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  $t \rightarrow T$  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  $t \rightarrow T$ :

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

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

$$\eta_{\Delta}^{LRSE} = 100 \times \left\{ \left( 1 + \frac{\tilde{\eta}_s}{100} \right)^{\Delta} - 1 \right\}. \quad (25)$$

$\lim_{\Delta \rightarrow \infty} \eta_{\Delta}^{LRSE} = +\infty$ , 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 158,412 parcels in  $U(1988)$  and 13,068 of these transition into  $B(1988)$ , so in 1989 there are 145,344 parcels available for construction and so on. At the end of 2011, 19,350 parcels remain in  $U(2011)$  of which 669 became constructed on in that year. Pooling the parcels in the sets available for construction in the beginning of each year, we get 1,825,252 observations.

Let  $\Phi$  denote a vector that contains the dispersion parameter  $\lambda_t$  for each year and the constant  $\mathbb{C}_{ct} = \mathbb{C}_{c(i)t} \forall i \in c$  for each city  $c$ , and year  $t$  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  $\Phi$  we must specify  $\Sigma_{\xi}$ , the variance-covariance matrix of  $G(\xi | \Sigma_{\xi})$ . Recall that  $\xi_{it} = e^{\theta_{it}}$  and that, therefore, since  $\theta_{it}$  are normally distributed,  $\xi_{it}$  are log-normally distributed. Then  $\Sigma_{\xi}$  is implied by  $\Sigma_{\theta}$ . The diagonal elements of  $\Sigma_{\theta}$  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  $\Sigma_{\theta}$  (and, hence, of  $\Sigma_{\xi}$ ) are zero. But some covariance may exist in  $\Sigma_{\theta}$  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 variances in  $\Sigma_{\theta}$  are  $v^j, v^k$  and the corresponding covariance is  $v^{j,k}$ . Then  $\text{cov}\left(\frac{\xi_{it}^j}{\xi_{it}^k}, \frac{\xi_{it}^k}{\xi_{it}^j}\right) = e^{\left(\frac{v^j + v^k}{2}\right)} \left(e^{v^{j,k}} - 1\right)$ . 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  $G(\xi|\Sigma_\xi)$ , the Partial Maximum Simulated Likelihood Estimator (PMSLE) of  $\Phi$  is denoted by  $\hat{\Phi}$  and is obtained by maximizing the simulated log-likelihood function

$$\hat{\Phi} = \operatorname{argmax} SLL_t = \sum_{\forall c} \sum_{\forall i \in c \cap U(t)} y_{it} \log \tilde{Q}_{it}^d + (1 - y_{it}) \log (1 - \tilde{Q}_{it}^d). \quad (26)$$

$\hat{\Phi}$  is consistent and asymptotically normal even if the NIPS  $u_{it}^{nd}$  and  $u_{it}^d$ , which were 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  $\hat{\Phi}$  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 NIPS  $u_{it}^{nd}, u_{it}^d, t = 1, 2, \dots, T$ . 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.<sup>12</sup>

The city-year constants,  $\mathbb{C}_{ct}$  ensure that none of our explanatory variables are endogenous and so  $\hat{\Phi}$  is a consistent estimator of  $\Phi$ . 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<sup>13</sup>, 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

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<sup>12</sup> 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.

<sup>13</sup> 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.

employing the BLP procedure (Berry (1994) and Berry, Levinsohn, Pakes (1995)) to calibrate 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  $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_T)$

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

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

*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  $\tilde{Q}_{it}^d$  given by equation (14), an unbiased and asymptotically efficient estimator of the true choice probability;<sup>14</sup>

*Step 6: (BLP procedure):*  $A_i$  is the land area of parcel  $i$ . Given  $\lambda_t$  for each year  $t$ , adjust the city-

year constants,  $\mathbb{C}_{ct}$ , where  $r$  is the iteration counter, so that  $\mathbb{C}_{ct}^{r+1} = \mathbb{C}_{ct}^r + \log \left( \frac{\sum_{i \in c \cap U(t)} A_i y_{it}}{\sum_{i \in c \cap U(t)} A_i {}^r \tilde{Q}_{it}^d} \right)$

$\forall (c, t)$ . 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  $r = R$

:  $\left| \sum_{i \in c \cap U(t)} A_i (y_{it} - {}^R \tilde{Q}_{it}^d) \right| < tol$  where  $tol$  is an appropriately small tolerance. Hence observed and predicted city land shares are matched as required by the BLP procedure, and consequently

$$\mathbb{C}_{ct}^{R+1} = \mathbb{C}_{ct}^R.$$

<sup>14</sup> 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  $\lambda_t$  according to a numerical optimization procedure which maximizes the simulated log-likelihood function.<sup>15</sup>

*Step 8:* Given the  $\lambda_t$  found in step 7 we return to step 0 and we continue the loop of step 0 to step 8 until the value of  $\lambda_t$  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  $\lambda_t$  is separately estimated for each year; the risk-premium is set as  $\rho = 0.07$ ; and the covariance terms in  $\Sigma_\xi$  are ignored. We will, however, test the sensitivity of the benchmark model by modifying it in three ways; (i) by making  $\lambda$  constant over time, and by making it uniform within each of the three historical periods; (ii) by including the covariance terms in  $\Sigma_\xi$ ; and (iii) by seeing how the risk-premium  $\rho$  affects the  $\lambda$  estimates. The results are shown in Figures 3, 4 and 5; and the benchmark is reported in column three of Table 2 and in the top third of Table 3.

[FIGURES 3, 4, 5 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 NIPS than by the price and cost-based systematic factors. This is seen from panel (a) of Figure 3 which shows that the variance of the shocks estimated in the benchmark model sharply surged ( $\lambda$  sharply dropped) during housing price booms, and then fell severely ( $\lambda$  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. Although the crises differed a great deal as to causes, they share this common characteristic. We will return to this issue below.

The non-financial costs  $\mathbb{C}_{ct}$  in panel (b) of Figure 3, calibrated as the BLP constants, are negatively valued. Hence, as explained in the Introduction, we interpret these measuring the effect of city-year specific costs of regulatory and geographic constraints that impede

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<sup>15</sup> 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.

construction. For each year, the average value of the constants across the 85 cities is displayed. These impediments amounted to about \$30 per square foot of land prior to 2000 but increased sharply during the house price boom, 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 intra-metropolitan 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. When we regressed the sales values of land parcels against the  $\mathbb{C}_{ct}$  we found a highly significant positive relationship which indicates that the home-voter hypothesis of Fischel (2001) holds: cities with higher land values show higher regulatory impediments, or to put it differently, the high land prices themselves do not fully explain the low level of the construction activity.

Panel (c) of Figure 3 shows how much the annual construction and stock elasticity varied in 1988-2012. The construction elasticity varied between 2 and 4, while the stock elasticity ranged between just above zero and 0.053. 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 4). The annual stock elasticity peaked in 2000 and 2003 and then fell dramatically as new construction dried up, rebounding in 2008-2011. Panel (d) of Figure 3 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 4 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.<sup>16</sup> Panel (d) of Figure 4 provides another way of seeing the difference in exuberance 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 4 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 0.60% over the entire period from 1988-2012, while panel (f) of Figure 4 shows that during the bubble-like periods, entropy climbed as a percentage 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 16% of the investor reservation price, then receding before house prices peaked. It happened again, in 2004-2006 prior to the mortgage crisis when entropy eked above 38%, then sharply receding just before the 2007 peak year in house prices. That the peak in entropy was reached before the 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 noisy part of their expectations, the housing price bubble reached its bursting point trapping ordinary housing consumers.

## 7.2 Less variation in $\lambda$ over time

In the benchmark model,  $\lambda_t$  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  $\lambda$  over time that depart from the benchmark model. In the second model in Table 3,  $\lambda$  is estimated to be different for each of the three historical periods, but remains uniform for the years within each period. Hence, a single  $\lambda$  is estimated for each period by pooling the years of that period. In the third model in Table 3,  $\lambda$  is assumed to remain constant over the entire 24 year period and is estimated by pooling all of the years. Panel (a) of Figure 3 juxtaposes the  $\lambda$  values of the three variations.

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<sup>16</sup> 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.

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 expected return of 6.21 percentage points, while during the mortgage crisis and recovery period all three models predict that reservation prices were 2.06 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 1.08% 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 0.33% 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 years. 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- $\lambda$  and 3-period- $\lambda$  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 and the national 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  $-0.78$  or a bit more, in absolute value, than one fourth the elasticity with respect to the year-ahead house price;  $-1.48$  with respect to the unit construction cost; and  $-0.006$  with respect to the risk-free interest rate.

### 7.3 Sensitivity to the risk premium $\rho$

Figure 6 shows how the maximum likelihood estimate of  $\lambda$  changes depending on the value of the risk premium  $\rho$  when it is varied in the wide range of zero above to seventeen percentage points above the one-year T-bill rate. For each value of  $\rho$ , the  $\lambda$  on the vertical axis is the simple average of the  $\lambda_t$  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  $+7.5\%$  to  $-7.5\%$  per year while the  $\lambda$  changes mildly from 0.123 to 0.147. This range of  $\lambda$  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,  $\rho$ , 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  $\rho$ , 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%.<sup>17</sup>

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  $\rho$  equal the long term average return of the stock market. To adapt 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 5, 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  $\Sigma_{\xi}$ , 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

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<sup>17</sup> Other evidence about homebuilder profits 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 premiums would have to be 24.1% to 9.5% after netting out a risk-free rate of 4.1%.

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 between them does not exceed two years. To estimate  $\Sigma_{\xi}$ , 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:  $Cov(\theta_{it}^{nd}, \theta_{it}^d) = 0.17$ ,  $Cov(\theta_{it}^d, \theta_{it}^f) = 0.05$ ,  $Cov(\theta_{it}^{nd}, \theta_{it}^f) = 0.23$ .

Column 6 of Table 2 includes the effect on the results of the benchmark model when these estimated covariance terms are included in  $\Sigma_{\xi}$ . The average value of  $\lambda$  increased from 0.13 in the benchmark case to 0.14, the construction elasticity increased by only 25%, while the annual stock elasticity decreased by only about 12%. The expected excess returns increased from nearly +0.6% to +2.88%, which means that a somewhat higher risk premium than  $\rho = 0.07$  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  $\bar{f}_i$ ,  $\bar{P}_i$ ,  $\bar{L}_i$ , since the logit does not permit stochastic treatment of the variables that appear in the systematic portion of profit. The dispersion parameter  $\lambda$  of the idiosyncratic shocks is different each year, varies between 0.001 and 0.05, and on average  $\lambda = 0.004$ . This turns out to be unacceptably low implying a very high standard deviation of the idiosyncratic shocks of  $\sigma_u = (\pi / \sqrt{6}) / \bar{\lambda} \approx \$320$  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 143% 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  $\lambda$ , 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.<sup>18</sup> 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**

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<sup>18</sup> Revelt and Train (1998), reach a similar conclusion in their use of the mixed logit to model consumer choice of household appliances.

**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,  $A_i$ .

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

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

$$(ii) A_i \Pi_{it}^d = \frac{A_i (P_{i,t+1} - c_t) f_{it}}{1+r_t+\rho} + A_i C_{ct}^d + A_i u_{it}^d - A_i L_{it}.$$

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

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

the scaling (i) and (ii) and the  $\lambda_{it}$  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:

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

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

$$\begin{aligned} \frac{1}{\lambda_t} \ln Q_{it}^d &= \pi_{it}^d - \frac{1}{\lambda_t} (\exp \lambda_t \pi_{it}^{nd} + \exp \lambda_t \pi_{it}^d), \\ \frac{1}{\lambda_t} \ln Q_{it}^{nd} &= \pi_{it}^{nd} - \frac{1}{\lambda_t} (\exp \lambda_t \pi_{it}^{nd} + \exp \lambda_t \pi_{it}^d). \end{aligned}$$

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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		Eq.(2a)	Eq.(2b)	Eq.(2c)
Independent variables		LAND VALUE	HOUSE VALUE	FLOOR AREA RATIO
	Dependent variable	$\ln(V^{nd})$	$\ln(V^d)$	$\ln(f)$
	Samples (1988-2012)	Land parcels sold	Houses sold	Houses built
	Size of sample	13,903	610,440	124,134
	Number of year constants	24	24	24
	Number of city constants	80	85	85
<i>CBD</i>	Distance to downtown L.A.	-0.04 (0.0035)	-0.01 (0.0001)	-0.008 (0.0004)
<i>JSC</i>	Distance to nearest job sub-center	---	-0.01 (0.0001)	-0.01 (0.0005)
<i>ROAD</i>	Distance to major road	0.06 (0.0054)	0.01 (0.0004)	-0.006 (0.0009)
<i>COAST</i>	Distance to coastline	-0.03 (0.0026)	-0.004 (0.0001)	-0.002 (0.0004)
log ( <i>H</i> )	log(Floor space)	---	0.70 (0.0011)	---
log ( <i>A</i> )	log(Lot size)	0.37 (0.0093)	0.17 (0.0011)	---
	$R^2$	0.41	0.80	0.22
	Standard error of regression ( $\sqrt{v^j}$ )	1.26	0.28	0.38

**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 <sup>a</sup>					Benchmark mixed logit after adding covariance <sup>b</sup>	Binary logit model <sup>c</sup>
	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%
<b>Results</b>							
Average value of yearly $\lambda$	0.14	0.13	0.13	0.13	0.12	0.14	0.004
Range of yearly $\lambda$	0.03-0.40	0.01-0.30	0.03-0.29	0.03-0.29	0.03-0.28	0.03-0.72	0.001-0.05
Expected excess returns <sup>d</sup> (average of annual)	-7.6%	-0.58%	0.60%	2.2%	7.4%	2.88%	143.3%
Construction elasticity <sup>e</sup> (average of annual)	2.95	2.93	2.89	2.98	2.94	3.25	0.23
Stock elasticity <sup>f</sup> (average of annual)	0.0263	0.0256	0.0260	0.0273	0.0258	0.0230	0.0010
Long run stock elasticity (24 yr) <sup>g</sup>	0.63	0.61	0.63	0.65	0.62	0.55	0.02
Log likelihood <sup>h</sup>	-471,012	-470,791	-470,963	-471,064	-470,735	-476,355	-477,997

**TABLE 2**

The benchmark mixed logit model and variations of it

**NOTES:** <sup>a</sup> (i) For each model, the panel data consist of 1,825,252 observations, comprised of 158,412 parcels that are initially undeveloped in 1988 and which appear as observations until they are developed. At the end of 2011, 19,350 parcels remain undeveloped; (ii) each model is estimated with 100 independent draws to sample FAR, House Price and Land Prices for each parcel and year, the results are unchanged with 200 repetitions; (iii)  $\Sigma_{\theta}$  is diagonal with  $\nu^{nd} = 1.59, \nu^d = 0.08, \nu^f = 0.14$  ;

<sup>b</sup> Covariances  $\nu^{nd,d} = 0.17, \nu^{nd,f} = 0.23, \nu^{d,f} = 0.05$  included in  $\Sigma_{\theta}$  ;

<sup>c</sup> The logit was estimated by imputing all house and land prices and FARs from the regressions, ignoring deviations from the regression line;

<sup>d</sup>  $E_t \left[ \left( \frac{\hat{L}_t - \bar{L}_t}{\bar{L}_t} \right) \right] \times 100$ , based on equations (15), (16);

<sup>e</sup> Reported as the average over the years of the simple average of the construction elasticity of each parcel for each year;

<sup>f</sup> Calculated for each year from equation (20) or (23), then reported as the average value over the years;

<sup>g</sup> From equation (24).

<sup>h</sup> Sum of the log likelihoods over all the years.

	1988-2012	<i>S &amp; L crisis and recovery</i> 1988-1999	<i>Irrational exuberance</i> 2000-2007	<i>Mortgage crisis and recovery</i> 2008-2011
<b><i>Year-by-year-<math>\lambda</math> model</i></b>				
<i>Idiosyncratic dispersion, <math>\lambda</math></i> (standard error)	0.13 (0.0004)	0.18 (0.0005)	0.05 (0.0001)	0.10 (0.0006)
<i>Expected excess return<sup>a</sup></i>	0.60%	-2.24%	6.21%	-2.06%
<i>Construction elasticity<sup>b</sup></i>	2.89	3.11	2.49	3.06
<i>Annual stock elasticity<sup>c</sup></i>	0.026	0.034	0.026	0.002
<i>Long run stock elasticity<sup>d</sup></i>	0.63	0.41	0.21	0.01
<b><i>Three-period-<math>\lambda</math> model</i></b>				
<i>Idiosyncratic dispersion, <math>\lambda</math></i> (standard error)	---	0.17 (0.0001)	0.04 (0.00002)	0.09 (0.0003)
<i>Expected excess return<sup>a</sup></i>	0.47%	-2.72%	6.46%	-1.92%
<i>Construction elasticity<sup>b</sup></i>	2.78	3.15	2.19	2.85
<i>Annual stock elasticity<sup>c</sup></i>	0.027	0.039	0.022	0.002
<i>Long run stock elasticity<sup>d</sup></i>	0.66	0.47	0.17	0.01
<b><i>Constant-<math>\lambda</math> model</i></b>				
<i>Idiosyncratic dispersion, <math>\lambda</math></i> (standard error)	0.06 (0.00001)	---	---	---
<i>Expected excess return<sup>a</sup></i>	1.5%	0.34%	4.70%	-0.93%
<i>Construction elasticity<sup>b</sup></i>	2.06	1.39	3.02	2.15
<i>Annual stock elasticity<sup>c</sup></i>	0.018	0.015	0.031	0.009
<i>Long run stock elasticity<sup>d</sup></i>	0.44	0.18	0.25	0.007

**TABLE 3**

The year-by-year- $\lambda$  (benchmark), 3-period- $\lambda$  and constant- $\lambda$  models

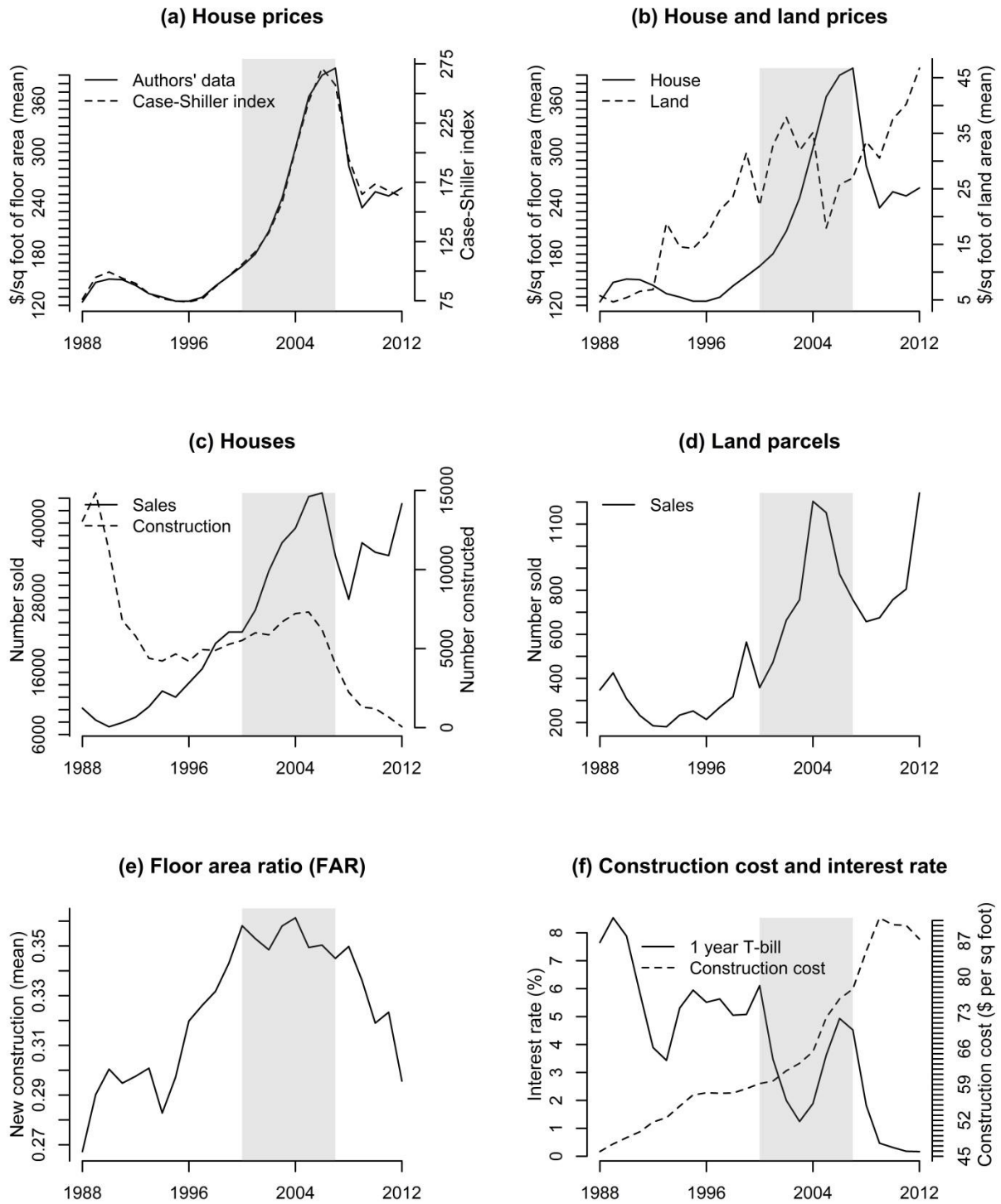
**NOTES:** All models estimated with  $\rho = 0.07$ ; All  $\lambda$  estimates are statistically significant at the 1% level or better; In the 3-period- $\lambda$  and year-by-year- $\lambda$  models, the  $\lambda$ , the standard errors in parentheses, the expected excess returns, the construction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

<sup>a</sup>  $E_t [(\hat{L}_t - \bar{L}_t) / \bar{L}_t] \times 100$ , based on equations (15) and (16);

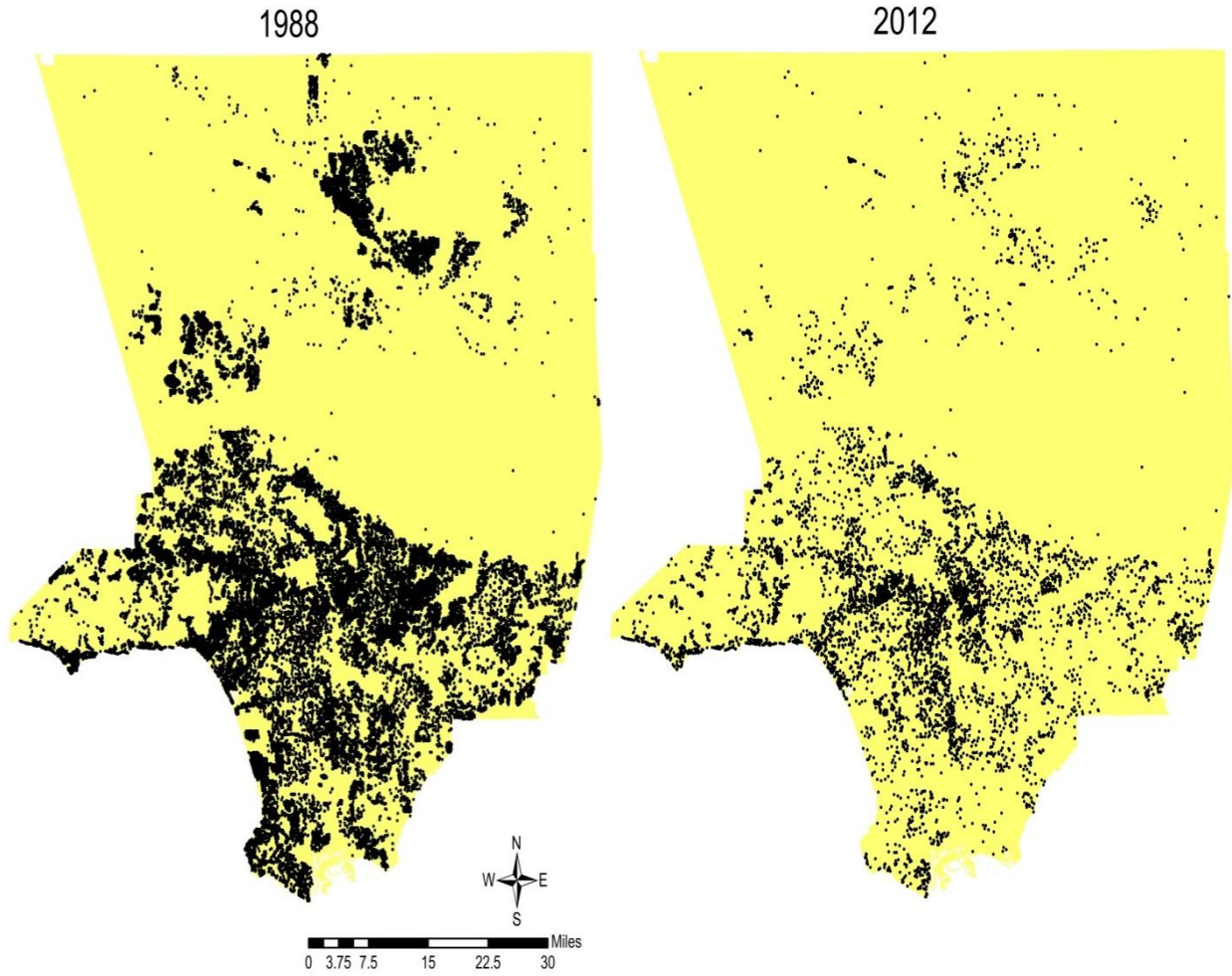
<sup>b</sup> Reported as the average over the relevant years of the simple average of the construction elasticity of each parcel for each year;

<sup>c</sup> From equation (20) or (23), then reported as the average value over the years;

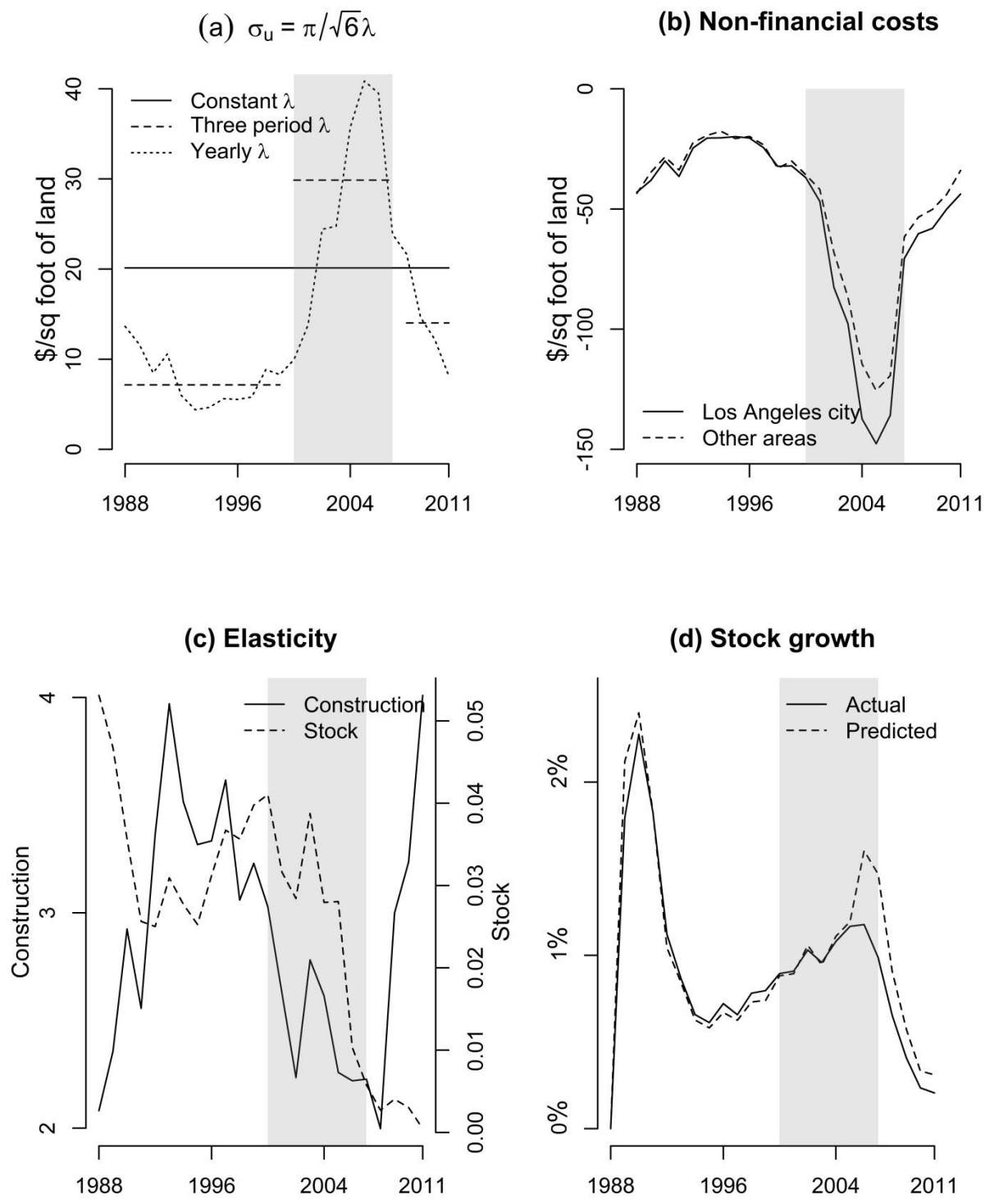
<sup>d</sup> From equation (24).



**FIGURE 1**  
 Los Angeles County, 1988-2012



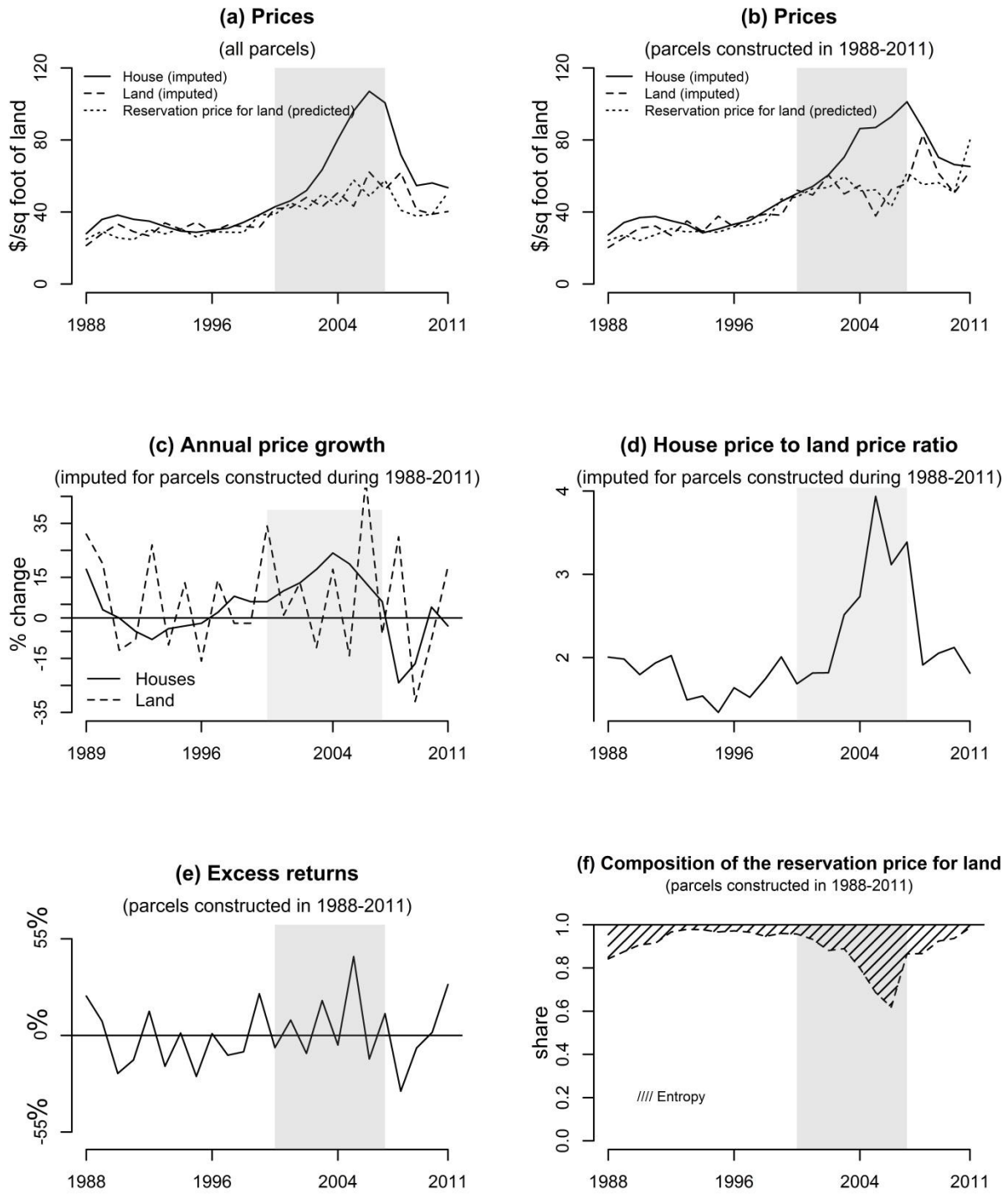
**FIGURE 2**  
Undeveloped parcels, LA County



**FIGURE 3**

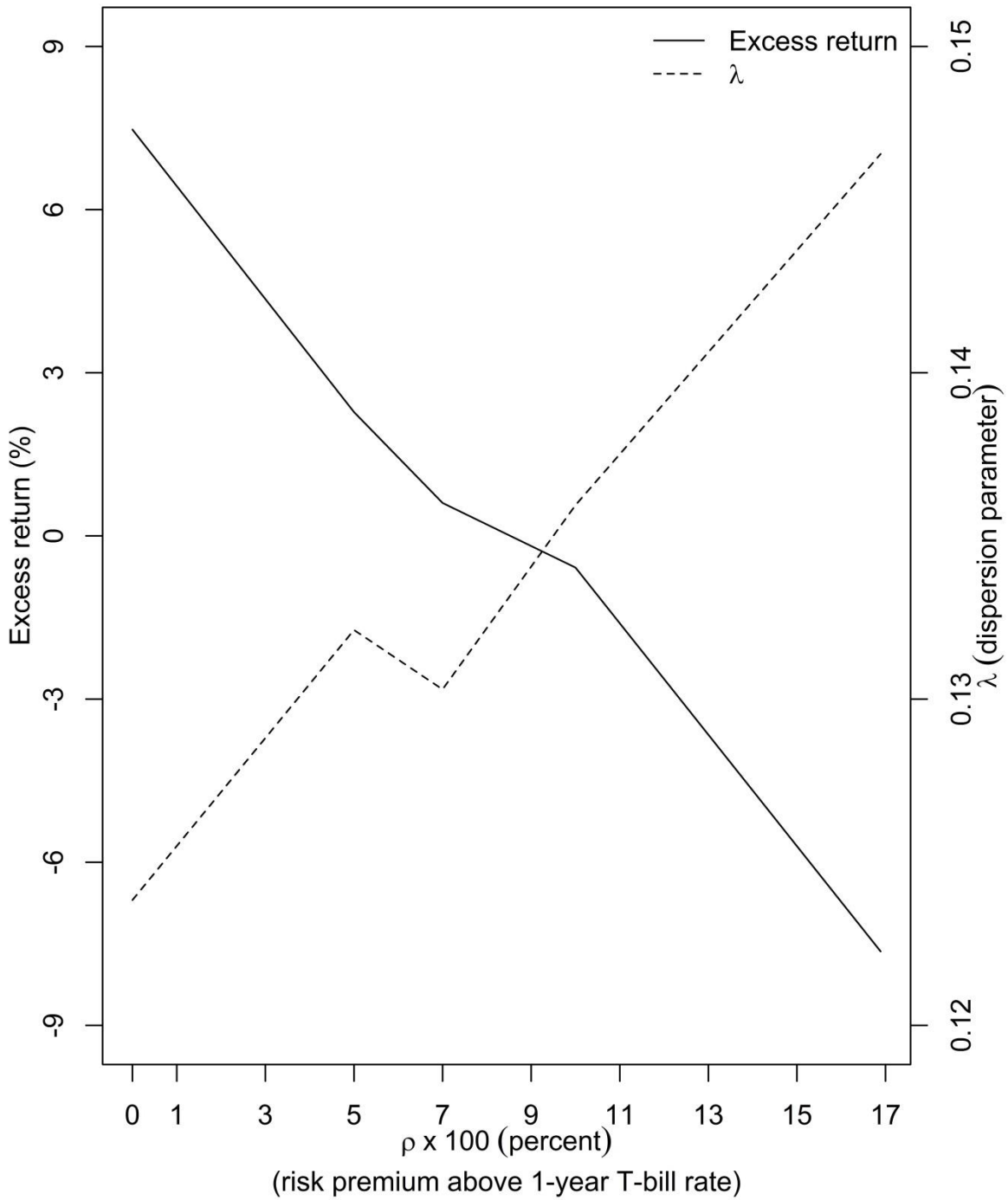
Estimates, elasticity and stock growth in the benchmark model





**FIGURE 4**

Predicted prices and returns in the benchmark model



**FIGURE 5**

Effect of  $\rho$  on  $\lambda$  and predicted excess returns