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

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ABSTRACT

We model decisions to construct housing under uncertainty, from a panel of land parcels zoned single family residential in LA County. The period 1988 to 2012 includes two price booms followed by the savings and loans and the recent mortgage crises, respectively. The probability of construction depends on structural density and on profits from post-construction housing prices that vary stochastically among investors, and on a start-up cost that we model as noisy. The model detects the exuberance during the price booms as an expectation of a high return from investing in land (animal spirits) and, at the same time, a growing sensitivity to noise than to prices. Measured by entropy, during the 2000-2007 boom, noise climbed to 38% of the reservation price for land, but receded before house prices peaked. Reservation prices exceeded land prices by 6.21% during the boom of 2000-2007, trailing by 2.06% during the crash. We derive the elasticity of housing supply from the annual construction elasticity on each land parcel, remedying the aggregative approach in the extant literature.

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Rationality and exuberance in land prices and the supply of new housing[1]

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1. Introduction

We introduce a new microeconomic and microeconometric approach for modeling single-family housing construction decisions under uncertainty. An investor in land will build in a given year, if he expects doing so to be more profitable than postponing the construction. Profit expectations are based on forward estimates of land and housing prices that vary stochastically according to unobserved attributes of the investor and the land parcel; and on the noisy perceived opportunity cost of starting the construction. To treat these aspects, we specify the probability that a land parcel will become developed in a given year as a mixed logit model.

Theoretical microeconomic models of land development under rational expectations assume that all rents on buildings grow with random motion around an exponential trend, and that all land investors have identical expectations about the future. In such an idealized environment, it would be plausible that investors in land can see deep into the future and act confidently with rational expectations. Using such assumptions, Capozza and Helsley (1990) modeled when in the future it is optimal for the land to be developed; and Capozza and Li (2002) examined at what structural density it is optimal to develop the land. Earlier, in a model with just two periods, Titman (1985) treated one investor who constructs in period 1 and faces either a high or a low building price in period 2. Using such a model, he examined the effect of uncertainty in the building price on the price of land.

The ideal conditions assumed in the theoretical models are not reflected in our data which consists of a large panel of land parcels zoned for single family housing spanning the years from 1988 to 2012 in Los Angeles County. During this long time span, the markets had large cyclical price and quantity fluctuations that included a boom followed by the savings and loan crisis and its aftermath through the nineties, then the speculative house price bubble of 2000-2007, followed by the crash in prices and then the mortgage crisis. In addition to these temporal cycles, the data

reflects the wide spatial heterogeneity in parcel attributes, and in housing and land prices within LA County which includes 85 local jurisdictions.

These highly non-stationary market price fluctuations from 1988 to 2012 were impossible for market agents to foresee, and it is not plausible to treat profit maximizing land developers as looking deep into the future with rational expectations. Pesaran (1987; page 2) observed that the rational expectations hypothesis "*is based on extreme assumptions and cannot be maintained outside the tranquility of a long-period steady state*", and our data exhibits no tranquility. Manski (2004), in his study of expectations, concluded that "*rational expectations assumptions are often implausible in the extreme.*" (page1335). Case and Shiller (1989) found that housing and real estate markets are not efficient. More recent observations by Shiller (2005), Akerlof and Shiller (2009; chapter 12) and Shiller (2014; section E, pp. 1501-1504) strongly support the view that exuberance and animal spirits rather than rational expectations are common not only in stock and other financial asset markets but also in housing and real estate markets. Recent surveys have emphasized the roles of heterogeneous beliefs in the formation of financial bubbles (Xiong, 2013; Brunnermeier and Oehmke, 2013). Armed with this perspective, our econometric formulation allows for profit maximizing behavior, but one that is buffeted by investor exuberance that arises from both systematic factors common to all investors and from idiosyncratic heterogeneity among investors. To achieve such a model formulation, we confront and resolve three modeling issues about the behavior of land investor-developers.

The first issue is that of an appropriate time horizon. Housing developers construct housing and expect to sell soon after construction. Almost all single family housing takes a year or less from permit issuance to completion and to sale.[2] In our benchmark model we assume that investors rationally forecast – albeit within considerable uncertainty which we model – the year-ahead expected market price of their land parcel that would hold should they choose not to construct, and the year-ahead housing market price at which they would sell if they choose to construct housing at a particular structural density. In our variations of the benchmark model we consider two alternative expectations behavior: investors are backward looking and forecast the year-ahead housing price as the moving average of past prices; or investors are forward-looking and forecast the year-ahead housing price as the moving average of several future prices, which we assume

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[2] The Census reports that 25% of houses are sold on completion, the rest evenly split as "not yet started" or "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.

they can somehow perceive. We find that, between these two, the backward looking assumption gives more satisfactory results.

The second issue concerns the well-known fact that houses and land sell infrequently on average. Because of this, investors must infer the expected market prices for their land and for the prospective housing they might build by valuing the observable attributes of similar properties that sold, and from stochastic idiosyncratic attributes that are their private knowledge or expectation but are not observed in the market. It is widely held that land and housing are indeed valued by reference to comparable properties that sold, from which implicit prices for attribute can be inferred. Rosen (1974) developed such a theory of implicit prices for competitive markets of highly differentiated products such as housing, and this is how we model year-ahead expected prices.

The third issue is modeling the opportunity cost of starting a construction project, which we treat as a fixed cost, not to be confused with the cost of the construction itself which is a variable cost that increases with structural density. This startup cost includes unobservable up-front pecuniary and non-pecuniary costs of dealing with regulations and complying with local codes that vary by jurisdiction. A temporally varying part of the startup cost includes such things as assessing the post-construction economy and overcoming the psychological resistance to committing to the construction project, given that the deeper future is not clearly visible. A third component of the startup cost varies idiosyncratically among the investors, and we treat it as a white-noise random variable.

Concerning the inter-jurisdictional component of the startup cost, the extant literature recognizes that local geographic features and land use regulations can raise development costs, limiting supply and driving up house prices. Rose (1989) has modeled geographic constraints, while Glaeser, Gyourko and Saks (2005) emphasized the role of regulations in raising real estate prices. Quigley and Raphael (2005) showed that California cities have strong powers to regulate land use, and some cities do restrict new development to various degrees, causing higher development costs and higher house prices. The "home-voter hypothesis" of Fischel (2001), provides an explanation for why regulations arise in the first place and how they vary by jurisdiction. Fischel claimed that local jurisdictions with high house prices politically choose stricter land use regulation, because incumbent residents seek to protect their home investments from losing value. In our empirical results we will present evidence that restrictive regulatory

policies may be causing higher startup costs; and that, controlling for the effect of these regulations, the startup cost of development is indeed associated with higher house values.

The commonly held temporal component of land investors' startup costs is explained by strong trends in housing prices that can influence developer expectations. As Shiller (2014) has reemphasized recently and Case and Shiller (1989) had demonstrated, average house prices in many markets do not follow a random walk, but tend to go up or down in the same direction for many years in a manner that is not related to fundamentals. In LA County, for example, prices rose consistently and sharply year after year from 1997 through 2005. If developers operating in such markets learn to demand returns bigger than a normal hurdle rate, they could postpone construction and speculate by keeping the land undeveloped which drives up house prices even higher. We refer to temporally increasing average startup costs as evidence of *animal spirits*.[3] We find that both the time trend of house prices and the annual percentage change in house prices may play significant roles in influencing the rise and fall of animal spirits in speculative land investing. This explains in part a relatively slow rise in construction from 2000-2005, during rapidly rising house prices.

The rise and fall in commonly held animal spirits is accompanied by a concomitant rise and fall in the variance of the noisy part of the startup cost, which reduces the sensitivity of the construction probability to financial profit during the years of booming house prices. To show the consequences of this on investing, we calculate an investor's reservation price for holding onto land, and decompose this into parts explained by the year-ahead expected profit from construction, a probability-weighted expectation of profit, plus a measure of *entropy* explained by the noise in the startup cost. We show that during the booms, the share of entropy in the reservation price rose to between 16%-38% from negligible levels in normal periods. But entropy receded sharply before prices peaked. In our benchmark model, during the exuberance of the 2000-2007 price boom, reservation prices for land ran ahead of market prices by 6.21% per year on average, and trailed by about 2.06% per year during the subsequent price crash, when zero excess economic returns held on average over the longer span from 1988 to 2012. Over this long period, a 1% per year excess of reservation over market land prices was associated with a 1.08% increase in next year's land prices, but had no significant association with next year's house prices.

A benefit of our microeconomic model of new housing supply is that it provides a basis for the rigorous determination of elasticity. Our mixed logit model combines the intensive and

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[3] We will see that our term animal spirits is similar to that of Shiller (2014).

extensive margins of housing supply, studied separately in the literature. The former group of studies has relied on micro data to estimate the weights of land and non-land inputs in a housing production function. The approach is traceable to Muth (1969) and the early work was surveyed by McDonald (1981). A difficulty with this approach was the absence of reliable data on land prices and on the quantity of housing services. But recently Epple, Gordon and Sieg (2010) used nonparametric methods to treat housing services and prices as latent variables.

The latter group of studies has relied on aggregative approaches to measure housing market responsiveness in the extensive margin. In Topel and Rosen (1988) and DiPasquale and Wheaton (1994), a time series of the national housing stock is related to average housing prices, taking care to identify demand and supply schedules. Mayer and Somerville (2000) showed that if changes in housing stocks are related to changes in average housing prices, then doing so gives lower but more reasonable estimates of the construction and supply elasticity. Green, Malpezzi and Mayo (2005) showed that the price elasticity of housing supply is higher in fast growing, less land use regulated and smaller metropolitan areas. Using long term aggregated data, Saiz (2010) showed that supply elasticity can be lower due to land use regulations and geographic limitations on developable land.

Using our model, the responsiveness of construction to house prices, construction costs and interest rates is obtained by aggregating over the micro decisions of land developers. This yields a clear path from the housing price elasticity of new construction on each land parcel to the short term and long term price elasticity of the housing stock. Our housing stock elasticity increases as the time horizon into the future lengthens, slowly approaching perfect elasticity over time. This clears up the ambiguity in the literature about the relationship between construction and the long run stock elasticity. During 1988 - 2012, our annual construction 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. The long run stock elasticity can be calculated 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 a percent higher each year. In our benchmark model and its variations, the long run stock elasticity over our study period for LA County lies between 0.45 and 0.63, somewhat below the estimate for the entire LA metropolitan area over 1970-2000 and which Saiz (2010) obtained from aggregated data.

The paper is organized as follows. In section 2 we explain our modeling framework, and its consistency with the real option theory of land investment. We show how the model detects commonly held animal spirits and noisy departures from pure profit maximization as two sources of exuberant market behavior. Section 3 derives the mixed logit model of the probability of construction and the reservation price for land; and section 4 derives the construction and stock elasticity. Section 5 describes our panel data set and surveys the fluctuation of prices and quantities from 1988 to 2012. Section 6 is on how structural density and year-ahead price expectations and their covariance structure are estimated, and section 7 is on the estimation of the mixed logit model. Section 8 presents the benchmark model and a number of variations of it demonstrating robustness of the empirical results. Section 9 concludes.

2. Modeling year-ahead profit expectations and exuberance

2.1 Year-ahead state-dependent profits

As explained in the Introduction, our developer-investors are able to see rationally as far as the year-ahead. For conceptual clarity suppose that a year t is divided into two stages as shown in Figure 1. In stage 1, the developer i knows the information necessary to forecast next year's expected market prices and prospective structural density for his parcel i, and knows the probability distributions of the random variables that would affect the parcel. Based on this information, the developer can calculate in stage 1, $\breve{L}_{i,t}$, the reservation price under uncertainty for the land parcel, which is the minimum price at which the developer would sell the parcel and the maximum he would pay to buy it. In stage 2, draws of the random variables are realized for each parcel, and based on these each developer decides whether to construct on his parcel in year t for sale in $t+1$ (the d state) or to postpone the decision to $t+1$ (the nd state).

[FIGURE 1 HERE]

Year-ahead cash flows are discounted at a *risk-adjusted normal rate of return* $r_t + \rho$, where r_t is the risk-free one-year T-bill rate and ρ is a time-invariant risk-premium appropriate to a long run internal rate of return for single family housing development.[4] We specify the full economic profits of *nd* and *d* states as follows:

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[4] We will discuss ρ in more detail in the empirical results in section 8.

$$\Pi_{i,t}^{nd} = \underbrace{\frac{L_{i,t+1}}{1+r_t+\rho} + u_{i,t}^{nd}}_{\equiv \pi_{i,t}^{nd}} - L_{i,t},$$ (1a)

$$\Pi_{i,t}^{d} = \underbrace{\frac{\left(P_{i,t+1}-k_t\right)f_{i,t}}{1+r_t+\rho} - \left(F_{c(i),t}-u_{i,t}^{d}\right) - L_{i,t}}_{\equiv \pi_{i,t}^{d}}.$$ (1b)

$\pi_{i,t}^{nd}$ and $\pi_{i,t}^{d}$ will be used later to abbreviate some equations. In (1a) $L_{i,t+1}$ is the year-ahead market price of land per unit land area of parcel i if it remains undeveloped in year t. In (1b), $P_{i,t+1}$ is the year-ahead market price of housing per unit floor area if the parcel is developed in year t, and $f_{i,t}$ is the prospective structural density (floor to land area ratio or FAR) that would be built. Construction cost exclusive of land costs is k_t per unit of floor area. $L_{i,t}$, the market price of the parcel's land in year t, is subtracted in (1a) and (1b) to calculate the full economic profit of each state, but it is a sunk cost and plays no role in the decision of whether to construct or not.

We assume that the year-ahead expected market price of land and housing, and the prospective FAR are imputed to each parcel, by the stochastic functions $L_{i,t+1} \equiv L\left(v^L, \mathbf{Z}_{i,t+1}\right)\xi_{i,t+1}^L$, $P_{i,t+1}, \equiv P\left(v^P, \mathbf{Z}_{i,t+1}\right)\xi_{i,t+1}^P$, $f_{i,t} \equiv f\left(v^f, \mathbf{Z}_{i,t}\right)\xi_{i,t}^f$, where $\mathbf{Z}_{i,t+1}$, $\mathbf{Z}_{i,t}$ are observed attributes of the parcels, and $\boldsymbol{\xi}_{i,t} \equiv \left(\xi_{i,t+1}^L, \xi_{i,t+1}^P, \xi_{i,t}^f\right) \in (0,+\infty)$ is a random vector with $E\left[\boldsymbol{\xi}_{i,t}\right] = \mathbf{1}$, that depends on idiosyncratic and unobservable attributes of the parcel and the investor. $E\left[L_{i,t+1}\right] \equiv L\left(v^L, \mathbf{Z}_{i,t+1}\right)$, $E\left[P_{i,t+1}\right] = P\left(v^P, \mathbf{Z}_{i,t+1}\right)$, $E\left[f_{i,t}\right] \equiv f\left(v^f, \mathbf{Z}_{i,t}\right)$ are the expected market price and prospective FAR functions, to be estimated in section 6; and we will see there that $v^j = \ln\left(1+\mathrm{var}\left(\xi_{i,t}^j\right)\right)$ for $j = L, P, f$. Provided these functions are well specified, as we shall see in section 6, the $\boldsymbol{\xi}_{i,t}$ will be uncorrelated with $\mathbf{Z}_{i,t+1}$, $\mathbf{Z}_{i,t}$. The reason FAR, is subscripted by t and depends on $\mathbf{Z}_{i,t}$, but prices are subscripted by $t+1$ and depend on $\mathbf{Z}_{i,t+1}$ is because of our assumption that the developer commits to an FAR in stage 2 of year t, but plans for construction and sale to be completed in year $t+1$. The $\boldsymbol{\xi}_{i,t}$ are drawn in stage 2 of each year from a time-invariant joint cumulative

distribution $G\left(\xi_{i,t}\mid\Sigma_{\xi}\right)$. In section 6 we will see how to empirically infer and numerically generate it.

$F_{c(i),t}-u_{i,t}^{d}$ in (1b) is the *perceived opportunity cost of starting construction* which includes both monetary and the monetary-equivalent of nonmonetary costs. This is a fixed cost because – unlike the construction cost $k_{t}f_{i,t}$ – it does not increase with the FAR. Note that this fixed cost has two components, $F_{c(i),t}$, which is common across investors in the same city $c(i)$ where parcel i is located, and $u_{i,t}^{d}$ which varies across investors. For the nd state, the corresponding perceived cost of holding land is just $u_{i,t}^{nd}$. We will assume that $\mathbf{u}_{i,t}=\left(u_{i,t}^{nd},u_{i,t}^{d}\right)\in(-\infty,+\infty)$ with $E\left[\mathbf{u}_{i,t}\right]=\mathbf{0}$ are additive random components of the state-dependent costs that vary by parcel each year and are i.i.d. While the $F_{c(i),t}$ capture the spatiotemporal commonly held trend of the startup costs, the $\mathbf{u}_{i,t}$ capture the stochastic variation around the trend. $W\left(\mathbf{u}_{i,t}\mid\sigma_{t}^{2}\right)$ is the cumulative distribution of $\mathbf{u}_{i,t}$ to be specified later. We will discuss the econometric implications of our model in section 6 and 7. In particular, we will explain how we deal both with endogeneity issues and with possible serial correlation in $\xi_{i,t}$ and in the $\mathbf{u}_{i,t}$.

2.2 Land investment as a real option and exuberance

Investing in land is analogous to buying a perpetual call option where the option's strike price is the cost of constructing a building. In the case of our model, an investor can see the year-ahead post-construction future, and once the $\xi_{i,t}$ and the $\mathbf{u}_{i,t}$ are revealed, the call option to build is exercised if $\Pi_{i,t}^{d}-\Pi_{i,t}^{nd}\geq0$, that is if:

$$\underbrace{\frac{P\left(v^{P},\mathbf{Z}_{i,t+1}\right)f\left(v^{f},\mathbf{Z}_{i,t}\right)}{1+r_{t}+\rho}\xi_{i,t+1}^{P}\xi_{i,t}^{f}}_{Value\ of\ housing}\geq\underbrace{\frac{k_{t}f\left(v^{f},\mathbf{Z}_{i,t}\right)}{1+r_{t}+\rho}\xi_{i,t}^{f}}_{\substack{Construction\ cost\\(Variable\ cost)}}+\underbrace{F_{c(i),t}+\hat{u}_{i,t}}_{\substack{opportunity\ cost\ of\\project\ start-up\\(Fixed\ cost)}}+\underbrace{\frac{L\left(v^{L},\mathbf{Z}_{i,t+1}\right)}{1+r_{t}+\rho}\xi_{i,t+1}^{L}}_{\substack{Value\ of\ land\\(Fixed\ cost)}}. \qquad (2a)$$

On the left side is the present value of the housing created by exercising the option to build. The right side is the total present value cost of exercising the option: the first term is the construction cost that increases with the FAR and the second term is the opportunity cost of starting the project, consisting of the mean cost $F_{c(i),t}$ and the noisy additive deviation, $\hat{u}_{i,t}\equiv u_{i,t}^{nd}-u_{i,t}^{d}$. The first two

terms on the right comprise the strike price while the third is the value of the land, that is the market value of the option contract itself. Exercise of the option is triggered by a high enough expected housing market price $P(v^P, \mathbf{Z}_{i,t+1})$; or a high enough random deviation, $\xi^P_{i,t+1}$, from the expected price; or a highly negative $\hat{u}_{i,t}$ (a highly positive $u^{nd}_{i,t}$) that reduces the startup cost. We now decompose the $F_{c(i),t}$ into year and time effects as explained in the Introduction. More precisely, $F_{c,t} = \mathbb{C}_{c,t} + \Theta_t$, where $\mathbb{C}_{c,t}$ is the component that depends on the regulations of city c and other time-invariant city characteristics such as geo-physical features, and Θ_t is the temporal component. Under certain market conditions, developers will perceive a high opportunity cost of committing to develop in the current year perhaps in expectation of even better house prices later, although they are unable or unwilling to forecast that far with any precision. Thus a high Θ_t indicates a willingness to keep holding land as a speculative investment beyond year t. Θ_t will be our measure of commonly held *animal spirits*. Shiller refers to a valuation of stocks in excess of the expected present value of their future dividend stream as animal spirits (Shiller (2014), eq. (4), p. 1498). We similarly define animal spirits to be an excess expected return from holding on to a land investment after accounting for a normal risk premium ρ.

The marginal investor who builds draws such a value of $\hat{u}_{i,t} \equiv u^{nd}_{i,t} - u^d_{i,t}$ that he makes zero profit from exercising the option to build, whereas infra-marginal investors make positive profit. The value of the house built by the marginal investor is then $Pf = L + kf + (1 + r + \rho)(\mathbb{C} + \Theta + \hat{u})$, where subscripts are removed for simplicity. Pf equals the sum of the cost of the land, L, the construction cost, kf, the startup cost $\mathbb{C} + \Theta + \hat{u}$, and the return on it. Thus the house buyer pays an exuberance premium of $(1 + r + \rho)\Theta$ to satisfy the animal spirits of land investors. Rearranging (2a) in abbreviated notation, we see below in (2b), that construction occurs when the financial profit from construction, after satisfying animal spirits yields a rate of return that exceeds the hurdle rate:

$$\underbrace{\frac{\left(P_{i,t+1}-k_t\right)f_{i,t}-L_{i,t+1}-(1+r_t+\rho)\Theta_t}{\mathbb{C}_{c,t}+\hat{u}_{i,t}}-1}_{\textit{Rate of return of project}} \geq \underbrace{r_t+\rho}_{\textit{Hurdle rate}} \quad [5] \tag{2b}$$

The model is applicable to periods with bubbles because it can help detect several types of market exuberance:

(i)   If too many investors contagiously believe in high upward deviations, $\xi^P_{i,t+1}$, from the expected market prices $P\left(v^P, \mathbf{Z}_{i,t+1}\right)$, then more construction would occur. This would be deemed an exuberant market because it may be statistically implausible that such expectations would be sustained by many rational investors at the same time;

(ii)   If the variance of the noisy part of the start-up cost becomes higher, more investors draw a negative enough $\hat{u}_{i,t}$ reducing the startup cost and causing the hurdle rate to be exceeded resulting in more construction. Such behavior would be deemed exuberant because decisions to construct would show high sensitivity to the white noise, $\hat{u}_{i,t}$, and reduced sensitivity to the financial profit from construction, $\left(P_{i,t+1}-k_t\right)f_{i,t}-L_{i,t+1}$;

(iii)   If investors are possessed by animal spirits, that is by high Θ_t, then – on average – higher year-ahead financial profit is required to develop the land. Such animal spirits can arise over extended periods of sharply rising housing prices and begin to recede once investors realize that prices are topping out. In this case, the exuberance in land speculation results in less construction which can drive up house prices even more. This is analogous to the exuberance of stock investors not selling overvalued stocks, expecting even higher returns in the future.

In our empirical results, we will see evidence of both (ii) and (iii), especially during the period from 2000 to 2005 when average house prices were sharply rising year after year on a sustained basis. We will show that the two effects worked against each other: the commonly held animal spirits, Θ_t, which were rising restrained construction by inducing more land speculation,

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[5] If $\hat{u}_{i,t}$ is viewed as noise around Θ_t, (2b) can also be written as $\dfrac{\left(P_{i,t+1}-k_t\right)f_{i,t}-L_{i,t+1}-(1+r_t+\rho)\left(\Theta_t+\hat{u}_{i,t}\right)}{\mathbb{C}_{c,t}}-1 \geq r_t+\rho$.

but the growing noise in $\hat{u}_{i,t}$ idiosyncratically caused more land investors to build, offsetting some of the effect of Θ_t.

2.3 The reservation price for investing in land

Of interest is the reservation price for investing in land (or buying the option-to-build). This is the maximum price the investor would bid for the land or the minimum price at which he would sell it, when the investor faces uncertainty. Suppose that $\xi_{i,t}$ is revealed, but $\mathbf{u}_{i,t}$ is not yet revealed, we denote the reservation price conditional on $\xi_{i,t}$ as $\hat{L}_{i,t}(\xi_{i,t})$:

$$\int_{\mathbf{u}_{i,t}} \left(\max\left(\pi_{i,t}^{nd}(\xi_{i,t}) + u_{i,t}^{nd}, \ \pi_{i,t}^{d}(\xi_{i,t}) + u_{i,t}^{d} \right) \right) \omega(\mathbf{u}_{i,t}) d\mathbf{u}_{i,t} - \hat{L}_{i,t}(\xi_{i,t}) = 0, \tag{3a}$$

where $\omega(\mathbf{u}_{i,t})$ is the probability density. Before $\mathbf{u}_{i,t}$ and $\xi_{i,t}$ are revealed, the reservation price is denoted $\breve{L}_{i,t}$, the weighted average of $\hat{L}_{i,t}(\xi_{i,t})$ given the joint probability density $g(\xi_{i,t})$:

$$\int_{\xi_{i,t}} \hat{L}_{i,t}(\xi_{i,t}) \, g(\xi_{i,t}) d\xi_{i,t} - \breve{L}_{i,t} = 0. \tag{3b}$$

(3a) and (3b) are zero-expected-profit conditions. They generalize the conventional fact in land economics that – in the absence of uncertainty – the price of land is the *residual value* remaining after all costs have been subtracted from the price of housing. In our setting, since there is uncertainty, the residual value condition holds ex-ante: the reservation price for land from the zero profit condition (3b) is the *expected residual value* that remains after costs in each state of the world have been subtracted from value in that state. The market and reservation price on land are not equal and either one can be higher as we see next.

2.4 Excess expected returns

Recall that in stage 1 of year t, the investor does not yet know the draws of the random variables (Figure 1). The expected market price of land parcel i will be $E[L_{i,t}] = L(v^L, \mathbf{Z}_{i,t})$. Meanwhile, the reservation price is $\breve{L}_{i,t}$. If $\breve{L}_{i,t} < E[L_{i,t}]$ the investor is better off to sell the parcel in the market, but if $\breve{L}_{i,t} \geq E[L_{i,t}]$, then the investor is better off to buy or keep the land parcel and to wait for the random variables to be revealed in stage 2, at which time he would decide whether to build or not (Figure 1). In order to use the model to evaluate the efficiency of the land market, we are interested in quantifying the excess expected economic returns predicted by the model. Let

A_i be the land area of parcel i for all $i \in B(t)$, where $B(t)$ is the set of parcels that got built on in year t. Then, we calculate the area-weighted average expected excess return in year t as

$$EER_t = \frac{\sum_{i \in B(t)} A_i \left(\breve{L}_{i,t} - E\left[L_{i,t} \right] \right)}{\sum_{i \in B(t)} A_i E\left[L_{i,t} \right]}.$$ We take how little this deviates from zero as an indication of the

market's aggregate efficiency in year t. In our empirical work we set the long term average risk

premium, ρ, over the period 1988-2012 so that $\left(\sum_{t=1}^{24} EER_t \right) / 24 \approx 0$, and we then examine the

deviation from zero in different sub periods. We will see in the empirical results that during years of booming house prices, the reservation prices for land reflected the exuberance by running ahead of the market prices, and in the subsequent crashes by trailing the market prices.

2.5 The probability of construction

The data tell us in which year a lot was constructed on and at what FAR, but our model predicts, $Q_{i,t}^d$, the *probability* that a particular lot will be built on in a given year and its FAR. This probability conditional on a draw of $\xi_{i,t}$ is defined from stochastic profit maximization:

$$Q_{i,t}^d \left(\xi_{i,t} \right) = Prob\left[\Pi_{i,t}^d - \Pi_{i,t}^{nd} \geq 0 \right] = Prob\left[\pi_{i,t}^d \left(\xi_{i,t} \right) - \pi_{i,t}^{nd} \left(\xi_{i,t} \right) \geq u_{i,t}^{nd} - u_{i,t}^d \right], \tag{4a}$$

$Q_{i,t}^{nd} \left(\xi_{i,t} \right) = 1 - Q_{i,t}^d \left(\xi_{i,t} \right)$. And when both $\xi_{i,t}$ and $\mathbf{u}_{i,t}$ are not yet revealed, then the probability of construction is a weighted average of the (4a) probabilities:

$$\breve{Q}_{i,t}^d = \int_{\xi_{i,t}} Q_{i,t}^d \left(\xi_{i,t} \right) g\left(\xi_{i,t} \right) \mathbf{d}\xi_{i,t}, \quad \breve{Q}_{i,t}^{nd} = 1 - \breve{Q}_{i,t}^d. \tag{4b}$$

3. A mixed logit model of the decision to construct

The mixed logit model is a flexible specification because any random choice model can be approximated by a mixed logit as explained by McFadden and Train (2000). Below, we specify (3a), the reservation price, and (4a), the construction probability as those of a binary logit model and then our *mixed binary logit model* is obtained by integrating over the $\xi_{i,t}$ as in (3b) and (4b).[6]

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[6] Barry, Levinsohn, Pakes (1995) estimated a mixed logit model by integrating over consumer income which entered utility nonlinearly. We integrate over developers' expected prices and the FAR which enter profit nonlinearly.

The logit model does not permit non-additive random effects. Therefore, we get the logit either by assuming that $\xi_{i,t}$ are known to the investors and are constants; or by setting all $\xi_{i,t} = \mathbf{1}$ meaning that year-ahead prices do not deviate from their expected values. $\mathbf{u}_{i,t} = \left(u_{i,t}^{nd}, u_{i,t}^{d} \right)$ is still uncertain, and the *binary logit model* is derived by assuming that the $\mathbf{u}_{i,t}$ are i.i.d. type I extreme value with variance σ_t^2 or dispersion $\lambda_t = \pi / \left(\sigma_t \sqrt{6} \right) \geq 0$. Since $u_{i,t}^{nd}, u_{i,t}^{d}$ are i.i.d. extreme value, $\hat{u}_{i,t} \equiv u_{i,t}^{nd} - u_{i,t}^{d}$ is logistic and the model can also be derived by assuming this directly which is nearly equivalent to assuming that the $\mathbf{u}_{i,t}$ are i.i.d. normal (Train (2009), p. 35). The derivation of the model by McFadden (1974) or Train (2009) for a consumer, transfers to the setting of profit maximization. Then, the reservation price and probability of the binary logit from (3a) and (4a) are:

$$\hat{L}_{i,t}\left(\xi_{i,t}\right) = \frac{1}{\lambda_t} \ln\left(\exp \lambda_t \pi_{i,t}^{d}\left(\xi_{i,t}\right) + \exp \lambda_t \pi_{i,t}^{nd}\left(\xi_{i,t}\right) \right), \tag{5}$$

$$Q_{i,t}^{d}\left(\xi_{i,t}\right) = \frac{\exp \lambda_t \pi_{i,t}^{d}\left(\xi_{i,t}\right)}{\exp \lambda_t \pi_{i,t}^{d}\left(\xi_{i,t}\right) + \exp \lambda_t \pi_{i,t}^{nd}\left(\xi_{i,t}\right)} = \frac{\exp \lambda_t \left(\pi_{i,t}^{d}\left(\xi_{i,t}\right) - \pi_{i,t}^{nd}\left(\xi_{i,t}\right) \right)}{1 + \exp \lambda_t \left(\pi_{i,t}^{d}\left(\xi_{i,t}\right) - \pi_{i,t}^{nd}\left(\xi_{i,t}\right) \right)}. \tag{6}$$

To abbreviate, we write $Q_{i,t}^{d}$. (6) is a sigmoid curve asymptotic to zero as $\pi_{i,t}^{d} - \pi_{i,t}^{nd} \to -\infty$ and to one as $\pi_{i,t}^{d} - \pi_{i,t}^{nd} \to +\infty$. Note that (6) is the expected supply function conditional on $\xi_{i,t}$. The path integral of (6) with respect to $\pi_{i,t}^{d}, \pi_{i,t}^{nd}$ is unique and the producer surplus is (5), same as the reservation price. [8] The mixed logit model is obtained by applying (3b) to (5) and (4b) to (6). Since properties of the mixed logit flow largely from the logit, we discuss properties of the logit that are important in our context:

(i) *The construction probability is homogeneous of degree zero in lot area*: economists treat housing production as constant returns to scale as in Muth (1969), or Epple, Gordon and Sieg (2010), which allows us to model housing production on a unit-sized land parcel. In part A of the

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[7] A logit model of probabilistic real estate transitions was proposed in Anas and Arnott (1991).
[8] Small and Rosen (1981) proved that the consumer's choice probability is the expected demand function, and the consumer surplus is the integral of the logit probability.

Appendix, we prove that the construction probability $Q_{i,t}^d$ is homogeneous of degree zero in land

area A_i. The expected constructed land area is $A_i Q_{i,t}^d$ and is homogeneous of degree one in A_i.

(ii) *Construction becomes inelastic to prices as profits become noisier*: The elasticity, $\eta_{\pi_{i,t}^d}$,

of $Q_{i,t}^d$ with respect to $\pi_{i,t}^d$ is as follows:

$$\frac{\partial Q_{i,t}^d}{\partial \pi_{i,t}^d} = \lambda_t Q_{i,t}^d \left(1 - Q_{i,t}^d\right) > 0, \text{ and } \eta_{\pi_{i,t}^d} = \lambda_t \pi_{i,t}^d \left(1 - Q_{i,t}^d\right) > 0. \tag{7}$$

Note that as $\sigma_t \to +\infty$, $\lambda_t \to 0$, $Q_{i,t}^d \to 0.5$ and $\eta_{\pi_{i,t}^d} \to 0$. Investors appear irrational as their

choices become uncorrelated with the financial profit and highly sensitive to the noise.

(iii) *The entropy or noise premium in the reservation price*: In part B of the Appendix we
prove that the reservation price given by (5) decomposes into two parts:

$$\hat{L}_{i,t} = \underbrace{\frac{1}{\lambda_t} \ln \left(\exp \lambda_t \pi_{i,t}^d + \exp \lambda_t \pi_{i,t}^{nd}\right)}_{\text{Reservation price}} = \underbrace{\pi_{i,t}^{nd} Q_{i,t}^{nd} + \pi_{i,t}^d Q_{i,t}^d}_{\substack{\text{Return due to} \\ \text{systematic profit}}} \underbrace{- \frac{Q_{i,t}^d \ln Q_{i,t}^d + Q_{i,t}^{nd} \ln Q_{i,t}^{nd}}{\lambda_t}}_{\substack{\text{Return due to noisy} \\ \text{cost reduction (entropy)}}}. \tag{8}$$

Note that on the right side of (8) the average profit from systematic factors is augmented by the

return due to the random $\hat{u}_{i,t}$ in the startup cost. This second term is the expected information of

Theil (1967) or *entropy*, normalized by the dispersion parameter λ_t. Keynes famously observed

that "…*our decisions to do something positive … can only be taken as the result of … a*

spontaneous urge to action rather than inaction, and not as the outcome of a weighted average

of quantitative benefits multiplied by quantitative probabilities." (Keynes, 1936] pp. 161-162). In

equation (8) while the first term on the right side is a probability-weighted expected return, the

second term is an additional expected return from unobservable factors, a possible quantification

of the psychic return that Keynes termed "spontaneous urge".

(iv) *Uncertainty in year-ahead prices raises the reservation price for investing in land*:
Differentiating (5), and using (8) to simplify the derivative:

$$\frac{\partial \hat{L}_{i,t}}{\partial \lambda_t} = \frac{1}{\lambda_t} \left[\pi_{i,t}^{nd} Q_{i,t}^{nd} + \pi_{i,t}^d Q_{i,t}^d - \frac{1}{\lambda_t} \ln \left(\exp \lambda_t \pi_{i,t}^d + \exp \lambda_t \pi_{i,t}^{nd}\right) \right] = \frac{Q_{i,t}^d \ln Q_{i,t}^d + Q_{i,t}^{nd} \ln Q_{i,t}^{nd}}{\lambda_t^2} < 0. \tag{9}$$

Since investors are maximizing, noisier profits (smaller λ_t) offer more chance to draw a highly

favorable startup cost shock $\mathbf{u}_{i,t}$ and realize a bigger profit $\Pi_{i,t}^d$. The reservation price (8) also

increases in the variance of the year-ahead price expectations $P_{i,t+1}$ or $L_{i,t+1}$ that is in

$v^j = \ln\left(1 + \text{var}\left(\xi_{i,t}^j\right)\right)$, for $j = P, L$ as we shall see in section 6. A higher variance of the FAR

distribution, v^f, increases the reservation price on land as long as $P_{i,t+1} - k_t > 0$. Thus higher levels

of all the uncertainties in the model make land more valuable for investors, a result found also in

the simple model by Titman (1985).

(v) "*Sell now not later" rule*: Part C of the Appendix proves that $\hat{L}_{i,t} > \dfrac{L_{i,t+1}}{1 + r_t + \rho}$, which means

that if $L_{i,t} > \hat{L}_{i,t}$, then $L_{i,t} > \dfrac{L_{i,t+1}}{1 + r_t + \rho}$. Hence, if it is preferable to sell the land in stage 1 of year t

(see Figure 1) because the expected market price exceeds the reservation price, then it is never

preferable to postpone the sale to $t+1$. In a perfectly efficient market, sellers would be indifferent

between selling and not selling, or between selling this year versus next. The inefficiency comes

from our assumption that investors can only look one year ahead.

4. Construction and stock elasticity

The logit's elasticity of the construction probability with respect to year-ahead house price is:

$$\eta_{Q_{i,t}} \equiv \frac{\partial Q_{i,t}^d / \partial P_{i,t+1}}{Q_{i,t}^d / P_{i,t+1}} = \lambda_t \frac{P_{i,t+1} f_{i,t}}{1 + r_t + \rho}\left(1 - Q_{i,t}^d\right). \tag{10}$$

And in the case of the mixed binary logit, the elasticity of $\breve{Q}_{i,t}^d$, given by (4b), with respect to the

expected price $\overline{P}_{i,t+1} \equiv E\left[P_{i,t+1}\right] = P\left(v^P, \mathbf{Z}_{i,t+1}\right)$ is as follows, since $P_{i,t+1} = \overline{P}_{i,t+1}\, \xi_{i,t+1}^P$:

$$\breve{\eta}_{Q_{i,t}} \equiv \frac{\partial \breve{Q}_{i,t}^d}{\partial \overline{P}_{i,t+1}} \frac{\overline{P}_{i,t+1}}{\breve{Q}_{i,t}^d} = \frac{1}{\breve{Q}_{i,t}^d}\int_{\xi_{i,t}} \lambda_t \frac{P_{i,t+1} f_{i,t}}{1 + r_t + \rho} Q_{i,t}^d \left(1 - Q_{i,t}^d\right) g\left(\xi_{i,t}\right) \mathbf{d}\xi_{i,t}. \tag{11}$$

Construction is an annual flow of floor space. The stock of housing grows by the

accumulation of the construction flows. Let S_t be the stock of housing at the start of year t, then

the stock expected in year $t+1$ is S_t plus the expected floor space to be added by construction

during t on parcels that are undeveloped at the start of t. A_i is the lot area of parcel i, and $f_{i,t}$ is the

FAR constructed on i in year t. Then, $E\left[A_i f_{i,t} \breve{Q}_{i,t}^d\right] = A_i \overline{f}_{i,t} \breve{Q}_{i,t}^d$, where $\overline{f}_{i,t} \equiv f\left(v^f, \mathbf{Z}_{i,t}\right)$ is the

expected FAR. Let $U(t)$ be the set of parcels undeveloped at the start of t. Then,

$$S_{t+1} = S_t + \sum_{\forall i \in U(t)} A_i \bar{f}_{i,t} \breve{Q}_{i,t}^d . \tag{12}$$

The price elasticity of the aggregate stock is the expected expansion of that stock by construction when all floor prices rise proportionally. Writing prices as $\hat{P}_{i,t+1} = \kappa P_{i,t+1}$, where κ is the constant of proportionality, the stock elasticity in year t is $\breve{\eta}_{S,t} \equiv \dfrac{dS_{t+1} / d\kappa}{S_{t+1} / \kappa}\bigg|_{\kappa=1}$:

$$\breve{\eta}_{S,t} = \frac{\displaystyle\sum_{\forall i \in U(t)} A_i \bar{f}_{i,t} \int_\xi \lambda_t \frac{P_{i,t+1} f_{i,t}}{1 + r_t + \rho} Q_{i,t}^d \left(1 - Q_{i,t}^d\right) g\left(\xi_{i,t}\right) \mathbf{d}\xi_{i,t}}{S_t + \displaystyle\sum_{\forall i \in U(t)} A_i \bar{f}_{i,t} \breve{Q}_{i,t}^d} = \frac{\displaystyle\sum_{\forall i \in U(t)} A_i \bar{f}_{i,t} \breve{Q}_{i,t}^d \breve{\eta}_{Qi,t}}{S_{t+1}}, \tag{13}$$

by noting that the integral in the numerator is $\breve{Q}_{i,t}^d \breve{\eta}_{Q_{i,t}}$. Define weights:

$$w_{i,t} \equiv \frac{A_i \bar{f}_{i,t} \breve{Q}_{i,t}^d}{\displaystyle\sum_{\forall \ell \in U(t)} A_\ell \bar{f}_{\ell,t} \breve{Q}_{\ell,t}^d} . \tag{14}$$

Suppose tentatively that the stock S_t, in the beginning of the period, is negligibly small. Then, with $S_t \cong 0$ in the denominator of (13), the stock elasticity collapses to the weighted average value of the construction elasticity over all the parcels:

$$\breve{\eta}_{S,t}\big|_{S_t \cong 0} \cong \sum_{\forall i \in U(t)} w_{i,t} \breve{\eta}_{Q_{i,t}} . \tag{15}$$

But as, S_t, the stock inherited from the past becomes bigger, the stock elasticity (13) becomes 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 if the construction elasticity under current economic conditions were the same in the two markets. 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 (13):

$$\breve{\eta}_{S,t} = \left(\sum_{\forall i \in U(t)} w_{i,t} \breve{\eta}_{Q_{i,t}}\right)\left(\frac{S_{t+1} - S_t}{S_{t+1}}\right). \tag{16}$$

To see this, we plug into (16) the weights, $w_{i,t}$, from (14) and $S_{t+1} - S_t$ from (12) and cancel terms getting the right side of (13). From (16), the stock elasticity for any year is the weighted average of the parcel-specific construction elasticity multiplied by the fraction of the year $t+1$ stock added during year t. Thus, the annual stock elasticity increases with higher weighted average construction elasticity, but this effect is weakened by a low stock growth rate, due to a high initial stock S_t.

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. This LRSE is calculated by compounding the annual stock elasticity over $t \to T$:

$$\eta_{t \to T}^{LRSE} = 100 \times \left\{ \prod_{\tau=t}^{T} \left(1 + \frac{\breve{\eta}_{S,\tau}}{100} \right) - 1 \right\} \tag{17a}$$

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

$$\eta_{\Delta}^{LRSE} = 100 \times \left\{ \left(1 + \frac{\breve{\eta}_S}{100} \right)^{\Delta} - 1 \right\}. \tag{17b}$$

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

5. Data

Our data are from the property records for Los Angeles County in 2012.[9] The County is represented by 85 cities (LA being the biggest) and all unincorporated parts comprise an 86th geographic area. The observations are separately titled land parcels zoned for single family housing and are either undeveloped at the start of 1988, or are houses built earlier. A parcel in the data which is undeveloped in 1988 may become developed until the end of 2012. If, during 1988-2012, an undeveloped parcel was subdivided into separately titled parcels or if undeveloped parcels were merged, then the subdivisions or the merged parcel appear in our data as individual parcels from 2012 back to 1988. The data contains the sales year and sale value for parcels with single family housing or for undeveloped land parcels if such parcels sold in 1988-2012. For land

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[9] Records originally obtained from SCAG (Southern California Association of Governments), were later supplemented with records from Dataquick© . The two data sets are mutually consistent, include the same attributes and originate from the same publicly available property assessments. Pre 1988 data are not reliable due to many missing observations.

parcels that were constructed on in 1988-2012, the data includes the year of construction and the floor space built. All our variables are in nominal dollars. Notably, as is common with publicly available real estate data, the data set does not contain information on the owners, hence no information on investor characteristics.

[FIGURE 2 AND 3 HERE]

The six panels of Figure 2 illustrate the temporal structure of the key variables. We refer to the 12 years from 1988-1999 as the *S & L Crisis and Recovery.* The middle 8 years from 2000 through 2007 saw a huge spike in housing prices and, inspired by Shiller (2005), we call it the period of *Irrational Exuberance.* In Figure 2 this period is shaded for easy visual identification. To the last five years from the price top in 2008 we refer as the *Mortgage Crisis and Recovery*.

Panel (a) of Figure 2 shows the S&P/Case-Shiller index of housing price for the Los Angeles MSA, derived from repeat sales of houses, 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. Notably, from panel (b) during the period of irrational exuberance, average house prices increased 2.39 times, but average land prices made a big fluctuation with little net change.

From panel (c), the number of houses sold increased six fold from a bottom in 1990 to a peak in 2006, 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 parcel*, or 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 RSMeans Building Construction Cost Data handbooks for1988-2012 by scaling the construction cost of low-rise buildings by the Los Angeles 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 3 shows the geographic distribution of the

undeveloped land parcels at the starts of 1988 and 2012. In all years, these are evenly distributed both north and south of the mountain ranges.

6. Estimating expected market prices and the FAR

From the data that we have described above, we will estimate $L_{i,t+1} \equiv L(v^L, \mathbf{Z}_{i,t+1})\xi^L_{i,t+1}$, $P_{i,t+1}$ $\equiv P(v^P, \mathbf{Z}_{i,t+1})\xi^P_{i,t+1}$, $f_{i,t} \equiv f(v^f, \mathbf{Z}_{i,t})\xi^f_{i,t}$. This involves two steps: (i) to estimate $L(v^L, \mathbf{Z}_{i,t+1})$, $P(v^P, \mathbf{Z}_{i,t+1})$ and $f(v^f, \mathbf{Z}_{i,t})$ that will be used to impute the year-ahead expected market prices and FAR to the undeveloped parcels; and (ii) to estimate the joint cumulative distribution $G(\xi_{i,t}|\Sigma_\xi)$ from which the random vector $\xi_{i,t}$ will be sampled to generate fluctuations around the expected market prices and the FAR.

6.1 Land and housing prices and the FAR

The data for a year t includes $V^H_{i,t}$, the sales value for houses sold; $V^L_{i,t}$, the sales value for undeveloped land parcels sold;[10] and $f_{i,t}$, the FAR if housing is constructed. Our attribute vector is $\mathbf{Z}_{i,t} = (\mathbf{X}_{i,t}, A_i, H_i)$ where A_i is the parcel's land area (or lot size), H_i is the observed or prospective floor space on the lot, and $\mathbf{X}_{i,t}$ all other attributes which we will see shortly. We specify three regressions and assume normally distributed residuals $\theta^L_{i,t}, \theta^P_{i,t}, \theta^f_{i,t}$:

$$\ln(V^L_{i,t}) = \mathbf{a}^L \mathbf{X}_{i,t} + \alpha \ln(A_i) + \theta^L_{i,t}, \tag{18a}$$

$$\ln(V^H_{i,t}) = \mathbf{a}^P \mathbf{X}_{i,t} + \beta \ln(H_i) + \gamma \ln(A_i) + \theta^P_{i,t}, \tag{18b}$$

$$\ln(f_{i,t}) = \mathbf{a}^f \mathbf{X}_{i,t} + \theta^f_{i,t}. \tag{18c}$$

Land values from (18a), and house values from (18b) 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 housing. The FAR from (18c) varies due to economic considerations of capital for land substitution, but also due to regulation and zoning. To control for the spatiotemporal variations in the three regressions, our independent

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[10] Note that these are not unit prices but sales values for entire houses and lots.

exogenous variables $\mathbf{X}_{i,t}$ include 85 city-specific and 24 year-specific fixed effects. The city fixed effects pick up the influences of public services and regulations that vary spatially, while the year fixed effects pick up the national, regional and local factors that affect sales values or FAR, reducing or eliminating the correlation between the regression residuals and the independent variables. The $\mathbf{X}_{i,t}$ include location attributes measured by geo-coding methods as the 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;[11] to the nearest highway; and to the Pacific coastline. For undeveloped parcels, (18a) includes the lot size, A_i, and – for built parcels – regression (18b) includes A_i and H_i, the floor space.

The regressions were estimated by Ordinary Least Squares (OLS) from separate samples each spanning 1988-2012. For (18a) there are 13,903 undeveloped land parcel sales, 3,504 of which are in the City of LA. For such parcels, $V_{i,t}^L$, the land's sales value is in the data, but house value or the FAR do not exist since there is no building. The observations for (18b) are the 610,440 houses sold, 179,040 of which are in the City of LA. For such parcels, $V_{i,t}^H$, the house value and the FAR are in the data, but land value is not observable since the land under the building is not separately valued by the market, and if the land was sold before the house was built it was, in most cases, many years ago. For the FAR regression (18c) there are 124,134 parcels on which houses got constructed during 1988-2012, 18,067 in the City of LA. For these parcels the data gives $f_{i,t}$, the FAR, but not land value in the same year unless the land was also sold in the year of construction, which is rare.

[TABLE 1 ABOUT HERE]

All independent variables in Table 1 are significant at 1% or better. FAR decreases with the distances from the CBD, the nearest sub-center, the nearest road and the coast.[12] House and land sales values fall with distance from downtown LA, confirming that the market values accessibility

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[11] Subcenter definitions for the LA region are from Arnott and Ban (2012).

[12] 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, δ_1 (ONE)(COAST) $+ \delta_2$ (1-ONE)(COAST) where (ONE =1 if COAST < 1 mile, ONE=0 otherwise). All results and the R^2 estimates are essentially unchanged, but FAR increases slightly for COAST < 1 mile, that is $\delta_1 > 0$, $\delta_2 < 0$. 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.

to the biggest jobs center. But downtown LA had 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, since the supply of floor space at a dear location is elastic because it 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 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. Note that since (dis)amenities are capitalized into land value, the slope coefficients of the nearest-distance variables are larger in the land value than in the house value regression. The elasticity of land value with respect to lot size is 0.37 (α in (18a)). House value elasticity with respect to floor space is 0.7 (β in (18b)) and 0.17 with respect to lot size (γ in (18b)).

Since the regressions are based on different samples of land parcels, we do not have a covariance matrix among the residuals. But covariance may exist because an unobserved attribute that affects land value is also likely to affect the house value or the FAR of a parcel thus creating correlation in the residuals. To estimate the covariance in Σ_θ, we used a much smaller common sample for which land value, house value and FAR observations are available for the same parcel. There are only 5,421 such parcels for which the time between the sale of the housing after construction and the sale of the land before construction does not exceed two years and none of the three events is missing. Jointly estimating (18a)-(18c) from this smaller sample by the Seemingly Unrelated Regressions (SUR) procedure gives less reliable results for the regression coefficients because of the much smaller sample size. To estimate Σ_θ, we fixed the regression coefficients of (18a)-(18c), except the city and year constants, to their OLS values from the larger samples reported in Table 1. Then, the Seemingly Unrelated Regressions procedure was run on the smaller common sample to estimate the covariance of the residuals, and the city-year constants, obtaining $\text{cov}\left(\theta_{i,t}^L, \theta_{i,t}^P\right) = 0.17$, $\text{cov}\left(\theta_{i,t}^P, \theta_{i,t}^f\right) = 0.05$, $\text{cov}\left(\theta_{i,t}^L, \theta_{i,t}^f\right) = 0.23$. Variances in Σ_θ are the squares of the standard errors of the separately estimated regressions reported in Table 1. For our

benchmark mixed logit model reported in section 8, we will assume that the off-diagonals of Σ_θ are zero. Then, we will re-estimate a variation of the benchmark that includes the covariance.

6.2 Imputing FAR and prices to undeveloped parcels

The estimated regressions (18a)-(18c) are used to impute year-ahead land value, prospective FAR and prospective house value for any undeveloped parcel in any year. Each regression is transformed by taking the exponential of both sides. If the residuals $\theta_{i,t}^j$ are multivariate normal with zero means, variance v^j, and covariance $v^{j,k}$, for $j \neq k$; then the multiplicative residuals

$e^{\theta_{i,t}^j} \equiv e^{v^j/2} \xi_{i,t}^j$ are multivariate lognormal with means $E\left[e^{\theta_{i,t}^j}\right] = e^{v^j/2} E\left[\xi_{i,t}^j\right] = e^{v^j/2}$ because

$E\left[\xi_{i,t}^j\right] = 1$; $\mathrm{var}\left[e^{\theta_{i,t}^j}\right] = \left(e^{v^j/2}\right)^2 \mathrm{var}\left(\xi_{i,t}^j\right) = e^{v^j}\left(e^{v^j} - 1\right)$, and therefore $\mathrm{var}\left(\xi_{i,t}^j\right) = \left(e^{v^j} - 1\right)$;

$\mathrm{cov}\left[e^{\theta_{i,t}^j}, e^{\theta_{i,t}^j}\right] = e^{\frac{v^j + v^k}{2}} \mathrm{cov}\left(\xi_{i,t}^j, \xi_{i,t}^k\right) = e^{\frac{v^j + v^k}{2}}\left(e^{v^{j,k}} - 1\right)$, and therefore $\mathrm{cov}\left(\xi_{i,t}^j, \xi_{i,t}^k\right) = \left(e^{v^{j,k}} - 1\right)$

for $j \neq k$.

The functions that forecast land and housing price and FAR, are now defined as follows from the transformed regressions (18a)-(18c):

$$L_{i,t+1} \equiv \frac{V_{i,t+1}^L}{A_i} = \underbrace{\exp\left(\frac{v^L}{2} + \mathbf{a}^L \mathbf{X}_{i,t+1}\right) A_i^{\alpha-1}}_{\equiv L\left(v^L, \mathbf{Z}_{i,t+1}\right)} \xi_{i,t+1}^L, \tag{19a}$$

$$P_{i,t+1} \equiv \frac{V_{i,t+1}^H}{H_i} = \underbrace{\exp\left(\frac{v^P}{2} + \mathbf{a}^P \mathbf{X}_{i,t+1}\right) A_i^\gamma H_i^{\beta-1}}_{\equiv P\left(v^P, \mathbf{Z}_{i,t+1}\right)} \xi_{i,t+1}^P, \tag{19b}$$

$$f_{i,t} = \underbrace{\exp\left(\frac{v^f}{2} + \mathbf{a}^f \mathbf{X}_{i,t}\right)}_{\equiv f\left(v^f, \mathbf{Z}_{i,t}\right)} \xi_{i,t}^f. \tag{19c}$$

(19c) is used to impute the prospective FAR to each undeveloped land parcel i in year t. Then, the prospective floor area is $H_i \equiv H_{i,t} = f_{i,t} A_i$. Prospective housing floor prices and land prices for the year ahead are then imputed from (19b) and (19a) respectively.

Why do we impute FAR from (19c) instead of calculating the FAR that maximizes the developer's profit? From (19b), the profit from $H_{i,t}$ square feet of floor space built in year t is $P_{i,t+1}(H_{i,t})H_{i,t} - k_t H_{i,t}$, where $P_{i,t+1}(H_{i,t})$ given by (19b). This is maximized by:

$$H_{i,t}^* = \left(\frac{\beta A_i^\gamma \exp\left(\frac{\nu^P}{2} + \mathbf{a}^P \mathbf{X}_{i,t+1} \right) f\left(\nu^f, \mathbf{Z}_{i,t} \right)}{k_t} \right)^{\frac{1}{1-\beta}} \quad \Rightarrow \quad f_{i,t}^* = \frac{H_{i,t}^*}{A_i}. \tag{20}$$

For each parcel that underwent construction, we calculated $f_{i,t}^*$ from (20). This had a substantially higher median and mean than both the data FAR and the regression-imputed FAR from (19c). The discrepancy is explained by zoning and building regulations which favor lower FAR, especially in the City of LA, or by the need felt by developers to conform to the established FAR of the neighborhood in order to add value to their housing. 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 with higher FAR. Given these realities, we use (19c) the regression-imputed FAR in our empirical work.

7. Mixed logit estimation

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 undeveloped parcels at the start of t. During t, construction occurs on a set of parcels in $B(t) \subset U(t)$, which are removed from $U(t)$ to get $U(t+1)$. The data starts with 158,412 LA County 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 at the start of each year, we get 1,825,252 observations.

The behavioral model described in section 2 has attractive features for econometric estimation. Firstly, the development start-up costs, $F_{c(i),t}$, mitigate endogeneity concerns by capturing year and city specific effects, $F_{c(i),t}$, making the correlation between $\mathbf{u}_{i,t}$ and $\mathbf{Z}_{i,t}, \mathbf{Z}_{i,t+1}$ zero; and provided the profits $\pi_{i,t}^{nd}, \pi_{i,t}^d$ (the latter of which includes the $F_{c(i),t}$) are well specified, the idiosyncratic $\mathbf{u}_{i,t}$ become white noise. Secondly, our behavioral model describes the

probability of land development by an investor in a particular year, and not the entire joint multivariate distribution of the decision vector $y_{i,1}, y_{i,2}, ..., y_{i,T}$ where $y_{i,t} = 1$ if construction occurs on parcel $i \in B(t) \subset U(t)$ in year t, otherwise $y_{i,t} = 0$. This means that we are spared from specifying a complete inter-temporal covariance matrix for the $\mathbf{u}_{i,t}$, $t = 1, 2, ..., T$ which would make estimation computationally difficult and our results less robust. We instead use the Partial Maximum Simulated Likelihood Estimator (PMSLE) to find the model parameters. The PMSLE requires only the specification of the marginal probability of the dependent variable and is consistent and asymptotically normal even in the presence of arbitrarily serial correlation in the errors. The existence of any serial correlation in the $\mathbf{u}_{i,t}$ only requires that the standard errors of the estimated parameters be adjusted by using the robust asymptotic variance matrix estimator. Hess and Train (2011; pp. 4-6) test the application of partial maximum likelihood methods in a panel data setting; while Woolridge (2010, pp. 401-412) provides a general discussion. Berry, Levinsohn and Pakes (1995; pp. 862-863) deal with serial correlation in their panel data set by a robust covariance matrix estimator as we do here.

Let Φ denote a vector that contains the dispersion parameter λ_t for each t and the constants $F_{c,t} = F_{c(i),t}$ $\forall i \in c$ for each city c, and year t. Given $G\left(\xi_{i,t} \middle| \Sigma_\xi\right)$, the Partial Maximum Simulated Likelihood Estimator (PMSLE) of Φ is denoted by $\hat{\Phi}$ and is obtained by maximizing the simulated log-likelihood function:

$$\hat{\Phi} = argmax\, SLL_t = \sum_{\forall c} \sum_{\forall i \in c \cap U(t)} y_{i,t} \ln \breve{Q}_{i,t}^d + \left(1 - y_{i,t}\right) \ln\left(1 - \breve{Q}_{i,t}^d\right). \tag{21}$$

$\hat{\Phi}$ is consistent and asymptotically normal even if the $\mathbf{u}_{i,t}$ are arbitrarily serially correlated.

Our sample spans 85 cities (plus one unincorporated area) and 24 years[13], hence we must estimate nearly 2000 city-year constants, less a few city-years for which no construction was observed. Estimating so many constants using a gradient based numerical optimization procedure is infeasible. The problem is solved by employing the BLP procedure of Berry (1994) and Berry, Levinsohn, Pakes (1995) to calibrate these constants so that the model's predicted land

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[13] Since regressions for 2013 are not available, 2013 prices expected by 2012 investors cannot be forecast. Therefore, the year 2012 was not included in the mixed logit model.

development matches the land development observed in the data for each city-year combination. The PMSLE algorithm which includes the BLP procedure is outlined in part D of the Appendix.

8. 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 set to zero. We will, however, test the robustness of this benchmark by modifying it in four ways by: (i) making λ_t constant over 1988-2011, and by making it uniform within each of the three historical periods; (ii) seeing how a risk-premium ρ in the range from 0.01 to 0.17 affects the λ_t estimates and other results; (iii) re-estimating the model with the covariance in Σ_ξ included; (iv) imputing the year-ahead housing prices with alternative backward-looking and forward-looking assumptions; (v) estimating the logit model which ignores the stochastic variation around the year-ahead prices and the FAR. The benchmark model and all these variations are reported in Table 2. Table 3 compares in more detail the benchmark yearly-λ model, to the constant-λ and three-period-λ models. Results discussed in this section, are shown in Figures 4, 5 and 6.

[TABLES 2, 3 AND FIGURES 4, 5, 6 HERE]

8.1 The benchmark model

BLP constants, noise, entropy

Benchmark estimation results are shown in Table 2 and in the four panels of Figure 4. From panel (a), the signs of the λ_t are positive for each year indicating that the probability of construction increases with financial profit despite the noisy factors, supporting the hypothesis that developers choose the higher profit state and are, therefore, acting rationally on the whole. The BLP city-year constants, $F_{c,t}$, are positive, reflecting that there is a perceived startup cost of constructing in LA County. The BLP constants for LA City are larger each year indicating higher startup costs in the City of LA than in the suburbs. The BLP constants and the standard deviation of the noise around them, measured by $\sigma_t = \pi / \left(\lambda_t \sqrt{6} \right)$, both surged during the Irrational Exuberance period, peaking in 2005 before crashing in 2006 and 2007 ahead of the 2007 peak in house prices which we saw in panels (a) of Figure 2. A similar peaking occurred before 1988 prior to the 1990 peak in house

prices during the speculative years that had led to the S&L Crisis. Although the S&L and Mortgage crises differed as to causes, they shared this characteristic.[14]

The surge of the BLP constants suggests that during the 2000-2005 boom in house prices, investors became possessed by animal spirits and demanded a sharply growing premium return from land development on average because they perceived a rising opportunity cost of not postponing construction, perhaps because the rising house prices made them believe that profits would be even higher later. During the boom, the noise around the higher opportunity cost also increased sharply, becoming critical in investment decisions. This is also confirmed from panel (c) of Figure 4 which shows that entropy as a share of investors' reservation prices for land (see equation (8)) climbed to a high, before starting to recede. This happened in 1988 prior to the S&L Crisis, when entropy had reached nearly 16% of reservation prices, receding before house prices peaked in that cycle. It happened again in 2004-2006 prior to the mortgage crisis when entropy eked above 38%, then sharply receded just before the 2007 peak in house prices. The peaking of the $F_{c,t}, \sigma_t$, and of entropy ahead of the peaking of housing prices indicates that investors in land, although initially possessed by animal spirits, became aware of the limits to their exuberance before house prices reached top levels.

Quigley and Rafael (2005) document the power of California cities to implement land use regulations that restrict growth. The home-voter hypothesis of Fischel (2001) argues that such regulations are adopted under pressure by incumbent home owners seeking to support their property values. According to these observations the $\mathbb{C}_{c,t}$ component of $F_{c,t}$ (our BLP constants) should vary systematically across cities. Meanwhile, the Θ_t component of the $F_{c,t}$ changes over time, due to sustained market conditions that may contribute to animal spirits, the irrational belief that house prices will keep rising sharply after the year-ahead hence it is beneficial to postpone the development decision. The following regression with an R^2 of 60.1% , helps test these hypotheses:

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[14] Haughwout (2011) and Duca, Muellbauer and Murphy (2011) recognize that the mortgage crisis was caused by the extensive and loose growth of mortgages and collateral on the demand-side. Geanakoplos (2009) provides a general equilibrium model of the leverage cycle. The S&Ls had to pay higher interest rates on deposits than the rate at which they could borrow which eventually led to their bankruptcy affecting real estate prices.

$$F_{c,t} = -205.10 + \underbrace{0.37\left(EXCL_c\right) + 0.43\left(GROW_c\right) + 25.15 LOG\left(HP_{c,t}\right)}_{\equiv \mathbb{C}_{c,t}}$$

$$\underbrace{+66.23 LOG\left(HPT_t\right) + 68.29\left(\%\Delta HPT_{t-1}\right) - 1.21\left(TBILL_t\right)}_{\equiv \Theta_t} \tag{22}$$

All variables except *GROW* are significant at 0.1% or better. *GROW* is insignificant. *EXCL* and *GROW* from Quigley and Rafael (2005) measure the presence of exclusionary land use and of policies favoring growth.[15] $HP_{c,t}$ is the floor-space-weighted average housing price in a city after removing the time trend. Some temporal variation remains in $HP_{c,t}$ due to compositional changes over time. HPT_t is the Countywide time trend in housing prices, and $\%\Delta HPT_{t-1}$ is the lagged percentage change in HPT_t.[16] $TBILL_t$ is the one-year T-bill rate. The sign of *EXCL* confirms Quigley and Raphael's finding that exclusionary land use raises development costs. The positive sign of $HP_{c,t}$ confirms Fischel's homevoter hypothesis. Our results should be treated with caution, because a potential problem of reverse causality may exist: since higher BLP constants indirectly cause higher house values by deterring construction, then values could be endogenous. But since the Raphael and Quigley data was based on a 1992 survey which is near the beginning of our study period, we can probably treat land use regulations as exogenous since they could not possibly be influenced by our BLP constants. We did not apply panel data fixed effects or first-differences, since then we would not be able to identify the effects of the time invariant land use measures on the BLP constants.

In (22), the variables in Θ_t decompose the Countywide time trend. Both the trend and the lagged rate of change in Countywide housing prices are important. The trend itself is responsible for 48% of R^2. Adding $HP_{c,t}$ raises it to 55%, adding $\%\Delta HPT_{t-1}$ to 59% and adding $TBILL_t$ to

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[15] *EXCL* is the unweighted sum of several exclusion measures. *GROW* is the un-weighted number of hospitality measures having Likard scale 1-5, ranked by the city in increasing "importance" , and receiving at least a 3.

[16] To separate the time trend in housing prices from intercity differences we use the regression $\ln\left(P_{i,t}\right) = \sum_{\tau=1,\ldots,24} b_\tau + e_{i,t}$ where the b_t are estimated year constants and $e_{i,t}$ the residual. $HP_{c,t} = \sum_{i\in c} H_i \exp(e_{i,t}) / \left(\sum_{i\in c} H_i\right)$, where H_i is the floor space weight, are the de-trended house prices, and $HPT_t = \exp\left(\sum_{\tau=1,\ldots,t} b_\tau\right)$, is the house price trend.

60%.[17] House prices are often positively auto-correlated as in the period 1997-2006 and in 2007-2011. This may foster a belief among developers that when house prices go up (or down), they are more likely to keep going up (or down), which could lead to animal spirits (or excessive pessimism) on the way up (down). The sign of $\%\Delta HPT_{t-1}$ captures this simply. The sign of $TBILL_t$ suggests that lower rates may also contribute to animal spirits perhaps because they signal future increases in home buying.

Elasticity

Panel (d) of Figure 4 shows that the annual construction elasticity of the benchmark model varied from 2 to 4 while the annual stock elasticity ranged from zero to 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 the entropy caused by noise had already receded as we saw earlier. The annual stock elasticity peaked in 2000 and 2003 and then fell dramatically as new construction dried up.

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. They 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, by 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 (17a). LA County having more housing than the average county in the nation, the denominator of (16) is lower for the average county hence similar construction elasticity in LA and other places would result in a higher stock elasticity for the nation. Our stock elasticity for LA County 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 (17b) brings 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

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[17] Correlation coefficients between $TBILL_t$ and $\%\Delta HPT_{t-1}$ and $LOG(HPT_t)$ are 0.22 and -0.46 respectively. $\%\Delta HPT_{t-1}$ and $LOG(HPT_t)$ have a correlation of 0.19 but all other correlation coefficients among the independent variables are under 0.09. Dropping $TBILL_t$ from the regression has negligible effect on the results.

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 in that year, *and keeping all else constant*, then at the end of the century the stock is only 2.63% larger.

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, 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. The elasticity of the logit with respect to the interest rate is:

$$\eta_{Q_{i,t}:r_t} = -\frac{r_t}{\left(1+r_t+\rho\right)}(1-Q_{i,t}^d)\left\{\underbrace{\ln\left(\frac{Q_{i,t}^d}{1-Q_{i,t}^d}\right)}_{<0}+\underbrace{\lambda_t F_{c(i),t}}_{>0}\right\}. \tag{23}$$

The annual average $Q_{i,t}^d$ has varied from 0.03 to 0.16, and hence the first term in the bracket is negative in most cases. Therefore, a positive elasticity occurs when there is sufficiently large uncertainty, that is when the variance of the noise in the startup costs is large (λ_t is small), which as we saw is more likely to happen during booms with rising housing prices. These conditions are similar to those expressed in the real option literature (Capozza and Li, 2001). In our data, the share of parcels with positive interest rate elasticity reaches as high as 40% in some years.

Reservation prices, excess returns and stock growth

Panels (a) and (b) of Figure 5 provide a visual of how well predicted reservation prices track the expected market prices of land, while panel (c) of Figure 5 shows that the ratio of market housing price to market land price doubled during the period of irrational exuberance. Since the reservation price of land is the residual expected profit, the divergence between housing and land prices is due to the 30% spurt in construction costs in 2000-2007, seen in panel (f) of Figure 2 plus the surge in the BLP constants seen in panel (a) of Figure 4, plus the uncertainty premium in reservation prices due to the surging noise in panel (b) of Figure 4. Panel (d) of Figure 5 shows that average land price *changes* displayed higher year-to-year volatility than did average house prices, but maintained a flat long term trend. Recall panel (b) of Figure 2 which shows that average land sale prices in 2000-2007 made a huge round trip. Panel (e) of Figure 5 illustrates how the expected excess returns of investors, fluctuated around a mean of 0.60% over the entire period

from 1988-2012. Panel (f) of Figure 5 illustrates that the year-by-year stock growth predicted by the model tracks closely the path of actual stock growth in the 24-year period.

8.2 Less variation in λ over time

Table 3 shows two modifications of the variation of λ over time. In the second model in Table 3, a single λ is estimated for each historical period by pooling the years in that period, and in the third, λ is estimated as constant over the entire 24-year period, by pooling all the years. In panel (b) of Figure 4, the λ of these three variations are juxtaposed.

All three models compared in Table 3 predict that in an environment of strongly rising prices, exuberance was causing expectations to run ahead of the market, with the opposite occurring when prices were falling sharply. In the benchmark model the excess expected return was 6.21 percentage points per year during the Irrational Exuberance period, while during the Mortgage Crisis and Recovery period reservation prices trailed market prices by 2.06 percentage points per year. How did the exuberance or pessimism in a particular year correlate with the actual land and housing price change in the subsequent year? To see this, we separately regressed the percent land and housing price changes, that is $\left(E[L_{t+1}] - E[L_t]\right) / E[L_t]$ and $\left(E[P_{t+1}] - E[P_t]\right) / E[P_t]$, against the expected excess returns $\left(\breve{L}_t - E[L_t]\right) / E[L_t]$. The effect of the excess returns on housing prices is not statistically significant. But we find that a 1% excess return in period t, causes a 1.08% increase in the market price of land of the following year and is highly significant. This makes sense, since investors would be buyers of land when their expectations are exuberant and sellers of land when they are pessimistic, driving land prices up and down accordingly. Nevertheless, forward causality is hard to distinguish from backward causality if high expectations in a year are caused by investors' being able to perceive that prices will be rising in the subsequent year. 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 along with panels (a)-(c) of Figure 5, that land and housing markets were decoupled during the bubble years.

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.

8.3 Sensitivity to the risk premium ρ

Figure 6 shows how the maximum likelihood estimate of λ, and the monetary excess economic returns, both averaged over the 24 years change depending on the investor's risk premium, ρ. As the risk premium rises from zero to seventeen percent, the average excess returns predicted by the model fall from about +7.5% to -7.5% per year while the average λ changes mildly from 0.123 to 0.147 affecting other results of the estimated model only marginally as shown in Table 2 which juxtaposes $\rho = 0.07$ and $\rho = 0.10$. There is, therefore, some latitude in deciding which value of the risk premium, ρ, to adopt without much consequence on the model's results. For values of ρ ranging between 0.07 and 0.10, average excess returns are very close to zero percent. It is, however, useful to see how the choice of such a range for ρ agrees with other sources from the literature.

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 a time-invariant ρ 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 sales in our data was 15% per year. Netting out the average one-year T-bill rate of 4.10% over 1988-2012, we get a risk premium of 10.9%. This is only a little higher than our 7%-10% range for ρ shown in Table 2. On page 250 of their book, Geltner et al. (2013) cite a survey of apartment developers who reported a total return expectation of 8.78%-10.98%, implying risk premiums from 4.78% to 6.98%, not too far from our range.

8.4 Adding covariance

Table 2 shows the effect on the benchmark model when the estimated covariance matrix Σ_θ is used to simulate the covariance in Σ_ξ in the maximum likelihood estimation. The average value of λ increased from 0.13 in the benchmark case to 0.14, the construction elasticity increased by 25%, while the annual stock elasticity decreased by about 12%. The expected excess returns increased from nearly +0.6% to+2.88%, which means that a higher risk premium than ρ =0.07, something around ρ =0.10 gives near zero percent average excess returns. The model with covariance then is not so different from the benchmark. Perturbations of the covariance structure had similarly marginal impact on the benchmark. There is therefore little lost by setting to zero the off-diagonal elements of Σ_ξ.

8.5 Alternative expectations of the year-ahead housing price

We experimented with alternative calculations of the year-ahead housing prices:

$$P_{i,t+1} = \frac{1}{\tau+1}\left(\sum_{k=0}^{\tau} P\left(v^P, \mathbf{Z}_{i,t+\psi k}\right) \xi_{i,t+\psi k}^P \right). \tag{23}$$

In a *forward-looking* variation of the benchmark we set $\psi = 1$, and the year-ahead housing price is then the simple average of the imputed prices of the current and some forward years. This causes expected year-ahead prices to run ahead of market prices when prices are continually rising and to fall more rapidly when prices are continually falling. This provides an alternative way in which the model captures exuberance. In a *backward-looking* variation we set $\psi = -1$, and the year-ahead housing price is extrapolated as the moving average of the current and several most recent imputed prices. This causes the year-ahead expected prices to trail market prices when prices are continually rising and to fall less rapidly when prices are continually falling. Table 2 presents a backward-looking model with $\tau = 4$ and a forward looking one with $\tau = 2$. Results are close to those of the benchmark. The forward-looking model tends to drive up expected excess returns and appears less reasonable than the backward looking one.

8.6 Binary logit model

We also estimated the binary logit model reported in the last column of Table 2. Because the logit model does not permit stochastic treatment of the $\xi_{i,t}$, we imputed land price, house price and FAR by setting all $\xi_{i,t} = 1$. The maximum likelihood estimate of the dispersion parameter λ_t varies by year between 0.001 and 0.05, and $\lambda = 0.004$ on average. This turns out to be unacceptably low implying a very high standard deviation of the noise in profits of $320 per square foot of land, which 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, 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 white noise in costs, ignoring the fact that there is substantial uncertainty around the future prices of the land they hold, or of the prices of the houses they would build, and the floor area they would construct. The mixed logit model, as we saw, corrects this misattribution, by shifting the major part of the uncertainty away from the noise, placing it on the developers' expectations of year-ahead prices and the FAR.[18]

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

9. Conclusions

We demonstrated that the probability to construct increases with the financial profit from constructing. This confirms our a priori belief that developer-investors act rationally. But we also discovered that the rationality of investors is weakened by exuberance during long periods of booming house prices. During such times noisy factors related to unobserved variables increase the probability of constructing while not dominating over the financial profit; and broadly held animal spirits favor land speculation, apparently in hope of even higher profits from construction in the future, decreasing the probability of constructing currently. The exuberance due to the noisy factors shows up as an entropy premium in the reservation price that investors would bid to buy the land. During the booms reservation prices run ahead of the market prices for land, and trail during crashes. Both the entropy premium and the animal spirits rise sharply but begin to decline before house prices peak. These findings suggest the importance of behavioral economics in better understanding land market dynamics.

The microeconomic nature of our model leads to a better understanding of the relationship between the elasticity of construction at the level of a land parcel and the aggregate housing stock elasticity. We showed how to derive the latter from the former, something that was neglected in the extant literature.

Synthesizing complex microscopic models of the demand side with models of the supply side such as ours would lead to a microsimulation framework that can be used to study the equilibrium dynamics of the housing market. The econometrics of discrete choice that we employed here to explain the behavior of land investors can also be used to explain tenure choice in the housing market, mortgage choice, the decision to default or not and other aspects of the demand side. Recently Geanakoplos et al. (2012) presented a microscopic agent-based model of housing consumers' bounded rational behavior in the presence of systemic risk.

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, $Q_{i,t}^d$, the logit choice probability given by* (6)*, remains unchanged. Hence,* (6) *is homogeneous of degree zero in parcel size, A_i.*

Proof: Scaling the profits by parcel size, A_i, profits per parcel become:

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

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

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

(iii) $\lambda_{it} = \dfrac{\pi/\sqrt{6}}{A_i \sigma_t} = \dfrac{\lambda_t}{A_i}$, 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 (6) we see that it is not changed by the scaling.

B. Derivation of (8)

We write the two probabilities as:

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

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

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

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

Next, we multiply the first of the above by $Q_{i,t}^{d}$ and the second by $Q_{i,t}^{nd}$. Then, add the two resulting equations and apply $Q_{i,t}^{d} + Q_{i,t}^{nd} = 1$ to get (8).

C. Proof of "sell now not later" rule

$\dfrac{Q_{i,t}^{d}}{1-Q_{i,t}^{nd}} = \exp \lambda_t \left(\pi_{i,t}^{d} - \dfrac{L_{i,t+1}}{1+r_t+\rho}\right)$. Solving, $\dfrac{L_{i,t+1}}{1+r_t+\rho} = \pi_{i,t}^{d} - \dfrac{1}{\lambda_t} \ln Q_{i,t}^{d} + \dfrac{1}{\lambda_t} \ln\left(1-Q_{i,t}^{d}\right)$.

Taking the log of both sides of (6), dividing by λ_t and rearranging terms: $\hat{L}_{i,t} = \pi_{i,t}^{d} - \dfrac{1}{\lambda_t} \ln Q_{i,t}^{d}$.

Subtracting, we get $\hat{L}_{i,t} - \dfrac{L_{i,t+1}}{1+r_t+\rho} = -\dfrac{1}{\lambda_t} \ln\left(1-Q_{i,t}^{d}\right) > 0$.

D. The PMSLE procedure

The PMSL estimation steps are as follows:

Step 1: For each parcel i and year t, sample the additive multivariate normal $\theta_{i,t}$, and then take their exponentials to generate multivariate lognormal $\xi_{i,t}$. Generate one hundred such samples. [We verified that doubling the number of draws to 200 leaves the maximum likelihood estimates essentially unchanged.];

Step 2: Impute house values, land values and FARs to each parcel $i \in U(t)$, $t = 1,...,T$ for each of the 100 generated samples using the procedure discussed in section 6 and the $\xi_{i,t}$ of that sample;

Step 3: Guess the initial $\lambda = (\lambda_1,...,\lambda_T)$ and $F_{c,t}$, $\forall (c,t)$;

Step 4: Using the λ_t and the $F_{c,t}$, calculate the binary logit probability $Q_{i,t}^d$ for $\forall (i,t)$ from equation (6), for each sampled $\xi_{i,t}$, that is 100 times;

Step 5: Take the simple average of the 100 logit probabilities $Q_{i,t}^d$ for each (i,t) to get an estimate of the mixed logit probability $\breve{Q}_{i,t}^d$ of equation (4b), an unbiased and asymptotically efficient estimator of the true choice probability;

Step 6: (BLP *procedure loop*): Given the λ_t for each year t from step 3, adjust the city-year constants so that $F_{c,t}^{r+1} = F_{c,t}^r + log\left(\dfrac{\sum_{i \in c \cap U(t)} A_i y_{i,t}}{\sum_{i \in c \cap U(t)} A_i {}^r \breve{Q}_{i,t}^d} \right)$ for $\forall (c,t)$ where A_i is the land area of parcel i and r is the iteration counter. The numerator inside the parenthesis is the aggregate land quantity in city c that becomes developed in year t in the data. The denominator is the expected aggregate land amount that becomes developed as predicted by the model. We update $F_{c,t}^r$ in this way and recalculate ${}^r\breve{Q}_{i,t}^d$, until at some iteration $r = R$, $\left| \sum_{i \in c \cap U(t)} A_i \left(y_{i,t} - {}^R\breve{Q}_{i,t}^d \right) \right| < tol$ where *tol* is a very small tolerance. Hence observed and predicted city land shares are matched as required by the BLP procedure, and $F_{c,t}^{R-1} - F_{c,t}^R < tol$;

Step 7: (*Maximizing likelihood*): Setting $F_{c,t} = F_{c,t}^R$ for t, we adjust λ_t according to a numerical iterative optimization procedure which maximizes the simulated log-likelihood function for year $t = 1,...,T$. The software R implements the robust inverse parabolic method of Brent (1973) which

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does not require derivatives. [If the inverse parabolic method gives a new implausible guess, the algorithm switches to a golden section search];

Step 8: Given the λ_t found in step 7 and the $F_{c,t}$ set in the beginning of step 7, we return to step 4 and we continue the loop of step 4 through step 7 until the value of λ_t converges to within a small tolerance.

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Independent variables		LAND VALUE Eq.(18a)	HOUSE VALUE Eq.(18b)	FLOOR AREA RATIO Eq.(18c)
	Dependent variable	$\ln\left(V^{L}\right)$	$\ln\left(V^{H}\right)$	$\ln\left(f\right)$
	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
CBD	Distance to downtown L.A.	-0.04 (0.0035)	-0.01 (0.0001)	-0.008 (0.0004)
JSC	Distance to nearest job sub-center	---	-0.01 (0.0001)	-0.01 (0.0005)
ROAD	Distance to major road	0.06 (0.0054)	0.01 (0.0004)	-0.006 (0.0009)
COAST	Distance to coastline	-0.03 (0.0026)	-0.004 (0.0001)	-0.002 (0.0004)
$\log\left(H\right)$	log(Floor space)	---	0.70 (0.0011)	---
$\log\left(A\right)$	log(Lot size)	0.37 (0.0093)	0.17 (0.0011)	---
	R^{2}	0.41	0.80	0.22
	Standard error of regression $\left(\sqrt{v^{j}}\right)$	1.26	0.28	0.38

TABLE 1

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

NOTES: All estimated coefficients are significant at 1% or better; * 5 cities did not have any land sales

	Mixed logit models [a]					
	Benchmark Model 1988-2011	Benchmark with higher risk premium 1988-2011	Benchmark Model with covariance [b] 1988-2011	Backward looking (5-year) 1992-2011	Forward looking (2-year) 1988-2009	Binary logit model [c] 1988-2011
Risk premium, above one year T-bill rate $(\rho \times 100)$	7%	10%	7%	7%	7%	7%
Average value of yearly λ	0.13	0.13	0.14	0.15	0.17	0.004
Range of yearly λ	0.03-0.29	0.01-0.30	0.03-0.72	0.03-0.29	0.005-0.79	0.001-0.05
Expected excess returns [d] (average of annual)	0.60%	-0.58%	2.88%	-0.15%	8.00%	143.3%
Construction elasticity [e] (average of annual)	2.89	2.93	3.25	3.10	2.90	0.23
Stock elasticity [f] (average of annual)	0.0260	0.0256	0.0230	0.0257	0.0219	0.0010
Long run stock elasticity [g]	0.63	0.61	0.55	0.46	0.50	0.02
Log likelihood[h]	-470,963	-470,791	-476,355	-297,072	-430,127	-477,997

TABLE 2

The benchmark mixed logit model and variations of it

NOTES: [a] (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 the $\xi_{i,t}$ for FAR, House Price and Land Price for each parcel and year; (iii) In the benchmark model Σ_θ is diagonal with $\nu^L = 1.59, \nu^P = 0.08, \nu^f = 0.14$;

[b] Covariance terms $\nu^{L,P} = 0.17, \nu^{L,f} = 0.23, \nu^{P,f} = 0.05$ included in Σ_θ;

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

[d] $E\left[EER_t\right] \times 100.$ See section 2.4.

[e] Reported as the average over the years of the simple average of the construction elasticity of each parcel for each year from equation (11);

[f] From equation (16) or equivalently from (13), reported as the average value over the years;

[g] From equation (17a).

[h] Sum of the likelihoods over all years.

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

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] $E[EER_t] \times 100$. See section 2.4.

[b] Reported as the average over the relevant years of the simple average of the construction elasticity over the parcels for each year from equation (11);

[c] From equation (16) or equivalently (13), reported as the average value over the years;
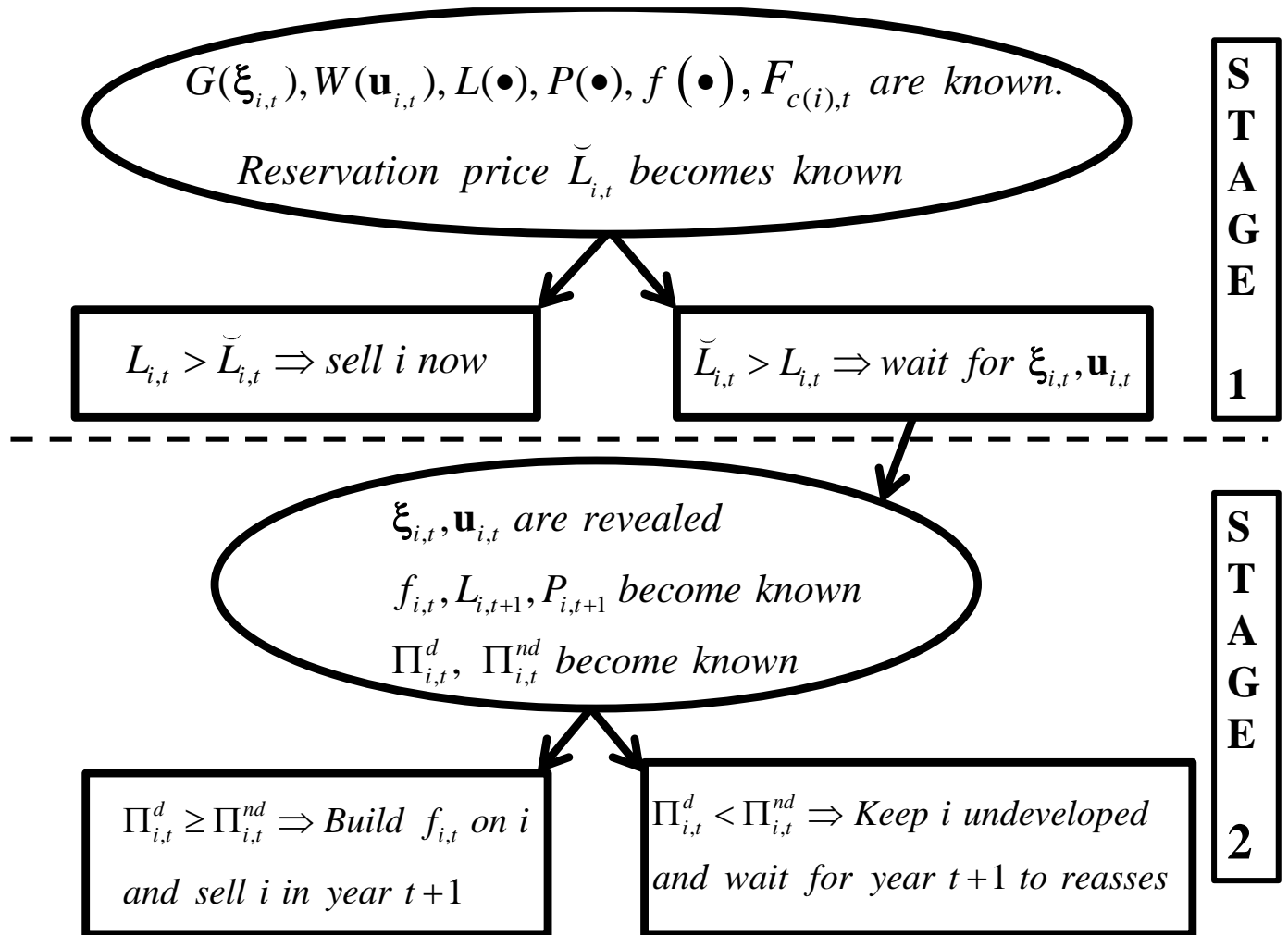
[d] From equation (17a).

$G(\xi_{i,t}), W(\mathbf{u}_{i,t}), L(\bullet), P(\bullet), f(\bullet), F_{c(i),t}$ *are known.*

Reservation price $\breve{L}_{i,t}$ *becomes known*

$L_{i,t} > \breve{L}_{i,t} \Rightarrow$ *sell i now*

$\breve{L}_{i,t} > L_{i,t} \Rightarrow$ *wait for* $\xi_{i,t}, \mathbf{u}_{i,t}$

S T A G E 1

- -

$\xi_{i,t}, \mathbf{u}_{i,t}$ *are revealed*

$f_{i,t}, L_{i,t+1}, P_{i,t+1}$ *become known*

$\Pi_{i,t}^{d}, \ \Pi_{i,t}^{nd}$ *become known*

$\Pi_{i,t}^{d} \geq \Pi_{i,t}^{nd} \Rightarrow$ *Build* $f_{i,t}$ *on i and sell i in year* $t+1$

$\Pi_{i,t}^{d} < \Pi_{i,t}^{nd} \Rightarrow$ *Keep i undeveloped and wait for year* $t+1$ *to reasses*

S T A G E 2

FIGURE 1

Timing of events and developer's decisions during year t

(a) House prices

(b) House and land prices

(c) Houses

(d) Land parcels

(e) Floor area ratio (FAR)

(f) Construction cost and interest rate
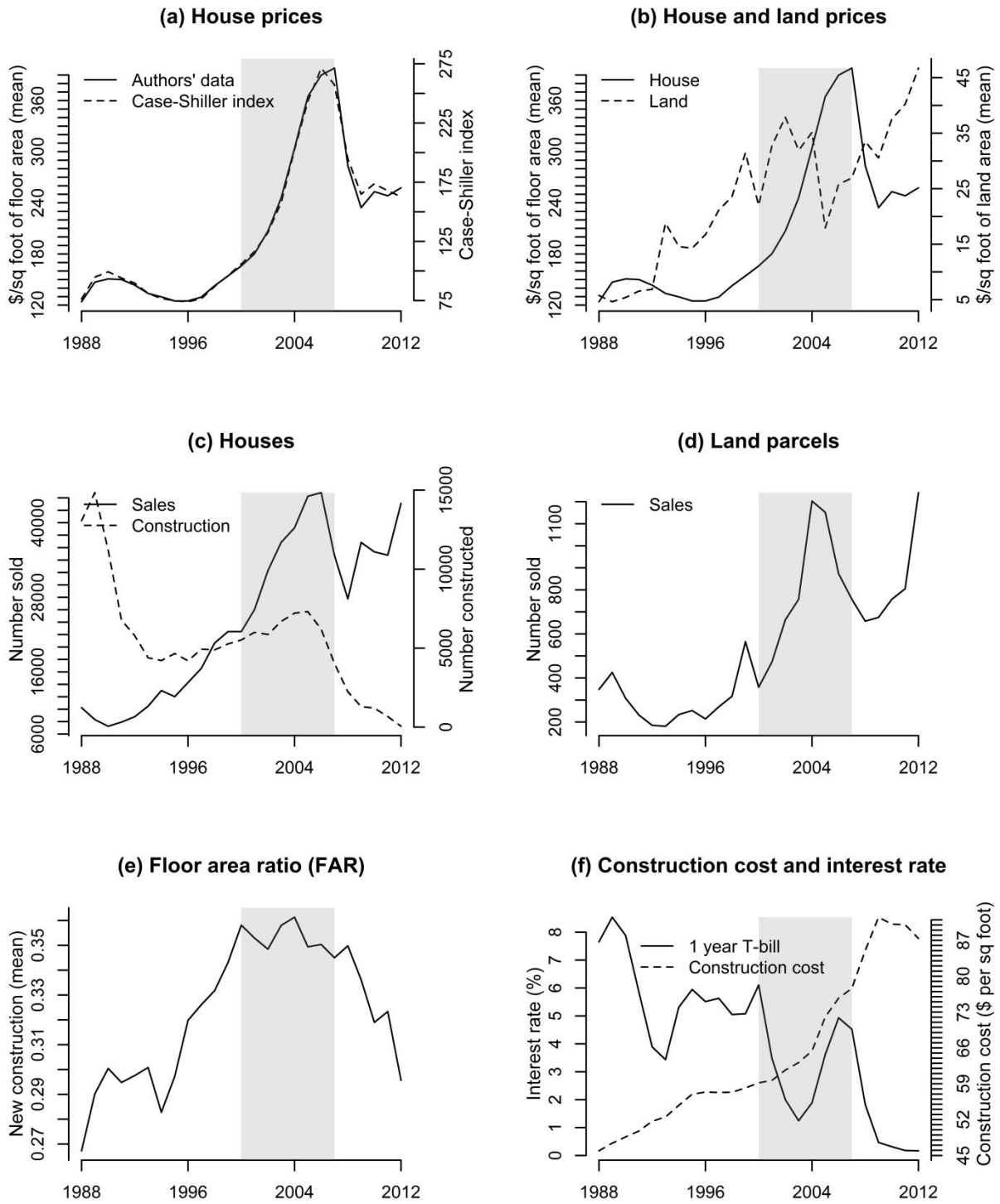
FIGURE 2

Los Angeles County, 1988-2012

45
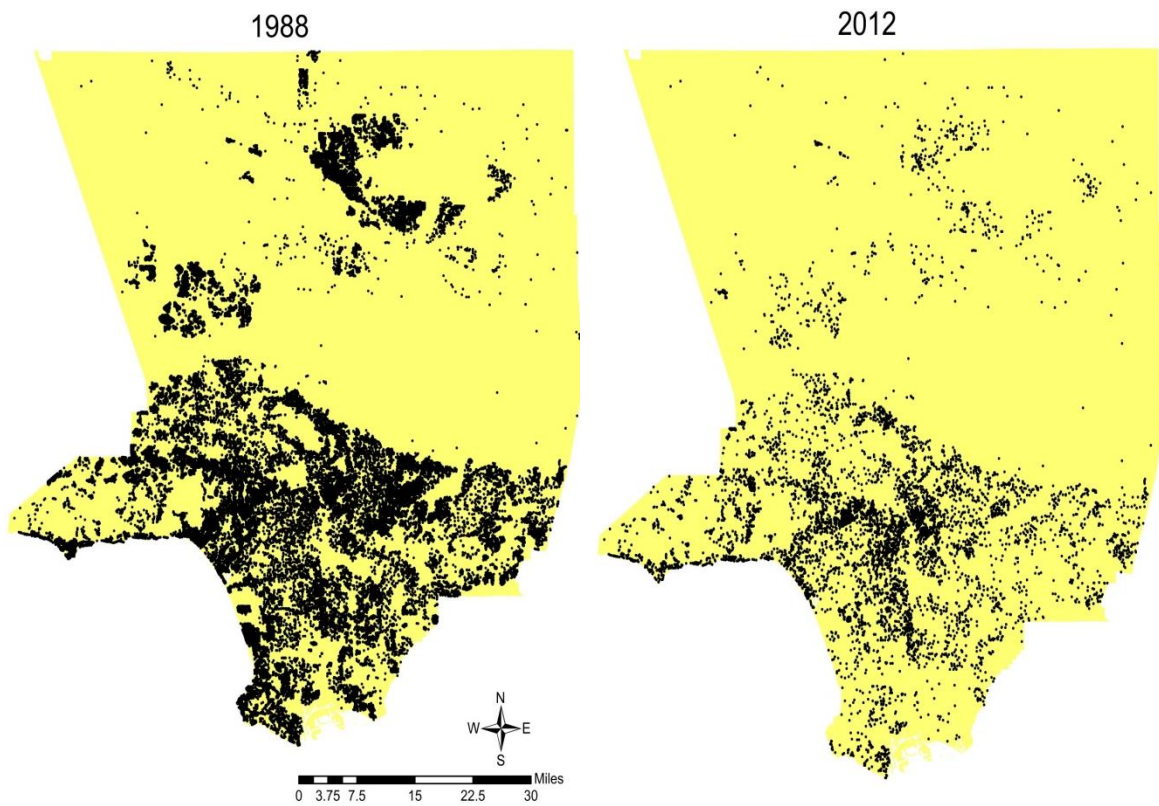
1988

2012

FIGURE 3

Undeveloped parcels zoned single family in LA County in 1988 and 2012

(a) F_{ct}

— Los Angeles city
- - - Other areas

$/sq foot of land

(b) Std.dev of u_{it}

— Constant λ
- - - Three period λ
······ Yearly λ

$\sigma_u = \pi/\sqrt{6}\lambda$

$/sq foot of land

(c) Share of entropy in reservation price
(parcels constructed in 1988-2011)

//// Entropy

(d) Elasticity

— Construction
- - - Stock

Construction
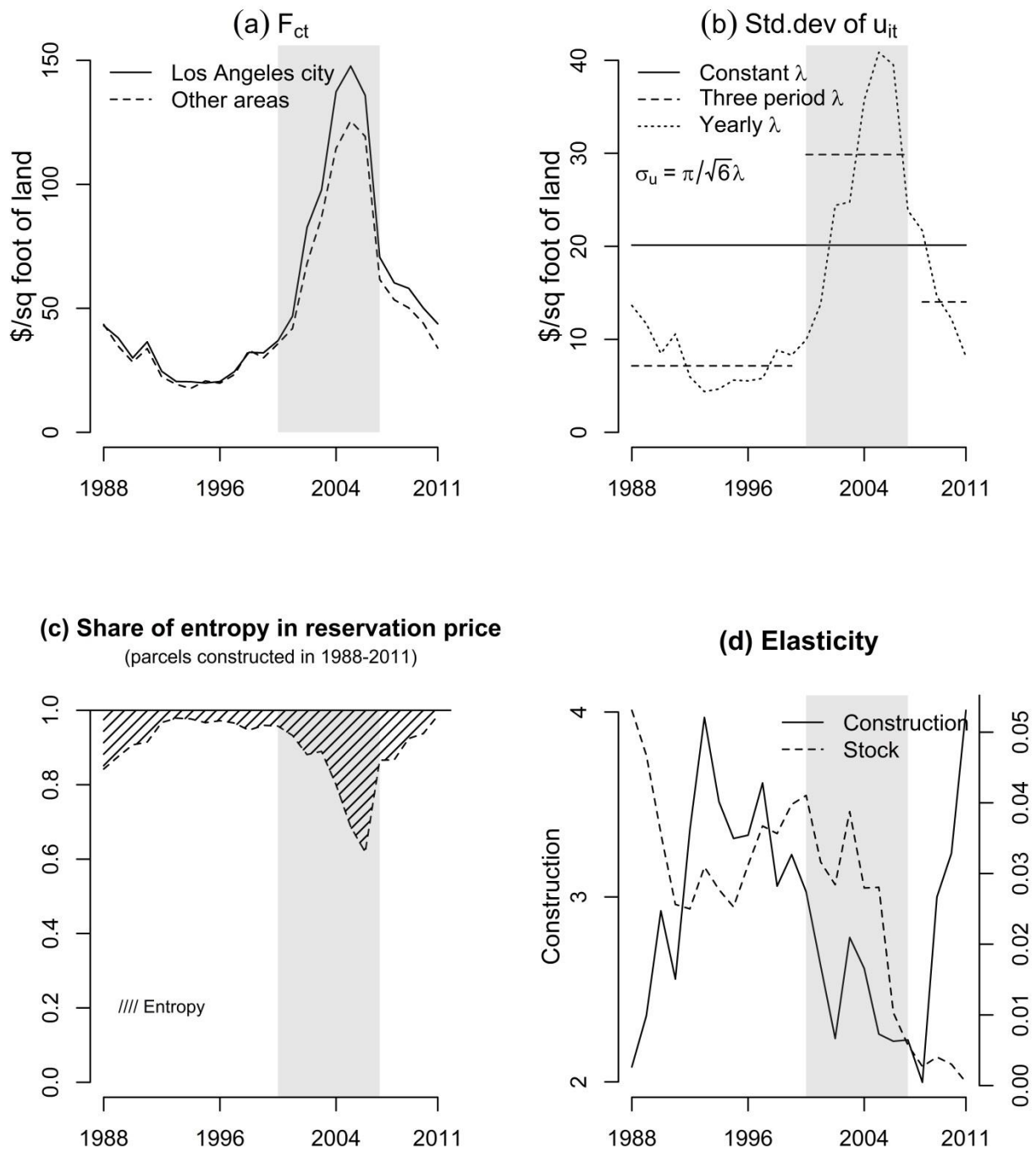
FIGURE 4
Estimates, entropy and elasticity in the benchmark model
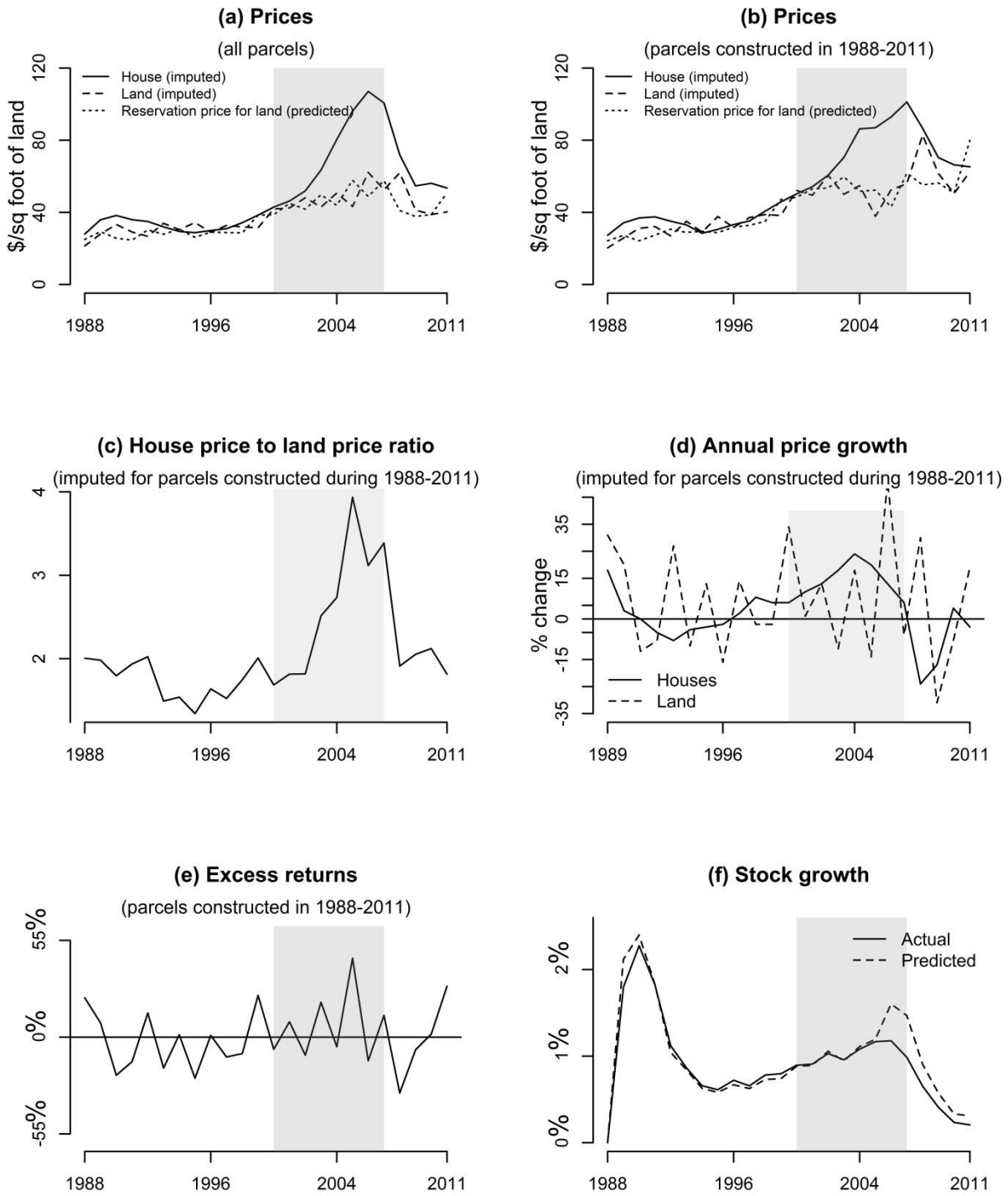
FIGURE 5
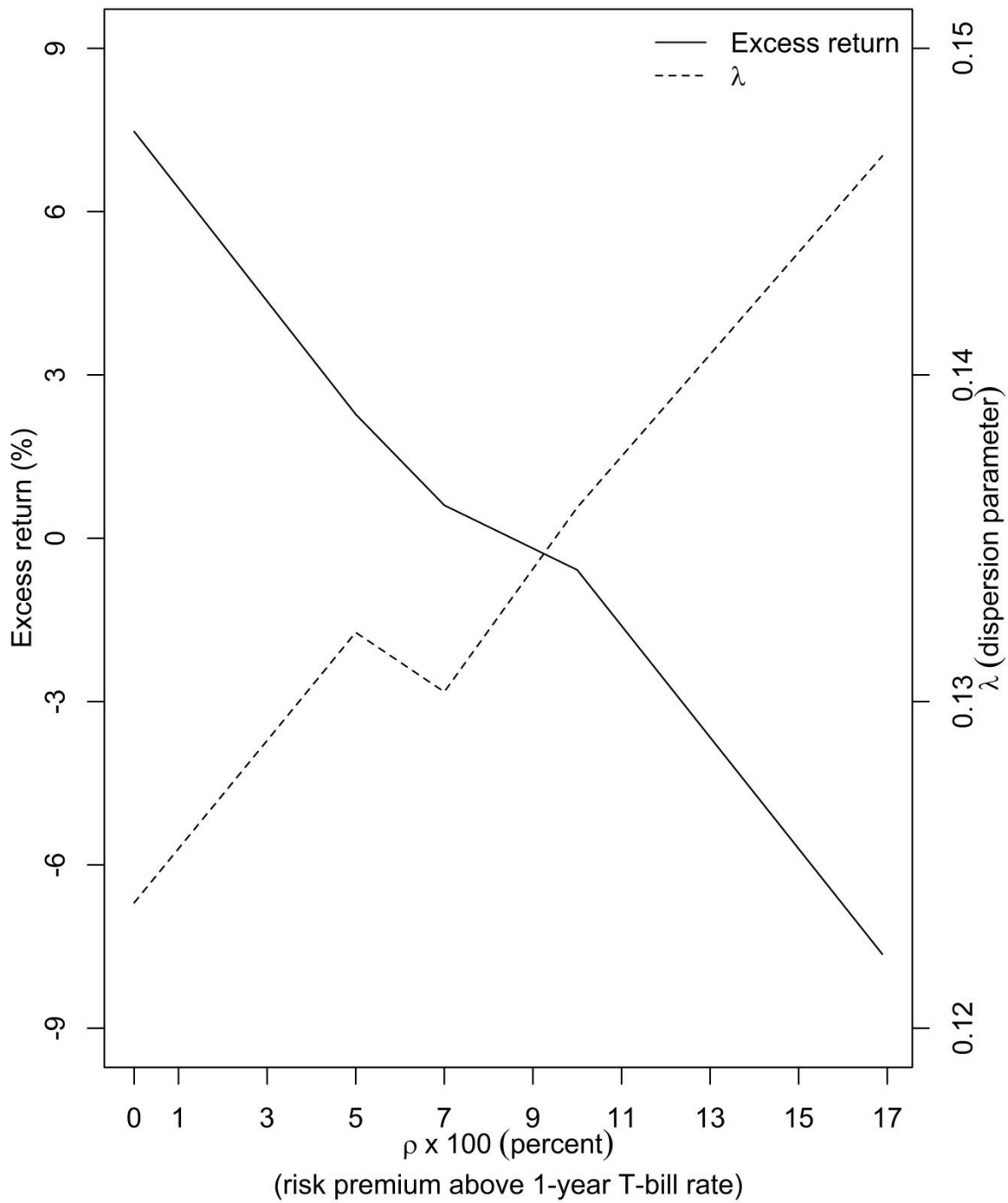Prices, excess returns and stock growth in the benchmark model

FIGURE 6

Effect of ρ on λ and predicted excess returns