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A Dynamic Model of Housing Supply†

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This paper estimates a dynamic microeconometric model of housing supply. The model features forward-looking landowners who optimally choose both the timing and the nature of construction while taking into account expectations about future prices and costs. The model is estimated using a unique dataset describing individual landowners in the San Francisco Bay Area. Results indicate that geographic and time-series variation in costs are key to understanding where and when construction occurs. Pro-cyclical costs provide an incentive for some landowners to build before price peaks. Results also indicate that landowners actively "time" the market, which reduces the elasticity of supply. (*JEL* C51, D12, E32, R21, R23, R31)

The length and severity of housing cycles, combined with the size of the construction industry, make obvious that understanding housing supply is an important issue.[1] To explore the microfoundations of the housing market, I estimate a microeconometric model of housing supply using data describing owners of individual parcels of land in the San Francisco Bay Area.

Given the irreversible nature of development, one would expect landowners to be forward-looking with respect to both future prices and future costs. I incorporate this forward-looking behavior and find that it plays a critical role in determining construction activity. In particular, I find that this forward-looking behavior substantially reduces the housing-supply elasticity as landowners view current price increases as predictors of higher future prices and attempt to time the market, and that this effect is particularly strong during housing booms. In addition, I find that pro-cyclical costs reduce construction volatility as developers build ahead of price peaks as they anticipate rising costs and hence declining profits.

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[1] Although the majority of the housing literature has been concerned with demand-side issues, the housing supply literature has been growing since the review article of DiPasquale (1999), which outlines two broad alternative approaches to modeling housing markets: an investment/asset market approach (e.g., Poterba 1984 and Topel and Rosen 1988) and an urban spatial theory approach (e.g., DiPasquale and Wheaton 1994 and Mayer and Somerville 2000).

I obtain these results by developing a dynamic microeconometric model of housing supply and estimating it using a rich new dataset. In the model, landowners choose both the optimal timing of and the optimal size of construction. These owners take into account current profits and expectations about future profits, balancing expected future prices against expected future costs. Analyzing these decisions with a dynamic framework allows one to meaningfully separate the effects of current profits on supply from the effects of expected future profits on supply, which is the key mechanism through which forward-looking behavior reduces the housing supply elasticity.

The starting point for the empirical analysis is a unique micro-level dataset describing the owners of individual parcels of land in the San Francisco Bay Area, which I create by merging observed real estate transactions data with geocoded parcel data over the period 1988–2004. In the combined dataset, I observe which parcels of land are developed and, if a parcel is developed, I observe when the house is built and the characteristics of the house. The analysis focuses on the development of single-family homes on individual parcels. This type of infill construction covers approximately one-half of all single-family residential construction in the San Francisco Bay Area over the sample period. The richness of these data allow me to identify the parameters of the landowner's profit function at a fine level of geography.

I estimate three distinct results relating to prices, variable costs, and broadly-defined fixed costs, respectively. First, I find that the primary determinant of observed increases in house prices is an increase in the location-price premium and not an increase in construction costs. This result is consistent with the implications of Glaeser, Gyourko, and Saks (2005), which suggest that regulation is responsible for observed house price increases. Second, I find that variable costs vary pro-cyclically over the time period. This result is in contrast to previous research that has found physical construction costs (which are the key component of variable costs) to be relatively flat over time. I provide external validation of these variable-cost estimates by comparing them to cost indexes derived from construction-industry input prices. Third, I find that fixed-costs vary considerably over both geography and time. These fixed costs capture any additional costs such as set-up costs and regulatory stringency and play a large role in explaining observed patterns of construction activity.

An interesting implication of these cost results is that pro-cyclical costs reduce construction volatility. The effects of time-varying prices have been documented by Case and Shiller (1989) and subsequent authors. However, less has been written about the effect of time-varying costs. A simple model focused only on prices would suggest that landowners will wait until the peak of prices to develop their land. However, in the case of the San Francisco Bay Area, many landowners developed parcels in the mid-to-late-1990s at prices much lower than they would have received in expectation had they waited. Results show that pro-cyclical costs provided an incentive to these landowners to build before the peak of prices, as waiting for higher prices implied also waiting for higher costs.

The results also yield important implications for the housing supply elasticity. Forward-looking behavior substantially reduces the responsiveness of landowners to current price changes. This reduction occurs because rising prices make building today more attractive, but also signal higher future prices, making waiting more attractive, thus reducing the responsiveness to current price. Interestingly, this forward-looking behavior suppresses the responsiveness to current price by a much greater extent during boom periods with rapidly rising land and house prices.

The remainder of this paper proceeds as follows. Section I discusses the existing literature. Section II introduces the data that I use to estimate the model. Section III outlines the model of housing supply (when and how parcel owners choose to develop their land) and Section IV explains the estimation procedure. Section V presents results, Section VI discusses the implications of these results for the housing-supply elasticity, and Section VII concludes.

I. Related Housing-Supply Literature

This paper builds upon three distinct branches of previous literature, respectively relating to the ability of costs to predict construction activity, the need to include forward-looking behavior in housing-supply models, and the nature of the data used to estimate housing prices and costs.

A key result found in the previous literature is that construction costs have little to no effect on construction levels, e.g., Poterba (1984), Topel and Rosen (1988), and DiPasquale and Wheaton (1994). More recent studies have used industry-supplied data (both cross-sectional and time-series) and have concluded that physical construction costs are not responsible for increases in house prices. One possible explanation, as suggested in Somerville (1999), is that the cost measures used by this literature may not have captured the entire cost environment. Therefore, in contrast to previous papers that take costs from the data, I estimate costs using a model where both prices and costs determine construction activity.[2]

Another result found in the literature is that current price is not a sufficient statistic in determining supply and that dynamics are playing an important role, e.g., Topel and Rosen (1988).[3] Building upon this result, a series of papers have used the insights of the real-options literature to explain the timing of housing development decisions, e.g., Williams (1991); Grenadier (1996); Capozza and Li (1994); Bulan, Mayer, and Somerville (2009); and Dye and McMillen (2007).[4] The hazard-model approaches found in the empirical, real-options housing papers may be

[2] Another important topic in the housing-supply literature has been the impact of regulation. Papers such as Glaeser, Gyourko, and Saks (2006); Quigley and Raphael (2005); and Ortalo-Magné and Prat (2007) have examined the role of increased regulation in generating rising house prices, and Saiz (2010) examines the role of both physical and regulatory barriers to new construction. Quigley (2006), Kahn (2008), and Ortalo-Magné and Prat (2007) draw attention to the possible role of existing residents in limiting housing supply. The role of supply within a dynamic equilibrium setting is an important component of the work by Glaeser et al. (2014), who develop a dynamic equilibrium model, and calibrate its parameters using macro moments.

[3] Topel and Rosen (1988) estimates both short-run and long-run supply elasticities and argue that a lower estimated short-run elasticity implies that developers have expectations about future prices. In subsequent work, Paciorek (2013) specifies a dynamic model of the build/not-build decision and differs from this paper by using aggregate data (instead of micro data) across multiple cities.

[4] Capozza and Li (1994) develops a theoretical model of both the optimal timing and the optimal intensity of construction. Bulan, Mayer, and Somerville (2009) uses a real options framework to estimate how uncertainty affects housing development and Dye and McMillen (2007) estimates a model of teardown and redevelopment in Chicago.

interpreted as reduced forms of the structural approach taken in this paper. Although the computational tractability of the hazard-model approach is attractive, it does not facilitate the estimation of structural cost parameters, which I find to be important determinants of construction volatility. Another difference is that the real-options literature typically uses data describing only the timing of building while this paper uses data describing both the timing and the size of construction. This additional data facilitates the separate identification of fixed and variable costs of construction.

Finally, in contrast to much of the existing literature, this paper employs micro data. The main recommendation of DiPasquale (1999) was that research should incorporate micro data on new construction to study the microfoundations of housing supply. Due to data limitations, this recommendation has, for the most part, yet to be taken up.[5]

II. Data

In this section, I describe a new dataset that I have assembled by merging information about parcels suitable for construction with housing transactions data for the San Francisco Bay Area. In contrast to most of the previous literature on housing supply, I use micro data at the parcel level. This allows me to observe both when and how individual parcels are developed. From a set of undeveloped parcels in 1988, I observe the year of construction, if the parcel was developed, and the type of construction, e.g., square footage and number of rooms, etc. The dataset provides information about parcels of land that were developed between 1988–2004 and those that remained undeveloped. I focus on land parcels that were potentially suitable for small scale construction and do not consider subdivisions and major developments by large construction companies. The type of construction I consider covers approximately 55 percent of all construction in the San Francisco Bay Area during this time period.

The empirical analysis in this paper uses the six core counties of the San Francisco Bay Area: Alameda, Contra Costa, Marin, San Francisco, San Mateo, and Santa Clara. The San Francisco Bay Area contains some of the wealthiest neighborhoods in the United States and has a limited supply of land. The cities of the Bay Area, in particular San Francisco, are good examples of so called “Superstar Cities” as defined by Gyourko, Mayer, and Sinai (2013); they are characterized as having disproportionately high-income households who pay a premium to live there but can generally expect high growth rates in housing prices. Albouy and Ehrlich (2012) estimate a productivity index that measures how difficult it is to convert land into housing and based on this index, the Bay Area is the most difficult-to-build metro area in the United States. This reflects the Bay Area’s high regulatory and geographic constraints on new housing.

The time period analyzed in the estimation is between 1988 and 2004 and the dataset that I construct is drawn from two main sources. The first data source is DataQuick, a national real estate data company, which provides information about

[5] Exceptions include Epple, Gordon, and Sieg (2010) and Combes, Duranton, and Gobillon (2016), both of which use micro data to estimate the parameters of a housing production function.

every housing unit sold in the core counties of the Bay Area. Overall, compared with the census micro data, the set of measured housing characteristics are considerably more complete. Further details on how new, single-family houses are identified in this data are provided in the online Appendix.

The second component of the dataset is the California Statewide Infill Study. The Institute of Urban and Regional Development (IURD) at the University of California, Berkeley conducted the study during 2004–2005 and the data provide a geocoded parcel inventory of all potential infill parcels in California. Using county assessors' parcel data, these data identify both vacant and economically underutilized sites. County assessor records include every legal parcel in a county and are updated whenever a parcel is bought, sold, subdivided, or combined. Each record includes the area of each parcel, its principal land use, the assessed value of the land and any improvements, as well as its parcel address. Infill parcels are designated according to whether the parcel is vacant or has a low improvement-value-to-land-value ratio. As I look at potential development of single family properties, I include vacant parcels and parcels with noncommercial residences that have a low improvement-value-to-land-value ratio, and further details are provided in the online Appendix.

To construct the dataset used in estimating the model, I merge the two datasets based on the census tract. The infill dataset provides data on all the infill parcels available in 2004. I construct the number of suitable parcels available in 1988 as the above number plus all properties built between 1988 and 2004 that were not part of subdivisions or large developments. The new dataset then contains all parcels from 1988 and includes information about tract, parcel square footage, and date of construction if building occurred.

As discussed below, some prices and costs are estimated at the census tract level. Typically, census tracts are areas with approximately 1,500 houses, although there is some variation in size. Tracts with very low levels of sales (less than 15) are excluded from the analysis and the remaining tracts number 613.

Descriptive Analysis/Trends in the Data.—The key feature of the data is variation in both the cross-sectional and time series dimensions of prices, housing characteristics, and construction levels. I illustrate some of this important variation in the data in Figures 1, 2, and 3.

Figure 1 reports overall house price levels in the Bay Area from 1988 to 2004, where the index of real house prices is normalized to 1 in 1988. The estimated price levels are derived from a repeat sales analysis in which the log of the sales price (in 2000 dollars) is regressed on a set of year fixed effects as well as house fixed effects. The figure reveals a run-up in prices in the late 1980s followed by falling real prices between 1990 and the mid-1990s. Prices rose fairly quickly again between the mid-1990s and 2004. Overall, house prices were nearly twice as high (in real terms) in 2004 as they were in 1988.

In addition to the aggregate pattern, there was considerable heterogeneity across neighborhoods in terms of both the total levels of appreciation and the timing of when booms began. Figure 2 shows the geographic pattern of total real appreciation between 1990 and 2004. For ease of exposition, I show appreciation rates at the level

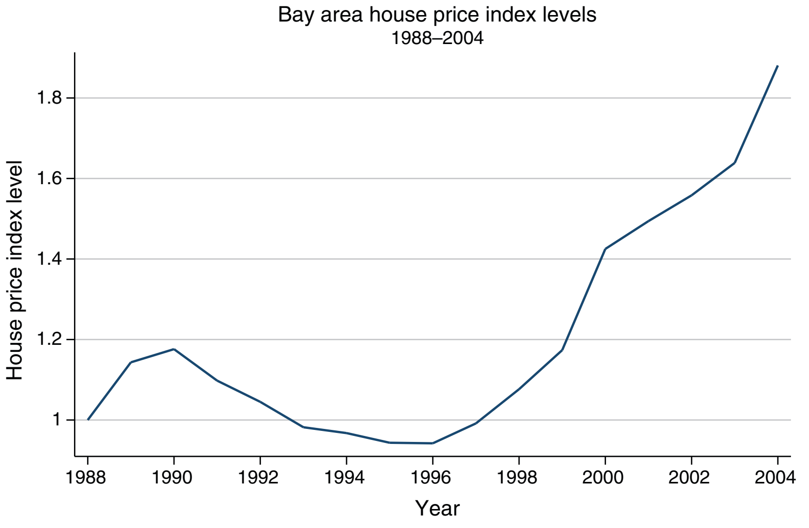

Figure 1. Bay Area Real House-Price Appreciation Rate

Notes: Real price levels. 1988 real price level normalized to one.

of Public Use Microdata Areas (PUMAs). The variation in total appreciation rates is large: some PUMAs saw as little as 50 percent real appreciation between 1990 and 2004, whereas others more than doubled in real terms.

Total levels of construction of all single family residences are illustrated in Figure 3, panel A. As expected, construction trends are positively correlated with prices—this can be seen by comparing Figure 1 and Figure 3, panel A. We see a pronounced dip in construction levels in the early 1990s, followed by increasing levels from the mid-1990s onward. Construction levels drop off again as prices slow (or fall in many areas) in 2000 and 2001. Figure 3, panel B, shows the time trend of the square footage index in new infill construction between 1988 and 2004. The extent to which changes in new house size correlate with changes in marginal price of square footage will be important later for identifying cost parameters.

III. A Dynamic Model of Housing Construction

This section outlines a model of housing construction, where the economic agents are the owners of parcels of land who decide when and how to develop their parcels.

A. *Model*

In each period, each parcel owner makes two decisions to maximize lifetime expected profits. First, the parcel owner decides whether or not to build on her parcel. This decision is denoted by $d_{nt} \in \{0, 1\}$, where $d = 0$ when choosing to not build, $d = 1$ when choosing to build, n indexes parcel owner and parcel, and t indexes time, which is measured in years. If a parcel owner decides to build, she makes a second decision about the level of housing services to construct, denoted

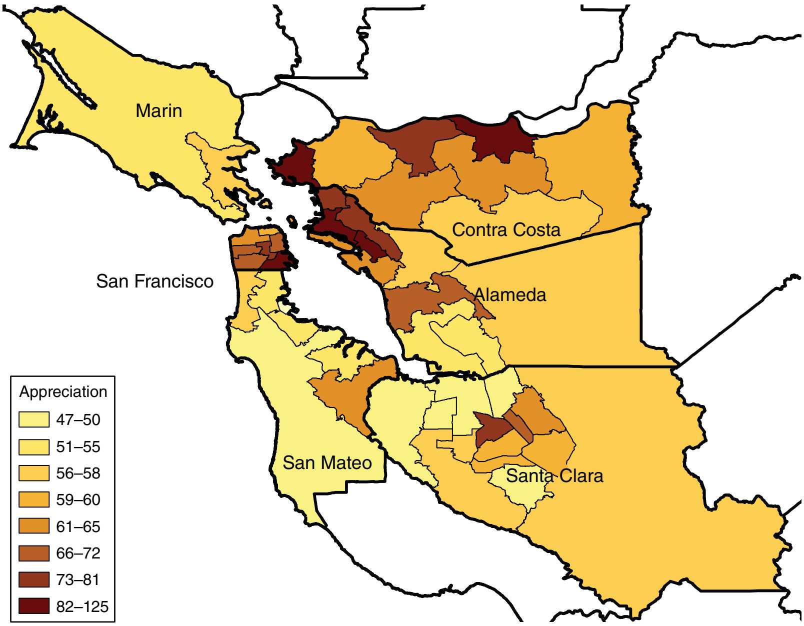

Figure 2. Real House-Price Appreciation Rates by PUMA: 1990–2004

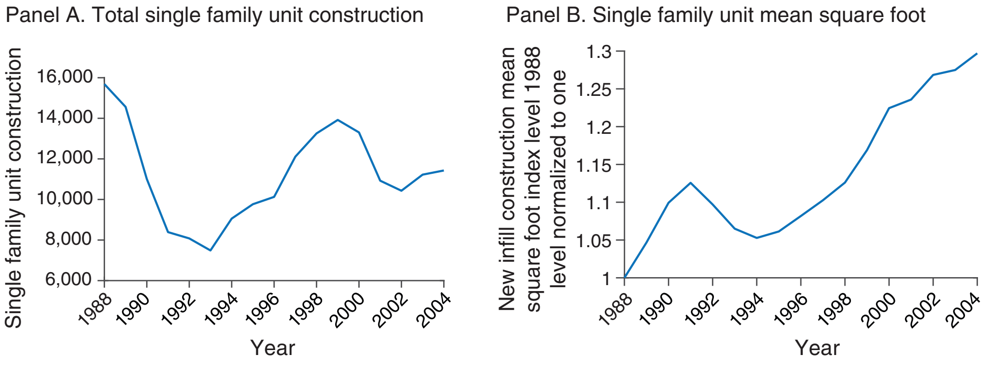

Figure 3. Construction Trends

Notes: Figure 3, panel B, is generated by regressing the log of observed square footage for new construction on the log of lot size, tract dummies, and year dummies and plotting the exponent of the time-dummy coefficients. The index is normalized to one for 1988.

by *h*. The parcel owner makes her decision to build or not knowing that she will choose the level of housing services optimally in the second decision. Once a parcel owner decides to build in a period, that period becomes a terminal period—this allows me to view the parcel owner's problem as an optimal stopping decision, formulated in a familiar dynamic programming setup. The model therefore incorporates two decisions—when to build and how much to build—and generates three outcomes—whether the parcel owner built or not in each period, the level of housing services chosen, and a sales price for the property.

Neighborhoods, which in practice are census tracts, are indexed by j, where $j \in \{1, \ldots, J\}$, and the census tract that parcel n is located in is denoted by $j(n)$. For notational convenience, I write $j(n)$ simply as j. The vector of observable parcel characteristics that affect the per period profits a parcel owner $n \in \{1, \ldots, N\}$ located in neighborhood j may receive from choosing to build in period t is denoted by $\mathbf{x}_{njt}$. Included in $\mathbf{x}_{njt}$ are direct characteristics of the parcel n, as well as characteristics of the neighborhood in which parcel n is located. The vector $\mathbf{x}_{njt}$ can be divided into two components: parcel-level variables, $\mathbf{x}_n$, and neighborhood-level variables, $\mathbf{x}_{jt}$. Price and variable cost shocks are denoted by ν_{nt} and η_{nt}, respectively. There is also an unobserved idiosyncratic overall profit shock, $\boldsymbol{\epsilon}_{nt} = (\epsilon_{0nt}, \epsilon_{1nt})$, which determines the profit parcel owner n receives from not building or building in period t. Finally, the vector of observable state variables is denoted by $\boldsymbol{\Omega}_{njt}$, where $\boldsymbol{\Omega}_{njt}$ contains $\mathbf{x}_{njt}$ as well as any other observable variables (such as lagged prices and lagged costs) that predict future values of $\mathbf{x}_{njt}$.

The primitives of the model are given by (π, q, β). Taking each in turn, $\pi_d = \pi_d(h_{njt}, \mathbf{x}_{njt}, \nu_{nt}, \eta_{nt}) + \epsilon_{dnt}$ is the direct per period profit function associated with choosing option d and housing services, h; $q = q(\boldsymbol{\Omega}_{njt+1}, \boldsymbol{\epsilon}_{nt+1} | \boldsymbol{\Omega}_{njt}, \boldsymbol{\epsilon}_{nt})$ denotes the transition probabilities of the observables and unobservables, where the transition probabilities are assumed to be Markovian; and β is the discount factor.

Finally, in principle, housing services, h, could include all observable characteristics of a house that the parcel owner is able to choose. One could use a continuous index of housing services to reduce the dimension of building choices (e.g., number bedrooms, number of bathrooms, square footage) to a single dimension. However, in practice, I include only square footage in h so that I can directly compare my estimates of price and cost per square foot with other estimates in the literature.

B. *Per Period Profits*

The direct per period profit function is given by

$$\text{(1)} \quad \pi_1(h_{nt}, \mathbf{x}_{njt}, \nu_{nt}, \eta_{nt}) + \epsilon_{1nt}$$
$$= P(h_{nt}, \mathbf{x}_{njt}, \nu_{nt}) - (VC(h_{nt}, \mathbf{x}_{njt}, \eta_{nt}) + FC(\mathbf{x}_{njt})) + \epsilon_{1nt}.$$

Prices are given by

$$\text{(2)} \quad P(h_{nt}, \mathbf{x}_{njt}, \nu_{nt}) = \rho_{jt} Q(h_{nt}, \mathbf{x}_n, \nu_{nt}),$$

where $Q(h_{nt}, \mathbf{x}_n, \nu_{nt}) = h_{nt}^{\gamma_{1jt}} \mathbf{x}_n^{\gamma_{2jt}} e^{\nu_{nt}}$. Therefore, prices are equal to the price of a unit of housing quality, ρ_{jt}, times the quantity of housing quality, Q_{nt}. The price of a unit of housing quality, ρ_{jt}, varies by neighborhood and year, incorporating the effects of $\mathbf{x}_{jt}$ on house price. Housing quality is composed of three terms: the choice variable, housing services, h; the fixed parcel characteristics, $\mathbf{x}_n$; and a normally distributed error term, ν_{nt}, with variance σ_ν^2. In practice, h is house square footage, $\mathbf{x}_n$ includes lot size, and ν_{nt} is assumed to be independent of $\boldsymbol{\Omega}_{njt}$. The vector of price parameters, which I denote by $\boldsymbol{\gamma}$, varies by neighborhood, j, and time, t. I assume that the parcel owner knows the current price parameters, γ, and parcel characteristics when making her build/don't build decision, but that the price error, ν_{nt}, is not revealed until after construction and time of sale. The price function is an equilibrium price equation, where each parcel owner (who is small relative to the total market) takes the prices as given.[6]

Costs are comprised of two components, variable costs, $VC(h_{nt}, \mathbf{x}_{njt}, \eta_{nt})$, and fixed costs, $FC(\mathbf{x}_{njt})$. Variable costs are specified as

$$VC(h_{nt}, \mathbf{x}_{njt}, \eta_{nt}) = (\alpha_{0jt} \mathbf{x}_n^{\boldsymbol{\alpha}_1} e^{\eta_{nt}}) \cdot h_{nt} \tag{3}$$

and increase at a linear rate in the quantity of housing services, where the rate is determined by the parcel characteristics, neighborhood, time, and a normally distributed error term, η_{nt}, with variance σ_η^2. I assume that the parcel owner observes the cost shock before the housing-services decision is made, but after the decision to build is made, and that it is independent of $\boldsymbol{\Omega}_{njt}$.

Variable costs, by definition, include any costs that vary with h. As such, in addition to physical construction costs, they capture any regulatory burdens that increase with housing services. Furthermore, any variation across geographic space or time in this type of regulatory burden will be reflected in variation across space and time in the variable costs measures.

The second component of costs, $FC(\mathbf{x}_{njt})$, captures the broader cost environment. These remaining costs are labeled fixed costs because they capture any costs associated with construction that do not vary with the size of the house. Factors such as difficulty in obtaining a building permit will cause fixed construction costs to vary spatially. Fixed costs vary at the county-by-year level and are specified as $FC(\mathbf{x}_{njt}) = \delta_{ct}$, where c denotes the county in which parcel h is located.

The final component to profits is a profit shock, ϵ_{dnt}, which is assumed to be distributed i.i.d. Type 1 Extreme Value with scale parameter, σ_ϵ, and mean equal to zero. This shock, whose current value is observed by the parcel owner before they decide to build, can be interpreted as a shock to fixed costs and could reflect factors at the parcel level or idiosyncratic parcel owner characteristics. For example, shocks to health, family, or employment status could make developing a parcel more or less attractive in a given year. As the per period profit is additively separable in this error, it does not affect the optimal housing services decision.

I assume that the three errors are independent—the assumption of independence between price and costs shocks would only be violated if a parcel owner could pass on a cost shock to the buyer, however, as the model is estimated at a fine level of geography, this seems unlikely.[7]

[6] Using a similar dataset, Bayer et al. (2016) estimates a dynamic discrete-choice model of neighborhood choice in the San Francisco Bay Area to recover the willingness to pay for neighborhood amenities. Analogously to this paper, households are assumed to be small relative to the total market and to take neighborhood house prices as given.

[7] Although correlation between the variable cost shock and fixed cost shock is a possibility, the fine level of geography should also mitigate against this. One could model correlation among the errors by allowing a common component to come from a finite mixture distribution using the framework developed in Arcidiacono and Miller (2011).

C. *Optimal Housing Services*

Conditional on choosing to build, a parcel owner will choose h to maximize profits. As the price error, ν_{nt}, is unobserved at the time of that decision, the agent takes the expectation of prices with respect to ν_{nt} and the first-order condition for maximization is given by[8]

$$\gamma_{1jt}\rho_{jt}h_{nt}^{\gamma_{1jt}-1}\mathbf{x}_n^{\gamma_{2jt}}e^{0.5\sigma_\nu^2} - \alpha_{0jt}\mathbf{x}_n^{\boldsymbol{\alpha}_1}e^{\eta_{nt}} = 0. \tag{4}$$

The second-order conditions require $\gamma_{1jt} < 1$, which is always satisfied in the empirical results. Therefore, solving (4) yields the optimal housing services, h^*:

$$h_{nt}^* = \left(\frac{\gamma_{1jt}\rho_{jt}\mathbf{x}_n^{\gamma_{2jt}}e^{0.5\sigma_\nu^2}}{\alpha_{0jt}\mathbf{x}_n^{\boldsymbol{\alpha}_1}e^{\eta_{nt}}}\right)^{\frac{1}{1-\gamma_{1jt}}}. \tag{5}$$

D. *Optimal Discrete Choice*

Plugging (5) into (1) yields the indirect flow profit function associated with building, $\pi_1(h_{nt}^*(\mathbf{x}_{njt}, \eta_{nt}), \mathbf{x}_{njt}, \nu_{nt}, \eta_{nt}) + \epsilon_{1nt}$. However, as the price error, ν_{nt}, and variable cost error, η_{nt}, are observed after the decision to build is made, the relevant object for the optimal discrete choice is the expected indirect flow profit, which is denoted by $\overline{\pi}_1(\mathbf{x}_{njt})$. Denoting $E_{\nu_{nt},\eta_{nt}}[P_{nt}(h_{nt}^*(\mathbf{x}_{njt}, \eta_{nt}), \mathbf{x}_{njt}, \nu_{nt}) \,|\, \boldsymbol{\Omega}_{njt}]$ with $\overline{P}(\mathbf{x}_{njt})$ and denoting $E_{\eta_{nt}}[VC_{nt}(h_{nt}^*(\mathbf{x}_{njt}, \eta_{nt}), \mathbf{x}_{njt}, \eta_{nt}) \,|\, \boldsymbol{\Omega}_{njt}]$ with $\overline{VC}(\mathbf{x}_{njt})$, the expected indirect flow profit, $\overline{\pi}_1(\mathbf{x}_{njt})$, is given by[9,10]

$$\overline{\pi}_1(\mathbf{x}_{njt}) = \overline{P}(\mathbf{x}_{njt}) - (\overline{VC}(\mathbf{x}_{njt}) + FC(\mathbf{x}_{njt})) + \epsilon_{1nt}. \tag{6}$$

The deterministic component of the per period profits from choosing to not build $(d = 0)$ is normalized to zero, so that the indirect flow profit function (associated with not building) is $\pi_0(\mathbf{x}_{njt}) + \epsilon_{0nt} = \epsilon_{0nt}$.

Lifetime expected profits can be represented by a Bellman Equation which decomposes the value function into the per period profits at time t and the expected sum of per period profits from time $t+1$ onward. Under the assumption that the process ends when building occurs and the normalization of deterministic per period profits (associated with not building) to zero, the value function can be written as

$$V_t(\boldsymbol{\Omega}_{njt}, \epsilon_{nt}) = \max\left\{\overline{\pi}_1(\mathbf{x}_{njt}) + \epsilon_{1nt},\ \epsilon_{0nt} + E[\beta V_{t+1}(\boldsymbol{\Omega}_{njt+1}, \boldsymbol{\epsilon}_{nt+1}) \,|\, \boldsymbol{\Omega}_{njt}, \epsilon_{nt}]\right\}. \tag{7}$$

[8] $E_{\nu_{nt}}[P_{nt} \,|\, \boldsymbol{\Omega}_{njt}, h_{nt}] = \rho_{jt}h_{nt}^{\gamma_{1jt}}\mathbf{x}_n^{\gamma_{2jt}}e^{0.5\sigma_\nu^2}$.

[9] $\overline{P}_{nt} = \rho_{jt}\left(\frac{\gamma_{1jt}\rho_{jt}\mathbf{x}_n^{\gamma_{2jt}}e^{0.5\sigma_\nu^2}}{\alpha_{0jt}\mathbf{x}_n^{\boldsymbol{\alpha}_1}e^{\frac{-0.5\gamma_{1jt}}{1-\gamma_{1jt}}\sigma_\eta^2}}\right)^{\frac{\gamma_{1jt}}{1-\gamma_{1jt}}}\mathbf{x}_n^{\gamma_{2jt}}e^{0.5\sigma_\nu^2}$.

[10] $\overline{VC}_{nt} = \left(\alpha_{0jt}\mathbf{x}_n^{\boldsymbol{\alpha}_1}e^{\frac{-0.5\gamma_{1jt}}{1-\gamma_{1jt}}\sigma_\eta^2}\right)^{\frac{-\gamma_{1jt}}{1-\gamma_{1jt}}}\cdot\left(\gamma_{1jt}\rho_{jt}\mathbf{x}_n^{\gamma_{2jt}}e^{0.5\sigma_\nu^2}\right)^{\frac{1}{1-\gamma_{1jt}}}$.

Given the assumption that the profit shocks are distributed i.i.d., Type 1 Extreme Value and assuming that the problem has an infinite horizon allows me to define the choice-specific value functions as follows:[11]

$$(8)\quad v_1(\boldsymbol{\Omega}_{njt}) = \overline{\pi}_1(\mathbf{x}_{njt}),$$

$$v_0(\boldsymbol{\Omega}_{njt}) = \beta\sigma_\epsilon\Big(\int \log\big[\exp(v_0(\boldsymbol{\Omega}_{njt+1})/\sigma_\epsilon) + \exp(\overline{\pi}_1(\mathbf{x}_{njt+1})/\sigma_\epsilon)\big]q(\boldsymbol{\Omega}_{njt+1}|\boldsymbol{\Omega}_{njt})\, d\boldsymbol{\Omega}_{njt+1}\Big).$$

The choice-specific value function is the deterministic component of the lifetime expected utility an agent would receive from choosing option d. It includes the two avenues through which today's choice affects utility/profits. The first is the current profit associated with choosing d. The second is the expected value of the best option next period conditional on choosing d this period; that is, how this period's decision affects next period's payoffs. By convention, the choice-specific value function, v_d, does not include the error term, ϵ_{dnt}. Therefore, an agent will choose $d \in \{0,1\}$ to maximize $v_d(\boldsymbol{\Omega}_{njt}) + \epsilon_{dnt}$.

IV. Estimation

There are three outcomes associated with the model. The first two are choices made by the parcel owner: the binary decision to build or not in each period, and the housing service provision decision made conditional on building. The final outcome is the sales price of all properties that sell.

Let $\boldsymbol{\theta}_p$ denote $(\boldsymbol{\rho}, \gamma_1, \gamma_2, \sigma_\nu)$, $\boldsymbol{\theta}_h$ denote $(\boldsymbol{\alpha}_0, \boldsymbol{\alpha}_1, \sigma_\eta)$, and $\boldsymbol{\theta}_d$ denote $(\boldsymbol{\delta}, \beta, \sigma_\epsilon)$. Given the timing of the decisions and the assumption of independence across errors, the log-likelihood function can be broken into the following three pieces: $L_p(\boldsymbol{\theta}_p|\mathbf{P}, \boldsymbol{\Omega})$, the log-likelihood contribution of prices; $L_h(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h|\mathbf{h}, \boldsymbol{\Omega})$, the log-likelihood contribution of housing services; and $L_d(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h, \boldsymbol{\theta}_d|\mathbf{d}, \boldsymbol{\Omega})$, the log-likelihood contribution of the binary construction decision. The total log-likelihood function is the sum of the three components:

$$(9)\qquad L(\boldsymbol{\theta}) = L_p(\boldsymbol{\theta}_p|\mathbf{P}, \boldsymbol{\Omega}) + L_h(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h|\mathbf{h}, \boldsymbol{\Omega}) + L_d(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h, \boldsymbol{\theta}_d|\mathbf{d}, \boldsymbol{\Omega}),$$

where $\boldsymbol{\theta} = (\boldsymbol{\theta}_p, \boldsymbol{\theta}_h, \boldsymbol{\theta}_d)$.

In theory, I could choose $\boldsymbol{\theta}$ to maximize (9) directly. However, given the large number of parameters, in practice I estimate the model in stages. In the first stage, I estimate $\boldsymbol{\theta}_p$ by maximizing $L_p(\boldsymbol{\theta}_p|\mathbf{P}, \boldsymbol{\Omega})$. Then, using the estimates of $\boldsymbol{\theta}_p$, I estimate $\boldsymbol{\theta}_h$ by maximizing $L_h(\hat{\boldsymbol{\theta}}_p, \boldsymbol{\theta}_h|\mathbf{h}, \boldsymbol{\Omega})$. Finally, I can obtain consistent estimates of $\boldsymbol{\theta}_d$ by taking the estimates of $\boldsymbol{\theta}_p$ and $\boldsymbol{\theta}_h$ as given and choosing $\boldsymbol{\theta}_d$ to maximize $L_d(\hat{\boldsymbol{\theta}}_p, \hat{\boldsymbol{\theta}}_h, \boldsymbol{\theta}_d|\mathbf{d}, \boldsymbol{\Omega})$. To estimate the third stage, which is a dynamic discrete choice model, I use a two-step estimator similar to Arcidiacono and Miller (2011) where transition

[11] Similar to Rust (1987), I am also assuming that $\boldsymbol{\epsilon}_{nt}$ has no predictive power for $\boldsymbol{\Omega}_{njt+1}$. That is, $q = q(\boldsymbol{\Omega}_{njt+1}, \boldsymbol{\epsilon}_{nt+1}|\boldsymbol{\Omega}_{njt}, \boldsymbol{\epsilon}_{nt}) = q(\boldsymbol{\Omega}_{njt+1}|\boldsymbol{\Omega}_{njt})q(\boldsymbol{\epsilon}_{nt+1})$. The infinite horizon assumption implies $V_t(\boldsymbol{\Omega}_{njt}, \boldsymbol{\epsilon}_{nt}) = V(\boldsymbol{\Omega}_{njt}, \boldsymbol{\epsilon}_{nt})$ and $d_t(\boldsymbol{\Omega}_{njt}, \boldsymbol{\epsilon}_{nt}) = d(\boldsymbol{\Omega}_{njt}, \boldsymbol{\epsilon}_{nt})$.

and choice probabilities are estimated in a first step and the structural parameters are estimated in the second step.

Estimating the model in stages does not affect the consistency of the estimates, but does reduce efficiency. To account for the multiple stage procedure, a bootstrap procedure is used to calculate the standard errors.[12]

Finally, it is first worth noting that the functional form assumptions made in the paper are not required to secure identification. They do, however, provide a number of important benefits. The first is that they reduce the computational burden. The second is that they allow for closed-form solutions that make identification more transparent. The third is that they avoid over fitting the data. That said, the standard downsides of making parametric assumptions apply and, as such, I conduct a sensitivity analysis to the key parametric assumptions, which I discuss below and in the online Appendix.

A. *Estimation—Housing Prices*

To estimate the parameters of the price function given in (2), I estimate the following equation separately for each tract × year combination:

$$\log(P_{nt}) = \log(\rho_{jt}) + \gamma_{1jt}\log(h_{nt}) + \gamma_{2jt}\log(\mathbf{x}_n) + \nu_{nt}, \quad (10)$$

where P_{nt}, h_{nt}, and $\mathbf{x}_n$ denote observed sales price, house square footage, and lot size.[13] To improve the efficiency of the estimates, I use a standard, Locally Weighted Regression approach. The approach is a special case of Locally Weighted Regression sometimes called Conditionally Parametric Regression or Geographically Weighted Regression. McMillen and Redfearn (2010) describes this class of estimator, which is related to the estimation approach outlined in Racine and Li (2004). More specifically, for a given tract/year regression, I use all sales in that year, but weight the observations differently depending on how far from the given tract each house is. I also use both sales of new houses and sales of second-hand houses and weight the new-house sales more heavily.[14]

This hedonic price function, where house prices are modeled directly as a function of the observable characteristics of the house, allows the implicit price of square footage to vary both by tract and by year. This is important in the context of the model and the nature of limited land availability in the Bay Area. With limited land, the increase in house prices in the Bay Area is driven more by the increasing value of

[12] I employ a standard, nonparametric bootstrap and resample the data 250 times to reestimate the model. As the price regression is specified at the tract-by-year level, I resample the sales data separately by tract-year.

[13] As outlined in Section IIIA, $\mathbf{x}_n$ represents the vector of parcel-level characteristics. In the empirical application, this vector is one-dimensional and denotes lot size.

[14] The weight is determined by the product of three subweights: the first is a continuous, normal-kernel weight based on how far the house is from the centroid of the tract of interest (with a bandwidth of two times the standard deviation of distance); the second is a discrete-kernel weight, which is twice as large if the house is in the same county as the tract of interest; and the third is a discrete-kernel weight, which is twice as large if the house is a new house. I choose the weights based on a visual inspection of the data, and the results are not sensitive to the choice of weights. As this estimator contains a nonparametric component, standard issues of finite-sample bias arise and a greater number of observations within each tract-year would reduce this bias. Smoothing is only used in the estimation of equation 10 and is not required for the cost regressions described in Sections IVB and IVC.

land rather than other housing attributes such as square footage. One would assume that if we see a house double in price over the sample period, the component of price explained by square footage would have increased by far less than a factor of two. As the model predicts that parcel owners will respond to the implicit price of housing services, it is important to accurately estimate this return.[15]

B. *Estimation—Variable Costs*

Given estimates of the pricing parameters, I can rearrange the equation for optimal housing services (5) to get the following housing service regression equation

$$(11)\quad (\gamma_{1jt} - 1)\log(h_{nt}) + \log(\gamma_{1jt}) + \log(\rho_{jt}) + \gamma_{2jt}\log(\mathbf{x}_n) + 0.5\,\sigma_\nu^2 = \log(\alpha_{0jt}) + \boldsymbol{\alpha}_1\log(\mathbf{x}_n) + \eta_{nt}.$$

I parameterize $\log(\alpha_{0jt})$ as

$$(12)\quad \log(\alpha_{0jt}) = \log(\alpha_0) + \log(\alpha_j) + \log(\alpha_t).$$

Estimating (11) by least squares yields estimates of $\log(\alpha_0)$, $\log(\alpha_j)$, $\log(\alpha_t)$, $\boldsymbol{\alpha}_1$, and the variance of η_{nt}.[16]

An alternative way to look at this regression is to use the first-order condition from profit maximization where the standard result dictates that marginal revenue should be equal to the marginal cost of adding one additional square foot. Given that marginal revenue is known at all points from the first-stage regression, we can identify marginal costs at points observed in the data and therefore recover the variable cost function.

As discussed above, variable costs capture any regulatory costs that vary with size, which may suggest that the variable cost function could be nonlinear and presumably convex. To address this potential concern, I conduct a sensitivity analysis in the online Appendix, which allows for a quadratic variable-cost function. The variable cost function is estimated to be convex. However, the degree of nonlinearity is very small and, as such, the results are similar. I include the linear variable-cost function as the primary specification as it allows for the closed-form solution for optimal housing size in (5) and (11), which makes the identification of the variable cost parameters more transparent.

[15] The common alternative to a hedonic pricing model is a repeat sales model (Bailey, Muth, and Nourse 1963; Case and Shiller 1987; and Case and Shiller 1989). The repeat sales framework controls for time-invariant unobserved house characteristics. However, it imposes that the relative implicit prices of housing attributes remain constant. Another alternative is a hybrid repeat-sales and hedonic approach, such as Case and Quigley (1991), which allows the relative implicit prices of housing attributes to vary over time.

[16] The approach of combining estimates of the price function with the size of construction is closely related to the estimation of Rosen (1974) style models. Ekeland, Heckman, and Nesheim (2004) showed formally that such models are identified even in single markets with nonlinear price gradients. As I estimate the price function separately for each tract and year, but include a common time-trend in log variable costs, I effectively have multi-market data making the identification even richer.

C. *Estimation—Dynamic Discrete Choice*

Given results of the first two stages, the remaining structural parameters are $\boldsymbol{\theta}_d = (\boldsymbol{\delta}, \beta, \sigma_\epsilon)$. One estimation approach would be to use an estimator similar to Rust (1987), where the value functions are computed by a fixed point iteration for each guess of the parameters to be estimated. Such an approach, while efficient, would be computationally prohibitive in the context of this model. Therefore, I use a computationally more simple two-step estimation approach. To simplify the problem, I use insights from Hotz and Miller (1993) and Arcidiacono and Miller (2011) to take advantage of the terminal state nature of the dynamic discrete choice problem and rewrite $v_0(\boldsymbol{\Omega}_{njt})$ (from equation 8) as the expected future per period profit of choosing to not build and a function of the next period probability of choosing to build:

$$(13) \quad v_0(\boldsymbol{\Omega}_{njt}) = \beta\Big(\int \big(\overline{\pi}_1(\mathbf{x}_{njt+1}) - \sigma_\epsilon \log\left[P_1(\boldsymbol{\Omega}_{njt+1})\right]\big) q(\boldsymbol{\Omega}_{njt+1} \,|\, \boldsymbol{\Omega}_{njt})\, d\boldsymbol{\Omega}_{njt+1}\Big),$$

where $P_1(\boldsymbol{\Omega}_{njt})$ is the conditional choice probability of choosing to build and is given by

$$(14) \qquad P_1(\boldsymbol{\Omega}_{njt}) \equiv \Pr(d_{nt} = 1 | \boldsymbol{\Omega}_{njt}) = \frac{1}{1 + e^{v_0(\boldsymbol{\Omega}_{njt})/\sigma_\epsilon - \overline{\pi}_1(\mathbf{x}_{njt})/\sigma_\epsilon}}.$$

Using the definition of expected indirect flow profits, $\overline{\pi}_1(\mathbf{x}_{njt})$, the difference in value functions is given by

$$(15) \quad v_1(\boldsymbol{\Omega}_{njt}) - v_0(\boldsymbol{\Omega}_{njt}) = (\overline{P}_{nt} - \overline{VC}_{nt}) + (\beta E_t \delta_{ct+1} - \delta_{ct})$$
$$- \beta\Big(\int \big(\overline{P}_{nt+1} - \overline{VC}_{nt+1} - \sigma_\epsilon \log\left[P_1(\boldsymbol{\Omega}_{njt+1})\right]\big) q(\boldsymbol{\Omega}_{njt+1} \,|\, \boldsymbol{\Omega}_{njt})\, d\boldsymbol{\Omega}_{njt+1}\Big).$$

Equation (15) forms the basis of a straightforward two-step estimator. The first step involves estimating both the transition probabilities, $q(\boldsymbol{\Omega}_{njt+1} | \boldsymbol{\Omega}_{njt})$, and the conditional choice probability, $P_1(\boldsymbol{\Omega}_{njt+1})$. The second step then takes estimates of $\overline{P}_{nt}$, $\overline{VC}_{nt}$, $\overline{P}_{nt+1}$, $\overline{VC}_{nt+1}$, $\int \log\left[P_1(\boldsymbol{\Omega}_{njt+1})\right]$, and $q(\boldsymbol{\Omega}_{njt+1} \,|\, \boldsymbol{\Omega}_{njt})\, d\boldsymbol{\Omega}_{njt+1}$ as data and estimates the remaining structural parameters, $\boldsymbol{\theta}_d = (\boldsymbol{\delta}, \beta, \sigma_\epsilon)$, via maximum likelihood, where the coefficients on a set of county $\times$ year dummies will be estimates of $(\beta E_t \delta_{ct+1} - \delta_{ct})$. Further details of this two-step procedure can be found in the online Appendix.

It is clear from (15) that additional assumptions regarding expectation formation are necessary to separately identify δ_{ct} from $(\beta E_t \delta_{ct+1} - \delta_{ct})$. However, for the analysis below, the term of most interest is $(\beta E_t \delta_{ct+1} - \delta_{ct})$, which can be roughly interpreted as expected growth in the latent fixed costs.

Finally, fixed costs vary at the county $\times$ year level. Ideally, one would allow the fixed costs to vary at a finer level of geography like, for example, the price coefficients. However, the price data are more numerous, have a continuous outcome, and geographic weights are used to estimate the price coefficients. These features are not available or appropriate for the dynamic-discrete-choice outcome. The online Appendix presents the results of a sensitivity analysis where fixed costs vary at the

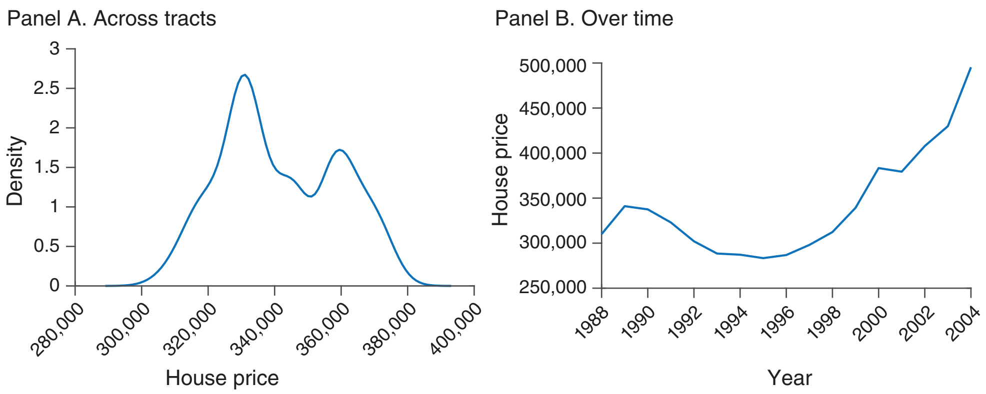

FIGURE 4. PRICE OF A TYPICAL HOUSE

Notes: Panel A plots a kernel density estimate of the distribution across census tracts of the expected price of a new house with 1,670 square feet of living space and a lot size of 6,800 square feet. 1,670 and 6,800 correspond to the sample means for house size and lot size, respectively. The expected price for each census tract is an average of the yearly expected prices between 1988 and 2004. Density is measured in units of 1/100,000. Panel B plots the time trend of the expected price, where the expected price for each year is an average of the census tract expected prices. All prices are in year-2000 dollars.

PUMA × year level, which (at approximately 100,000 residents) is a considerably smaller level of geography. For PUMAs which include a small number of observations in PUMA × year combinations, the results are noisy; however, for most of the PUMAs, the trends are qualitatively similar to the county × year case.

V. Empirical Results

In this section, I present estimates of the parameters of the profit function. For simplicity, I present the results separately for each stage.

A. *Hedonic Price Regressions*

With over 600 tracts and 17 years of data, the estimates from (10) are too numerous to report here. Therefore, I highlight key features of the results in Figures 4 and 5. Figure 4, panel A, shows the distribution of the expected price (in year-2000 dollars) of the "typical" house across census tracts. This "typical" house is the same across tracts and years and is defined as a new house with 1,670 square feet of living space and 6,800 square feet of lot size, corresponding to the sample means in the data. The figure shows considerable variation over tracts in the price of this consistently-defined house. Figure 4, panel B, illustrates the time-series variation in the price of a typical house.

The key reason for estimating prices using the hedonic-price approach is to capture the variation in the implicit price of housing size, both over geography (U.S. census tracts) and through time. For each tract and year, I can calculate the marginal price of adding an additional square foot to the typical house. Figure 5, panel A, shows the distribution of these marginal prices across tracts, which will serve as one of the key sources of identification of variable housing costs. The other source

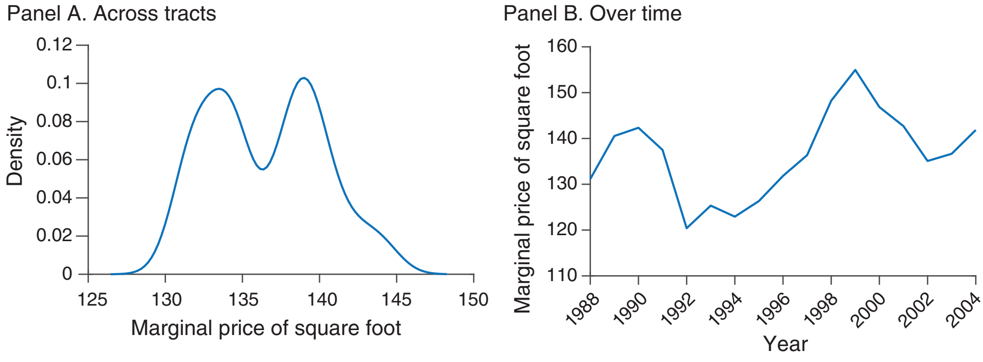

Figure 5. Marginal Price of Square Footage in a Typical House

Notes: Figure 5, panel A, plots a kernel density estimate of the distribution across census tracts of the marginal price of square footage. The marginal price is calculated for a new house with 1,670 square feet of living space and a lot size of 6,800 square feet. 1,670 and 6,800 correspond to the sample means for house size and lot size, respectively. The marginal price for each census tract is an average of the yearly marginal prices between 1988 and 2004. Figure 5, panel B, plots the time trend of the marginal price, where the marginal price for each year is an average of the census tract marginal prices. All prices are in year-2000 dollars.

of variation that I use to identify variable housing costs is the time-series variation in the marginal price of square footage, which is shown in Figure 5, panel B. The online Appendix presents county-specific versions of Figures 4 and 5 and shows that the overall Bay Area time trend arises from a mix of county-specific time trends. The online Appendix also presents versions of Figures 4 and 5 for houses with the twenty-fifth and seventy-fifth percentile of house size and lot size.

A notable feature of the price results is the decreasing importance of overall square footage in determining sales prices. The results strongly suggest that the value of a buildable parcel of land has increased dramatically over the period of the data. This may be seen informally by comparing the price of a typical house in 1988 with one in 2004. The estimated mean price of a typical house is \$310,031 in 1988 (with a standard error of \$549) and is \$495,308 by 2004 (with a standard error of \$924). In contrast, as shown in Figure 5b, the marginal price of an additional square foot is almost the same in the two years: \$131.15 in 1988 (with a standard error of \$1.30) versus \$141.84 in 2004 (with a standard error of \$1.62), suggesting that appreciation in the value of land is the dominant factor. This is consistent with the results found in Glaeser, Gyourko, and Saks (2005).

Given that increases in the value of buildable parcels is driving housing-price increases, it is interesting to compare the time trend in Figure 3, panel B, with that in Figure 4, panel B. This comparison shows that the size of housing and the price of a typical house are correlated. As the price of a typical house controls for house size, this suggests that parcel owners build larger houses as the price of land gets bid up.

B. *Variable Cost Regression*

In the second stage, I recover the parameters of the variable cost function by estimating (11) where all the parameters on the left-hand side of (11) are known from the price regressions.

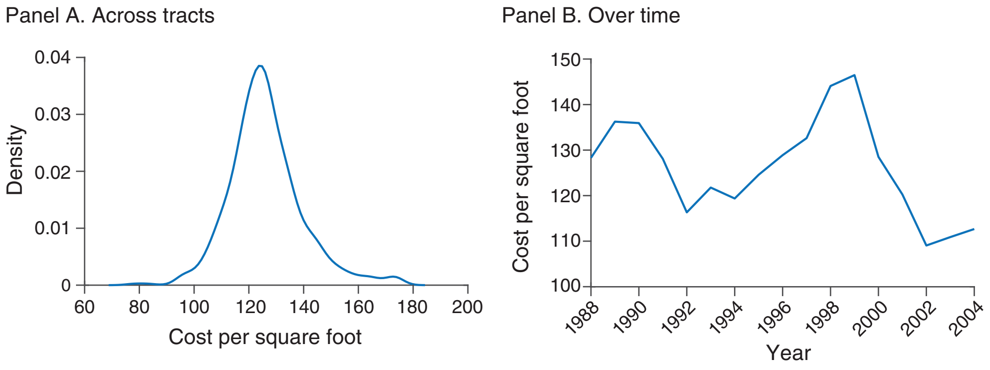

Figure 6. Cost per Square Foot

Notes: Figure 6, panel A, plots a kernel density estimate of the distribution across census tracts of cost per square foot. The cost for each census tract is an average of the yearly costs between 1988 and 2004. Figure 6, panel B, plots the time trend of cost per square foot, where the cost for each year is an average of the census tract costs. All prices are in year-2000 dollars.

Before presenting the results, it is worthwhile considering how the variation in the marginal revenue of adding square footage over neighborhoods and time helps identify the cost coefficients. For example, if the return to square footage increases (falls) through time, we would expect the square footage of new construction to increase (fall). The extent to which the square footage of new construction changes with price changes, either across tracts or through time, will identify the cost patterns. Size does indeed change as returns increase, as can be seen by comparing Figure 3, panel B (which shows the time trend in mean square footage in new construction) with Figure 5, panel B (which shows the time trend in the marginal price of square foot). The size of observed changes in size relative to changes in marginal price is what identifies the time trend in variable costs.

Figure 6, panel A, illustrates the distribution over tracts in estimates of cost per square foot and Figure 6, panel B, shows the time trend in cost per square foot. The estimated mean cost per square foot is \$126.13 (with a standard error of \$0.36). As the approach to identifying costs is different here from previous research, it is not completely straightforward to compare results. My variable cost estimates include any costs that increase as house size increases. In addition to raw building supplies and labor, this could also include any additional costs imposed by regulation or local opposition to building that increase with house size. As such, these costs could be higher than costs estimated from physical costs alone.

Comparing the cost results found here with the R.S. Means Company cost data used in Gyourko and Saiz (2006) provides an indication of the external validity of these variable cost estimates. R.S. Means is a data provider and consultant to the home building industry that estimates construction costs (including materials and labor) for different styles and sizes of housing. In particular, the R.S. Means data reveal the cost per square foot of building "Economy," "Average," "Custom," and "Luxury" houses in the Bay Area as \$74, \$98, \$127, and \$151, respectively in

2004.[17] The median cost per square foot in 2004 estimated by the structural model is \$111.56 (with a standard error of \$1.48) and the interquartile range is \$105.60 to \$118.37 (with associated standard errors of \$1.39 and \$1.56), suggesting that the model's estimates match closely with the industry data.

An important difference between the results here and the R.S. Means cost data used in previous literature is that I allow cost per square foot to vary within a metropolitan area. Physical construction costs for the same product are unlikely to differ within the Bay Area. However, the quality of house will likely vary from tract to tract. That is, neighborhoods can differ in two ways: they may have different amenities, but they also may have different prices because of the mean quality of construction. Both factors may drive price differences. For construction costs, however, only the quality of construction matters. The underlying assumption is that the quality of square foot is homogeneous within a tract, but can vary across tracts.

Finally, as shown in Figure 6, panel B, the time pattern of mean tract costs, which comes from the common time trend, suggests that variable costs are pro-cyclical, falling by approximately 25 percent following a downturn in construction levels around 2000. Variable costs are a little lower overall at the end of the time period compared with the beginning, a feature that matches closely what is found in the R.S. Means data. However, the overall volatility of variable costs is an interesting result, as it is higher than that found in previous work that uses construction industry data. However, the sensitivity of costs to construction levels in previous literature, such as Wheaton and Simonton (2007) and Gyourko and Saiz (2006) was based of cross-sectional variation in construction and not the within-metropolitan time-series variation used here.

C. *Dynamic Discrete Choice Results*

Step One—Conditional Choice and Transition Probabilities.—The first step of the dynamic discrete choice estimation involves estimating transition probabilities for costs and prices as well as flexible conditional choice probabilities. The online Appendix provides the autoregressive coefficients for prices and costs. The conditional choice probability estimation results (not shown) capture in a flexible way that the probability of construction is increasing in prices, falling in costs, and differs significantly across neighborhoods.

Step Two—Structural Parameters.—The remaining structural parameters are the discount parameter, β, the scale of the Type 1 Extreme Value error, σ_ϵ, and the county-by-year effects on fixed costs. The discount parameter, β, is set at 0.95 and the other parameters are estimated via maximum likelihood.

As the profit function is measured in dollars, the scale of the extreme value error, σ_ϵ, is identified and is estimated at \$35,660 (with a standard error of \$8,883). Using

[17] These numbers are derived using the *Residential Cost Data*, *2005* and *Means Construction Cost Indexes*, *January 2005*. For each of the four categories, I calculate the cost of building as the average cost of a 1,600 square foot home with an unfinished basement, where the average is taken over siding type and city within the Bay Area. The R.S. Means deflator is used to get the figures for 2004. See Gyourko and Saiz (2006) for a detailed discussion of the R.S. Means data.

the properties of the Type 1 Extreme Value distribution, this yields an estimated standard deviation of the error equal to $\sigma_\epsilon \cdot \pi/\sqrt{6} = \$45{,}735$. Given the mean (\$332,884) and standard deviation (\$162,516) of observed house prices in the data, the size of the error scale suggests the model fits the data quite well.

The fixed costs are allowed to vary at the county-by-year level and, as shown in (15), the coefficients on a set of county $\times$ year dummies will be estimates of $(\beta E_t \delta_{ct+1} - \delta_{ct})$. The fixed costs reflect any components of costs not captured by the variable costs. As such, they reflect the physical costs of construction that do not vary with house size. In addition, they also capture the regulatory environment.

It is worthwhile considering what patterns in the data identify the fixed cost parameters. Estimates of prices, variable costs, expected future prices, and expected future variable costs are treated as data at this stage. The parameters reflecting the expected growth rate of fixed costs are chosen to best explain observed development patterns at the county-year level. For example, if in a given county-year, we observe a small difference between prices and variable costs and a large difference between expected future prices and expected future variable costs, this would suggest that delaying development is optimal in the absence of time-varying fixed costs. However, if development is actually high, this will identify an expected growth in fixed costs. Similarly, if development rates are low in that county-year, this will identify small or negative expected growth in fixed costs.

Figure 7 presents the estimates of $\beta E_t \delta_{ct+1} - \delta_{ct}$ for each of the six core counties in the Bay Area for 1989–2004. The results show moderate cross-sectional but large time-series variation in the expected growth of fixed costs. Expectations about fixed costs are strongly pro-cyclical. For example, in San Mateo in 1992, costs are \$30,545 (with a standard error of \$6,116) higher than the discounted value of the expected costs in 1993. As prices boom later in the sample period, this reverses. In 2004, parcel owners expect costs to rise substantially—discounted expected costs in San Mateo for 2005 exceed 2004 costs by \$23,911 (with a standard error of \$5,106). The cost changes are sufficiently high that in boom periods the expected discounted value of next period's costs significantly exceeds current period costs. This smooths construction levels and helps explain the observed construction volatility levels. Interestingly, growth in fixed costs flattens out (or falls) after 2001, which corresponds with the period of falling construction levels in the Bay Area that is shown in Figure 3, panel A. The estimates are relatively precisely estimated, which can be seen in the online Appendix where the estimates are shown with 95 percent confidence intervals.

Different explanations could be offered as to why these fixed costs rise in boom times. Contractors may become more difficult or more expensive to hire in a boom. Another explanation is that regulatory factors are more binding in boom times. For example, the demand for permits may exceed what a municipality is capable of supplying during a construction boom. The fixed costs capture the probability that a permit may not be issued. It makes sense that this probability should increase in boom times when demand for permits is high. Similarly, this probability may vary across counties, helping explain the cross-sectional variation in fixed costs.

An insight from these costs results is that the pro-cyclicality of costs discourages landowners from building at the peak of prices and consequently that predictable

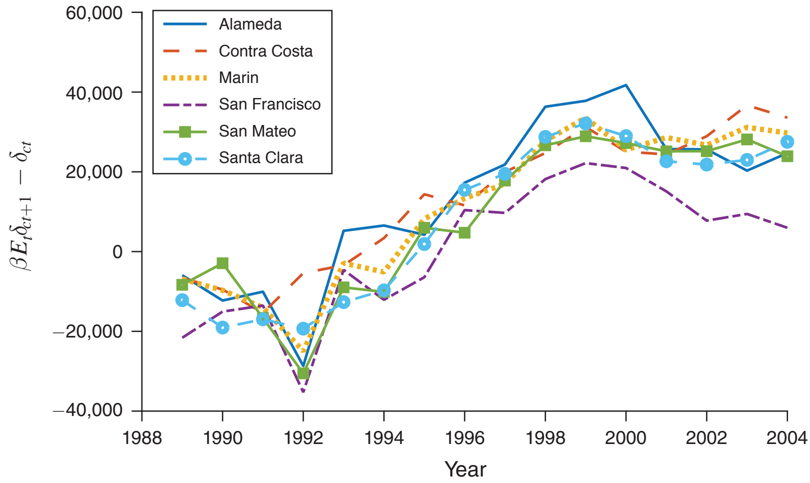

Figure 7. Time Trend of Expected Fixed Cost Growth by County

Note: Figure 7 shows the county- and year-specific estimates of $\beta E_t \delta_{ct+1} - \delta_{ct}$, i.e., the difference between the discounted expected one-year-ahead fixed costs and current fixed costs.

trends in costs reduce construction volatility. A naïve model, which ignored expectations over cost trends, would predict very high levels of construction volatility. In the extreme case where prices were perfectly predictable, costs were constant, and discounting of future profits were low, we would expect to see construction occur only at the peak of prices. In the data, a sizable amount of construction occurs in the mid-to-late-1990s, when prices are much lower than owners would have received in expectation had they waited to build. This is a puzzling fact if one is not considering expectations about cost changes and a fact that cannot be addressed using models that focus exclusively on the role of prices in determining new supply. However, this fact can be addressed using the framework laid out here; results indicate that expectations of rising costs discourage landowners from waiting until the peak of prices to build, as waiting for higher prices also involves waiting for higher costs. Consequently, pro-cyclical costs reduce construction volatility. Importantly, the observed levels of volatility can only be explained empirically by including fixed-cost trends—the discount factor, prices, and variable costs are not enough.[18]

Given the role cost patterns play in determining construction volatility, it is noteworthy that both measures of costs are, broadly speaking, pro-cyclical. This is interesting as variable costs are identified by variation in the size of construction and the growth in fixed costs are identified by variation in the propensity to develop.

[18] A potential alternative explanation for this observed pattern is that if the time required to build is sufficiently long relative to the typical cycle of prices, it would make sense for parcel owners to begin building early in the price cycle. Empirical evidence does not support this alternative explanation. According to figures from the Census of Construction, 91 percent of construction in the West Census Region is completed within 12 months, a very short period when compared with the length of the typical price cycle. See Coulson (1999) for an analysis of the relationship between starts, completions, and housing inventory.

VI. Implications for Housing Supply

The estimates presented in Section V can be used to provide an important economic insight in regards to our understanding of housing markets: forward-looking behavior substantially reduces the housing-supply elasticity. In addition, this effect is particularly prevalent during boom times when land prices and house prices are rapidly increasing.

To illustrate the impact of price increases on the decision to build, I use the model to simulate year-specific contemporaneous development elasticities, i.e., the percentage change in the development rate in a given year associated with a percentage change in price in that year. This elasticity is calculated as 100 times the simulated percentage change in total development for a 1 percent change in price, where total development is given by the sum of the development probabilities for all parcels making development decisions in that year. The formula for this elasticity is given by

$$\text{elasticity}_t = 100 \times \frac{\sum_{n=1}^{N_{d,t}} P_1(\boldsymbol{\Omega}'_{njt}) - \sum_{n=1}^{N_{d,t}} P_1(\boldsymbol{\Omega}_{njt})}{\sum_{n=1}^{N_{d,t}} P_1(\boldsymbol{\Omega}_{njt})}, \tag{16}$$

where $N_{d,t}$ is the observed number of development decisions in year t and $\boldsymbol{\Omega}'_{njt}$ is equal to the vector $\boldsymbol{\Omega}_{njt}$, but with the price used in $\boldsymbol{\Omega}'_{njt}$ set to 1.01 multiplied by the baseline price used in $\boldsymbol{\Omega}_{njt}$. The probability of building, $P_1(\cdot)$, is calculated using (14) and (15).

This development elasticity is a key determinant of the overall housing-supply elasticity and captures the effects of a change in price on both contemporaneous profits and expectations over future profits. The overall housing supply elasticity is commonly estimated in the literature and captures the percentage change in the total quantity of developed land in response to a change in price. As discussed in Mayer and Somerville (2000), we would expect the development elasticity to be much higher than the supply elasticity.

As I estimate a dynamic model of individual landowner behavior, I can distinguish between the impact of current prices on current profits and the impact of current prices on expected future profits. To do this, I decompose these effects by resimulating the development elasticity in (16), but where the change in price only affects current profits. That is, I hold constant expected future profits (i.e., $\int (\overline{P}_{nt+1} - \overline{VC}_{nt+1} - \sigma_\varepsilon \log[P_1(\boldsymbol{\Omega}_{njt+1})])\, q(\boldsymbol{\Omega}_{njt+1}|\boldsymbol{\Omega}_{njt})\, d\boldsymbol{\Omega}_{njt+1})$ when calculating the relative profitability of building in (15).

These two elasticities are shown in Figure 8. The first result to note is that the counterfactual, constant-future-profits elasticity is considerably larger than the estimated-model elasticity. The differences are statistically significant (the 95 percent confidence intervals are shown in the online Appendix) and show that forward-looking behavior substantially reduces the responsiveness of landowners to price changes. This occurs because while rising prices make building today more attractive, they also make waiting more attractive, thus reducing landowners

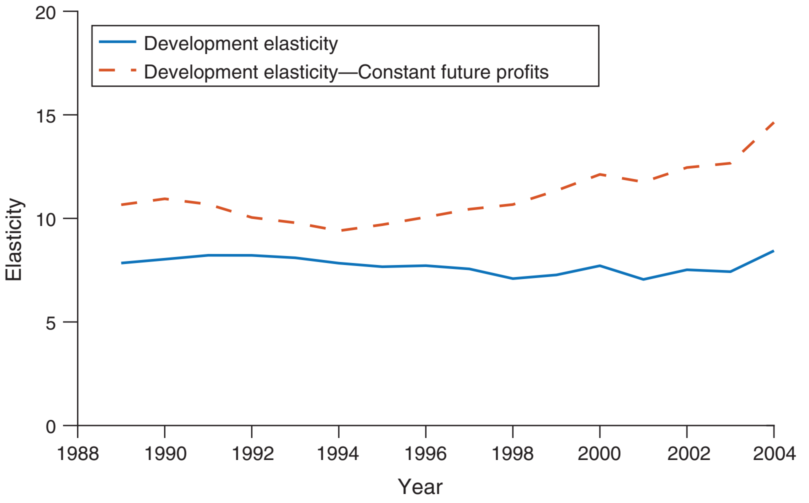

Figure 8. Year-Specific Development Elasticities: 1989–2004

Notes: The development elasticity is calculated as the percentage change in the development rate associated with a 1 percent change in house prices, where the change in price also affects expectations about future profits. The counterfactual, constant-future-profits development elasticity is calculated as the percentage change in the development rate associated with a 1 percent change in house prices, where expectations about future profits are held constant.

responsiveness to price. Driving this result is the effort of landowners to "time" the market, i.e., landowners are choosing *when* to build rather than *if* to build.[19]

The second result to note is that the difference between the two elasticities varies quite substantially over time. The elasticities are close to one another during the slump in housing prices observed in the mid 1990s and are much farther apart during the boom observed at the end of the period. This indicates that forward-looking behavior plays a considerably larger role in lowering the development elasticity when the market is hot and prices are high. We see a greater difference in boom times for a number of reasons. The underlying value of waiting is higher when parcel owners predict continuing price increases, which makes timing the market an important factor during boom times. Also, development is more likely to be profitable when prices are high, so timing the market (versus waiting for the first profitable opportunity) becomes more relevant then.

Understanding the factors that determine the elasticity of housing supply is valuable given the well-documented relationship between housing-supply elasticities and housing-price volatility. For example, Glaeser, Gyourko, and Saiz (2008)

[19] These elasticities are contemporaneous elasticities. Alternatively, one could pick a given year and show the development rate in subsequent years corresponding to the impulse response from the baseline-year price increase. As long as expected future prices are lower in the constant-expectations case, the constant-future-profits development rate will be higher. This logic applies to development rates and not quantities, so that a higher development rate for a number of years would result in a lower stock of parcels against which the development rate applies.

find that cities with lower supply elasticities have more volatile price cycles.[20] The added insight here is that forward-looking behavior reduces the supply elasticity (especially in hot markets) and could therefore contribute to greater price volatility.

VII. Conclusion

The importance of the housing market to the overall economy has been well-documented, but the literature on housing supply is surprisingly small. Short-run volatility in both prices and construction levels has significant welfare implications in terms of a typical household's asset portfolio and in terms of industry-wide employment effects.

Understanding the way that economic primitives influence individual behavior is crucial in explaining the aggregate patterns of construction and prices observed in macro data. To that end, I estimate a model of individual parcel owners' development decisions. By combining the continuous choice of *what* (size) to build with the dynamic discrete-choice of *when* to build, I estimate the parameters of the profit function at a fine level of geography and still retain computational tractability.

Results indicate that changes in overall housing prices are driven by changes in the value of the right-to-build. Results describing the variable costs of construction (which are validated with input cost data) and the fixed costs of construction indicate significant volatility of physical and latent costs. An analysis of these results suggests that pro-cyclical cost environments provide an incentive for some landowners to build before price peaks, as waiting for higher prices involves also waiting for higher costs. Results also indicate that forward-looking behavior substantially reduces the housing supply elasticity.

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[20] Diamond (2017) shows that a less elastic housing supply increases the government's ability to extract rents from private citizens.

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