THE MICROFOUNDATIONS OF HOUSING MARKET DYNAMICS

by

Alvin D. Murphy

Department of Economics
Duke University

Date: ____________________________

Approved:

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Patrick Bayer, Supervisor

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Peter Arcidiacono

__________________________
Thomas Nechyba

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Christopher Timmins

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Jacob Vigdor

Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics in the Graduate School of Duke University

2008
ABSTRACT

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Abstract

The goal of this dissertation is to provide a coherent and computationally feasible basis for the analysis of the dynamics of both housing supply and demand from a microeconomics perspective. The dissertation includes two papers which incorporate unique micro data with new methodological approaches to examine housing market dynamics. The first paper models the development decisions of land owners as a dynamic discrete choice problem to recover the primitives of housing supply. The second paper develops a new methodology for dynamically estimating the demand for durable goods, such as housing, when the choice set is large.

In the first paper, using the new data set discussed above, I develop and estimate the first dynamic microeconometric model of supply. Parcel owners maximize the discounted sum of expected per-period profits by choosing the optimal time and nature of construction. In addition to current profits, the owners of land also take into account their expectations about future returns to development, balancing expected future prices against expected future costs. This forward looking behavior is crucial in explaining observed aggregate patterns of construction. Finally, the outcomes generated by the parcel owners’ profit maximizing behavior, in addition to observable sales prices, allow me to identify the parameters of the per-period profit function at a fine level of geography.

By modeling the optimal behavior of land owners directly, I can capture important aspects of profits that explain both market volatility and geographic differences in construction rates. In particular, the model captures both the role of expectations and of more abstract costs (such as regulation) in determining the timing and volatility of supply in way that would not be possible using aggregate data. The model returns estimates of the various components of profits: prices, variable costs, and the fixed
costs of building, which incorporate both physical and regulatory costs.

Estimates of the model suggest that changes in the value of the right-to-build are the primary cause of house price appreciation, that the demographic characteristics of existing residents are determinants of the cost environment, and that physical and regulatory costs are pro-cyclical. Finally, using estimates of the profit function, I explain the role of dynamics in determining the timing of supply by distinguishing the effects of expected future cost changes from the effects of expected future price changes. A counterfactual simulation suggest that pro-cyclical costs, combined with forward looking behavior, significantly dampen construction volatility. These results sheds light on one of the empirical puzzles of the housing market - what determines the volatility of housing construction?

In the second paper, I outline a tractable model of neighborhood choice in a dynamic setting along with a computationally straightforward estimation approach. The approach allows the observed and unobserved features of each neighborhood to evolve in a completely flexible way and uses information on neighborhood choice and the timing of moves to recover semi-parametrically: (i) preferences for housing and neighborhood attributes, (ii) preferences for the performance of the house as a financial asset, and (iii) moving costs. In order to accommodate a number of important features of housing market, this approach extends methods developed in the recent literature on the dynamic demand for durable goods in a number of key ways. The model and estimation approach are applicable to the study of a wide set of dynamic phenomena in housing markets and cities. These include, for example, the analysis of the microdynamics of residential segregation and gentrification within metropolitan areas. More generally, the model and estimation approach can be easily extended to study the dynamics of housing and labor markets in a system of cities.
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Acknowledgements

I am very grateful to my advisor, Pat Bayer, and committee members, Peter Arcidiacono, Tom Nechyba, Chris Timmins, and Jake Vigdor, for advice, encouragement, and comments. I also thank participants of Duke’s Applied Microeconomics lunch groups for their helpful comments as well as Jon James for G.I.S. assistance.

Chapter 3 of this dissertation is based on joint work with Pat Bayer, Rob McMillan, and Chris Timmins.

I thank my parents, family, and friends for all their support. Most importantly, I would like to thank my lovely wife, Kelly, for all her help, love, and encouragement – I could not have done it without you.
Chapter 1

Introduction

The goal of this dissertation is to provide a coherent and computationally feasible basis for the analysis of the dynamics of both housing supply and demand from a microeconomics perspective. The importance of the housing market within the U.S. economy has been well documented. The national average portion of income spent on housing related expenditures is over thirty percent and housing constitutes two-thirds of the average household’s asset portfolio. The current empirical housing and urban literature uses aggregate data to document and explain interesting housing market patterns across metropolitan areas and through time. However, a constraint on the current literature has been the lack of micro data. Therefore, in order to address a new set of housing questions, I develop new data sets. I then use these data to estimate microeconometric models that examine the fundamentals underlying previously documented housing market patterns of prices and construction levels.

The starting point for the analysis in my dissertation is the creation of two unique data sets. On the supply side, I combine micro level construction and transactions data with an inventory of individual land parcel data. At the level of the street address, I observe which parcels were developed and when they were developed. In addition, the richness of construction and transactions data means that the type of construction (e.g., square footage, lot size, and number of rooms) is also observed. By capturing development and construction at a very fine level of geography, this data set facilitates new research that would not be possible using previous city-level, aggregate construction data. To address housing demand, I use the transactions data set and link household level data describing the buyers and sellers. In addition to demographic and economic information about buyers
and sellers, this data set contains information about the structure and lot, transaction price, attributes of the mortgage, exact location, exact sales date, and a house ID that identifies repeat sales of the same property.

The two chapters briefly outlined below incorporate this micro data with new methodological approaches to examine housing market dynamics. Chapter 2 models the development decisions of land owners as a dynamic discrete choice problem to recover the primitives of housing supply. Chapter 3 develops a new methodology for dynamically estimating the demand for durable goods, such as housing, when the choice set is large.

Chapter Two: A Dynamic Model of Housing Supply

Using the new data set discussed above, I develop and estimate the first dynamic microeconometric model of supply. Parcel owners maximize the discounted sum of expected per-period profits by choosing the optimal time and nature of construction. In addition to current profits, the owners of land also take into account their expectations about future returns to development, balancing expected future prices against expected future costs. This forward looking behavior is crucial in explaining observed aggregate patterns of construction. Finally, the outcomes generated by the parcel owners’ profit maximizing behavior, in addition to observable sales prices, allow me to identify the parameters of the per-period profit function at a fine level of geography.

By modeling the optimal behavior of land owners directly, I can capture important aspects of profits that explain both market volatility and geographic differences in construction rates. In particular, the model captures both the role of expectations and of more abstract costs (such as regulation) in determining the timing and volatility of supply in way that would not be possible using aggregate data. The model returns estimates of the various components of profits: prices, variable costs, and the fixed costs of building, which incorporate both physical and regulatory costs.

Estimates of the model suggest that changes in the value of the right-to-build are the
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Chapter Three: A Dynamic Model of Housing Demand

In this chapter, I develop a tractable model of neighborhood choice in a dynamic setting along with a computationally straightforward estimation approach.\(^1\) The approach, which combines and extends the insights of Rust (1987), Berry (1994), and Hotz and Miller (1993) allows the observed and unobserved features of each neighborhood to evolve in a completely flexible way and uses information on neighborhood choice and the timing of moves to recover semi-parametrically: (i) preferences for housing and neighborhood attributes, (ii) preferences for the performance of the house as a financial asset, and (iii) moving costs. In order to accommodate a number of important features of housing market, this approach extends methods developed in the recent literature on the dynamic demand for durable goods in a number of key ways. The model and estimation approach are applicable to the study of a wide set of dynamic phenomena in housing markets and cities. These include, for example, the analysis of the microdynamics of residential segregation and gentrification within metropolitan areas. More generally, the model and estimation approach can be easily extended to study the dynamics of housing and labor markets in a system of cities.

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\(^1\)This chapter is based on joint work with Pat Bayer, Rob McMillan, and Chris Timmins
Chapter 2

A Dynamic Model of Housing Supply

2.1 Introduction

Housing markets often exhibit a high degree of volatility in prices and quantities, with significant economic consequences for both homeowners and the construction sector. Comparing the first six months of 2007 with the first six months of 2006, for example, housing price appreciation rates fell by almost two-thirds and housing starts fell by over a quarter.\(^1\) As an asset, housing constitutes two thirds of the average household’s portfolio,\(^2\) meaning that the typical household faces a large uninsurable risk from price volatility, with correspondingly large welfare effects; and on the supply side, construction volatility has substantial direct impacts on employment levels and the demand for raw materials.\(^3\)

Cyclical patterns are a consistent feature of housing markets, with alternating periods of price increases and downturns often being evident.\(^4\) The cyclicality of housing markets naturally arises through the interaction of demand and supply forces. Suppose a demand shock, such as a shock to wages, pushes up prices. Because supply is then slow to respond, prices continue rising and overshoot; and when supply eventually responds fully, prices mean-revert. These patterns have been carefully documented using aggregate data. As Glaeser and Gyourko (2007) convincingly show, future house prices tend to be strongly predictable, being serially correlated in the short run and displaying mean-reversion in the

---

2Tracy, Schneider, and Chan (1999) report the portfolio share figure.
3According to the BLS, http://www.bls.gov/news.release/empsit.nr0.htm, employment in the construction sector fell by almost 125,000 in the past year.
4The Bay Area, which provides the focus for this study, experienced high price growth in the late 1970s, the late-1980s, and since the mid-1990s, with downturns in the early-1980s and early-1990s.
medium run.

In this dynamic process, the determinants of the timing of the supply response are not well-understood, even though the timing of supply responses is central to the length and severity of housing cycles. To complement research that has used aggregate data to document housing market cycles, this paper sets out a micro-oriented approach designed to shed light on the way individual behavior helps drive the dynamics of the housing market. Accordingly, I develop and estimate the first dynamic microeconometric model of housing supply with a rich new housing data set.

In the model, the owners of parcels of land maximize the discounted sum of expected per-period profits by choosing the optimal time and nature of construction. Each period, parcel owners make two decisions: they decide whether or not to build a house upon their parcel and, conditional on building, they choose the size (or type) of the house. In addition to current profits, parcel owners take into account their expectations about future returns to development, balancing expected future prices against expected future costs. The outcomes generated by the parcel owners’ profit maximizing behavior, in addition to observable sales prices, allow me to identify the parameters of the per-period profit function, allowing profits to vary at a fine level of geography.\(^5\)

While existing housing supply models typically use aggregate time-series data, a key contribution of this paper is the use of micro data on individual land parcel owners to look at the microfoundations of housing supply. I have assembled a new data set by merging observed real estate transactions data with geo-coded parcel data for the Bay Area over the period 1988-2004.\(^6\) In the combined data set, I observe which parcels of land get developed, and if a parcel is built upon, I also observe when the house was built and characteristics

\(^5\)Many of the profits function parameters are Census tract specific.

\(^6\)The transactions data are drawn from a national real estate data company and provide information on every housing unit sold in the core counties of the Bay Area. The parcel data are drawn from the California Statewide Infill Study conducted in 2004-2005 by the Institute of Urban and Regional Development at the University of California at Berkeley.
of the house. The analysis focuses on the development of individual parcels, where this type of infill construction covers approximately fifty percent of all single family residential construction over the sample period.\(^7\)

Certain features of housing markets present potential obstacles to estimation. Given that housing prices have a predictable component, it is important to capture all the relevant information that parcel owners use to predict future prices.\(^8\) In the context of a dynamic discrete choice model, this necessitates a very large state space, making traditional full-solution estimation infeasible. I overcome this problem by using a two-step (conditional choice probability) estimator based on Hotz and Miller (1993) and Arcidiacono and Miller (2007). Another feature of housing markets that presents a potential estimation difficulty is the fine level of geography at which house prices and costs vary, making the number of parameters to be estimated prohibitively large in the context of a dynamic discrete choice estimator. The solution I use involves taking advantage of the separability of the log likelihood functions governing observed prices, housing services, and construction, and estimating the model in three stages, where many of the parameters are estimated in stages prior to the dynamic discrete choice estimation. One final estimation issue is that the fixed costs of construction, which are parameters estimated within the dynamic discrete choice estimation routine, are time-varying; this is analogous to the time-varying brand parameters in industrial organization papers such as Gowrisankaran and Rysman (2006). A contribution of this paper is to incorporate expectations about future fixed cost parameters within a two-step estimation routine.

The model returns four distinct results relating to prices, variable costs, cross-sectional variation in fixed costs and the time pattern of fixed costs. The price estimates indicate that changes in the value of the right-to-build play the primary role in the increase in house

\(^7\)I exclude large housing developments or new subdivisions.

prices. Between 1988 and 2004, the typical house value doubled in real terms, whereas the marginal price of an additional square foot of living space remained constant. These results are consistent with the theoretical implications of Glaeser, Gyourko, and Saks (2005), who suggest that regulation is responsible for increasing house prices.

Estimates of the overall levels of variable physical construction costs are similar to cost indexes derived from input prices. However, I find that variable costs vary pro-cyclically over the time period, suggesting that costs are more responsive to overall metropolitan area construction levels than previous studies suggested.

Prices and variable construction costs do not fully explain observed construction patterns. I therefore estimate parameters of the broader cost environment, which vary considerably by geographic area and through time. These cost environment parameters (or fixed costs) capture any additional costs, such as set-up costs and the regulatory environment. The cross-sectional variation in the cost environment suggests that existing home owners influence the regulatory environment: I find that it is more difficult to develop land in communities characterized by higher rates of home ownership. However, neighborhood racial composition and education levels do not have any effect on costs.

While the ability of agents to forecast housing prices has been well-documented since Case and Shiller (1989), less has been written about the effect of time-varying costs. Using estimates of the model, I can distinguish between the effects of expected future cost changes and expected future price changes and shed light on one of the empirical puzzles of the housing market - what determines construction volatility levels? A feature of the data is how quickly construction levels increase once prices begin to rise. Given that landowners can only develop their land once, and that prices are somewhat predictable in the short-to medium-run, a simple model would suggest that land owners should wait for higher prices before developing their land. In practice in the Bay Area, once house prices begin to pick up in the mid-1990s, construction levels also pick up. Therefore, many parcel
owners developed parcels in the mid-to-late-1990s at prices much lower than they would have expected to receive if they had waited.

I examine the role of expectations about future costs in a counterfactual experiment. As I estimate a structural model, I can simulate what construction patterns would have looked like if land owners were not forward-looking in terms of the overall cost environment. The results provide an important insight into the decision of parcels owners regarding when to develop their land. Without forward looking behavior, land owners wait for much higher prices before building. The implication is that without pro-cyclical costs and forward-looking behavior, construction volatility would be substantially greater. That is, pro-cyclical costs provide an incentive for some land owners to build before price peaks, as waiting for higher prices implies also waiting for higher costs.

The remainder of the paper proceeds as follows. Section 2 examines the existing literature. Section 3 introduces the parcel, building, and sales data I use to estimate the model. Section 4 specifies the model of housing supply (when and how parcel owners choose to develop their land), and Section 5 explains the estimation procedure. Section 6 presents the results of the model. Section 7 examines the implications of dynamic behavior, and Section 8 concludes.

2.2 Related Housing Supply Literature

While it remains true that the majority of the housing literature is concerned with demand-side issues, increasing attention is now being diverted in an effort to better understand housing supply. In particular, the literature has been growing since the review article of DiPasquale (1999).\footnote{The discussion of the pre-1999 housing literature draws on DiPasquale’s review.}

In addition to early literature, such as Muth (1960), Follain (1979), and Stover (1986) which looked primarily at the elasticity of supply with somewhat conflicting conclusions,
DiPasquale (1999) outlines two broad alternative approaches to modeling housing markets: an investment/asset market approach and an approach based on urban spatial theory. Examples of literature that model the housing market from an asset market perspective are Poterba (1984) and Topel and Rosen (1988). Poterba (1984) assumes that housing is provided by competitive firms, where supply is driven by the price of output (housing prices) and the price of factors of production. Topel and Rosen (1988) estimate both short run and long run supply elasticities. They argue that a lower estimated short run elasticity implies developers have expectations about future prices and they reject a myopic model. Both Poterba (1984) and Topel and Rosen (1988) find that construction costs have no impact on housing starts, a puzzling result and one that differs from the results found in this paper.

A feature of Poterba (1984), Topel and Rosen (1988), and the investment approach is that they do not incorporate land as an input. In contrast, the importance of land as an input is addressed in the urban spatial literature, where land prices depend explicitly on the housing stock. An early example is DiPasquale and Wheaton (1994), where new construction takes place when a shock pushes the long run equilibrium housing stock above the current stock. Construction costs were again found to have no effect on construction levels. This is a surprising result, however, it suggests that their cost measures may not have captured the entire cost environment. Mayer and Somerville (2000) extend the urban spatial literature using more sophisticated time series methods with a model that suggests that housing starts should vary with price changes instead of price levels, and find higher short run elasticities of supply. While not explicitly modeling builders as dynamic agents, a common conclusion in both the asset and urban spatial papers cited above is that current price is not a sufficient statistic and that dynamics are playing an important role.

In addition to land, another important component of the housing supply process is construction costs. Recent studies have used data on physical construction costs to look
at both cross sectional and time series variation in costs. Gyourko and Saiz (2006) analyze data from R.S. Means Company, a consultant to the home building industry, which provides measures of the cost of building a typical house in 140 metropolitan areas. Using a different data set, Wheaton and Simonton (2007) look at the costs of building office space. The key similarities between these papers is the use of direct measures of physical costs and the conclusion that construction costs are not responsible for increasing house prices.\footnote{Various approaches to estimating housing prices, such as repeat sales and hedonics, are discussed in the estimation section.} Given the flat time profile of physical construction costs, recent papers such as Glaeser, Gyourko, and Saks (2006), Quigley and Raphael (2005), and Ortalo-Magné and Prat (2005) have examined the role of increased regulation in rising house prices.

The role of supply within a dynamic equilibrium setting is an important component of the work by Glaeser and Gyourko (2007), who develop a dynamic equilibrium model, and calibrate its parameters using macro moments. The model, which incorporates dynamics into a Roback (1982) framework, describes the movement of construction (and housing prices) around steady-state levels. The responsiveness of supply to a demand shock is governed by two cost parameters that capture the impact of the stock of housing and the flow of new construction. The empirical results suggest the model does very well at fitting medium-run housing market trends, but has difficulty matching higher frequency data, especially in high-volatility markets in coastal California.

All the applied work discussed above has in common the use of aggregate data. Aggregate data is sufficient for addressing cross metropolitan variation in key housing features such as prices and costs. Additionally, aggregate data works well for documenting housing market time series properties, such as the short-run persistence and medium-run mean reversion of prices. However, to better understand the individual behavior that determines these aggregate patterns, it is necessary to incorporate micro data with models of individual
behavior. 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.\textsuperscript{11}

2.3 Data

In this section, I describe a new data set 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 1998, I observe 1) year of construction, if the parcel was developed, and 2) the type of construction, e.g. number of square foot, number of rooms, etc. The data set provides information about parcels of land that were developed between 1988-2004 and those that remained undeveloped. I consider land parcels that were potentially suitable for small scale construction; I do not consider subdivisions and major developments by large construction companies. The type of construction I consider covers about 55\% of all construction in the Bay Area during this time period.

The empirical analysis in this paper uses the core counties of the San Francisco Bay Area; Alameda, Contra Costa, Marin, San Francisco, San Mateo, and Santa Clara. Figure 2.1 shows the six core counties of the Bay Area with Census tract boundaries drawn in. The Bay Area contains some of the wealthiest neighborhoods in the U.S. and is generally considered to have a limited supply of land. The cities of the Bay Area, in particular San Francisco, are excellent examples of so called “Superstar Cities.” Gyourko, Mayer, and Sinai (2006) define superstar cities as areas where demand exceeds supply. 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. Price growth

\textsuperscript{11}An exception is Epple, Gordon, and Sieg (2007) who use microdata on housing construction in Allegheny County, Pennsylvania to estimate parameters of a housing production function.
in a typical superstar city is driven by high quality amenities, limited construction, and a lack of close substitutes. To support their assertion that the San Francisco primary metropolitan statistical area is a model superstar city, Gyourko, Mayer, and Sinai (2006) cite a price growth rate between 1950 and 2000 that was two percentage points higher than the national average, in addition to higher income growth over the same period.

**Figure 2.1**: Bay Area: Counties and Tracts

The data set that I construct is drawn from two main sources. The first comes from Dataquick, a national real estate data company, and provides information on every housing unit sold in the core counties of the Bay Area between 1988 and 2004. The buyers’ and sellers’ names are provided, along with transaction price, exact street address, square
footage, year built, lot size, number of rooms, number of bathrooms, number of units in building, and many other housing characteristics. Overall, the housing characteristics are considerably better than the those provided in Census micro data. Based on information about the sellers’ names, the year the property was built, the street address, and a subdivision indicator, I can identify new construction that was not part of a subdivision or major development.12 As the data contains all houses sold in the Bay Area as well as the year built, I can calculate measures of construction activity for any given area at each point in time.

If a house is built but not sold, it will not show up in the sales data set.13 To address such missing construction, I use data on permits issued in each city over the sample period. Based on permit data and the perfectly observed levels of large developments, I can impute total small scale construction. I then reweigh the observed small scale construction to match the observed construction in the micro data to the levels suggested by the permit data.14 As new construction is less likely to show up in the data set when the time between year built and the end of the sample in 2004, I do not use data from 2003 and 2004 to estimate some parts of the model. 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 632.15

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12 Any subdivision was excluded. A major development is defined as ten or more houses built by the same construction company in the same year on the same street or block. The vast majority of exclusions were based on a property being deemed a subdivision.

13 This is relatively common for the single unit type construction studied in this paper but very rare for large developments/subdivisions.

14 Permit data give the date the permit was issued which is different from date of construction. The Census provides a distribution of time between receipt of permit and commencement of construction as well as a distribution of construction length. These two distributions in combination with the permit figures can be used to impute an expected level of construction in each period.

15 The transactions data contain information back as far as 1988. To look at trends from pre-1988, I use data from OFHEO, the Office of Federal Housing Enterprise Oversight. This provides price trends in the three metropolitan areas of Oakland, San Francisco, and San Jose from 1975
The second component of the data set is drawn from the California Statewide Infill Study. This study was conducted during 2004-2005, through the Institute of Urban and Regional Development (IURD) at the University of California, Berkeley and provides a geocoded parcel inventory of all potential infill parcels in California. Using county assessors parcel data, the data identifies both vacant and economically underutilized sites.\textsuperscript{16} 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 then designated if the parcel is vacant or has a low improvement-value-to-land-value ratio.

A vacant parcel is defined as one that has no inhabitable structure or building. Sites with structures too small to be inhabited, or for which the structure value is less than $5,000 (measured in constant 2004 dollars), are also deemed to be vacant. Furthermore, the parcel must be privately owned and available and feasible for potential urban development, excluding all public lands as well as undeveloped farms, ranges, or forestlands owned by private conservancies, and parcels with slopes in excess of 25 percent.\textsuperscript{17}

The second type of infill parcel is underdeveloped land called “refill” parcels. When a parcel is assessed, it is given two separate values – the value of the land and the value of any improvements (buildings). A low improvement-value-to-land-value ratio indicates that the parcel is being underutilized and could be redeveloped. Therefore, refill parcels are defined as privately owned, previously-developed parcels where the improvement value to land value ratio is less than 1.0 for commercial and multi-family properties, and less onwards.

\textsuperscript{16} The Infill Study also used additional data from the Census and various local government agencies

\textsuperscript{17} The data does not exclude sites where regulatory/political issues would make construction of new residences difficult.
than 0.5 for single-family properties.\textsuperscript{18} As I look at potential development of single family properties, I include vacant parcels and parcels with single family residences that have an improvement value to land value ratio less than 0.5.

To construct the data set used in estimating the model, I merge the two data sets on the basis of the Census tract. The Infill data set 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 sales of properties between 1988 and 2004 that were new construction but not part of subdivisions or large developments. The new data set then contains all parcels from 1988 and includes information about tract, parcel square footage, and date of construction if building occurred. As construction occurs, the appropriate parcels leave the set of available parcels until the set of available parcels is equal to the infill data set at the end of 2004.

The key features of the data are the cross-sectional time-series variation in prices, housing characteristics, and overall construction levels. These features can not be seen in a summary statistic table, therefore, I illustrate below some of the important variation in the data.

2.3.1 Descriptive Analysis / Trends in the Data

As I estimate a dynamic model of construction decisions, the variation in the evolution of prices across regions of the Bay Area is a key identifying component of the data. The precision of the estimation of the dynamic aspects of the model likely depends critically on the fact that rates of house price appreciation and construction are not uniform across census tracts. Space constraints limit me from showing cross-sectional and time-series variation in all of the key variables, however, I include below some of the more important

\textsuperscript{18}The cut off points are somewhat arbitrary. Some parcels with a ratio of less than one-half will not be suitable for redevelopment and some development has occurred on parcels with a ratio of greater than one. Sensitivity analysis suggests that the results are not sensitive the choice of cutoff.
measures of variation in the data.

Figure 2.2: Bay Area Prices

Figure 2.2 reports overall price levels in the Bay Area from 1988 to 2004. 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 county-year fixed effects as well as house fixed effects. The values on the vertical axis indicate the real price level of house prices (in percentage terms) relative to 1988. 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.

The section on estimation discusses the different approaches to measuring house prices. The use of a repeat sales analysis here is to give a simple illustration of trends in house prices.
The was considerable heterogeneity across neighborhoods in terms of both the total levels of appreciation and the timing of when booms began. For example, a small dip in prices was observed in San Francisco, San Mateo, and Santa Clara in 2001, whereas Alameda, Contra Costa, and Marin saw continued appreciation. Over the longer sample period there was large variation in total price changes. Figure 2.3 shows the geographic variation in total real appreciation between 1990 and 2004. The appreciation rates were obtained using a separate repeat sales analysis for each geographic area. The geographic areas are PUMAs, Public Use Microdata Areas. The variation in total appreciation rates is large – some PUMAs saw as little as fifty percent real appreciation between 1990 and 2004, whereas others more than doubled in real price terms.
Levels of construction are illustrated in Figure 2.4. The construction figures represent single family residences which are not part of a development/subdivision. Over the time period for which I have estimated the model, this represents approximately fifty-five percent of total single family construction in the Bay Area. As expected, construction trends are positively correlated with prices – this can be seen by comparing Figure 2 and Figure 4. We see a dip in construction levels in the early 1990s, followed by increasing levels from the mid-1990s onwards. Construction levels drop off again as prices slow (or fall in many areas) in 2000 and 2001. Two effects may cause the dip in construction after 2000. The first is falling prices, and the second is falling land availability. While both factors probably contribute to some extent, separate data suggests that construction and prices increase for
2003-2006.\textsuperscript{20} The data also suggest the construction levels respond to market forces at least as quickly as prices do; however, as the data is annual, one must be careful in identifying which series responds first.

2.4 A Dynamic Model of Housing Construction

The following sections outline a model of housing construction that generates observable levels of prices, housing services, and overall construction, where the economic agents are the owners of parcels of land who decide when and how to develop their parcels.

2.4.1 Model

In each period, each agent makes two decisions to maximize profits. First, the agent decides whether or not to build on their parcel. If the agent decides to build, she then must choose how much housing services to provide in the second stage decision. The parcel owner’s decision to build or not is made taking into account 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, which allows me to view the parcel owner’s problem as an optimal stopping decision. The general model can therefore be formulated in a familiar dynamic programming setup, where a Bellman equation illustrates the determinants of the optimal choice.\textsuperscript{21}

Each parcel owner is assumed to behave optimally in the sense that both her first-stage and second-stage actions are taken to maximize lifetime expected profits. 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 they choose to provide, and a sales price for the property.\textsuperscript{22} The problem is dynamic

\textsuperscript{20}This data includes permit figures from the Census and house price indexes from OFHEO, Office of Federal Housing Enterprise Oversight.

\textsuperscript{21}See Rust (1994) for an overview of dynamic discrete choice problems.

\textsuperscript{22}Also observed is the sales price of all properties that sold, not just new properties.
as the agent has expectations about future prices and costs. A static model would predict
that a parcel owner would build the first time it becomes profitable, whereas the dynamic
model allows a parcel owner to delay building (even when profitable) in order to attain
higher profits at a future date. As noted above, a key feature of the housing market is that
housing prices are somewhat predictable. The predictability of housing price movements
strongly suggests that agents will behave dynamically and that a static model would fail
to capture certain important aspects of housing supply.

The vector of observable parcel characteristics that affect the per-period profits a parcel
owner \( n \in \{1, \ldots, N\} \) may receive from choosing to build in period \( t \) is denoted by \( x_{njt} \).
Included in \( x_{njt} \) are direct characteristics of the parcel \( n \), as well as characteristics of
the neighborhood in which parcel \( n \) is located. Neighborhoods are indexed by \( j \), where
\( j \in \{1, \ldots, J\} \), and the neighborhood that parcel \( n \) is located in is denoted by \( j(n) \). \( x_{njt} \) can
then be divided into two components: parcel-level variables, \( x_{nt} \), and tract-level variables,
\( x_{jt} \). There is also an unobserved idiosyncratic profit shock, \( \epsilon_{ndt} \), which determines the profit
parcel owner \( n \) receives from building or not building in period \( t \).

The three determinants of a parcel owner’s ‘don’t build/build’ decision in time period
\( t \) are the unobserved shocks in period \( t \) \((\epsilon_{nt})\), the observed variables affecting per-period
profits in period \( t \) \((x_{njt})\), and any variables that predict future values of \( x \), which I denote
by \( \Omega_{nt} \). As current values of observables predict future values, \( x \) is included in \( \Omega \). The
decision variable, \( d_{nt} \), is therefore given by the function \( d_{nt} = d(\Omega_{nt}, \epsilon_{nt}) \). \( d_{nt} \in \{0, 1\} \) where
\( d = 0 \) is choosing to not build and \( d = 1 \) is choosing to build. If a parcel owner decides to

\(^{23}\)Case and Shiller (1989) develop a test for market efficiency, which rejects the hypothesis of
housing prices following a random walk. The empirical evidence suggests that housing prices
exhibit positive persistence in the short run with mean reversion over the medium to long run.
Glaeser and Gyourko (2007) find that a one dollar increase in prices in one year predicts a seventy
cent increase in the next year and that a one dollar increase over a five year period predicts a
thirty five cent decrease over the next five years.

\(^{24}\)I will eventually assume that \( \epsilon \) is distributed i.i.d. over time and is independent of the observables.
Therefore, \( \epsilon \) is not included in \( \Omega \)
build, she then chooses the level of housing services, $h$, to construct. The housing services index is discussed in greater detail below.

The primitives of the model are given by $(\pi, q, \beta)$. In turn, $\pi_d = \pi_d(x_{njt}, \epsilon_{nt})$ is the per period profit function associated with choosing option $d$; $q = q(\Omega_{njt+1}, \epsilon_{nt+1}, |\Omega_{njt}, \epsilon_{nt}, d_{nt})$ denotes the transition probabilities of the observables and unobservables, where the transition probabilities are assumed to be Markovian; and $\beta$ is the discount factor.25

The per-period profits (given the decision to build, $d = 1$) are given by $\pi_1(h, x_{nj}, \epsilon_{n1})$. Choosing $h$ to maximize per-period profits yields $h^* = h^*(x_{nj})$.26

The optimal decision rule for the discrete build/don’t build decision is denoted by $d^*$. When the sequence of decisions, $\{d_n\}$, is determined according to the optimal decision rule, $d^*$, lifetime expected profits are given by the value function.

$$V_t = \max_{d \in \{0, 1\}} \left\{ E \sum_{s=t}^{T} \beta^s (\pi_d(x_{nj s}, \epsilon_{ns}) | \Omega_{njt}, \epsilon_{nt}, d_{nt} = d) \right\}$$ (2.1)

I can break out the lifetime sum into the per-period profits at time $t$ and the expected sum of per-period profits from time $t + 1$ onwards. This allows me to use the Bellman equation to express the value function at time $t$ as the maximum of the sum of flow utility at time $t$ and the discounted value function at time $t + 1$:

$$V_t(\Omega_{njt}, \epsilon_{nt}) = \max_{d \in \{0, 1\}} \left\{ \pi_d(x_{njt}, \epsilon_{nt}) + E \beta V_{t+1}(|\Omega_{njt}, \epsilon_{nt}, d_{nt} = d) \right\}$$ (2.2)

I assume that the problem has an infinite horizon.27 I also assume that the per-period profit function is separable in the idiosyncratic error term and that this error term is distributed i.i.d. over time and options; the role of the error term and its interpretation

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25In principal, the Markovian assumption does not cause a loss of generality as lags of variables can always be included in $\Omega$. In practice, I include 7 years lags of prices and two years lags of costs.

26This assumes that optimal housing services is not influenced by the error, $\epsilon_{n1}$

27This implies $V_t(\Omega_{njt}, \epsilon_{nt}) = V(\Omega_{njt}, \epsilon_{nt})$ and $d_t(\Omega_{njt}, \epsilon_{nt}) = d(\Omega_{njt}, \epsilon_{nt})$
are discussed in detail below. This allows me to define the choice-specific value function, \( v_d(\Omega_{nj}) \):

\[
v_d(\Omega_{nj}) = \pi_d(x_{nj}) + \beta \int G(\cdot)q(\Omega'_{nj}|\Omega_{nj}, d_n = d) d\Omega'_{nj}
\]

(2.3)

where \( G(\cdot) = \int V(\Omega'_{nj}, \epsilon'_{n})q(\epsilon'_{n})d\epsilon'_{n} = \int \max d'[v_d'(\Omega'_{nj}) + \epsilon'_{nd}']q(\epsilon'_{n})d\epsilon'_{n} \).

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 deterministic component of per-period profits associated with choosing \( d \). The second is the expected value of the best option tomorrow conditional on choosing \( d \) today; that is, how today’s decision affects tomorrow’s payoffs. By convention, the choice-specific value function, \( v_d \) does not include the error term. Therefore, an agent will choose \( d \in \{0, 1\} \) to maximize \( v_d + \epsilon_d \).

2.4.2 Empirical Specification

Recall that each parcel owner makes two (potential) decisions in each period. The first decision is whether to build \((d = 1)\) or not build \((d = 0)\), and the agent chooses \( d \in \{0, 1\} \) to maximize \( v_d(\cdot) + \epsilon_d \), where \( v_d(\cdot) + \epsilon_d \) is the lifetime expected utility (choice-specific value function) of choosing option \( d \). The second decision is to choose optimal housing services, \( h \), to maximize \( v_1 + \epsilon_1 = \pi_1 + \epsilon_1 \) where \( \pi_1 \) is the deterministic flow profits associated with building. As each agent will take into account the optimal level of housing services when deciding to build, I begin with a discussion of the housing service decision and then outline the dynamic discrete choice problem.

Optimal Housing Services

For a given parameterization of sales prices and constructions costs, we can recover the optimal level of housing service provision, \( h^* \). In principal, housing services, \( h \), could include all observable characteristics of a house that the parcel owner could choose. One could use a continuous index of housing services to reduce the dimension of building choices (e.g.
number bedrooms, number bathrooms, square footage) to a single dimension. However, for
the results reported here, I include only square footage in $h$. This allows me to directly
compare my estimates of price and cost per square foot with other estimates in the literature
at a price of using less information. The overall results are not sensitive to this specification.

Parcel owners therefore choose $h$ to maximize flow profits, $\pi_1(h, x) + \epsilon_d$, where per-period
profits are given by $^{28}$:

\[
\pi_1(x) + \epsilon_1 = E_t[P_{nt}] - C_{nt} + \epsilon_1
\]
\[
\pi_0(x) + \epsilon_0 = \epsilon_0
\]

Prices are given by $P_{nt} = \rho_{j(n)t} Q_{nt}$, where $Q_{nt} = h_{nt}^{\gamma_1(n)t} x_n^{\gamma_2(n)t} e_{\nu_n}^n$. Therefore, prices
are equal to the price of a unit of housing quality, $\rho_{j(n)t}$, times the quantity of housing
quality, $Q_{nt}$. Housing quality is composed of three terms: the choice variable, housing
services, $h$; the fixed parcel characteristics, $x_n$; and a normally distributed error term, $\nu_n$. $^{29}$
$h$ is house square footage, and $x_n$ includes lot-size. The vector of implicit prices of $h$ and $x$,
which I denote by $\gamma$, varies across neighborhood, $j$, and time, $t$. The expectation operator
$E_t[\cdot]$ reflects the fact that the parcel owner only knows the implicit price of housing services
and parcel characteristics when making her decisions, as the price error is not revealed until
after construction/time of sale. This can be viewed as an equilibrium price equation, where
each parcel owner (who is small relative to the total market) takes the prices as given.

The costs, $C_{nt}$, are separated into two components:

\[
C_{nt} = VC_{nt} + FC_{nt}
\]

where $VC_{nt} = \exp(\alpha_0 j t + \alpha_1 x_n) \cdot h$ and $FC_{nt} = x_{j(n)t}^j \lambda^j + x_{t}^t \lambda^t + \xi_{j(n)} + \xi_t = \delta_{j(n)} + \delta_t$

$^{28}$ $\epsilon_d = \epsilon_d^* - \sigma \gamma$ where $\epsilon_d^*$ is distributed Type 1 Extreme Value with location parameter equal to zero
and scale parameter equal to $\sigma$. By the properties of the Type 1 Extreme Value distribution,
the mean of $\epsilon_d^*$ is $\sigma \gamma$ where $\gamma$ is Euler’s constant. $\epsilon_d$ is therefore mean zero.

$^{29}$ If $x_n$ contains $K$ variables and $K$ is greater than one, prices should be written $P_{nt} = \rho_{j(n)t}^{h_{nt}^{\gamma_1(n)t}} \prod_{k=1}^{K} x_{n,k}^{\gamma_2(n)t,k} e_{\nu_n}^n$
The first component is made up of the variable costs determined by level of housing services. Variable costs increase at a linear rate in the quantity of housing services, where the rate is determined by parcel characteristics, neighborhood, and time. The second component of costs, $FC_{nt}$, 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 (which may be a function of neighborhood demographics) will cause fixed construction costs to vary by neighborhood. Fixed costs are parameterized as a function of time-invariant neighborhood observables, $x_{j(n)}$, unobserved (time invariant) neighborhood attributes, $\xi_j$, time-varying Bay Area observables, $x_t$, and unobserved time varying Bay Area attributes, $\xi_t$. Let $\delta_{j(n)} = x'_{j(n)}\lambda_j + \xi_{j(n)}$ and $\delta_t = x'_{t}\lambda_t + \xi_t$ capture all neighborhood-specific and year-specific factors not already included in prices and variable costs. In practice, I decompose the neighborhood effects, $\delta_{j(n)}$, into a function of the observables $x_{j(n)}$ but do not use any Bay Area time-varying observables, $x_t$, to decompose the time effects, $\delta_t$.

The final component to profits is a profit shock, $\epsilon_{nt}$. This shock is distributed i.i.d. over parcels and time and can be interpreted as a shock to fixed costs. Whether or not a permit can be obtained in a given time period affects profits. Idiosyncratic parcel owner characteristics will also change from year to year. For example, shocks to health, family, or employment status could make developing a parcel more or less attractive in that year.

The flow profits associated with building can then be written as:

$$\pi_{1nt} = \rho_{j(n)t}h_{nt}^{\gamma_j(n)t}x_{n}^{\gamma_2(n)t}e^{5\sigma^2} - \left(\exp(\alpha_0jt + \alpha_1x_n) \cdot h + \delta_{j(n)} + \delta_t \right) + \epsilon_{nt} \quad (2.5)$$

Conditional on choosing to build, a parcel owner will choose $h$ to maximize (2.5). The

---

30Taking expectations of $\rho_{j(n)t}h_{nt}^{\gamma_j(n)t}x_{n}^{\gamma_2(n)t}e^{5\sigma^2}$ with respect to the normal error, $\nu_n$, yields $\rho_{j(n)t}h_{nt}^{\gamma_j(n)t}x_{n}^{\gamma_2(n)t}e^{5\sigma^2}$.
first order necessary condition is given by:

\[ \gamma_{1j(n)t} \rho_{j(n)} t h_{nt}^{-\gamma_{1j(n)t} - 1} x_n^{\gamma_{2j(n)t}} e^{-5\sigma_2^2} - \exp(\alpha_{0jt} + \alpha_{1x_n}) = 0 \] (2.6)

Solving (2.6) yields the optimal housing services, \( h^* \):

\[ h^* = \left( \frac{\gamma_{1j(n)t} \rho_{j(n)} t x_n^{\gamma_{2j(n)t}} e^{-5\sigma_2^2}}{\exp(\alpha_{0jt} + \alpha_{1x_n})} \right)^{\frac{1}{1 - \gamma_{1j(n)t}}} \] (2.7)

The flow profit function is then obtained by plugging (2.7) into (2.5)

\[ \pi_{1nt} = \rho_{j(n)} t x_n^{\gamma_{2j(n)t}} e^{-5\sigma_2^2} \left( \frac{\gamma_{1j(n)t} \rho_{j(n)} t x_n^{\gamma_{2j(n)t}} e^{-5\sigma_2^2}}{\exp(\alpha_{0jt} + \alpha_{1x_n})} \right)^{\frac{1}{1 - \gamma_{1j(n)t}}} - \frac{\exp(\alpha_{0jt} + \alpha_{1x_n}) \cdot \frac{\gamma_{1j(n)t} \rho_{j(n)} t x_n^{\gamma_{2j(n)t}} e^{-5\sigma_2^2}}{\exp(\alpha_{0jt} + \alpha_{1x_n})}^{\frac{1}{1 - \gamma_{1j(n)t}}}}{VC_{nt}(\rho, \gamma_1, \gamma_2, \sigma_\nu, \alpha_0, \alpha_1)} + \frac{\delta_{j(n)} + \delta_t}{FC_{nt}(\delta_j, \delta_t)} + \epsilon_{nt} \]

which can be rewritten as:

\[ \pi_{1nt}(\rho, \gamma_1, \gamma_2, \sigma_\nu, \alpha_0, \alpha_1, \lambda, \xi_{j(n)}) = EP_{nt}(\rho, \gamma_1, \gamma_2, \sigma_\nu, \alpha_0, \alpha_1) - \left( VC_{nt}(\rho, \gamma_1, \gamma_2, \sigma_\nu, \alpha_0, \alpha_1) + FC_{nt}(\delta_j, \delta_t) \right) + \epsilon_{nt} \]

**Optimal Discrete Choice**

The deterministic component of the per-period profits from choosing to not build \((d = 0)\) is normalized to zero.

\[ \pi_0(x_{nt}) + \epsilon_{n0t} = \epsilon_{n0t} \] (2.8)

The value of choosing to not build is then simply the continuation value, or the present discounted value of the expected best decision in the next period. As I assume that the
profit shocks are distributed i.i.d, Type 1 Extreme Value, the value of not building, \( v_0 \), is a closed-form solution.

\[
v_0(\Omega) = \sigma \epsilon (\beta \int \log [\exp (v_0(\Omega')/\sigma \epsilon) + \exp (v_1(\Omega')/\sigma \epsilon)] q(\Omega'|\Omega, 0) d\Omega')
\]  

(2.9)

where \( \Omega \) includes both current \( x \) and anything that helps predict future \( x \). The transition probability for the state variables, conditional on choosing to not build, is given by \( q(\Omega'|\Omega, 0) \).

I assume that it is never optimal to build a property and then choose when to sell/use. Therefore, the decision to build is effectively the decision to build conditional on being rewarded immediately with the value of the property.\(^{31}\) Therefore, the parcel owner’s problem is terminated when she chooses to build and the choice-specific value function from building is always equal to the deterministic component of the per-period profits associated with building. This implies \( v_1(x_{njt}) = \pi_1(x_{njt}) \).

Given the structure of flow profits and recalling that \( x \) is a variable in \( \Omega \), I can summarize the lifetime utilities (choice-specific value functions) as:

\[
v_0(\Omega) = \sigma \epsilon (\beta \int \log [\exp (v_0(\Omega')/\sigma \epsilon) + \exp (\pi_1(x')/\sigma \epsilon)] q(\Omega'|\Omega, 0) d\Omega')
\]

(2.10)

\[
v_1(x) = \pi_1(x)
\]

2.5 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.

\(^{31}\)This is reasonable is we assume that the costs of holding a fully developed property (such as mortgage payments and foregone rent) are sufficiently high.
While all three outcomes are directly related to the full profit function, examining each outcome separately helps illustrate what are the sources of identification used to estimate the parameters of the full model. Much can learned by estimating the price outcome in isolation. However, for the housing service and the build/don’t build outcomes, deeper inference can only be obtained by also using information from the other outcomes.

The price outcomes reveal trends in prices, both across tracts and through time. It is straightforward what variation in the data identifies the parameters reflecting which tracts are high price tracts, or what are the broad time trends or prices. However, the data is also rich enough to identify more subtle patterns, such as how the different components of housing are valued. For example, controlling for lot-size and location, if big houses appreciating at slower rates than smaller houses, it suggests that the value of land is increasing at a faster rate than the value of living space.

The raw data reveal how much housing services (or square footage) each parcel owner chose to provide, if building occurred. While this data alone can be used to document cross-sectional and time series trends in square footage, more can be learned by combining this data with the price parameter estimates; with data on observed square footage, knowing the marginal benefit of adding a unit of square foot identifies marginal (and variable) costs. Similarly, on their own, the data on when and where building occurred only reveals broad cross-sectional and time-series patterns. However, if prices and variable costs are also known, the construction data can then be used to estimate fixed costs – controlling for prices and variable costs, different construction rates imply different fixed costs. These features of the model suggest the appropriateness of a multi-stage estimation strategy, which is more formally outlined below.

Let $\theta_p$ denote $(\rho, \gamma_1, \gamma_2, \sigma_\nu)$, $\theta_h$ denote $(\alpha_0, \alpha_1)$, and $\theta_d$ denote $(\sigma_\epsilon, \delta_j, \delta_t, \beta)$. As the errors across each of the outcomes are assumed independent, the log-likelihood function can be broken into three pieces:
1. $L_p(\theta_p, x) :$ the log-likelihood contribution of prices

2. $L_h(\theta_p, \theta_h, x) :$ the log-likelihood contribution of housing services

3. $L_d(\theta_p, \theta_h, \theta_d, x) :$ the log-likelihood contribution of the binary construction decision

The total log-likelihood function is the sum of the three components:

$$L(\theta) = \sum_{i=1}^{N_p} L_p(P|\theta_p, x_p) + \sum_{i=1}^{Nh} L_h(h|\theta_p, \theta_h, x_h) + \sum_{i=1}^{Nd} L_d(d|\theta_p, \theta_h, \theta_d, x_d) \quad (2.11)$$

where $\theta = [\theta_p, \theta_h, \theta_d]$, $N_p$ is the number of observed sales, $Nh$ is the number of observed developments, and $Nd$ is the number of observed parcels.

In theory, I could choose $\theta$ to directly maximize (2.11). However, given the large number of parameters and the reasoning outlined above, in practice I estimate the model in stages. In the first step, I estimate $\theta_p$ by maximizing $L_p(\theta_p, x_p)$. Then, using the estimates of $\theta_p$, I estimate $\theta_h$ by maximizing $L_h(\hat{\theta}_p, \theta_h, x_h)$. Finally, I can obtain consistent estimates of $\theta_d$ by taking the estimates of $\theta_p$ and $\theta_h$ as given and choosing $\theta_d$ to maximize $L_d(\hat{\theta}_p, \hat{\theta}_h, \theta_d, x_d)$.

The third stage is the dynamic discrete choice model. To estimate the dynamic discrete choice model, I use a two-step estimator similar to Arcidiacono and Miller (2007) where transition 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.\(^{32}\) However, the standard errors must be corrected to account for the multiple stage procedure. Procedures for correcting standard errors include reformulating all the stages as method of moments estimators and stacking the moments as discussed in Newey and McFadden (1994), calculating a Hessian to the total Likelihood function, or bootstrapping. Given

\(^{32}\)It does reduce efficiency. However, the loss of efficiency allows me to estimate the profit function parameters at a fine level of geography, which would not be possible using a one step (efficient) estimator.
the large number of equations (and parameters) estimated in the first stage, I choose to bootstrap the standard errors.33

2.5.1 Estimation - Housing Prices

There have traditionally been two main empirical approaches to estimating movements in house prices: repeat sales models and hedonic pricing models.34 Repeat sales models were originally proposed by Bailey, Muth, and Nourse (1963) and further developed by Case and Shiller (1987) and Case and Shiller (1989). The basic premise is to assume that a house’s price is determined by the price of a unit of housing times the quantity of housing, where the quantity of housing could be determined by (observed and unobserved) features of the house, such as size and quality. If the econometrician has data on houses that sell more than once, taking first differences of the log of the sales prices and regressing on time dummies will give a measure of the unit price of housing.35 In addition to its simplicity, the key benefit of the repeat sales framework is that by taking first differences, it controls for unobserved house characteristics. However, the repeat sales approach is based on two strong assumptions: that the houses observed to sell more than once are representative of all houses and that the implicit prices of housing attributes remain constant. Meese and Wallace (1997) provide evidence from Oakland and Fremont that these assumptions may not hold.36

In the context of my model and the nature of limited land availability in the Bay Area, the repeat sales analysis is clearly inappropriate. With limited land, the increase in house prices in the Bay Area is driven more by the increasing value of land rather than other

33The pricing equation will be estimated separately for very tract and year. There are over 600 tracts and 17 years of data.

34A third approach of using median house prices is sometimes used because of its simplicity.

35Case and Shiller (1989) extends this basic framework by using weighted least squares to account for heteroskedasticity.

36See also Clapham, Englund, Quigley, and Redfearn (2006) for an excellent overview of different approaches to the estimation of housing price indexes.
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 my model predicts that parcel owners will respond to the implicit price of housing services, it is important to accurately estimate this return.

To that end, I estimate a hedonic price function where house prices are modeled directly as a function of the observable characteristics of the house. The drawback of the standard hedonic approach is that it does not control for unobservable house characteristics, however, the approach taken below allows the implicit price of housing services to vary both by tract and by year. The results section provides strong evidence of the importance of allowing the implicit prices to vary over time.\footnote{While the value of a typical house doubled in real terms between 1988 and 2004, the return to a marginal increase in square foot was close to the same in 2004 as 1988.} The other issue associated with estimating hedonic price indices is the choice of functional form. As I allow the prices to vary at such a fine geographic level, I can not non-parametrically estimate the price function and instead assume a log-log functional form.\footnote{See Cropper, Deck, and McConnell (1988) for an excellent discussion of the choice of functional form.}

I use all previous sales to estimate the following regression equation separately for each tract/year combination. As the number of observations for each tract/year may potentially be small, I estimate the regression using the full sample each time but weight the observations differently each time depending on the tract/year I want to get estimates for. The price equation I estimate is:

\begin{equation}
\log(P_{nt}) = \log(\rho_{j(n)t}) + \gamma_{1j(n)t}\log(h_{nt}) + \gamma_{2j(n)t}\log(x_n) + \nu^P_n \tag{2.12}
\end{equation}
2.5.2 Estimation - Housing Services

I assume that observed housing services, $h$, are equal to the optimal housing services, $h^*$, scaled by an error term, $h = h^*e^{\eta_h}$. Given estimates of the pricing parameters, I can rearrange the equation for optimal housing services to get the following housing service regression equation:

$$\log(h_{nt}^{\gamma_1(j(n))t}) - \log(h_{nt}) + \log(\gamma_{1j(n)t}) + \log(\rho_{j(n)t}) + \log(x_{j(n)t}) + \log(\sigma_{\nu}) = \alpha_0 + \alpha_1 x_n + \tilde{\eta}_h^n$$

(2.13)

where $\tilde{\eta}_h^n = \eta_h^n \cdot (1 - \gamma_{1j(n)t})$. Estimating (2.13) by least squares yields estimates of $\alpha_0$, $\alpha_1$, and the variance of $\eta_h^n$.

2.5.3 Estimation - Dynamic Discrete Choice

Using the results of the first two stages, the flow profits, $\pi$ can then be expressed as:

$$\pi_{1nt} = \overline{EP}_{nt} - \overline{VC}_{nt} - \delta_j - \delta_t + \epsilon_{nt}$$

(2.14)

where $\overline{EP}_{nt}$ is the first-stage estimate of expected prices, $\overline{VC}_{nt}$ is the second-stage estimate of variable costs and $\delta_j$ and $\delta_t$ are the fixed costs parameters that capture the remaining cost environment. The remaining structural parameters to be estimated are $\theta_d = (\sigma_\epsilon, \delta_j, \delta_t, \beta)$.

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 (2007) to take advantage of the terminal state nature of the

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Various interpretations can be provided for the error term. The error term could be interpreted as any shock to variable costs that is revealed after the decision to build is made but before construction commences. Or, it can be thought of as optimization error that parcel owners don’t account account for when deciding when to build. Finally, one could think of the error as measurement error in $h$. As the first stage is estimated assuming $h$ is measured correctly, this final interpretation requires some small changes be made in the interpretation of the pricing error.

31
dynamic discrete choice problem. I can rewrite (2.9) as:

\[ v_0(\Omega) = \sigma \beta \left( \int \left( \log[1 + e^{v_0(\Omega')/\sigma} - \pi_1(x'/\sigma)] + \pi_1(x'/\sigma) \right) q(\Omega'|\Omega, 0) d\Omega' \right) \] (2.15)

Each agent chooses the option which yields the higher expected lifetime utility. Given the distributional assumptions on the error terms, the conditional choice probabilities (CCPs) of choosing to not build or to build are given by:

\[ \text{Prob}(d_n = 0|\Omega) = \frac{e^{v_0(\Omega)/\sigma - \pi_1(x)/\sigma}}{1 + e^{v_0(\Omega)/\sigma - \pi_1(x)/\sigma}} \] (2.16)

\[ \text{Prob}(d_n = 1|\Omega) = \frac{1}{1 + e^{v_0(\Omega)/\sigma - \pi_1(x)/\sigma}} \]

Letting \( P_1(\Omega) \) denote the probability that \( d_n = 1 \) conditional on \( \Omega \), I can rewrite (2.9) as the expected future per-period profit of choosing to not build and a function of the next period probability of choosing to build.\(^{40}\)

\[ v_0(\Omega) = \beta \left( \int (\pi_1(x') - \sigma \log[P_1(\Omega')]) q(\Omega'|\Omega, 0) d\Omega' \right) \] (2.17)

A straightforward two-step estimator can be formed based on (2.17). The first step involves getting estimates of both the transition probabilities, \( q(\Omega'|\Omega, 0) \) and the conditional choice probability, \( P_1(\Omega') \). The second step then takes \( \int log[P_1(\Omega')q(\Omega'|\Omega, 0)] d\Omega' \) as data and estimates the remaining structural parameters, \( \theta_d \).

**Estimation – Dynamic Discrete Choice: Choice and Transition Probabilities**

To estimate \( \int log[P_1(\Omega')q(\Omega'|\Omega, 0)] d\Omega' \), I first estimate flexibly the policy function \( P_1(\Omega) \) and the transition probability function \( q(\Omega'|\Omega, 0) \). I would ideally like to non-parametrically

\(^{40}\) The representation theorem of Hotz and Miller (1993) states that there is a one to one mapping between choice probabilities and lifetime utility differences. When the stochastic component of lifetime utility is distributed i.i.d., Type 1 Extreme Value, this mapping takes on the simple form used above.
estimate $P_1(\Omega)$, however, the dimensionality of $\Omega$ is too large. Instead, I use a flexible logit estimator, where I incorporate b-spline expansions of the current prices and costs, a linear function of the price and cost lags, and geographic and time dummies inside a logistic cumulative distribution function. The flexible logit framework estimates $P_1(\Omega)$ as

$$
\hat{P}_1(\Omega) = \Lambda \left( \sum_{bp=1}^{B_p} \varphi_{bp} S_{bp}(EP_{nt}) + \sum_{bc=1}^{B_c} \varphi_{bc} S_{bc}(VC_{nt}) + \sum_{l=2}^{L_p} \varphi_{1,l} EP_{nt-l} + \sum_{l=2}^{L_c} \varphi_{2,l} VC_{nt-l} + \varphi_3 f_n + \varphi_4 j + \varphi_5 t \right) \tag{2.18}
$$

where $\Lambda$ denotes the logistic CDF, $S(\cdot)$ are the basis functions of the relevant arguments and $\varphi$ are the coefficients to be estimated.\footnote{Any CDF, for example Normal, could be used here}

It is fairly straightforward to estimate the transition probabilities, $q(\Omega'|\Omega, 0)$. In the context of the decision to build or not, today's decision should have no impact on the transition probabilities. This is clear when we recall that the state variables include characteristics of the parcel and the parcel's census tract, such as the price of housing in the census tract, for example.\footnote{This assumes that each parcel owner is small relative to the market and can't influence prices.} Therefore, $q(\Omega'|\Omega, d_{nt} = 0) = q(\Omega'|\Omega)$. In addition, many of the components of $\Omega$ will not be time varying. This further simplifies the transition probability function. In general, only the market characteristics of the neighborhood in which the parcel is located will be time varying. The time varying variables are housing prices and costs. Finally, many of the state variables are lagged variables and, as such, transition deterministically. For example, as the information set, $\Omega$, includes anything that helps predict future prices and costs, it will include more than just today's price or costs. In practice, I model prices as being a function of seven lags of prices. Therefore, at any time the state vector, $\Omega$, will include seven lags of prices but six of these seven variables...
transition deterministically: similarly for costs, where two lags are used.

One possibility would be to use a kernel density estimator to estimate \( q(\Omega'|\Omega) \). However, this would require the state variables in \( \Omega' \) to be discretized. In addition, a fully non-parametric approach would suffer from a curse of dimensionality. Instead, I avoid discretizing the states by specifying a parametric transition process. I estimate the transition probabilities separately for \( \hat{EP}_{nt}, \hat{C}_{nt} \) and the year effects \( \varphi_5t \). The other determinants of the policy function transition deterministically (lagged prices and costs) or are not time-varying (lot-size and location).

The transition probabilities for \( \hat{EP}_{nt} \) are estimated according to:

\[
\hat{EP}_{nt} = \phi_{0,j} + \sum_{l=1}^{L} \phi_{1,l}\hat{EP}_{nt-l} + \phi_2t x_n + \phi_3t + \epsilon_{nt}^{EP} \tag{2.19}
\]

When parcel owners are forecasting tomorrow’s house price, they use today’s price, six lags of price, and the characteristics of their parcel, including location. They also assume prices follow a deterministic trend over time captured by the time trend, \( \phi_3t \). A similar specification is used for \( \hat{C}_{nt} \), but with fewer lags.

Finally, as time dummies are included in the policy function to capture any unobserved time varying variables, I must account for their transitions. With \( T \) periods of data, I estimate \( T \) coefficients on the year dummies. I then treat these coefficients as one variable, \( \varphi_{5t} \) (with \( T \) observations), which enters the policy function (2.18) with a coefficient of one. I then specify an AR(1) process for \( \varphi_{5t} \). I also include lags of Bay Area mean prices in the transition probability regression:

\[
\varphi_{5t} = \varphi_0 + \varphi_1\varphi_{5t-1} + \sum_{l=1}^{L} \varphi_{2,l}MeanPrice_{t-l} + \epsilon_t^{\varphi} \tag{2.20}
\]

Using the data, the coefficients estimated from (2.18) and (3.18), and the empirical distribution of \( \epsilon_{nt}^{PC} \), I can calculate \( \int log(\hat{P}_1(\Omega'))q(\Omega'|\Omega)d\Omega' \) by simulation. I do not need to
discretize the state space. The other part of the continuation value is \( \int \pi_1(x') \tilde{q}(\Omega'|\Omega) d\Omega' \).

As \( \pi_1(x) \) is linear in the remaining parameters to be estimated, I can simulate the expected future values of the variables, thus ensuring that once I simulate the future data once, the remaining problem is a linear-in-parameters logit model. While the construction of the expected continuation value is carried out by simulation, the fact that it only needs to be done once allows me to use a very large number of draws in the simulation.

**Estimation – Dynamic Discrete Choice : Structural Parameters**

Letting “hats” on variables denote their estimates from the first step, I can rewrite the choice-specific value functions as:

\[
v_0(\Omega; \theta) = \beta \left( \int \left( \pi_1(x') - \sigma \log(\tilde{P}_1(\Omega')) \right) \tilde{q}(\Omega'|\Omega) d\Omega' \right)
\]

\[
v_1(x; \theta) = \pi_1(x)
\]

A logit estimator can be formed using (2.21). Each parcel owner will choose to build \((d = 1)\) if \( v_1(x; \theta) + \epsilon_{n1} > v_0(\Omega; \theta) + \epsilon_{n0} \). Given the distribution of \( \epsilon \), I can estimate \( \theta \) using maximum likelihood, where the individual likelihood contributions are formed by plugging \( v_1(x; \theta) \) and \( v_0(\Omega; \theta) \) into (2.16).

To form the likelihood function using (2.16), I use the difference in choice-specific value functions divided by the logit scale. The difference in value functions is given by

\[
v_0(\Omega) - v_1(x) = \beta \left( \int \left( \pi_1(x') - \sigma \log(\tilde{P}_1(\Omega')) \right) \tilde{q}(\Omega'|\Omega) d\Omega' \right) - \pi_1(x)
\]

The deterministic component of the per-period profit function can be written as:

\[
\pi_{1nt} = \widehat{EP}_{nt} - \widehat{C}_{nt} - \delta_j - \delta_t
\]

where the hats denote the fact that \( EP_{nt} \) and \( C_{nt} \) are estimated in the earlier stages. The
difference in utilities that is plugged into the likelihood is then given by:

\[ v_0(\Omega) - v_1(x) = \beta \left( \int (\hat{\mathbb{E}} P_n' - \hat{\mathbb{C}}_n' - \sigma_n \log[\hat{\mathbb{P}}_1(\Omega_{nj})]) \tilde{q}(\Omega_{nj}', \Omega_{nj}) d\Omega_{nj}' \right) - (\hat{\mathbb{E}} P_{nt} - \hat{\mathbb{C}}_{nt}) + (1 - \beta) \delta_j + (\delta_t - \beta E_\delta_t \delta_{t+1}) \] (2.24)

I incorporate (unobserved) heterogeneity at the neighborhood level by controlling for (time invariant) unobservable characteristics of each neighborhood by including neighborhood fixed effects, \( \delta_j \), in the estimation of the dynamic discrete choice model. The coefficients on a set of neighborhood dummies will be estimates of \( (1 - \beta) \delta_j \), from which it is straightforward to recover \( \delta_j \). Including the fixed effects will capture the impact on profits of both unobservable, \( \xi_j \), and the observable neighborhood-level-time invariant variables not already captured in prices and variable costs. I can then decompose the fixed effects. I do this by regressing the fixed effects on time-invariant neighborhood level observables, such as mean tract income or race, in a step similar to Berry, Levinsohn, and Pakes (1995). With a large number of neighborhoods, it will still be feasible to estimate choice probabilities and transition probabilities in the first step of the dynamic discrete choice estimation. Additionally, as the second stage is simply a linear in parameters logit model, including neighborhood dummies is still computationally straightforward.\(^{43}\) In practice, for this part of the estimation, I use Public Use Microdata Areas (PUMAs) as neighborhoods. A PUMA is the smallest area for which the Census can provide micro data and must have at least 100,000 inhabitants. There are forty seven PUMAs in the Bay Area, with an average population of 123,539.

\(^{43}\) Alternatively, a Berry (1994) style contraction mapping could be used to recover neighborhood dummies. For any given value of the non-fixed-effect parameters, there will be a unique value for each neighborhood’s fixed effect that will match the share of individuals choosing to not build predicted by the model with the observed shares in the data. In Berry, Levinsohn, and Pakes (1995) a single contraction mapping is used to find a vector of fixed effects in a multinomial logit estimation. Here, a separate contraction mapping could be used for each neighborhood to recover a single fixed effect for each neighborhood.
I also include time dummies to capture changes in the overall Bay Area cost environment. This poses an additional estimation issue as parcel owners will obviously have expectations about future costs. The estimation difficulty arises as the parcel owners now take expectations over parameters estimated within the model, as distinct from data that is observed. A similar issue arises in Gowrisankaran and Rysman (2006) and Schiraldi (2006); however, the estimation routine is quite different. Here, expectations about future costs must be incorporated in two places; the calculation of the future conditional choice probability term, \( \log(\hat{P}_1(\Omega')) \) and the one-period-ahead time varying fixed costs, \( E_t\delta_{t+1} \). Details regarding calculating the future conditional choice probability term were discussed above.

It is clear from (2.24) that additional assumptions as to how expectations are formed are necessary to separately identify \( \delta_t \) from \( (\delta_t - \beta E_t\delta_{t+1}) \). In practice, I first directly estimate the term \( (\delta_t - \beta E_t\delta_{t+1}) \). This can be done simply by including time dummies. I then recover \( \delta_t \) by making assumptions as to how individuals form their expectations about future values of \( \delta_t \). The benefit of this approach is that for much of the analysis of dynamics discussed below, the term of most interest is \( (\delta_t - \beta E_t\delta_{t+1}) \). Appendix A discusses the details for recovering \( \delta_t \) and compares this approach with Gowrisankaran and Rysman (2006).

**Alternative Estimator**

An alternative estimation strategy is to get a nonparametric estimate of \( v_1(\Omega) - v_0(x) \). This estimate, \( \hat{v}_1(\Omega) - \hat{v}_0(x) \), is obtained by again applying the Hotz-Miller inversion and is simply equal to \( \log(\hat{P}_1(\Omega)) - \log(\hat{P}_0(\Omega)) \). I can then use a minimum distance estimator to choose the values of \( \theta \) and \( \beta \) that minimize the norm:

\[
\| (\hat{v}_1(\Omega) - \hat{v}_0(x)) - (v_1(\Omega; \theta) - v_0(x; \theta)) \| \quad (2.25)
\]

The natural choice of norm is the \( L_2 \) norm resulting in a least squares estimator.
2.5.4 Summary of Estimation Routine

Step 1: Using observed sales, estimate (2.12) (for each tract and year)
Step 2: Using observed construction and Step 1 estimates, estimate (2.13)
Step 3: To estimate dynamic discrete choice part, use the profit function:

\[
\pi_{1nt} = \hat{EP}_{nt} - \hat{C}_{nt} - \delta_j - \delta_t + \epsilon_{nt}
\]  

(2.26)

2.6 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.

2.6.1 Hedonic Price Regressions

For each tract and year, I regress the log of the observed sales price on a constant, the log of house square footage, the lot-size, and a dummy indicating if the house is a new sale or not:

\[
\log(P_{nt}) = \log(\rho_{j(n)t}) + \gamma_{1j(n)t}\log(sqft_{nt}) + \gamma_{2j(n)t}\log(lot-size_{n}) + \gamma_{3j(n)t}old + \nu_{n}
\]

I use both sales of new houses and sales of second-hand houses and therefore include the new sale dummy. To improve the efficiency of the estimates, I use a locally weighted regression approach. I use the full sample for each regression, but for a given tract and year, weigh the observations differently depending on how far from the given tract and year each house is in geographic and time space. Geographic distance is determined by whether two houses are in the same tract, PUMA, and county. I choose the weights based on a visual inspection of the data; however, in practice the weights on houses not in the same tract decay quite quickly as one moves out of the same PUMA and the weights on houses not in the same year decay extremely quickly.

With over 600 tracts and 17 years of data, the full results are too numerous to report. However, I highlight key features of the results in the figures below. Figure 2.5 shows the distribution of the expected price of a “typical house” across Census tracts. The typical
house is the same in each tract and year and is defined as one with 1,700 square feet of living square and a lot-size of 6,900 square feet, corresponding to the sample means for house size and lot-size. The expected price for each tract is a weighted average of the expected prices (fitted values) between 1988 and 2004, where all prices are in 2000 dollars. The figures show considerable variation over tracts in the price of the same type of house. 44

![Figure 2.5: Distribution of the Price of a Typical House across Census Tracts](image)

The time trend of the price of a typical house is illustrated in Figure 2.6 and the pattern is somewhat similar to the repeat sales analysis shown in Figure 2.2. Interestingly, a difference arises in the post 2000 price pattern between new houses and resales; the corresponding graph to Figure 2.6 for resales (not shown) shows a dip in prices in 2001, whereas no such slowdown was estimated for new houses.

The key reason for estimating prices using a hedonic price approach was to capture the variation in the implicit price of housing size over tracts and through time. I can calculate the marginal price of adding one square foot to the typical house in each tract and year. Figure 2.7 shows the distribution in the marginal price of square footage across tracts. This

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44The variance of the mean of actual sales prices per tract (not shown) is considerably higher as higher price neighborhoods generally have larger houses.
variation across tracts will be one of the key sources of identification of variable housing costs. The other source of variation I use to identify variable housing costs is time-series variation in the marginal price of square footage.

A notable feature of the pricing results is the heterogeneity in prices across both physical space and through time. The other key result is the decreasing importance of house size in determining sales price. The results strongly suggest that the value of a buildable parcel of
land has increased dramatically over the period. This can be informally seen by comparing the price of a typical house in 1989 and 2004. The Bay Area mean price in 1989 was a little over $300,000 and rose to a little over $450,000 by 2004. However, the marginal price of an additional square foot was almost the same in the two years - $134.50 in 1989 and $137.00 in 2004. As prices increase non-linearly in size, we can not formally measure the role of the typical parcel in housing price increases. However, these results suggest that appreciation in the value of buildable parcels is the dominant factor.

2.6.2 Variable Cost Regressions

In the second stage, observed square footage is regressed on a function of tract characteristics, where the functional form is dictated by the optimal value of square footage from maximizing per-period profits. The price components of optimal square footage are known and are constrained to be their values as estimated in the first-stage hedonic price function. 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 use the functional form of costs to recover the variable cost function.

The cost function is assumed to be linear in square footage, where the cost per square foot varies by tract, an overall Bay Area time pattern, and lot size: $VC_{nt} = \exp(\alpha_{0jt} + \alpha_1 x_n) \cdot h$ where $h$ is square footage, $x$ includes only lot-size, and $\alpha_{0jt} = \alpha_0 + \alpha_j + \alpha_t$.

Recalling that optimal square footage is given by:

$$h^* = \left( \frac{\gamma_{1j(n)t} \rho_{j(n)t} x_n^\gamma_{2j(n)t} e^{.5\sigma^2_v}}{\exp(\alpha_{0jt} + \alpha_1 x_n)} \right)^{\frac{1}{1-\gamma_{1j(n)t}}}$$

and that $h = h^* e^{\tilde{\eta}_n^h}$ yields the regression equation

$$\log(h_{nt}^{\gamma_{1j(n)t}}) - \log(h_{nt}) + \log(\gamma_{1j(n)t}) + \log(\rho_{j(n)t}) + \log(x_n^{\gamma_{2j(n)t}}) + .5\sigma^2_v = \alpha_{0jt} + \alpha_1 x_n + \tilde{\eta}_n^h$$

where $\tilde{\eta}_n^h = \eta_n^h \cdot (1 - \gamma_{1j(n)t})$.

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. To highlight that size does indeed change as returns increase, I regress the log of observed square footage for new construction on lot-size, tract dummies, and year dummies.

$$\log(sqft_{njt}) = \kappa_0 + \kappa_t I[year=t] + \kappa_j I[tract=j] + \kappa_{lot} lot - size_n + \nu_{nj}^{sqft}$$

Figure 2.9 plots $e^{\kappa_t}$ against year, showing the time trend of square footage in new construction between 1988 and 2004 and . It is worth noting that this regression is estimated using a different data set to the one that was used to estimate prices. Here, only new construction is used, whereas the price regression is run using all sales. The size of observed size changes relative to price changes is what identifies the time trend in variable costs.
Figures 2.10 illustrates the distribution over tracts in cost per square foot and Figure 2.11 shows the time trend in cost per square foot. The mean cost per square foot is $125. As the approach to identifying costs is different here from previous research, it is not completely straightforward to compare results. Here, the costs 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 increases with house size. As such, these costs could be higher than costs estimated from physical costs alone. Gyourko and Saiz (2006) report the average cost per square foot (of a 2000 \( ft^2 \) house) in San Francisco in 2003 was $72 for an economy quality house – higher costs apply to higher quality homes.\(^{45}\) The mean cost per square foot in 2003 estimated here is $110. However, given the the “economy” quality in Gyourko and Saiz (2006), the estimates do not appear to be that different.\(^{46}\)

An important difference between the results here and the data used in Gyourko and

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\(^{45}\)This figure was taken from R.S. Means Company cost data.

\(^{46}\)Wheaton and Simonton (2007) report costs for apartment and office buildings that are also quite similar.
Saiz (2006) is that I allow cost per square foot to vary within a metropolitan area. While physical construction costs for the same product are not expected to differ within the Bay Area, the quality of house will 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 drive price differences. For example, neighborhoods with views of the Bay or which are close to employment centers
will have higher prices, as will neighborhoods where it is common to use higher quality raw materials such as granite counter tops. For construction costs, however, only the quality of construction matters. The underlying assumption is that while the quality of square foot is homogenous within a tract, it can vary across tracts. This added flexibility is a result of the fine level of geography at which I estimate both price gradients and cost functions.

Finally, as shown in Figure 2.11, the time pattern of mean tract costs suggests that variable costs are pro-cyclical and maybe falling slightly over time. It is somewhat surprising that costs fall so sharply following a small downturn in prices and construction levels around 2000. The volatility of variable costs is an interesting result as it is higher than that found in other work.

2.6.3 Dynamic Discrete Choice Results

Step One - Transition Probabilities and CCPs

The first step of the dynamic discrete choice estimation involves estimating transition probabilities on costs and prices as well as reduced-form (flexible) conditional choice probabilities. As the prices and costs are estimated at a fine level of geography, I estimate their transitions in levels instead of first differences. Appendix B provides tables of autoregressive coefficients for prices and costs as well as an impulse response function showing the expected response of prices to a one standard deviation positive shock. The results show similar patterns to those estimated elsewhere in the literature. The coefficients on lagged levels imply similar qualitative results to Glaeser and Gyourko (2007), who use first differences. Both these results and those found in Glaeser and Gyourko (2007) imply short run (one year) persistence of price shocks with medium run (5 years) mean reversion.

The conditional choice probability estimation captures in a flexible way that the probability of construction is increasing in prices, falling in costs, and differs significantly across

47Case and Shiller (1989) discuss the problems associated with first-differenced price estimates.
neighborhoods.

**Step Two - Structural Parameters**

The remaining structural parameters, given the estimates of prices and variable costs from stages one and two, are the discount parameter, $\beta$, the scale of the Type 1 extreme value error, $\sigma_{\epsilon}$, and the neighborhood and year effects on fixed costs. The discount parameter, $\beta$ is set at .95 and the other parameters are estimated via maximum likelihood.

Table B.2 in Appendix B presents the results with the neighborhood effects suppressed. A full set of neighborhood dummies were included and the omitted year was 1989. As the profit function is measured in dollars, the scale of the extreme value error, $\sigma_{\epsilon}$ is identified and was estimated at $35,490. Using the properties of the Type 1 Extreme Value distribution, this yields an estimated standard deviation of the error equal to $\sigma_{\epsilon} \cdot \pi^2 / 6 = 58,385$. Given the mean ($352,489$) and standard deviation ($221,364$) of observed house prices in the data, the size of the error scale suggests the model fits the data quite well.

**Fixed Costs – Cross-Section**

The size of estimated fixed costs is quite high, with a mean of $284,180. However, it is important to interpret the costs correctly. These are estimates of the costs that a randomly picked parcel owner in a randomly picked time period would face from developing their land. Of greater interest are the costs faced by those who actually engaged in construction. To get this figure, I simply subtract the expectation of the logit error term conditional on a parcel being built. The conditional expectation is $141,150. Subtracting the conditional expectation of the error from the raw fixed cost estimates gives an estimate of the fixed costs incurred by those who developed their parcels.

The fixed costs are allowed to vary at the PUMA level and the results show substantial cross-sectional variation. 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. More interestingly, they also capture the regulatory environment. If we assume that the physical construction component of fixed costs is fixed across PUMA, then the cross-sectional variation reflects how the costs of regulation vary by area. If physical and regulatory costs are positively correlated, the cross-sectional differences in fixed costs can be interpreted as upper bounds on the differences in regulation. Figure 2.12 shows the adjusted fixed cost for each PUMA. Each PUMA’s cost is calculated as the mean cost over time and the range of costs across PUMAs is $81,710. \(^{48}\)

![Figure 2.12: Geographic Distribution of Fixed Costs](image_url)

Recent research, such as Glaeser, Gyourko, and Saks (2005) and Quigley and Raphael

\(^{48}\)The area in the North-East of San Francisco is blank because of low numbers of single family residential sales. San Francisco International Airport is the other blank area.
(2005) has discussed the role of regulation in house price growth. Quigley (2006) and Kahn
(2007) draw attention to the possible role of existing residents in limiting housing supply
and Ortalo-Magné and Prat (2005) develops a theoretical political economy model, which
models the incentives of voting residents in determining new construction.49 To get an idea
of how costs vary according to PUMA characteristics and demographics, I can decompose
the area fixed costs by regressing fixed costs on PUMA characteristics. I therefore estimate
\[ \delta_{j(n)} = x_{j(n)} + \xi_{j(n)} \] by OLS.

Table 2.1 shows the results from these regressions with various combinations of regres-
sors. Costs are estimated for each of 46 PUMAs. The PUMA containing Oakland is an
outlier in this regression. Given the small number of observations, and the sensitivity of
OLS to outliers, I estimate regressions using a median regression using all 46 PUMAs, and
using OLS with the Oakland PUMA omitted. The partial correlations shown in Table 2.1
suggest that costs are statistically significantly higher in high house price areas and areas
with older houses. Costs are higher, on average, in areas with lower household income and
higher rates of home ownership. Race and education are found to be insignificant in pre-
dicting fixed costs. The effects for race and education are relatively small and insignificant.
Estimating the equation using OLS and all 46 PUMAs gives similar results. The only sub-
stantial difference is that the coefficient on ownership rates falls in size by approximately a
half.

As the size of a PUMA is sufficiently large, there will be considerable heterogeneity in
tract characteristics and tract construction levels within each. Therefore, the regressions
are more suggestive than a true test of whether existing residents are blocking development.
The regression results reported here capture that costs are lower in parts of Contra Costa,
Alameda, and Santa Clara counties that are further from the central urban areas. These

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The realtor disagreed with Quigley that local residents were blocking construction and suggested
that Quigley was “too cynical.”
“newer” areas typically have lower property age, lower house prices, and higher incomes.

Future work will examine within-PUMA variation to look at a more causal relationship between demographics and development rates.

Table 2.1: Fixed Costs - Cross Section

<table>
<thead>
<tr>
<th></th>
<th>$FC_j$</th>
<th>$FC_j$</th>
<th>$FC_j$</th>
<th>$FC_j$</th>
</tr>
</thead>
<tbody>
<tr>
<td>% owner-occupied</td>
<td>598.34</td>
<td>520.52</td>
<td>549.09</td>
<td>449.96</td>
</tr>
<tr>
<td></td>
<td>[478.79]</td>
<td>[113.26]**</td>
<td>[242.49]*</td>
<td>[222.35]*</td>
</tr>
<tr>
<td>mean property age</td>
<td>669.28</td>
<td>820.76</td>
<td>864.34</td>
<td>879.76</td>
</tr>
<tr>
<td></td>
<td>[279.20]*</td>
<td>[71.20]**</td>
<td>[146.83]**</td>
<td>[136.95]**</td>
</tr>
<tr>
<td>mean income</td>
<td>-0.8</td>
<td>-0.41</td>
<td>-0.62</td>
<td>-0.47</td>
</tr>
<tr>
<td></td>
<td>[0.48]</td>
<td>[0.10]**</td>
<td>[0.24]*</td>
<td>[0.18]*</td>
</tr>
<tr>
<td>mean house value</td>
<td>0.12</td>
<td>0.08</td>
<td>0.11</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>[0.07]</td>
<td>[0.02]**</td>
<td>[0.03]**</td>
<td>[0.03]**</td>
</tr>
<tr>
<td>% white</td>
<td>220.98</td>
<td>135.21</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[195.01]</td>
<td>[95.92]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% degree</td>
<td>345.01</td>
<td>91.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[409.16]</td>
<td>[196.51]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>127,681</td>
<td>140,814</td>
<td>129,706</td>
<td>138,988</td>
</tr>
<tr>
<td></td>
<td>[34,315]**</td>
<td>[8,362]**</td>
<td>[17,887]**</td>
<td>[16,553]**</td>
</tr>
<tr>
<td>Regression</td>
<td>LAD</td>
<td>LAD</td>
<td>OLS</td>
<td>OLS</td>
</tr>
<tr>
<td>Observations</td>
<td>46</td>
<td>46</td>
<td>45</td>
<td>45</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.55</td>
<td>0.53</td>
<td>0.78</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Standard errors in brackets. * significant at 5%; ** significant at 1%

Fixed Costs - Time Series

The other dimension of fixed costs are the estimates of the time effects. The year coefficients by themselves are difficult to interpret. However, we can use the year coefficients combined with the mean PUMA effect to get an estimate of the mean $\delta_t - \beta E_t \delta_{t+1}$ for each year, where the mean is taken over the PUMAs. These results are reported in Table 2.2. The year effects suggest that fixed costs (or at least expectations about costs) are strongly pro-cyclical. For example in 1993, costs are $32,280 higher than the discounted value of the expected costs in 1994. As prices boom at the end of the sample, this reverses. In
2002, parcel owners expect costs to rise substantially – discounted expected costs for 2003 exceed 2002 costs by $36,682. 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 actually smooths construction levels in a dynamic model and helps explain the observed construction volatility levels. The role of dynamics (and in particular, the role of expectations of future costs) is discussed in greater detail in the section below.

<table>
<thead>
<tr>
<th>Year</th>
<th>$\delta_t - \beta E_t \delta_{t+1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>-$3,180</td>
</tr>
<tr>
<td>1990</td>
<td>$3,464</td>
</tr>
<tr>
<td>1991</td>
<td>$5,939</td>
</tr>
<tr>
<td>1992</td>
<td>$28,011</td>
</tr>
<tr>
<td>1993</td>
<td>$32,280</td>
</tr>
<tr>
<td>1994</td>
<td>$19,736</td>
</tr>
<tr>
<td>1995</td>
<td>$18,326</td>
</tr>
<tr>
<td>1996</td>
<td>$9,823</td>
</tr>
<tr>
<td>1997</td>
<td>-$5,482</td>
</tr>
<tr>
<td>1998</td>
<td>-$5,392</td>
</tr>
<tr>
<td>1999</td>
<td>-$11,519</td>
</tr>
<tr>
<td>2000</td>
<td>-$25,607</td>
</tr>
<tr>
<td>2001</td>
<td>-$33,452</td>
</tr>
<tr>
<td>2002</td>
<td>-$36,682</td>
</tr>
</tbody>
</table>

The year effects are estimated calculated using the mean neighborhood effect.

By making the assumption that fixed costs follow an AR(1) process and that parcel owners have rational expectations, I can back out estimates of the actual levels of fixed costs for each year. The exact procedure is outlined in the appendix. Subtracting the expectation of the error (conditional on building) from the fixed cost estimates gives an estimate of the fixed costs incurred by those who developed their parcels. This range of adjusted fixed costs over the time period is $105,980 to $217,710. Figure 2.13 plots the mean adjusted fixed cost for each year, where the mean is taken over the 46 PUMAs.

Different explanations could be offered for 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 willing to supply in a construction boom. The fixed costs capture the possibility 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 will vary across geographic areas, helping explain the cross-sectional variation in fixed costs.

Figure 2.13: Time Trend of Fixed Costs

2.7 Implications of Dynamic Behavior

With observed historical patterns of price and cost cycles and trends, it is clear that a dynamic model is necessary to understand the primitives that drive housing supply. Given the focus in the literature on prices, a naive model which ignored expectations about cost patterns would predict very large levels of construction volatility. In the extreme case where prices were perfectly predictable, discounting of future profits is low, and costs were constant, we would expect to see construction only at the peak of prices. In reality, a sizeable amount of construction occurs prior to the peak. Various explanations for this observed pattern could be offered: prices are not predictable, parcels owners heavily discount future
profits, the time to build is large, and costs are pro-cyclical. I can examine these different accounts and, using the estimates of the structural model, attribute the primary role to pro-cyclical costs.

If the time required to build was sufficiently long relative to the typical cycle of prices, it would make sense for parcel owners to begin building early in the price cycle. However, empirical evidence does not support this. According to figures from the Census of Construction, 54% of construction in the West Census Region is completed within six months and 91% is completed within twelve months. These time periods are short when compared with the length of the price cycle. The expected length of price growth is considerably longer, with prices usually only mean-reverting 5 years after a price shock.

The effects of the discount factor and price expectations are easier to rule out as they are not estimated directly in the dynamic discrete choice estimation. The discount factor, $\beta$, is set at .95, a level consistent with the literature. The transition probabilities are estimated outside of the final estimation routine and are estimated assuming parcel owners have rational expectations. The only factor estimated in the final step of estimation is the cost consideration term, $\delta_t - \beta E_t \delta_{t+1}$. Given the estimates of $\delta_t - \beta E_t \delta_{t+1}$, it is clear that without including cost considerations, the model would underpredict construction during the boom period beginning in the late 1990s. These coefficients are significantly negative in boom times, indicating that parcel owners believe that delaying construction will result in higher costs in the future. The implication of these results is that rising costs discourage parcel owners from only building at the peak and that cost trends and forward-looking behavior dampen construction volatility. Only by including the fixed cost patterns can the observed level of volatility be explained – the discount factor and prices are not enough.

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50 See Coulson (1999) for an analysis of the relationship between starts, completions, and housing inventory.

51 In the data used here, prices began to increase in the mid 1990s and continued to rise though the end of the sample period in 2004. Some areas experienced small reductions in real prices briefly in 2001.
This can be further illustrated using a counterfactual simulation. In the counterfactual simulation, I consider what would happen if parcel owners had adaptive expectations about the future cost environment. That is, $E_t \delta_{t+1} = \delta_t$. To do this, I use the estimates of $\delta_t$ obtained from the estimation along with the fixed discount factor, $\beta$, and the price transitions taken directly from the data. I then fully solve the model and predict construction in each period. I can then compare the path of the simulated construction with the actual path.\footnote{As the estimation routine effectively included time fixed effects the predicted construction trends from the true model will fit perfectly the true trends at the Bay Area level.}

![Figure 2.14: Counterfactual - Adaptive Expectations](image)

Figure 2.14 shows how the counterfactual construction levels compare with actual levels of construction. The first panel shows the number of observed and predicted residences built. The lower panel shows the observed and predicted portion of available parcels that were developed. During the downturn in the early 1990s, construction levels are actually higher with adaptive expectations. This is because in the counterfactual scenario parcel owners are not taking into account that costs are falling. However, the interesting pattern begins around 1996. This roughly corresponds to the beginning of the upturn in prices.
in the Bay Area. As prices begin to rise, so do expectations about future prices in both scenarios. However, in the counterfactual scenario, parcel owners do not take into account that costs will also rise in the future. Without the cost deterrent to waiting for a price peak, construction falls as owners delay construction waiting for the peak. Unfortunately for illustrative purposes, the time horizon of the data does not include a peak following this rapid price appreciation. However, if it did, we would expect to see construction in the counterfactual simulation to shoot up around the peak as there is a build-up of parcel owners who delayed construction in anticipation of such a peak. In contrast construction levels in the observed data increase gradually as prices increase. The construction early in the price boom is caused by the expectations of future cost increases.

This counterfactual experiment highlights the role of costs and cost expectations in dampening construction volatility. When parcel owners are only forward looking with respect to prices they will try and delay construction until a price peak. In reality, however, expectations about future cost increases flatten out the time profile of construction.

2.8 Conclusion

The importance of the housing market has been well-documented, but the literature on housing supply is surprisingly small. Short-run volatility in both price and construction levels has large welfare implications – in the case of prices, because of their effect on a typical household’s asset portfolio and, in the case of construction, because of its employment effects. Understanding the way that economic primitives influence the 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 parcel owners’ development decisions. By combing the static 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. By using a multi-step estimator, I incorporate a
large descriptive state space and estimate prices and variable costs at the Census tract level. Additionally, the estimation routine allows for time-varying parameters. Prices and variable costs are not sufficient for understanding the parcel owner’s decision process and therefore fixed costs (which capture the overall cost environment) are estimated.

The price results suggest that changes in housing prices are driven by changes in the value of the right-to-build. Cost results indicate that both variable costs and fixed costs are strongly pro-cyclical. There is also substantial variation in the fixed costs of building across neighborhoods, with high home ownership rates predicting higher costs. Forward-looking behavior is found to be very important in trying to understand construction volatility. Parcel owners look to the future about both prices and costs when deciding when to build. Using the fact that prices are partially predictable, this paper structurally incorporates these expectations into a model of supply. The literature on cost trends is more sparse. Here, the results suggest that trends in the overall cost environment are pro-cyclical and that forward looking dynamic behavior, with regard to these costs, is crucial in understanding and explaining observed construction patterns.
Chapter 3

A Dynamic Model of Neighborhood and Housing Demand

3.1 Introduction

The purchase of a primary residence is simultaneously the largest single consumption decision and largest single investment of the vast majority of US households; the typical household spends about 23 percent of its income on its house and its house constitutes two-thirds of its portfolio.\(^1\) As a result, the housing market not only constitutes an important sector of the economy but also blends the features of consumption and financial markets in unique and interesting ways.

Relative to simpler consumption decisions, the home-buying decision is complicated by the sheer amount of money involved in the transaction and the associated transaction costs. The latter ensure that this decision is very costly to adjust and, as a result, that dynamic considerations including the expected performance of the house as an asset and expected evolution of the property and neighborhood have an important role in the decision. These dynamic considerations add to the complexity of the static decision, which already folds a number of important dimensions of consumption (e.g., housing characteristics, commuting time, local schools, crime, and other neighborhood amenities) into a single decision.

As opposed to many standard financial instruments, the existence of large transaction costs, the predominance of owner-occupancy in large segments of the market, and the inherent difficulty of holding short positions limit the ability of professionals to eliminate pricing inefficiencies in the housing market. As a result, housing prices exhibit time-series

\(^1\)According to the American Household Survey in 2005, the national median percentage of income spent on housing was 23 percent. Tracy, Schneider, and Chan (1999) report the portfolio share figure.
properties at both high and low frequencies that are inconsistent with the standard implications of the efficient market hypothesis. In particular, previous research has consistently documented that prices exhibit positive persistence (inertia) in the short-run (annually) and mean reversion in the longer run (five years).  

Because professionals cannot eliminate the predictability of future prices, it is well understood that this predictability alone does not imply that the economic agents operating in the housing market are irrational. In fact, whether individual agents act with rational expectations remains very much an open question. This question is at the heart of the contentious debate over whether the recent upsurge in housing prices in many US metropolitan areas is a bubble fueled by unrealistic expectations or perfectly understandable in terms of the fundamentals.

In this paper, we develop an estimable model of the dynamic decision-making of individual home-owners with the aim of using the model to provide new insight into the microfoundations of housing market dynamics. In so doing, we seek to make explicit the link between the microeconomic primitives of the housing market (i.e., the factors governing individual buying and selling decisions) and the aggregate market dynamics characterized in the existing literature.

The starting point for our analysis is a unique dataset linking information about buyers and sellers to the complete census of housing transactions in the San Francisco metropolitan

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3For examples of research that argue that recent price increases are not driven by bubbles, see McCarthy and Peach (2004), and Himmelberg, Mayer and Sinai (2005). For a contrasting view, see Shiller (2005, 2006) and Baker (2006). Case, Shiller and Quigley have done some direct surveys about expectations. Researchers have been able to test some implications of market efficiency. See, for example, Rosenthal (1999). At some level, it may also be worth noting that the predictability of housing prices is not a very well known thing. Also note that Glaeser and Gyourko (2006) have a hard time fitting high frequency price volatility with their calibrated model.
area for a period of 15 years (1.5 million transactions in all). In addition to demographic and
economic information about buyers and sellers, this dataset contains information about the
structure and lot (e.g., square footage, year built, lot size), transaction price, attributes of
the mortgage, exact location, exact sales date, and a unique house ID that identifies repeat
sales of the same property. In most cases, it is also possible to link sellers of one property to
their newly purchased properties, provided they move within the same metropolitan area.
By linking information about buyers and sellers to houses at a fine level of granularity
in terms of both space and time, this dataset has significant advantages over the large-
scale datasets that have been used in previous research to characterize housing market and
neighborhood dynamics.

With this dataset in hand, we develop a tractable model of neighborhood choice in a
dynamic setting, along with a corresponding estimation approach that is computationally
straightforward. This approach, which combines and extends the insights of Rust (1987),
Berry (1994), and Hotz and Miller (1993), allows the observed and unobserved features of
each neighborhood to evolve in a completely flexible way and uses information on neigh-
borhood choice and the timing of moves to recover semi-parametrically: (i) preferences
for housing and neighborhood attributes, (ii) preferences regarding the performance of the
house as a financial asset (e.g., expected appreciation, volatility), and (iii) moving costs.
In order to accommodate a number of important features of housing market, this approach
extends methods developed in the recent literature on the dynamic demand for durable
goods in a number of key ways.4

The model and estimation method that we propose are potentially applicable to the
study of a wide set of dynamic phenomena in housing markets and cities. These include,
for example, the analysis of the microdynamics of residential segregation and gentrification

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4We discuss this literature in more detail in Section 2.
within metropolitan areas. More generally, the model and estimation approach can be extended straightforwardly to study the dynamics of housing and labor markets in a system of cities. A number of important lines of research within labor and urban economics draw intuitively on what would be a dynamic Roback (1982) framework and, yet, to our knowledge, there has been no attempt to estimate such a model directly. In this way, an important goal of this paper is to provide a coherent and computationally feasible basis for the analysis of the dynamics of housing and labor markets from a microeconomics perspective.

The remainder of the paper proceeds as follows. Section 3.2 briefly summarizes how our estimator relates to recent literature on dynamic demand for durable goods. Section 3.3 describes the dataset we develop. Our model and estimation strategy are presented in Sections 3.4 and 3.5, respectively.

3.2 Related Literature on Dynamic Demand

The model and estimation approach developed in this paper are related to a recent literature on the dynamic demand for durable goods. Much of this literature has focused on extending Berry, Levinsohn, and Pakes (1995) (BLP) style models to allow for forward looking behavior, while retaining the controls for unobserved product characteristics. Melnikov (2001) develops a tractable model without individual heterogeneity to estimate the demand for printers. Agents make two decisions: they decide what period (if any) to buy

---

5Recent theoretical research on aspects of the dynamic microfoundations of housing markets by Ortalo-Magne and Rady (2002, 2005, 2006) and Bajari, Benkard, and Krainer (2005) raise a number of additional interesting empirical questions that could be addressed using this framework.

6There a number of interesting spects of labor and housing market dynamics across cities at both high and low frequencies. Gyourko, Mayer, and Sinai (2004), for example, focus on low frequency dynamics of migration and housing prices across US cities. Glaeser and Gyourko (2006) calibrate a dynamic Rosen model and use it to explore both high and low frequency dynamics of the housing market. A long literature in labor economics following Blanchard and Katz (1992) explores both high and low frequency labor market dynamics and migration across cities and regions. Ultimately, all of these important dynamic features of housing and labor markets should be able to be viewed through the lens of a single dynamic Rosen framework.
a printer and then which brand to buy conditional on buying a printer. All the dynamic behavior lies in the timing of purchase and the brand choice is a static discrete choice. Carranza (2007) looks at the digital camera market and extends the Melnikov (2001) model to allow for random coefficients and captures the dynamic decision using a reduced form specification. By allowing consumers to make repeat purchases, Gowrisankaran and Rysman (2007) allow both the timing and product choices to be determined dynamically. They estimate the model by nesting a Rust (1987) style optimal stopping problem inside of the BLP style product choice model. Schiraldi (2007) extends the Gowrisankaran and Rysman (2007) model to include secondary markets and transaction costs.

Erdem, Imai, and Keane (2003) estimate a structural model of the demand for goods that are frequently purchased, branded, storable, and subject to frequent price fluctuations or promotions. They control for the effects of inventory build up and expectations about future price changes. The model, while computationally demanding, allows for individual heterogeneity. Using the market for laundry detergent, Hendel and Nevo (2006) estimate a similar model. They structure the model such that they can separate the brand choice and quantity choice. The quantity choice incorporates forward looking behavior and the brand choice is static. This separation of choices leads to computational simplifications, however, the model can not allow for individual heterogeneity.

A common issue in dynamic discrete choice models is the direct link between the size of the choice set and the size of the state space. Standard estimation approaches such as Rust (1987) quickly become infeasible with a large choice set. Melnikov (2001) proposed a potential solution to this problem where the logit inclusive value is treated as a sufficient statistic for predicting future continuation values. Tractability is maintained as the state space is reduced to one dimension by this assumption at a cost of a loss of information. Similar assumptions are made in Carranza (2007), Hendel and Nevo (2006), Gowrisankaran and Rysman (2007), and Schiraldi (2007).
Our model, which is based on individual level data, incorporates unobserved choice characteristics, endogenous wealth accumulation, and heterogeneous households. The static demand models of Berry (1994), and Berry, Levinsohn, and Pakes (1995) (BLP) introduced a framework for controlling for unobserved product characteristics while highlighting the importance of trying to capture individual heterogeneity. Given individual data, we capture heterogeneity by allowing individuals to value neighborhood attributes differently based on their observable characteristics. In addition to specifying a dynamic model, we also differ from BLP by allowing heterogeneity in the valuation of unobserved neighborhood characteristics.

Our approach differs from these models as it does not require the reduction of the state space to a univariate statistic. We can avoid the inclusive value sufficiency assumption as the computational burden our estimator is not affected by the size of the state space. We build upon the literature by estimating a semiparametric model with a computationally very straightforward approach. Given the low computational burden of our estimator we place no restrictions on the size of state space or the size of choice set. We also allow heterogeneity in valuation of both observed and unobserved neighborhood characteristics. Finally, we treat the object of choice (housing) as an asset and, as such, the wealth of households changes endogenously.

3.3 Data

In this section, we briefly describe the new dataset that we have assembled by merging information about buyers and sellers with the universe of housing transactions in the San Francisco metropolitan areas. We provide more details on the source data and demonstrate that the merge results in a high quality and representative dataset based on multiple diagnostic tests.

The dataset that we develop is drawn from two main sources. The first comes from a national real estate data company and provides information on every housing unit sold
in the core counties of the Bay Area (San Francisco, Marin, San Mateo, Alameda, Contra Costa, and Santa Clara) between 1990 and 2004. The buyers’ and sellers’ names are provided along with transaction price, exact street address, square footage, year built, lot size, number of rooms, number of bathrooms, number of units in building, and many other housing characteristics. Overall, the housing characteristics are considerably better than the those that are provided in Census microdata. A key feature of this transaction dataset is that it also includes information about the buyer’s mortgage including the loan amount and lender’s name for all loans. It is this mortgage information which allows us to link information about buyers (and many sellers) to this transaction dataset.

The source of the economic and demographic information about buyers (and sellers) is the dataset on mortgage applications published in accordance with the Home Mortgage Disclosure Act (HMDA), which was enacted by Congress in 1975 and is implemented by the Federal Reserve Board’s Regulation C. The HMDA data provides information on the race, income, and gender of the buyer/applicant as well as mortgage loan amount, mortgage lender’s name, and the census tract where the property is located. Thus, we are able to merge the two datasets on the basis of the following variables: census tract, loan amount, date, and lender name. Using this procedure, we obtain a unique match for approximately 70% of sales. Because the original transactions dataset includes the full names of buyers and sellers, we are also able to merge demographic and economic information about sellers into the dataset provided (i) a seller bought another house within the metro area and (ii) a unique match with HMDA was obtained for that house. This procedure allows us to merge information about sellers in for approximately 35-40 percent of our sample.

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7 The act requires lending institutions to report public loan data. The purpose of the act is to provide public loan data that can be used to determine whether financial institutions are serving the housing needs of their communities and whether public officials are distributing public-sector investments so as to attract private investment to areas where it is needed. Another purpose is to identify any possible discriminatory lending patterns. (see http://www.ffiec.gov/hmda for more details).
To ensure that our matching procedure is valid we conduct two diagnostic tests. Using public access Census micro data from IPUMS, we calculate the distributions of income and race of those who purchased a house in 1999 in each of the six Bay Area counties. We compare these distributions to the distributions in our merged dataset in Table 3.1. As can be seen, the numbers match almost perfectly in each of the six counties suggesting that the matched buyers are representative of all new buyers.

**Table 3.1**: Comparison of Sample Statistics for Transactions Data/HMDA and IPUMS

<table>
<thead>
<tr>
<th></th>
<th>ALAM</th>
<th>C.C.</th>
<th>MARIN</th>
<th>S.F.</th>
<th>S.M.</th>
<th>S.C.</th>
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</thead>
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<tr>
<td><strong>HMDA / Transactions Data</strong></td>
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<td></td>
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<td>Median Income</td>
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<td>121000</td>
<td>103000</td>
<td>108000</td>
<td>101000</td>
</tr>
<tr>
<td>Mean Income</td>
<td>98977</td>
<td>99141</td>
<td>166220</td>
<td>147019</td>
<td>137777</td>
<td>123138</td>
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<tr>
<td>Std Dev Income</td>
<td>96319</td>
<td>97928</td>
<td>176660</td>
<td>225646</td>
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<td>125138</td>
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<tr>
<td><strong>IPUMS</strong></td>
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<tr>
<td>Median Income</td>
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<td>76785</td>
<td>120000</td>
<td>100000</td>
<td>102400</td>
<td>100000</td>
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<td>Mean Income</td>
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<td>Std Dev Income</td>
<td>84823</td>
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<td>123451</td>
<td>99373</td>
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<table>
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<th>MARIN</th>
<th>S.F.</th>
<th>S.M.</th>
<th>S.C.</th>
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<tr>
<td>% White</td>
<td>49.85</td>
<td>68.27</td>
<td>90.65</td>
<td>59.12</td>
<td>60.08</td>
<td>49.07</td>
</tr>
<tr>
<td>% Asian</td>
<td>28.68</td>
<td>10.55</td>
<td>4.68</td>
<td>31.47</td>
<td>26.57</td>
<td>34.21</td>
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<tr>
<td>% Black</td>
<td>6.45</td>
<td>6.01</td>
<td>0.67</td>
<td>2.08</td>
<td>1.22</td>
<td>1.45</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>11.76</td>
<td>12.38</td>
<td>2.51</td>
<td>5.86</td>
<td>9.90</td>
<td>12.27</td>
</tr>
<tr>
<td><strong>IPUMS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% White</td>
<td>47.64</td>
<td>64.57</td>
<td>87.5</td>
<td>61.92</td>
<td>58.1</td>
<td>50</td>
</tr>
<tr>
<td>% Asian</td>
<td>27.34</td>
<td>11.37</td>
<td>3.3</td>
<td>23.37</td>
<td>25.41</td>
<td>33.51</td>
</tr>
<tr>
<td>% Black</td>
<td>7.77</td>
<td>6.05</td>
<td>2.3</td>
<td>2.8</td>
<td>1.24</td>
<td>1.16</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>14.62</td>
<td>14.2</td>
<td>3.62</td>
<td>8.18</td>
<td>12.5</td>
<td>12.09</td>
</tr>
</tbody>
</table>

A comparison of Tables 3.2 and 3.3 provides a second diagnostic check on the representativeness of the merged dataset in terms of housing characteristics. Table 3.2 provides sample statistics for a subset of the house level variables taken from the original dataset.
that includes the complete universe of transaction, while Table 3.3 presents sample statistics for the merged dataset. Both tables report variables in 2000 dollars. A comparison of the two tables suggests that the set of houses for which we have a unique loan record from HMDA are very representative of the complete sample of houses. The mean price for the houses in the matched sample is a little higher and the other means are very similar. Overall, our two diagnostic checks provide strong evidence in support the validity of our matching algorithm.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sale Price</td>
<td>1045920</td>
<td>354915</td>
<td>220886</td>
<td>16500</td>
<td>1521333</td>
</tr>
<tr>
<td>Lot Size</td>
<td>1045920</td>
<td>6857</td>
<td>11197</td>
<td>0</td>
<td>199940</td>
</tr>
<tr>
<td>Square Footage</td>
<td>1045920</td>
<td>1647</td>
<td>714</td>
<td>400</td>
<td>10000</td>
</tr>
<tr>
<td>Number Bedrooms</td>
<td>1045920</td>
<td>2.98</td>
<td>1.10</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Number Rooms</td>
<td>1045920</td>
<td>6.73</td>
<td>2.00</td>
<td>1</td>
<td>18</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Applicant Income</td>
<td>804699</td>
<td>114368</td>
<td>114212</td>
<td>0</td>
<td>10800000</td>
</tr>
<tr>
<td>First Loan Amount</td>
<td>804699</td>
<td>285257</td>
<td>143611</td>
<td>1181</td>
<td>2463707</td>
</tr>
<tr>
<td>White</td>
<td>804699</td>
<td>0.53</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Asian</td>
<td>804699</td>
<td>0.23</td>
<td>0.42</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Black</td>
<td>804699</td>
<td>0.03</td>
<td>0.18</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Hispanic</td>
<td>804699</td>
<td>0.11</td>
<td>0.32</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Applicant Gender</td>
<td>804699</td>
<td>0.22</td>
<td>0.41</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Co-Applicant</td>
<td>804699</td>
<td>0.67</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Finally, we close this brief data section by providing the reader with a sense of the
variation in the evolution of prices across regions of the Bay Area. The precision of the estimation of the dynamic aspects of the model of neighborhood choice developed below likely depends critically on the fact that rates of house price appreciation are not uniform across census tracts. Figure 3.1 reports price levels by county from 1990 to 2004. 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 county-year fixed effects as well as house fixed effects. The values on the vertical axis indicate the real price level of house prices (in percentage terms) relative to 1990 - 1990 price levels are normalized to one for all counties. The figure reveals that by 1995, house prices reached their lowest point in Santa Clara county at 20 percent lower than 1990 levels. In contrast, other counties, such as Contra Costa, experienced larger price depreciation up to 1997 but faster appreciation from 1997 to 2004. Overall, house prices were nearly twice as high (in real terms) in 2004 as they were in the mid 1990s.

3.4 A Dynamic Model of Neighborhood Choice

The previous literature that has explored the sorting of households across neighborhoods and communities has universally adopted a static approach.\(^8\) We introduce the dynamics of the neighborhood choice problem through three channels: wealth accumulation, neighborhood dynamics, and moving costs. Households have expectations about appreciation of housing prices and may choose a neighborhood that offers lower per-period utility in the current period in return for the increase in wealth that would accompany price increases in that neighborhood. Similarly, households likely make trade-offs between current and future neighborhood attributes, choosing neighborhoods based in part on demographic or economic trends. The final component of the neighborhood choice problem that induces

forward looking behavior on the part of households are moving costs. Because households typically pay 5-6 percent of the value of their house in real estate agent fees in addition to the non-financial costs of moving, it is clearly prohibitively costly to re-optimize every period. As a result, households will naturally account for their expectations of the future utility streams when deciding where to live.

We model households as making a sequence of location decisions that maximize the discounted sum of expected per-period utilities. Our general model can be formulated in a familiar dynamic programming setup, where a Bellman equation illustrates the determinants of the optimal choice. We model households as choosing between neighborhoods, where a neighborhood is defined as a U.S. Census tract. Census tracts are small areas with
approximately 1,500 housing units that are designed to be homogenous in terms of demographic characteristics.\footnote{See the Geographic Areas Reference Manual of the U.S. Census Bureau for more information.} Our data for the San Francisco Bay Area includes information on over one million house sales in approximately 800 census tracts between 1990 and 2004. Each period each household chooses whether to move or not. If they move, they incur a moving cost and then choose the neighborhood which yields the highest expected lifetime utility.

A key feature of our approach is that it controls for unobserved neighborhood heterogeneity in a dynamic model using a semi-parametric estimator that is computationally tractable. In addition, we have a novel way to capture the marginal utility of wealth that circumvents the traditional problem of the endogeneity of housing prices - thus avoiding the need to instrument for price. The model, as outlined below, temporarily abstracts from some important issues such as the decision whether to rent or to own as well as migration decisions. These are important features that will certainly be introduced into the model.

The observed state variables at time $t$ are $X_{jt}$, $Z_{it}$, and $H_{it}$. $X_{jt}$ is a vector of characteristics of the different choice options that affect the utility a household may receive from choosing neighborhood $j \in \{1, \ldots, J\}$. $Z_{it}$ is a vector of characteristics of each household that potentially determine the per period utility from living in a particular neighborhood, as well as the costs associated with moving. For example, $X$ may include variables such as price of housing, quality of local schools, or the average education level in the tract, and $Z$ may include such variables as income, wealth, or race. Let $H_{it}$ be another observable variable denoting the choice made in the previous period, i.e., $H_{it} = d_{it-1}$, where the decision variable, $d_{it}$, denotes the choice of household $i$ in period $t$. Therefore, in the context of our model, $H_{it}$ is the neighborhood in which household $i$ resides before making a decision in period $t$.

In addition to the decision variable, $d$, and the observable variables, $X_{jt}$, $Z_{it}$, and
H_{it}, there are three unobservable variables, \( \xi, \epsilon_{ijt}, \) and \( \zeta_{it} \). We include and control for unobserved neighborhood characteristics, \( \xi \).\(^{10} \) \( \epsilon_{ijt} \) is an idiosyncratic stochastic variable that determines the utility a household receives from living in neighborhood \( j \) and \( \zeta_{it} \) affects moving costs. Note that we assume for simplicity that \( \zeta_{it} \) is the same for all \( j \). The decision variable, \( d_{it} \), is given by the function \( d_{it} = d(\cdot) \) where the arguments of \( d(\cdot) \) are discussed below. For notational convenience, let \( W_{ijt} = [X_{jt}, \xi_{jt}, Z_{it}] \), and let \( \Omega_{it} \) denote an information set which includes all current characteristics, \( \{W_{ijt}\}_{j=1}^{T} \) and anything that helps predict future characteristics.

The primitives of the model are \((\tilde{u}, p, \beta)\). \( \tilde{u} = \tilde{u}(W_{ijt}, H_{it}, \zeta_{it}, \epsilon_{ijt}) \) is the per period utility function, where the tilde denotes that this flow utility includes moving costs if applicable. \( p = p(\Omega_{it+1}, H_{it+1}, \zeta_{it+1}, \epsilon_{it+1}, |\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}, j_{it}) \) denotes the transition probabilities of the observables and unobservables. The transition probabilities are assumed to be Markovian. \( \beta \) is the discount factor.

Each household is assumed to behave optimally in the sense that its actions are taken to maximize lifetime expected utility. \( d^{*} \) is the optimal decision rule and under the Markov structure of the problem is only a function of the state variables. That is, \( d_{it} = d^{*}_{it}(\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}) \). When the sequence of decisions, \( \{d_{i}\} \), is determined according to the optimal decision rule, \( d^{*} \), lifetime expected utility becomes the value function.

\[
V_{t} = \max_{j} \{E \sum_{s=t}^{T} \beta^{s}(\tilde{u}(W_{ij, s}, H_{is}, \zeta_{is}, \epsilon_{is})) |\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}, d_{it} = j \} \tag{3.1}
\]

We can break out the lifetime sum into the flow utility at time \( t \) and the expected sum of flow utilities from time \( t + 1 \) onwards. This allows us to use the Bellman equation to express the value function at time \( t \) as the maximum of the sum of flow utility at time \( t \)

---

\(^{10}\)We differ from previous work, such as Berry, Levinsohn, and Pakes (1995), that forces all individuals to have the same preferences for the unobserved neighborhood characteristic by allowing individuals to value the unobserved neighborhood characteristic differently depending on their demographic characteristics.
and the discounted value function at time $t + 1$.

$$V_t(\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}) = \max_j \{\tilde{u}(W_{ijt}, H_{it}, \zeta_{it}, \epsilon_{it}) + E\beta V_{t+1}(\cdot | \Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}, d_{it} = j)\} \quad (3.2)$$

We assume that the problem has an infinite horizon, $T = \infty$, which induces stationarity. By stationary, we mean $V_t(\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}) = \tilde{V}(\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it})$ and $d_{it}(\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it}) = d(\Omega_{it}, H_{it}, \zeta_{it}, \epsilon_{it})$. Under the assumptions of an infinite horizon and Markovian transition probabilities, we can rewrite the Bellman equation as:

$$V(\Omega_i, H_i, \zeta_i, \epsilon_i) = \max_j \{\tilde{u}(W_{ij}, H_i, \zeta_i, \epsilon_i) + \beta \int V'(\cdot | \Omega'_t, H'_t, d'_t \mid \Omega_i, H_i, \zeta_i, \epsilon_i, d_i = j)\} \quad (3.3)$$

Under certain technical assumptions, equation (3.3) is a contraction mapping in $V$. However, the difficulty is that $V$ is a function of both the observed and unobserved state variables. Therefore, we follow Rust (1987) and make a series of assumptions which simplify the model. We make the assumptions that the flow utility is separable in the idiosyncratic error term and that this error term is distributed i.i.d. over time and options.

This allows us to recursively define the value function, $V(\Omega_i, H_i, \zeta_i, \epsilon_i)$, and the choice specific value function, $\tilde{v}_j(\Omega_i, H_i, \zeta_i)$.

$$V(\Omega_i, H_i, \zeta_i, \epsilon_i) = \max_j [\tilde{v}_j(\Omega_i, H_i, \zeta_i) + \epsilon_{ij}] \quad (3.4)$$

$$\tilde{v}_j(\Omega_i, H_i, \zeta_i) = \tilde{u}(W_{ij}, H_i, \zeta_i) + \beta \int G(\cdot) \pi(d_{ij}|\Omega'_t, H'_t, \zeta'_i, \epsilon'_i | \Omega_i, H_i, \zeta_i, d_i = j) \quad (3.5)$$

where $G(\cdot) = \int V(\Omega'_t, H_i, \zeta'_i, \epsilon'_i) q(d\epsilon'_i) = \int \max_k [\tilde{v}_k(\Omega'_t, H'_i, \zeta'_i) + \epsilon'_{ik}] q(d\epsilon'_i)$

We break out the choice specific value function into two terms. The first term capturing the lifetime expected utility of choosing neighborhood $j$ ignoring moving costs and the second term involves moving costs. The second term capturing the difference between the lifetime expected utility of choosing neighborhood $j$ when the previous choice was $j$ and when the previous choice was not $j$. In order to do this, we modify Rust’s two assumptions.
Assumption (AS'): Additive Separability. We assume that the per period utility function can be broken out into two components: the flow utility from living in neighborhood $j$ and a term that the household pays only if they move in that period. Therefore we can express $\tilde{u}(W_{ij}, H_i, \zeta_i) + \epsilon_{ij}$ as:

$$\tilde{u}(W_{ij}, H_i, \zeta_i) + \epsilon_{ij} = u(W_{ij}) - TC(Z_i, H_i, \zeta_i) \cdot I_{[j \neq H_i]} + \epsilon_{ij}$$  \hspace{1cm} (3.6)

Assumption (CI'): Conditional Independence. We assume that the transition density for the Markov process $\{W, \epsilon, H, \zeta\}$ is given by:

$$p(d\Omega_{t+1}, d\epsilon_{t+1}, dH, d\zeta_{t+1}|W_t, \epsilon_t, \zeta_t, j_t) = q_{\epsilon}(d\epsilon_{t+1})q_{\zeta}(d\zeta_{t+1})q_H(dH_{t+1}|j_t)\pi(d\Omega_{t+1}|W_t, j_t)$$  \hspace{1cm} (3.7)

Then it can be shown that with the exception of $Z$, the choice specific value function is separable in the variables that affect moving costs and those that affect the non-moving cost portion of per-period utility. Similarly to the flow utility, the tilde indicates that the choice specific value function incorporates possible moving costs.

$$\tilde{v}_j(\Omega_i, H_i, \zeta_i) = v_j(\Omega_i) - TC(Z_i, H_i, \zeta_i) \cdot I_{[j \neq H_i]} \hspace{1cm} (3.8)$$

### 3.5 Estimation

The estimation of the primitives of the model proceeds in three stages. In the first stage, we recover the non-moving cost component of lifetime expected utility. In the second stage, we recover moving costs and the marginal utility of wealth. While a number of standard options for estimating the marginal utility of wealth are available, we propose recovering the marginal utility of wealth by utilizing outside information on the financial costs of moves. Having recovered moving costs and the marginal utility of wealth in the second stage, we estimate fully flexible estimates of the per-period utility in a final stage. With estimates of the per-period utility function it is straightforward to implement any of the applications discussed below. A key feature of our estimation strategy is its low computational burden.
3.5.1 Estimation - Stage One - Choice Specific Value Function

Consider the problem faced by a household that has chosen to move. It will choose the neighborhood \( j \neq H \) which offers the highest utility by maximizing over the choice specific value functions \( \tilde{v} \). Conditional on moving, the moving cost term, \( TC(Z_i, H_i, \zeta_i) \cdot I_{[j \neq H]} \), is identical for all neighborhoods. As an additive constant, it simply drops out and, conditional on moving, each household chooses \( j \) to maximize:

\[
v_j(\Omega_i) + \epsilon_{ij} = u(W_{ij}) + \beta \int \int \int G(\cdot)q(\zeta')q_H(dH', |j)\pi(dW', |W, j) + \epsilon_{ij}
\] (3.9)

Under certain technical assumptions discussed in Rust 1994, we can show (3.9) is a contraction mapping with a unique fixed point \( v \). Assuming that the idiosyncratic error term, \( \epsilon_{ij} \), is distributed i.i.d., Type 1 Extreme Value allows us to recover \( v_j(\Omega_i) \) in a number of ways.

Previous methods for estimating dynamic discrete choice models in the presence of a large choice set will be plagued by a curse of dimensionality. We employ a variant of Hotz and Miller (1993) based on the contraction mapping in Berry (1994) which avoids this problem. Specifically, based on household characteristics such as income, wealth, and race, we divide households into distinct types indexed by \( \tau \). Let \( \theta_{jt}^\tau = v_j(\Omega_i) \) when the characteristics of the household, \( Z_i \), imply that they are of type \( \tau \). \( \theta_{jt}^\tau \) is then the choice specific value a household of type \( \tau \) receives from choosing neighborhood \( j \). Letting \( \delta_{jt}^\tau \) denote the deterministic component of flow utility for a household of type \( \tau \), we can rewrite (3.9) using lifetime utilities, \( \theta_{jt}^\tau \).

\[
\theta_{jt}^\tau = \delta_{jt}^\tau + \beta \int \log \left( \exp(\theta_{jt+1}^\tau) + \sum_{k \neq j} \exp(\theta_{kt+1}^\tau - TC^\tau - \zeta_i) \right) q(d\zeta') p(d\theta_{t+1}^\tau|\theta_t)p(d\tau|\tau, j)
\] (3.10)

Household \( i \) of type \( \tau \) chooses neighborhood \( j \) if \( \theta_j^\tau + \epsilon_{ij} > \theta_k^\tau + \epsilon_{ik} \forall k \neq j \). Therefore, the probability of any household of type \( \tau \) choosing neighborhood \( j \) when \( \epsilon_{ij} \) is distributed
i.i.d., Type 1 Extreme Value can be expressed as:

$$P^\tau_j = \frac{e^{\theta^\tau_j}}{\sum_{k=1}^{J} e^{\theta^\tau_k}}$$  (3.11)

The vector of mean utilities, $\theta^\tau$, is unique up to an additive constant thus requiring some normalization for each $\tau$. We temporarily normalize the mean (over neighborhoods) of the fixed effects to zero for each type in each time period. Denoting the number of types as $M$ implies that we make $M$ normalizations. Therefore, instead of recovering $\theta^\tau_j$ for every neighborhood and type, we recover $\tilde{\theta}^\tau_j$ where $\tilde{\theta}^\tau_j = \theta^\tau_j - m^\tau$ and $m^\tau = 1/J \sum_j \theta^\tau_j$. Let $S^\tau_j$ and $S^\tau_j(\theta^\tau)$ denote the observed and predicted portion of households of type $\tau$ who reside in neighborhood $j$. $S^\tau_j(\theta^\tau)$ is given by $P^\tau_j$. We can then easily calculate $\tilde{\theta}^\tau_j$ as:

$$\tilde{\theta}^\tau_j = \log(S^\tau_j) - 1/J \sum_k \log(S^\tau_k)$$  (3.12)

As the number of types, $M$, grows large relative to the sample size, we may face some small sample issues with observed shares. Therefore, instead of simply calculating observed shares as the portion of households of a given type who live in an area, we use a weighted measure to avoid zero shares. We do this to incorporate the information from those of a similar types when calculating shares for any given type. For example, if we want to calculate the share of households with an income of $50,000 choosing neighborhood $j$, we would use some information about the residential decisions of those earning $45,000 or $55,000. Naturally, the weights will depend on how far away the other types are in type space. We denote the weights by $W^\tau(Z_i)$. The formula for calculating observed shares is given by:\footnote{If $W^\tau(Z_i) = I_{[Z_i = Z^\tau]}$, this results in the standard way for calculating shares.}

$$S^\tau_j = \frac{\sum_{i=1}^N I_{[d_i = j]} \cdot W^\tau(Z_i)}{\sum_{i=1}^N W^\tau(Z_i)}$$  (3.13)
where the weights are constructed as the product of $K$ kernel weights, where $K$ is the dimension of $Z$. Each individual kernel weight is formed using a standard normal kernel, $N$, and bandwidth, $h_k$.

$$W^\tau(Z_i) = \prod_{k=1}^{K} \frac{1}{h_k} N\left(\frac{Z_i - Z^\tau}{h_k}\right)$$  \hspace{1cm} (3.14)

### 3.5.2 Estimation - Stage Two - Moving Costs and the Marginal Utility of Wealth

Households behave dynamically by taking into account the effect their current decision has on future utility flows. In our model, the current decision affects future utility flows through two channels. Households are aware they will incur a transaction cost by re-optimizing in the future. In addition, the decision about where to live today affects wealth in the future. Equation (3.10) shows how the current action impacts both today’s flow utility and the future utility. It also suggests that if $\theta^\tau_{jt}$ (or $\tilde{\theta}^\tau_{jt}$) is known for all $\tau$ and $j$, we can estimate moving costs based on households decisions to move or stay in a given period.

Given estimates of $\tilde{\theta}^\tau_{jt}$ from the first stage, we can estimate moving costs in stage two by considering the move/stay decisions of households. From the model outlined above, we know that in any given period a household will move if the lifetime expected utility of staying in their current neighborhood is less than the lifetime expected utility of the best other alternative when moving costs are factored in.

We assume that moving costs, $TC$, are composed of financial costs, $F(H)$ and psychological costs, $\psi(Z_i) + \zeta_i$. The financial moving costs are a function of $H$ as households pay financial costs based primarily on the property the sell. The psychological costs are a function of the observable characteristics that define type, $Z$, as well as the unobserved stochastic component, $\zeta_i$. As the financial moving costs reduce wealth, choosing to move changes a households type. For example, if moving costs are $10,000, then a given household with $100,000 in wealth chooses where to live based on the utility of staying in their current
neighborhood with wealth of $100,000 and the highest alternative utility with a wealth of $90,000. In practice, we treat financial moving costs as observable and set them equal to 6% of the value of housing in the neighborhood a household is leaving, i.e. $F(H) = 0.06 \cdot \text{Price}_{H_i}$.

If a household of type $\tau$ living in neighborhood $j$ moves, we denote their new type as $\bar{\tau}_j$. The new type following a move reflects the reduction in wealth by the amount of $F(H)$.

A household who chose $j$ in the previous period, i.e. $H_i = j$, will choose to stay if:

$$\max_{k \neq j} [\tilde{\theta}_{j}^{\tau} + \epsilon_{ik}] - (\psi(Z_i) + \zeta_i) < \tilde{\theta}_{j}^{\tau} + \epsilon_{ij}$$ (3.15)

However, from the first stage we only recover the demeaned choice specific value functions, $\tilde{\theta}_{j}^{\tau}$, where $\tilde{\theta}_{j}^{\tau} = \theta_{j}^{\tau} - m_{\tau}$. We can then rewrite (3.15) as:

$$\max_{k \neq j} [\tilde{\theta}_{k}^{\tau} + \epsilon_{ik}] - (m_{\tau} - m_{\bar{\tau}_j}) - (\psi(Z_i) + \zeta_i) < \tilde{\theta}_{j}^{\tau} + \epsilon_{ij}$$ (3.16)

The term $m_{\tau} - m_{\bar{\tau}_j}$ is unobserved but can be estimated. In principle, we could estimate a separate term for each combination of $\tau$ and $F(H)$, however, we choose to flexibly parameterize it as a function of $Z$ and $F(H_i)$. Recall that $m_{\tau} = 1/J \sum_j \theta_{j}^{\tau}$ and, as such, $m_{\tau} - m_{\bar{\tau}_j}$ is the difference (averaged across neighborhoods) between having the utility associated with being type $\tau$ and the having the utility from the reduced wealth after paying the financial moving costs.

Note that the three stochastic terms are $\max_{k \neq j} [\tilde{\theta}_{k}^{\tau} + \epsilon_{ik}]$, $\epsilon_{ij}$, and $\zeta_i$. We estimate $m_{\tau} - m_{\bar{\tau}_j}$ and $\psi(Z)$ from a likelihood function based on the probability of a household staying in its current house

$$P_{i}^{\tau}(\text{Stay}|H_i = j) = \int_{-\infty}^{\infty} e^{\tilde{\theta}_{j}^{\tau} - (m_{\tau} - m_{\bar{\tau}_j}) - \psi(Z) - \zeta_i} \cdot \phi(\zeta_i)d(\zeta_i)$$ (3.17)

The first stage of our estimation approach involved making a normalization for each type of household (i.e., $\tilde{\theta}_{j}^{\tau}$ is mean zero across all locations $j$), where type could be defined by personal characteristics such as race, income, wealth. Once we set the mean choice
specific utility from no wealth to zero, we only need to know these baseline differences, 
\( m^\tau - m^\beta \), to recover the unnormalized choice specific value functions. As we can estimate 
the baseline differences, we can simply recover the true choice specific value functions as
\( \theta_j^\tau = \tilde{\theta}_j^\tau + m^\tau. \)

It is important to recover these baseline differences because they represent the extra 
utility a household would receive from extra wealth. A key aspect of the dynamic model is 
that the choice of neighborhood affects future type. Therefore, the baseline differences in 
utility across types represent potential future utility gains from wealth accumulation.

3.5.3 Estimation - Stage Three - Per-Period Utility

From stages one and two, we know the distribution of moving costs for each type, the 
marginal value of changing type and the true mean utility terms, \( \theta_j^\tau \). We can then estimate 
the transition probabilities \( p(d\theta^\tau_{t+1}|\theta_t) \) and \( p(d\tau'|\tau,j) \). In theory, we could estimate the 
transition probabilities fully non-parametrically, as we have a time series for each type 
and neighborhood. However, to increase the efficiency of our estimates of the transition 
probabilities, we can impose some symmetry restrictions on the transition probabilities. 
For example, within each type we could assume that the neighborhood mean utilities, \( \theta_j^\tau \), 
evolve according to an auto-regressive process where some of the coefficients are common 
across neighborhoods.

In practice, we estimate transition probabilities separately for each type but pool in-
formation over neighborhoods. To account for different means and trends we include a 
separate constant and time trend for each neighborhood’s choice specific value function for 
each type. We assume the transition of the choice specific value functions, \( \theta_j^\tau \), is given
by: \[ \theta_{jt}^\tau = \sum_{l=1}^{L} \alpha_{1,l}^\tau \theta_{jl-1}^\tau + \sum_{l=1}^{L} \alpha_{2,l}^\tau X_{jl-1} + \kappa_{0,j} + \kappa_{1,j} t + \varepsilon_{jt}^\tau \] (3.18)

We also need to know how housing wealth transitions to specify transition probabilities for types, \( p(d\tau'|\tau,j) \). We use sales data to construct prices indexes for each type, tract, year combination. With these price indexes we use a similar method to the choice specific value functions, \( \theta^\tau_{jt} \), to estimate transition probabilities on price levels. Given transition probabilities on price levels it is straightforward to estimate transition probabilities for wealth and type, \( \tau \).

Knowing \( \theta^\tau, \psi^\tau, p(d\theta^\tau_{t+1}|\theta_t) \), and \( p(d\tau'|\tau,j) \), allows us to calculate mean flow utilities for each type and neighborhood, \( \delta_{jt}^\tau \), according to:

\[
\delta_{jt}^\tau = \theta_{jt}^\tau - \beta \int \log \left( \exp(\theta_{jt+1}^\tau) + \sum_{k \neq j} \exp(\theta_{kl+1}^\tau - \psi_{\tau}^\tau - \zeta_{k}^\tau) \right) q(d\zeta') p(d\theta_{t+1}^\tau|\theta_t) p(d\tau'|\tau,j) \] (3.19)

For each type, \( \tau \), neighborhood, \( j \), and time, \( t \), we have the necessary information to calculate the integral on the right hand side of (3.19). It is then straightforward to recover the \( M \cdot J \cdot T \) values for the mean flow utilities, \( \delta_{jt}^\tau \).

Once we recover the mean per-period utilities, we can decompose them into functions of the observable neighborhood characteristics, \( X_{jt} \). We assume that \( \xi \) is uncorrelated with the other neighborhood characteristics and treat it as an error term in the following regression.

\[
\delta_{jt}^\tau = g(X_{jt}; \chi) + \xi_{jt}^\tau \] (3.20)

where \( g(X_{jt}; \chi) \) is a flexible function of \( X_{jt} \) known up to parameter \( \chi \). This decomposition of

\[ ^{12} \text{Depending on the number of regressors, we could make this specification more flexible by allowing the coefficients on the lags to be functions of the right-hand side variables. A straightforward way to do this would be to first detrend the } \theta \text{s and then use the local linear estimator of Fan (1992). Given the potentially large number of regressors we could follow Bajari and Khan (2005) and interpret the regression as flexible rather than truly non-parametric.} \]
the mean flow utilities is similar to Berry, Levinsohn, and Pakes (1995) or Bayer, McMillan, and Rueben (2004) with one important difference. In these models it was necessary to instrument for price in the regression equation (3.20). In our approach, we already know the coefficient on price as we have previously calculated the marginal utility of wealth.
Appendix A

Additional Estimation Details for Chapter 2

Two options are available for estimating $\delta_t$. The first option would be to assume a transition probability for $\delta_t$ – for example, an AR(1) specification – and use this within the estimation routine. This would involve guessing a parameter vector $\vec{\delta}_t$, estimating (via OLS) first order autoregressive process transition probabilities, and then evaluating the likelihood using both the chosen parameters and the expected future costs implied by those parameters. This approach would be most similar to Gowrisankaran and Rysman (2006).

The alternative which is used here is to simply estimate year effects to get $\delta_t - \beta E_t \delta_{t+1}$. Assuming that transition probabilities are given by an AR(1) process yields a set of unique values for $\delta_t$ for a given set of autoregressive coefficients. The autoregressive coefficients which minimize the sum of square residuals using the resulting values for $\delta_t$ are chosen.

To summarize, the steps are outlined below. Using the vector of estimates of $\delta_t - \beta E_t \delta_{t+1}$

1) Guess values for $\alpha$ in the equation $\delta_{t+1} = \alpha_0 + \alpha_1 \delta_t + \alpha_2 x_t + \nu_t$.
2) Solve for $\vec{\delta}_t$ using $\alpha$ and $\delta_t - \beta E_t \delta_{t+1}$.
3) Solve for residuals from the equation $\nu_t = \delta_{t+1} - (\alpha_0 + \alpha_1 \delta_t + \alpha_2 x_t)$, given $x$, $\vec{\delta}_t$ and $\alpha$.
4) Calculate the sum of squared residuals, $ssr_\nu = \sum_{t=1}^{T} \nu_t^2$.
5) Choose $\alpha$ to minimize sum of square residuals, $ssr_\nu$. 

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Appendix B

Additional Results for Chapter 2

B.1 Transition Probabilities

\[ EP_{nt} = \phi_{0,j} + \sum_{l=1}^{L} \phi_{1,l} EP_{nt-l} + \phi_2 lot - size_n + \phi_3 t + \epsilon_{nt}^{EP} \]

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<th>Coefficient</th>
<th>Standard Error</th>
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</thead>
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<tr>
<td>( \phi_{1,1} )</td>
<td>2.0460 ( \cdot ) .0868</td>
</tr>
<tr>
<td>( \phi_{1,2} )</td>
<td>-1.9206 ( \cdot ) .1680</td>
</tr>
<tr>
<td>( \phi_{1,3} )</td>
<td>1.4173 ( \cdot ) .1819</td>
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<td>( \phi_{1,6} )</td>
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<tr>
<td>( \phi_{1,7} )</td>
<td>0.2784 ( \cdot ) .0499</td>
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<td>( lot - size )</td>
<td>3.884e-6 ( \cdot ) 6.3162e-7</td>
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<td>( time )</td>
<td>.0070 ( \cdot ) .0015</td>
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<tr>
<td>( R^2 )</td>
<td>.9793</td>
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</tbody>
</table>

Area constants, \( \phi_{0,j} \), are suppressed. All coefficients significant at 1% level
Figure B.1: Impulse Response Function: One Standard Deviation Increase in Prices
### B.2 Structural Parameters

**Table B.2: Dynamic Discrete Choice - Structural Parameters**

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</table>

PUMA Dummies: yes

Observations: 1210478

Likelihood: -255450

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Bibliography


LAMONT, O., AND J. STEIN (2004): “Leverage and House-Price Dynamics in U.S. Cities,” mimeo, University of Chicago GSB.


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