House Price Differentials and Dynamics: Evidence from the Los Angeles and San Francisco Metropolitan Areas

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We thank Palle Andersen, John Krainer, Jose Lopez, and Rob Valletta for helpful comments.

This paper applies insights from economic theory to explain recent housing price patterns in California's two largest metropolitan areas. We pay particular attention to the role of migration between metropolitan areas in explaining overall housing price dynamics for a given metropolitan area, and we show how household mobility within a metropolitan area tends to attenuate price pressures in the most supply-constrained places. In reviewing various models' ability to explain California's house price patterns, we also provide some historical perspective on California's urban structure, population growth, and housing price trends.

Newly arrived residents of California shopping for a house are likely to be shocked. The San Francisco area has the highest house prices in the nation, and portions of Southern California and the remainder of the state are not far behind. Moreover, house prices in California have experienced significant volatility in the past few decades, including a sustained period of outright declines in the early and mid-1990s. Clearly, homeowners in California take on significant financial risks. Yet potential owner-occupants have relatively little information about the basic regional dynamics of house prices to help them make informed decisions about when (or whether) to purchase a home.

A quick review of California's house price patterns over the last 30 years points to several features in need of fuller assessment and interpretation. First, California's housing market outperformed the U.S. housing market in the 1970s and 1980s and then underperformed in the early and mid-1990s. In the 1970s, the median home price in California increased, on average, about 14 percent at an annual rate, about 3 percentage points faster than in the overall United States.[1] This differential persisted in the 1980s, with home prices in California rising, on average, about 8 percent at an annual rate, again about 3 percentage points faster than in the overall United States.[2]

In the early l990s, however, California housing prices dropped back sharply, while housing prices in the United States as a whole continued to increase. The bottom of the 1990s California housing market was reached in about 1995, with prices about 11 percent below their previous peaks. Since then, home prices have recovered to roughly the previous peak, given a large gain in 1998.

Second, significant differences in the behavior of house prices have been recorded across the major metropolitan areas within California—notably between the Los Angeles and San Francisco areas. Home prices increased faster in most San Francisco area counties over the 1980s than did home prices in the Los Angeles area, and they held up better in the 1990s. As a result, house price differentials between the two areas have widened considerably over the past two decades. Indeed, by 1997, the median price in the San

1. These figures are from the U.S. Census of Housing, 1970 and 1980.

2. These figures are from the Office of Federal Housing Enterprise Oversight (OFHEO) repeat sales housing price indices.

Francisco Area, at $293,000, was about two-thirds higher than the $176,000 median price in the Los Angeles metropolitan area.

Third, house price levels and dynamics vary considerably among the counties within each metropolitan area. For example, during the 1980s, the median home value within the Los Angeles area was higher and increased significantly more rapidly in Los Angeles County than in Riverside or San Bernardino counties. Within the San Francisco area, the 1980s rate of appreciation also was faster in the higher-priced San Francisco and San Mateo counties than in the lower-priced Alameda and Contra Costa counties. In the early 1990s, the declines in median home prices were larger in Los Angeles and San Francisco counties than in surrounding counties in each metropolitan area.

In this paper, we seek to evaluate and interpret California's regional house price dynamics. In so doing, we review some important insights from the economics literature and use them to help explain recent house price developments in California's two largest metropolitan areas. We pay particular attention to the role of migration, both in terms of how intermetropolitan migration influences overall house price dynamics for metropolitan areas as a whole and how household mobility within a metropolitan area can attenuate price pressures in the most supply-constrained places.

The results of our analyses suggest that the large swings in California net migration were a major factor in the performance of the state's house prices in recent decades. The fluctuations in California net migration, in turn, appear to be importantly driven by changes in economic opportunity, as proxied by state-level unemployment rate differentials. Our analyses also provide evidence against the notion that swings in the quality of life in California (i.e., the amenity value of the location) could have been responsible for the run-up in house prices in the late 1980s and the dropback in the early 1990s. Our research further indicates that migration between metropolitan areas is important in explaining overall house price dynamics for a given metropolitan area. Also, household mobility within each metropolitan area tends to alleviate price pressures in the most supply-constrained places.

Dynamics aside, we show that long-run persistent house price differentials between California counties can be explained in part by the geographic distribution of housing quality, worker quality, and amenities. Within the San Francisco area, house prices are highest in Santa Clara, San Francisco, San Mateo, and Marin counties. These counties also have the highest average worker quality and thus the highest average wage levels. Similarly, in the Los Angeles area, the highest house prices are in those counties (Orange and Ventura) where average worker quality is the highest. High wage levels in these counties appear to spill over partly into house prices, as, other things equal, workers bid up house prices nearer the higher paying employment centers to avoid longer commutes.

Many of the higher quality workers also appear to use their additional income to locate in the higher amenity areas, particularly if these are in outlying areas where higher quality housing can be found. For the San Francisco area the quality of the housing stock appears to be high in the peripheral counties of Marin and Contra Costa and for the Los Angeles area, we find higher housing quality in Orange and Ventura counties. Measured by either the difference between quality-adjusted wages and quality-adjusted housing expenditures or by levels of specific amenities, consumer amenity levels also appear to be relatively high in Orange and Ventura counties within the Los Angeles area and in San Mateo and Marin counties in the San Francisco area.

I. ECONOMIC MODELS OF HOUSE PRICE DETERMINATION

The substantial economics literature on house price determination, migration, and the evolution of urban structure can provide some perspective on the price dynamics observed in California housing markets over the past two decades. One strand of the literature demonstrates how differences in amenities across residential locations can explain large proportions of the longer-run cross-sectional differences in house prices and wages. Other strands of the literature identify dynamic long-run supply-side and demand-side housing price determinants (including amenities) and develop models of the short-run housing price dynamics around these long-run dynamic equilibria. Both strands start from the basic theory of house price determination, which is where we begin as well.

Basic Theories of Housing Price Differences

The basic theory of housing prices distinguishes between the rental value of housing services and the value of the house as a capital asset. In particular, the asset price, which is what we focus on in this paper, must satisfy several conditions for the housing services market to be in equilibrium. For example, individual household demand will be in equilibrium only if housing prices imply that the user cost of owner-occupied housing equals the marginal value of the housing service that can be purchased through the home rental market. Thus, housing prices will depend, in part, on the determinants of housing services demand. Similarly, from a supply standpoint, investment in housing (in excess of depreciation) will take place only to the extent that the cost of providing additional housing services (via new construction) is less than the marginal value of the additional housing services inherent in the new housing units. This implies that the prices of the existing stock will also depend upon the determinants of housing supply, including the level of construction costs.

The user cost of housing is an important concept for understanding the determinants of the demand for the housing asset. Although there are several variants, the user cost basically is a dollar value representing the net cost of holding the asset for one period and usually is expressed as a net rate times the level of the asset price during that period. For housing, this net cost is the difference between gross costs (mortgage interest, depreciation, property tax, and maintenance) and gross benefits (income tax savings and capital gains).

Most elements of net cost tend to be relatively unimportant when comparing the determinants of housing prices across geographic areas within the United States, however. For example, mortgage interest rates vary over time but not substantially across place, and the property depreciation and maintenance rates generally can be ignored in between area comparisons. Property tax rates do tend to vary substantially across broad geographic locales (e.g., states), but they have not differed measurably by county within California, at least for the period we study. Similarly, although the marginal income tax schedule does vary noticeably across states, it does not vary within California. The one component of net costs that might well vary substantially across counties is capital gains expectations. However, this factor is very difficult to measure, and we have abstracted from its effect on prices in our empirical analysis.

In contrast to the net cost component of user costs, many of the demand and supply determinants of housing services vary considerably across counties and thus can have significant effects on housing prices. Important factors on the demand side include the quality of the housing, the amenities available in that location, the prices of other commodities, and household income. In addition, shifts in the relationship between individual household demand and aggregate demand, such as the rate of increase in the number of households may be important. On the supply side of the market, there tends to be considerable variation across counties in the availability of land for residential development and in the costs of complying with land use regulations.

The Evolution of Urban Structure

Basic economic principles also help explain the specific structures of urban areas and in particular the observed relationships between amenities and housing prices within urban areas. Spatial and transportation issues figure importantly in the economics literature on urban structure, and early analyses adopted the simplifying assumption that distance was an adequate proxy for transportation costs. In addition, all employment was assumed to be at the center of a monocentric city in these simple models, and land supply was assumed to be perfectly inelastic at the center of the city and close to perfectly elastic at the fringe. With amenities assumed to be equal throughout the metropolitan area, these early models predicted a smoothly declining rent (housing price) gradient as one moved out from the city center. That is, workers were posited to be willing to absorb the added costs of commuting greater distances only if they were compensated by lower housing costs.

The predictions of the simple monocentric urban models did not match up well with observed urban rent gradients.[3] One shortcoming identified by economists was the assumption of equal amenities across locations within the metropolitan area. Tiebout (1956), in particular, argued that local jurisdictions within a geographic area differentiated themselves by producing varied mixes and levels of public services and taxes, and that households could be thought of as choosing the location within an area that best reflected their preferences for these bundles of local taxes, expenditures, and amenities. Subsequent research using this framework often assumed that central cities had low amenity levels and fiscal systems that were largely inefficient in providing local public goods. Accordingly more affluent central city residents were predicted to migrate to the suburbs, weakening the fiscal capacity of the central city.

A related limitation of the original literature was the lack of a means for rising per capita income to affect the development of metropolitan areas. In many cities, the residential areas nearest the employment center were developed first, when per capita incomes were much lower than in subsequent decades. Some economists argued that as incomes increased over time, the demand for larger houses increased and more people were able to afford the transportation costs of commuting long distances. Regardless of the distribution of amenities, this model predicts that higher per capita income would give rise to additional residential development on the periphery, where the more recent additions to the housing stock could be of higher quality (in terms of characteristics such as size of structure and lot size) than the existing closer-in stock.

3. For example, Voith (1991) found that suburban land rents are significantly higher than levels suggested by estimates of an urban land rent gradient based largely on employment access.

Capitalization of Amenities in House Prices and Wages

Building on the theoretical models of urban development, a number of economists turned to the question of how amenity differences across locations might affect wages and housing prices. Rosen (1979) provided the conceptual framework for this line of research by characterizing amenities as non-market-based local traits affecting either household utility or firm productivity. In particular, Rosen's model assumes that households maximize utility and firms minimize costs by choosing among alternative locations according to the wages, the prices of locally traded goods, and the amenity bundle associated with each location. Spatial equilibrium is attained in the model when moving neither improves any household's utility nor reduces any individual firm's costs. Because household valuations of alternative locations can be derived from an indirect utility function, it is possible, in principle, to calculate the amount of income needed to compensate a household for a small change in amenities.

One method of implementing this model empirically is to proxy the locally traded goods sector by housing expenditures and then to estimate separate reduced form equations for the effects of specific amenities on housing costs and wage income. The resulting coefficient estimates yield the necessary terms for calculating estimates of the amount of income needed to compensate a household for a small change in each of these amenities. The reduced form wage equation for individual i in location j at year t is

$$(1) \qquad \ln w_{ijt} = \beta_0 + \mathbf{X}_{it}\beta_1 + \mathbf{Y}_{it}\beta_2 + \mathbf{Z}_{jt}\beta_3 + u_{ijt}, \qquad u_{ijt} = \alpha_{jt} + \varepsilon_{it}\,.$$

Here, $\mathbf{X}_{it}$ is a vector of individual worker traits—such as age and educational attainment—that are correlated with worker productivity, $\mathbf{Y}_{it}$ is a vector of industry and occupational controls, and $\mathbf{Z}_{jt}$ is a vector of observed local amenity and fiscal attributes. At this juncture, we parameterize the contribution of unobserved locational characteristics to location-wide wages (the "group effect") as the α_{jt} component of the error term, u_{ijt}. A reduced form housing cost equation is defined similarly as

$$(2) \qquad \ln n_{ijt} = \gamma_0 + \mathbf{H}_{it}\gamma_1 + \mathbf{Z}_{jt}\gamma_2 + v_{ijt}, \qquad v_{ijt} = \delta_{jt} + \eta_{it}\,,$$

where $\mathbf{H}_{it}$ is a vector describing the characteristics of the housing unit occupied by individual i.

To simplify the later empirical work, we build on some previous research, in which we estimated the parameters (β_1, β_2, γ_1) needed for quality-adjusting wages and housing costs using annual microdata from the 1990 Census of Population and Housing. In estimating these regressions, we used observations from every state in the U.S. and collapsed the state-specific components of wages and housing costs into vectors of fixed effect parameters (λ, μ):

$$(3) \quad \ln w_{ij89} = \beta_0 + \mathbf{X}_{i89}\beta_1 + \mathbf{Y}_{i89}\beta_2 + \lambda_{j89} + \varepsilon_{i89}, \qquad \lambda_{j89} = \mathbf{Z}_{j89}\beta_3 + \alpha_{j89}$$

$$(4) \quad \ln n_{ij89} = \gamma_0 + \mathbf{H}_{i89}\gamma_1 + \mathbf{Y}_{i89}\beta_2 + \mu_{j89} + \eta_{i89}, \qquad \mu_{j89} = \mathbf{Z}_{j89}\gamma_2 + \delta_{j89}\,.$$

The results of the estimation of the quality-adjustment parameters are shown in Gabriel, et al. (1996).[4]

For the purposes of this paper, we use these first-stage estimation results to construct quality-adjusted average wages for each location in the benchmark year ($\ln w^*_{.j89}$) by subtracting from the actual average wages ($\ln w_{.j89}$) in area j the inferred contributions of the differences between the actual average worker characteristics in that area ($\mathbf{X}_{.j89}$, $\mathbf{Y}_{.j89}$) and the U.S. national average worker characteristics ($\mathbf{X}_{..89}$, $\mathbf{Y}_{..89}$):

$$(5) \qquad \ln w^*_{.j89} = \ln w_{.j89} - ((\mathbf{X}_{.j89} - \mathbf{X}_{..89})\hat{\beta}_1 + (\mathbf{Y}_{.j89} - \mathbf{Y}_{..89})\hat{\beta}_2)\,.$$

Quality-adjusted housing costs ($\ln n^*_{.j89}$) are similarly constructed, by imputing to each area the national average housing unit characteristics:

$$(6) \qquad \ln n^*_{.j89} = \ln n_{.j89} - (\mathbf{H}_{.j89} - \mathbf{H}_{..89})\hat{\gamma}_1\,.$$

The resulting county-specific quality-adjusted wage and housing cost levels are used below to infer patterns of amenity differences within California.

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4. As is generally found in the economics literature, the wage regression reveals that as workers age and gain more experience, they encounter a generally upward-sloping wage profile until they near retirement age. Similarly, educational attainment commands a significant wage premium. On the other hand, workers tend to receive lower wages if they have limitations from disabilities, are currently in school, or have difficulties speaking English well. Among occupations, farmers and sales people tend to be at the bottom of the wage scale, whereas physicians, dentists, and other specialized health care professionals such as optometrists tend to be at the high end of the wage scale. For a given occupation, industry affiliation also has significant explanatory power for wages. Miscellaneous and recreational service organizations such as museums, art galleries, and zoos tend to pay their workers at the low end of the range, and industries with highly specialized needs, such as oil and gas mining and railroad transportation, tend to pay their workers highly. Most of these estimated worker quality-adjustment coefficients are of an economically significant magnitude and are estimated precisely enough to be statistically distinguishable from zero.

The housing quality-adjustment results also are not surprising. Other things equal newer housing units and those with more total rooms or bedrooms command a premium. As these latter size measures are highly positively correlated with the type of structure, the additional premia for being higher quality types of structures generally are small and in many cases not statistically distinguishable from zero. Mobile homes are the exception to this generalization about the type of structure, as they are estimated to be of significantly inferior quality to other types of housing.

II. APPLICATIONS OF THE THEORY TO CALIFORNIA HOUSING MARKETS

In this section, we use the implications of the economic models described above to infer explanations for the behavior of California housing markets. We focus first on the cyclical performance of California house prices relative to that of the United States. We then provide a similar evaluation of house price dynamics across the San Francisco and Los Angeles metropolitan areas. Finally, we examine persistent long-run differences in house prices across counties within each metropolitan area and evaluate the role of housing quality, worker quality, and locational amenities in explaining those differentials.

Performance of California Housing Prices Relative to the U.S.

The top panel of Figure 1 shows that during the early and mid-1980s California house prices moved closely in tandem with those for the United States. In the final years of the decade, however, increases in California house prices outstripped the U.S. average by a considerable margin, widening the differential in housing costs substantially by 1990. Subsequently, in the early l990s California house prices dropped back, and with ongoing price increases elsewhere in the nation, the house price differential between California and the U.S. returned to its historical norm.

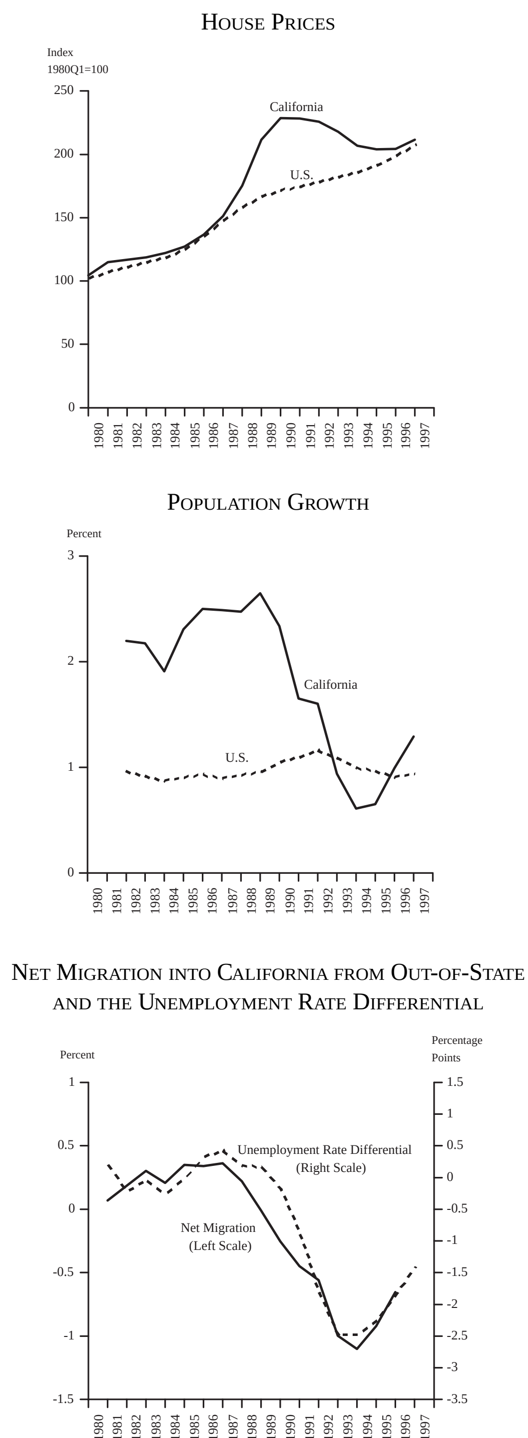
The middle panel shows the striking developments in population growth in California at that time. It accelerated over the course of the 1980s to a peak rate of slightly above 2½ percent in 1989, while the U.S. average rate of population growth remained near 1 percent throughout the decade. By the early 1990s, however, California population growth had slowed sharply, reaching a low of only about ½ percent in 1994.

Although these two pieces of evidence do not allow us to infer the nature of the causal relationship between house prices and population growth, it is worth noting that over the 1982–1997 period the raw correlation between the two for California relative to the U.S. was 0.71. Moreover, in a simple regression explaining the house price growth differential, the estimated coefficient on the population growth differential is 5.75, with a *t*-statistic of 3.8, indicating that the coefficient is statistically significantly different from zero. In such a regression, population growth differentials are able to explain about one-half of the year to year variance in the housing price growth differential.

The bottom panel of Figure 1 shows the importance of net migration to the variability of California's population growth, as well as its relation to economic conditions in the state. During the 1980s (as well as in earlier decades),

FIGURE 1

COMPARISON OF CALIFORNIA WITH U.S.



SOURCES: House prices are Office of Federal Housing Enterprise Oversight repeat sales home price indexes. Population growth figures are from the U.S. Bureau of the Census. Net migration rates are calculated from IRS state-to-state migration data, and the unemployment rate differential of the U.S. relative to California is calculated from BLS statistics.

a steady net positive flow of individuals moved from other states into California. In the early 1990s, however, the net flow reversed itself, with migration out of California becoming larger than the inflows. Although the net outflow slowed somewhat in the mid-1990s, as California's relative economic conditions improved, there was a cumulative net loss of roughly two million people to other states between early 1990 and mid-1996. Furthermore, Gabriel, et al. (1995) analyzed state-to-state directional migration flows, and those results suggest that deteriorating economic conditions in California were a particularly important factor leading to the shift in the direction of domestic migration flows and, ultimately, the decline in housing prices. Specifically, unemployment rate differentials appear to have much more explanatory power for the dynamics of between state migration than wage, housing price, age structure, or amenity differentials, and as the difference between the U.S. and California unemployment rates widened substantially in the early 1990s, net migration from California to other states accelerated. Since 1994, when a significant California economic recovery began to show through to unemployment rates, net out-migration from the state has slowed substantially.

In contrast, there is little evidence that changes in the quality of life in California (i.e., the amenity value of the state) were responsible for either the swing in state population growth or the cyclical fluctuations in house prices in the late 1980s and the early 1990s. Our estimates of a quality-of-life index for California using the methodology described in the previous section (and in Gabriel, et al. 1996) show virtually no change over this period. Moreover, with economic factors accounting for almost all of the observed flows in migration, there would seem to be little room for appealing to a falloff in California quality of life in the l990s.

From this informal evidence, we draw two conclusions. First, the boom and bust cycle in California house prices during the past two decades appears strongly related to the substantial swings in net migration evident over this period, which can be traced, in large part, to changes in economic conditions in the state. Second, there is no evidence that changes in the quality of life in California were responsible for the run-up in house prices in the late 1980s and the dropback in the early l990s.[5]

Differences between Los Angeles Area and San Francisco Area Housing Markets

In comparing overall house price trends in the Los Angeles area with those in the San Francisco area, two features are apparent in the top panel of Figure 2. First, both areas experienced a substantial appreciation in house prices in the late 1980s. Second, when the state housing market weakened noticeably in the early l990s, the declines in Los Angeles area house prices were larger than the declines in San Francisco area house prices.

As for the state as a whole, rapid population growth in the 1980s appears to have been a significant factor in the housing price booms for both areas. In the San Francisco consolidated metropolitan statistical area (CMSA), population growth in the 1980s ran at about a $1\frac{1}{2}$ percent average annual rate, and population growth in the Los Angeles CMSA was even faster, particularly outside of Los Angeles County. In both CMSAs, large flows of immigrants from abroad and natural forces (the excess of births over deaths) accounted for the bulk of the population gains in the 1980s; net domestic migration into each of the areas was near zero for much of the decade.

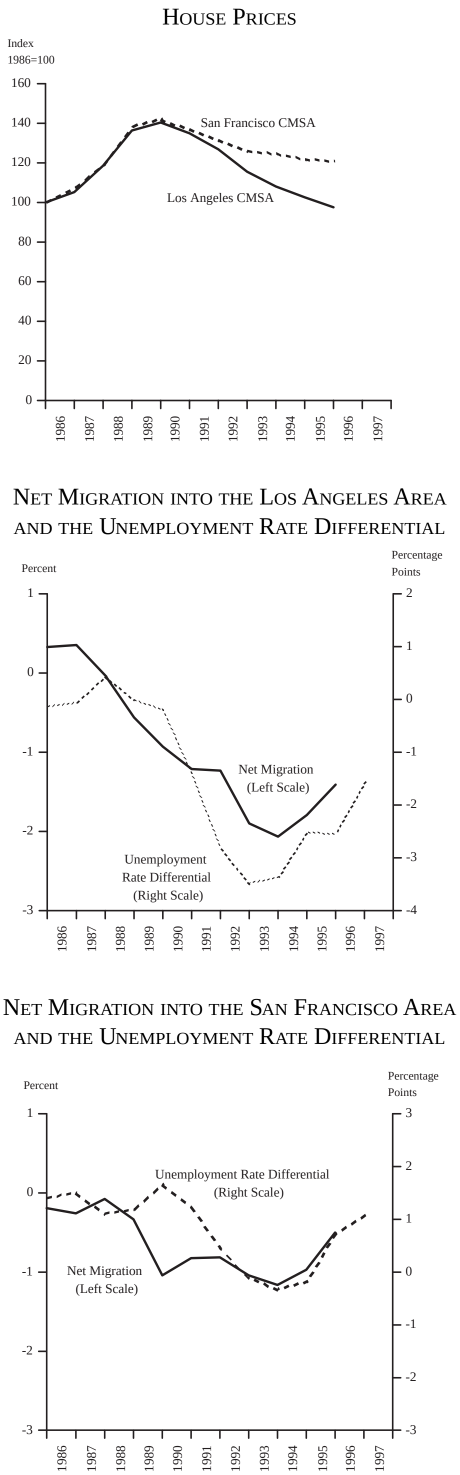
In contrast, a surge in net domestic outmigration contributed importantly to a slowing of population growth in the early 1990s in both areas. And, as can be seen in the middle panel of Figure 2, the increased outflow from the Los Angeles area was coincident with a worsening of employment prospects relative to that in other parts of the U.S.. To a large extent, this correlation between the rate of net outmigration from the area and the unemployment rate differential also is present in the data on the San Francisco area (bottom panel of Figure 2). However, in the immediate aftermath of the Loma Prieta earthquake in October 1989, the number of net outmigrants from the San Francisco area jumped sharply, while the San Francisco area unemployment rate remained near the national average.[6]

5. One competing explanation is that there was rapid growth and a subsequent retrenchment of capital gains expectations (Meese and Wallace, 1994). In particular, they show that the rate of house price appreciation in the San Francisco area exceeded the growth rate of the capitalized value of a housing rental rate series in the late 1980s, and they cannot rule out the possibility that these deviations were due to an asset market (capital gains expectation) bubble or nonrational expectations. Other commentators have emphasized the possible role of tight and perhaps tightened supply-side factors in contributing to the late 1980s spike in California house prices. Indeed, California does stand out as a supply-constrained place on many measures of residential land supply and land use regulation. For example, Rose (1989) identifies San Francisco as the most topographically constrained major urban area in the U.S. California cities also are among the highest on the land use regulatory indices presented by Malpezzi (1996). In part, this owes to the California Environmental Quality Act (CEQA), which requires developers to mitigate the potential environmental impacts of proposed development projects. In addition, the state stands out as a heavy user of development fees and exactions, which became increasingly prevalent in the late 1980s (Altshuler and Gomez-Ibanez 1993, Dresch and Sheffrin 1997).

6. See Hoag (1995) for a discussion of the San Francisco area migration patterns in the aftermath of the Loma Prieta earthquake.

FIGURE 2

COMPARISON OF SAN FRANCISCO WITH LOS ANGELES



SOURCES: House prices are aggregates of county-level Experian repeat sales indexes. Net migration rates are calculated from IRS county-level migration data, and the unemployment rate differentials of the U.S. relative to California CMSAs are calculated from BLS statistics.

As at the state level, the boom and bust pattern in house prices is positively correlated with the net migration component of household formations in each of these individual metropolitan areas. Moreover, although the directions of population flows followed the same general pattern in the two CMSAs over this period, the overall rate of net domestic outmigration from the Los Angeles area in the 1990s was considerably larger than from the San Francisco area and the severity of house price declines was larger in the Los Angeles area than in the San Francisco area. Thus, migration patterns appear to have been one of the important factors in explaining the observed differences in the movements of house prices in the Los Angeles and San Francisco CMSAs.[7]

Urban Spatial Structure and Longer-Run Differences in Metropolitan California Housing Markets

Within the Los Angeles and San Francisco metropolitan areas, the longer-run evolution of house price differentials represents an interesting example of the economic models presented in Section I. In particular, the spatial economic structures of both areas resemble some of the stylized features of the theories of evolving urban areas. For example, employment centers that developed early in the history of these urban areas now are densely populated, and subsequent development occurred in areas peripheral to the initial employment centers.

In the five-county Los Angeles CMSA, Los Angeles county—which has more than 9 million residents (about 60 percent of the CMSA population) and encompasses about 4,000 square miles of land area—was developed first. For the last several decades, population growth has been faster in the peripheral counties (Riverside, San Bernardino, Orange and Ventura) than in Los Angeles County (Table 1). Los Angeles County nonetheless has retained its role as the focal point for area-wide employment; as of 1990, the average time spent commuting by residents of peripheral

7. Other possible explanations include a faster rate of personal income growth in the San Francisco area than in the Los Angeles area, owing, in part, to the loss of many higher-paying defense-oriented manufacturing jobs in the Los Angeles area. Also, housing supply constraints appear to be tighter in the San Francisco area than in the Los Angeles area, particularly in terms of topographical constraints (Rose 1989). In terms of land use regulation, Malpezzi (1996) finds more tightness in the San Francisco area than in the Los Angeles area, while Landis, et al. (1995) find that both the San Francisco area and the Los Angeles area have some communities where CEQA has been less constraining. Last, Mattey and Wallace (1998) find evidence that the early 1990s declines in Los Angeles area house prices depressed home purchase activity there (perhaps reflecting lack of collateral for trade-up purchases), which likely reinforced the downward pressure on prices.

counties was significantly higher than in Los Angeles County, and a larger fraction of residents in the outlying counties commuted beyond their county boundaries (Table 2).

The San Francisco CMSA consists of counties in three large primary metropolitan statistical areas (PMSAs)—Oakland, San Francisco, and San Jose—and three smaller PMSAs—Santa Cruz, Santa Rosa, and Vallejo-Fairfield-Napa. The San Francisco PMSA—which includes Marin, San Francisco, and San Mateo counties—was the first San Francisco area PMSA to achieve substantial size, with much of the initial development taking place in San Francisco County. Both the Oakland PMSA—which consists of the East Bay counties of Alameda and Contra Costa—and the San Jose PMSA (Santa Clara County) experienced sizable population gains in the wake of World War II. However, the initial population density was much lower in San Jose than in Oakland, and only by the end of the 1970s did the San Jose PMSA begin to approach the density of the other San Francisco area PMSAs. Each of the remaining smaller PMSAs lies at an edge of the consolidated metropolitan area.

San Francisco County was the initial employment center of the San Francisco area. However, due in part to the irregular topography of this area, Alameda and Santa Clara counties also have developed into clearly defined employment centers. As a result, lower fractions of San Francisco, Alameda, and Santa Clara county residents commute beyond county boundaries than do residents of other San Francisco area counties, while Contra Costa, Marin, and San Mateo stand out as commuter counties.[8]

Among the counties in the three largest San Francisco area PMSAs, population growth statistics support the representation of Contra Costa as a fast-growing peripheral county. In the last three decades, its rate of population growth has exceeded the growth rate of the overall San Francisco CMSA. In contrast, even though Marin and San Mateo counties have a high fraction of long-distance commuters, their population has increased more slowly than that of the overall San Francisco CMSA.

House Prices and Wages in California Counties: Adjustments for Quality

To ascertain the implications of this pattern of urban development for housing markets, we need first to disentangle differences in the quality of housing and labor across counties from other potential factors driving wedges between the various counties' wages and counties' prices. We do this by applying the housing and worker quality-adjustment procedure described in Section I to calculate estimated differences between actual and quality-adjusted wage and house price expenditures by county.

For example, the median home price in Santa Clara County was $289,400 in 1990, about $62,000 above the $227,200 median home price in Alameda county (Table 3); moreover, this differential has persisted in percentage terms for several decades. One potential explanation for at least part of this differential is that Santa Clara, which is the heart of Silicon Valley, may, on average, attract higher-quality, and thus better paid, workers than Alameda County because of the differing mix of industries in the two counties. Indeed, average household annual earnings in Santa Clara County were $47,679 in 1990, about $11,000 more than the average in Alameda County (Table 4). As the share

TABLE 1

Population Growth

	Percent Change at an Annual Rate		
Area	1970–1980	1980–1990	1990–1997
Los Angeles CMSA	1.4	2.4	1.0
Los Angeles	0.6	1.7	0.4
Orange	3.1	2.2	1.4
Riverside	3.7	5.8	2.8
San Bernardino	2.7	4.7	1.7
Ventura	3.5	2.4	1.1
San Francisco CMSA	1.2	1.5	0.9
Alameda	0.3	1.5	0.7
Contra Costa	1.6	2.0	1.5
Marin	0.8	0.3	0.3
San Francisco	–0.5	0.6	0.2
Napa	2.3	1.1	1.0
San Mateo	0.5	1.0	0.9
Santa Clara	2.0	1.5	1.0
Santa Cruz	4.3	2.0	0.7
Sonoma	3.9	2.6	1.4
Solano	3.3	3.8	1.1

Source: U.S. Bureau of the Census.

8. Most commuters from Contra Costa to other counties go to Alameda, but a sizable number continue past Alameda to San Francisco. As of 1990, most out-of-county commuters from Marin and San Mateo traveled to San Francisco. San Mateo also sends many commuters to Santa Clara, and these numbers have increased significantly over time.

of income spent on housing is about 39 percent in the two counties, this overall earnings differential can be said to support a housing price differential of about $68,000, not far from the observed differential in 1990.[9]

If differences in worker quality were the entire explanation for the observed persistent earnings and housing price differentials between Santa Clara and Alameda counties, then we would expect the earnings differential to disappear once wage rates were adjusted for the different composition of worker and job characteristics. However, quality-adjusted wages also differ between the two counties, although not by as much as observed earnings. On balance, a comparison of the actual and quality-adjusted wage levels indicates that about $7,000 of the earnings differential between Santa Clara and Alameda counties is due to worker quality differences. Applying the same calculation as above, this suggests that worker quality differences can account for $44,000 of the income-related housing price differential between the two counties in the Census year. Similar computations suggest that, to a significant extent, high housing prices in Marin, San Francisco, and San Mateo counties also can be explained by the high quality of the work force employed there. Within the Los Angeles area Orange and Ventura counties stand out as having large gaps between unadjusted and quality-adjusted wages. However, the estimated levels of worker quality in these relatively affluent Los Angeles area counties are not as high as in the most affluent San Francisco area counties.

9. This estimate is computed by multiplying the earnings differential in dollars by the share of income spent on housing and then converting this figure to a housing price differential by dividing by the observed ratio of housing expenditures to housing prices in these counties in 1990 (about 6 1/4 percent).

TABLE 2

COMMUTING STATISTICS

COUNTY	Average Commuting Time Contribution to Quality-of-Life Index		Percent Workers Commuting to Other Counties	
	1980	1990	1980	1990
Los Angeles CMSA				
Los Angeles	–17885	–16045	4.1	5.9
Orange	–17370	–18768	20.6	18.4
Riverside	–16339	–20755	21.8	29.5
San Bernardino	–16044	–20166	25.8	32.0
Ventura	–17075	–18179	26.2	25.3
San Francisco CMSA				
Alameda	–18106	–18989	23.4	29.5
Contra Costa	–20019	–21565	40.7	40.2
Marin	–21123	–20902	43.0	41.4
San Francisco	–19062	–19798	14.4	19.6
Napa	–14499	–15750	24.3	25.5
San Mateo	–16781	–17664	40.3	41.9
Santa Clara	–16781	–17149	8.0	10.8
Santa Cruz	–16266	–17885	21.9	22.2
Sonoma	–16707	–17738	17.3	18.2
Solano	–16339	–20755	28.3	38.6

SOURCES: Commuting times and percent workers commuting are from the U.S. Census of Population and Housing, 1980 and 1990. Contributions of commuting times to quality-of-life index are authors' calculations based on methods and full implicit prices from Gabriel, et al. (1996).

A related question is whether the income-related housing price differentials reflect differences in the quality of housing or differences in nonhousing amenities that are capitalized in housing and land values. If the higher income individuals purchase large houses in the counties where they work, then the quality-related differential in wages should show through to a similar quality-related differential in housing expenditures in those counties. If, however the higher income individuals purchase large houses in counties other than the ones in which they work, then understanding this spillover also requires knowledge of the specific commuting patterns. (Note that wages are measured at the place of work, while house prices are measured at the place of residence.)

As can be seen in Table 4, the quality-adjustment terms are positive and relatively large for both labor and housing in some of the wealthier suburban counties—notably Orange and Ventura counties in the Los Angeles CMSA and Contra Costa and Marin counties in the San Francisco CMSA.[10] The fact that the high housing-quality counties are in the suburbs is consistent with the prediction of the early urban development literature that higher income individuals would tend to migrate to the suburbs in pursuit of better housing.

Also consistent with this literature is evidence that the quality component of housing expenditures is negative in some of the older, more urban counties. For example, both Los Angeles and San Francisco counties have a relatively low-quality housing stock, despite their relatively high-quality work forces. This would suggest that some of the high-quality workers in San Francisco are using their higher wages to purchase larger houses in Marin or Contra Costa counties. Indeed, the commuting patterns shown in Table 2 are consistent with this explanation as more than 40 percent of employed residents in Marin and Contra Costa counties work elsewhere. Separate data on the destinations of commuters (not shown) confirm a large flow of workers into San Francisco from residences in the suburban counties. Within the Los Angeles area, the distribution of housing quality also is consistent with a gradient of increasing housing quality from the Los Angeles county "core" to the Orange and Ventura county "periphery." However, one should not overemphasize between-county commuting as an explanation for this distribution of housing quality in the Los Angeles area; Los Angeles County is large in size, and a large fraction of Los Angeles County workers reside in that same county.[11]

Once the quality effects are stripped away, we can also turn to some other major themes in the literature on the evolution of urban structure. For example, even after adjusting for differences in housing quality, the level of housing expenditures is relatively high in the peripheral counties of Orange and Ventura in the Los Angeles area and Marin and San Mateo in the San Francisco area. This could be

10. By U.S. standards, California tends to have higher quality workers (the average quality adjustment is $3,092) and slightly lower quality housing (with a mean quality adjustment of –$200). The comparisons in this section should be interpreted as relative to the average quality effects in California.

11. The notion of a positive income elasticity of demand for amenities also is prevalent in the literature. Some researchers have argued that the development of high-amenity suburbs was facilitated by the interaction of trend real income growth, this positive income elasticity, and the ability of higher income individuals to overcome fixed-cost barriers to commuting from the suburbs. For example, the costs of owning an automobile used to be a substantial barrier to commuting, but this constraint has dissipated over time.

TABLE 3

House Prices

County	Level in 1990	Rate of Change over 1980–1990	Rate of Change over 1990–1997
Los Angeles CMSA			
Los Angeles	$226,400	9.9	–0.9
Orange	252,700	8.9	–0.4
Riverside	139,100	7.5	–0.6
San Bernardino	129,200	7.4	–0.8
Ventura	245,300	10.1	–0.9
San Francisco CMSA			
Alameda	$227,200	10.3	1.8
Contra Costa	219,400	8.8	1.4
Marin	354,200	8.9	1.2
San Francisco	298,900	11.1	0.0
Napa	183,600	8.9	0.0
San Mateo	343,900	10.7	1.5
Santa Clara	289,400	10.2	1.9
Santa Cruz	256,100	10.5	n.a.
Sonoma	201,400	8.6	0.7
Solano	147,300	8.1	–1.0

Sources: Census of Population and Housing, 1980 and 1990, median owner estimates of value and authors' calculations of 1990 and 1997 median home sales prices from California Market Data Cooperative (CMDC) microdata.

symptomatic of the capitalization in housing and land values of high levels of consumer amenities in these peripheral areas. According to the theory of compensating differentials, if the set of local traits consists only of consumer amenities (which affect household utility) and does not also include producer amenities (which affect firm productivity), then the better consumer amenities in peripheral counties would tend to raise housing prices and lower wages there. However, if the set of local traits also has productivity effects, then the effects of higher levels of consumer amenities on housing prices and wages depends on the sign and relative strength of the productivity effects.[12]

12. Empirical results in the literature generally suggest that higher levels of amenities preferred by households are capitalized as higher house prices, but the effects on wages are mixed.

Despite this theoretical ambiguity about the effect of amenities on housing prices and wages themselves, the difference between the two may be a useful quality-of-life indicator; preferred consumer amenities tend to lower the amount of quality-adjusted wage income left after housing expenditures are subtracted.[13] These insights are useful to keep in mind when examining the distribution of quality-adjusted wages and quality-adjusted house prices within California's major metropolitan areas for indications of where consumer amenities are highest (Table 4).

13. The notion that the difference between quality-adjusted wages and housing expenditures may be a useful quality-of-life indicator has both theoretical and empirical support. Theoretically, this measure can be thought of as a quality-of-life index if amenities are represented as (unobserved) fixed effects of locations. Empirically, Gabriel, et al. (1996) found a high, positive correlation between fixed effects and observed amenities estimates of quality-of-life indices.

TABLE 4

QUALITY ADJUSTMENTS TO WAGES AND HOUSING EXPENDITURES

	Unadjusted		Adjusted		
County	Wage	Housing Expenditure	Wage	Housing Expenditure	Wage after Housing
Los Angeles CMSA					
Los Angeles	$36,045	$14,334	$32,464	$16,220	$16,244
Orange	37,092	16,382	32,123	15,282	16,841
Riverside	29,715	9,841	28,991	10,644	18,347
San Bernardino	29,592	9,242	27,043	9,215	17,828
Ventura	35,481	16,488	30,009	15,291	14,719
San Francisco CMSA					
Alameda	$36,195	$14,179	$33,076	$14,869	$18,207
Contra Costa	35,869	16,023	31,131	13,970	17,160
Marin	33,768	21,948	28,789	20,556	8,233
San Francisco	41,147	14,599	33,837	19,138	14,699
Napa	31,558	12,680	31,608	13,562	18,046
San Mateo	38,079	21,096	33,501	21,098	12,403
Santa Clara	47,679	18,793	37,069	18,000	19,069
Santa Cruz	30,966	15,737	30,156	17,301	12,855
Sonoma	28,529	13,706	25,419	13,662	11,757
Solano	30,325	10,434	28,294	9,658	18,636

SOURCES: Authors' calculations using the 1990 Census Public Use Microdata and methods explained in Gabriel, et al. (1996).

Within the Los Angeles area, the counties of Los Angeles, Orange, and Ventura have the lowest quality-adjusted wages after housing expenditures are subtracted, suggesting that these are relatively high amenity locations. Most of the capitalization appears to take place through the housing market; quality-adjusted housing expenditures are relatively high in these counties, and although quality-adjusted wages also are relatively high in Los Angeles, Orange, and Ventura counties, those wage premia are not large enough to offset the housing expenditure differentials.

For the San Francisco area, the results are generally consistent with consumer amenities being higher in peripheral counties. Quality-adjusted wages after housing expenditures are relatively low in Marin, San Mateo, and Santa Cruz counties, suggesting that these are higher amenity places. In contrast, the counties of Alameda, Contra Costa, Napa, and Solano have relatively high quality-adjusted wages after housing, suggesting that these are lower amenity places.

Two other San Francisco area counties, Santa Clara and Sonoma, warrant separate mention. Santa Clara county stands out in the sense of having high wages after housing. However, we suspect that rather than indicating a particularly lower level of consumer amenities there, the high wage levels reflect the positive effects of some (unmeasured) local characteristics on worker productivity and wages. Sonoma county is at the other end of the spectrum; its low wages after housing reflect the lowest quality-adjusted wages in the San Francisco area and might embody the negative effects of some (unmeasured) local characteristics on worker productivity and wages.

Amenity Capitalization and Quality of Life among California Counties

Of course, there also is direct evidence on the distribution of some consumer amenities, and as described in Section I, it is possible to use the variation in quality-adjusted housing expenditures and wages, along with differences in levels of specific amenities, to compute households' implicit valuations of such amenities. The results can be aggregated across amenities to measure the so-called "quality of life" of each location. We applied this methodology to U.S. state-level data in an earlier paper (Gabriel, et al. 1996), in which we related quality-adjusted wages and housing costs to observed state amenity characteristics.

Consistent with the findings of earlier researchers who had focused only on compensating differentials at a point in time, we find in Gabriel, et al. (1996) that there is significant capitalization in wages and local housing expenditures of climatic and recreational attributes of states. For example, other things equal, wages tend to be higher or housing prices lower in areas with significant amounts of precipitation, humidity, temperature extremes (measured by amounts of heating and cooling effort required in degree days), or wind. On the other hand in the presence of positive recreational attributes, such as access to coastal waters, inland waters, and federal lands and national parks, workers will bid up house prices or accept wage discounts. Moreover, many of these climatic and recreational attributes make economically significant contributions to the differences in the levels of the quality-of-life indices across places (Table A1—see Appendix).[14]

In addition to the climatic and recreational attributes, which are measured as remaining constant over time, the amenity capitalization model of Gabriel, et al. (1996) also includes several time-varying local traits. Average commute times are used as a measure of traffic congestion and the spatial proximity of housing to jobs. Ozone and carbon monoxide concentrations are used as measures of air quality. Other variables attempt to measure the quality and composition of public services and the tax burdens that finance these services. For California, poor air quality and high commuting times stand out as particularly important disamenities that hold down the quality-of-life index relative to that for the average U.S. state. In addition, California is regarded by the model as having poor public school quality because of relatively high student-teacher ratios.

The full implicit prices from the state level model estimated in Gabriel, et al. (1996) also can be used to gain some perspective on differences in quality-of-life among California counties (Table 5). Although the absence of comparable data on all attributes prevents complete application of the model at the county level, we have county-specific measures from 1990 for selected important attributes. Using precipitation and the two measures of temperature extremes (heating and cooling degree days) as the climatic variables, the model implies that Orange County has the most attractive climate within the Los Angeles area, whereas Riverside and San Bernardino are less desirable, primarily because they experience more extremely hot days. Similarly, within the San Francisco area, climate is estimated to be most desirable in the counties with particularly moderate temperatures: Marin, San Francisco, and Santa Cruz. Inland counties that do not benefit as much from the mod-

14. For example, California experiences fewer cold days than the average U.S. state, which, according to the model, is worth to Californians $5,161 in annual wages. On balance, California's quality-of-life estimate also reflects a higher level of recreational attributes than the average U.S. state, with this showing through in the model primarily in terms of a higher than average proportion of national forests and other federal lands.

erating effects of the San Francisco Bay and the ocean have a larger negative contribution to the quality-of-life index from the climatic variables.

With regard to other characteristics, poor air quality is shown to be a particularly significant issue for the Los Angeles area. Within this area, the problem is much less severe in Ventura County; as evidenced in Table 5, the negative effects of air pollution on estimated quality of life in that area are one-half or less of those of Los Angeles and San Bernardino Counties. San Francisco area air quality is estimated to be the poorest in Santa Clara county, but even there the overall disamenity value of this pollution is less than in all Los Angeles area counties except Ventura.

The sum of the contributions of these selected amenities to the quality-of-life indices can be interpreted as a partial quality-of-life index that captures the compensating differential effects of the selected amenities for which we have data. For the selected climate and air quality traits, the quality-of-life in Los Angeles and in the Inland Empire counties (Riverside, San Bernardino) is estimated to be significantly lower than in the San Francisco area. Based on these measures alone, Orange and Ventura counties fall within the range evidenced for San Francisco area counties. Within the San Francisco area, Marin, San Francisco, and Santa Cruz have the best estimated aggregate climate and air quality.

Other measures of localized amenities, including crime rates and estimates of school quality, correlate with the indicators for climate, air quality, and access to employment discussed above to suggest the presence of relatively high quality of life in Orange and Ventura Counties in the Los Angeles area. As evidenced in Table 6, the violent crime

TABLE 5

CONTRIBUTIONS TO QUALITY-OF-LIFE INDICES

AREA	CLIMATE	AIR QUALITY	SUM	COMMUTING
LOS ANGELES CMSA				
Los Angeles	–5700	–11472	–17172	–17885
Orange	–4502	–7092	–11594	–17370
Riverside	–7466	–8431	–15897	–16339
San Bernardino	–8945	–8809	–17753	–16044
Ventura	–6145	–4769	–10914	–17075
SAN FRANCISCO CMSA				
Alameda	–6072	–4718	–10791	-18106
Contra Costa	–6492	–4177	–10669	–20019
Marin	–5879	–3070	–8949	–21123
San Francisco	–5871	–2716	–8587	–19062
Napa	–6849	–3626	–10475	–14499
San Mateo	–6573	–3874	–10446	–16781
Santa Clara	–6601	–5385	–11986	–16781
Santa Cruz	–5893	–2546	–8439	–16266
Sonoma	–6913	–3189	–10100	–16707
Solano	–6776	–4608	–11384	–16339

SOURCES: Calculations by the authors using full implicit prices from Gabriel, et al. (1996) and county amenity data on precipitation, heating and cooling degree days, ozone and carbon monoxide concentrations, and carbon monoxide commuting times. Climate data are county averages of observation by weather station from the National Oceanic and Atmospheric Administration (NOAA), air quality data are from the state Air Resources Board, and commuting times are from the 1990 Census.

rate in Ventura County is less than one-third that of neighboring Los Angeles County,[15] whereas public school student achievement on standardized SAT tests is relatively high in these peripheral counties.[16]

While commutes extract a relatively high toll from Marin County residents, that area is similarly characterized by relatively high levels of public safety, student achievement, climatic, and air quality amenities. As indicated in Table 6, the older, central core counties in each of these metropolitan areas—including Los Angeles in the south and San Francisco and Alameda in the north—are characterized by relatively elevated levels of violent crime and relatively low levels of public school student SAT achievement.

In sum, the equilibrium model is able to explain some of the long-run, persistent house price differentials between California counties in terms of the distribution of worker quality, housing quality, and amenity differences. Within the San Francisco area, house prices are the highest in Santa Clara, San Francisco, San Mateo, and Marin counties. Those counties also have the highest average worker quality and thus the highest average wage levels. Similarly, in the Los Angeles area, the highest house prices are in those counties (Orange and Ventura) where average worker quality is highest. High wage levels in these counties appear to spill over partly into house prices.

Many of the higher quality workers also appear to use their additional income to locate in the higher amenity areas, particularly if these are nearer the fringe of the urban area, where higher quality housing is available. As suggested above, the quality of the housing stock appears to be high in the peripheral San Francisco area counties of Marin and Contra Costa and in the Los Angeles area counties of Orange and Ventura. Measured either by amenity capitalization effects via wages and housing expenditures or by specific amenity levels, resident quality of life appears to be relatively high in Orange and Ventura counties in the south and in San Mateo and Marin counties in the north.

TABLE 6

Crime and Schooling Characteristics, 1996

Area	Crimes per 100,000 persons	Public School SAT Score
Los Angeles CMSA		
Los Angeles	1262	957
Orange	453	1073
Riverside	815	952
San Bernardino	793	963
Ventura	406	1049
San Francisco CMSA		
Alameda	1017	1014
Contra Costa	616	1058
Marin	329	1076
San Francisco	1295	965
Napa	345	1060
San Mateo	347	1039
Santa Clara	547	1065
Santa Cruz	728	1042
Sonoma	439	1056
Solano	806	989

Sources: Violent crime rate data are from the state Department of Justice and SAT score data are from the state Department of Education.

III. Introducing Short-Run House Price Dynamics

Although theoretical and empirical research has clearly demonstrated the existence of a long-run relationship between real house prices and fundamental determinants of value, actual prices have diverged sharply from the values implied by these fundamentals for extended periods of time in various markets on the East and West coasts. To model these deviations from the long-run equilibrium values, economists have turned to error-correction specifications such as those estimated by Abraham and Hendershott (1996)

15. Although our state-level model yielded a full implicit price estimate for violent crime that was not statistically different from zero, the 90 percent confidence interval for this estimate was very wide and included –\$1.40 (per crime per 100,000 persons) as a lower bound. Even taking a more conservative estimate of –\$1.00 for this full implicit price implies that residents of Orange and Ventura Counties would need to be compensated about \$800 per year in order to be indifferent about being exposed to the higher level of violent crime in Los Angeles County.

16. In our state-level analysis, school quality was measured by the ratio of students to teachers in public school classrooms. This picked up some of the substantial variation across states in the effort to educate students. However, within California, student-teacher ratios are relatively equal across counties, reflecting the important role of the state government in funding public schools and the legally required equalization of spending-per-pupil across public school districts. To a certain extent, wealthier districts have circumvented the effort to equalize public school funding by finding ways to finance supplemental efforts. In addition, even at equal levels of resource input to the educational process, outcomes can differ substantially, owing to household socio-economic, peer group, and other effects. Thus, measures of educational outcomes, e.g., student achievement on standardized tests such as the SAT, also are relevant to assessing the quality of the public school experience.

and Meese and Wallace (1994). These models find that after a boom period in which actual prices have risen above fundamental values, there will tend to be periods of very intense declines in real housing prices before prices start to recover, but that eventually equilibrium will be restored.

In extending our particular model of California house prices to incorporate a disequilibrium component, we use the error-correction form employed in Capozza, Mack, and Mayer (1997). In particular, letting Δp_{jt} denote the logarithmic change in real housing prices in area j in year t, we assume

$$\Delta p_{jt} = \xi \Delta p_{jt-1} + \delta(p_{jt-1} - p^*_{jt-1}) + \gamma \Delta p^*_{jt} + \varepsilon_{jt} \, . \tag{7}$$

The term p^*_{jt} is the underlying fundamental value of housing. Actual prices, p_{jt}, may temporarily deviate from this current fundamental value, but in the absence of additional demand or supply shocks, actual prices tend to revert to fundamental values over time. The coefficients ξ, δ, and γ and the realizations of the residual shocks ε_{jt} govern the speed and extent of this adjustment process.

As suggested by the preceding sections, the underlying model assumes that fundamental housing values for California counties are determined to a significant degree by real income levels and by amenities in these counties. We augment that specification in this section by assuming that housing supply in particular counties may be constrained by natural topographic features and land use regulations.[17] That is, population flows to a metropolitan area may have differential impacts on house prices in the counties comprising that metropolitan area, depending on supply-side factors in those counties. We subsume these factors into a single index which we label S_j.

We estimate the supply constraint index from data on the extent to which job growth in a county tends to engender an increase in the housing stock in that county, rather than an increase in commuting from other counties in the area. The supply factor index, S_j, for county j is specified as $e^{-\overline{resid_j}}$, where $\overline{resid_j}$ is the average value of the residual for that county in pooled OLS estimates of an equation explaining the growth rate of the single-unit housing stock in each county by the growth rate of county employment (by place of work). This equation was estimated using annual data from 1987 to 1996, pooling across 19 California counties and one rest-of-California geographic area. The resulting index values for counties in the Los Angeles and San Francisco CMSAs are displayed in Table 7. The estimated supply-side index, S_j, ranges from a low of about 0.2 in Riverside County to highs of 2.3 in Marin County and 2.7 in San Francisco and San Mateo counties. The estimates of the S_j index characterize Riverside and San Bernardino as the least supply-constrained counties in the Los Angeles area and Contra Costa, Sonoma, and Solano as the least supply-constrained counties in the San Francisco area.

TABLE 7

ESTIMATED SUPPLY CONSTRAINTS AND ACTUAL AND PREDICTED HOUSE PRICE GROWTH CHANGES FOR CALIFORNIA COUNTIES

Area	Supply Constraint Index ($\hat{S}_j$)	Percentage Point Change in Growth Rate of Real House Prices, 1988–1993: Predicted	Actual
Los Angeles CMSA			
Los Angeles	1.73	–0.22	–0.23
Orange	1.39	–0.18	–0.22
Riverside	0.18	–0.06	–0.12
San Bernardino	0.80	–0.11	–0.12
Ventura	1.61	–0.20	–0.24
San Francisco CMSA			
Alameda	1.98	–0.17	–0.13
Contra Costa	0.89	–0.10	–0.11
Marin	2.28	–0.22	–0.18
San Francisco	2.73	–0.19	–0.16
Napa	1.35	–0.16	–0.08
San Mateo	2.70	–0.22	–0.19
Santa Clara	2.28	–0.19	–0.15
Santa Cruz	2.52	–0.23	–0.12
Sonoma	0.91	–0.15	–0.14
Solano	0.34	–0.13	–0.10

SOURCES: Calculations by the authors using models explained in text. Real house prices are calculated from the Experian repeat sales home price indexes and the overall U.S. CPI as a deflator.

In this version of the model, the level of amenities in each county is captured by a set of fixed effects parameters, A_j. We then proceed as if other CMSA-wide demand-side determinants of fundamental values, $D_{m(j)t}$, interact multiplicatively with the supply-side factors S_j:[18]

$$p^*_{jt} = A_j + \theta S_j D_{m(j)t} \, . \tag{8}$$

17. See Rose (1989) for evidence that topographical features and land use regulations are important in explaining the variation across metropolitan areas in land prices.

18. Here $m(j)$ is an index representing the CMSA containing county j.

In particular, we assume that the rate of net migration of people to a CMSA, $y^{net}_{m(j)t}$, is a good proxy for changes in housing demand in that CMSA, $\Delta D_{m(j)t} = y^{net}_{m(j)t}$. Then, the implied equation for Δp_{jt}, solving out for within-sample values of p^*, is:

$$(9)\qquad \Delta p_{jt} = -\delta p^*_{j0} + \xi\Delta p_{jt-1} + \delta p_{jt-1} - \delta\theta S_j \sum_{\tau=1}^{t-1} y^{net}_{m(j)\tau} + \gamma\theta S_j\, y^{net}_{m(j)t} + \varepsilon_{jt}\ .$$

Non-linear least squares estimation of this equation yields parameter estimates of $\hat{\xi} = 0.50$, $\hat{\delta} = -0.35$, $\hat{\gamma} = 2.22$, and $\hat{\theta} = 1.28$. For comparison, Capozza, Mack, and Mayer (1997) report similar-sized estimated coefficients of $\hat{\xi} = 0.48$ and $\hat{\delta} = -0.24$ using an annual sample of 62 U.S. metropolitan areas from 1979 to 1995.[19]

To see what these estimated values of the coefficients imply about the dynamics of housing prices, we can examine the difference equations that govern these dynamics. In particular, let $a(L) = b(L)^{-1} = (1 - (1 + \xi + \delta)L + \xi L^2)^{-1}$; this is the lag polynomial describing the passthrough of residual shocks (ε_{jt}) to actual prices (p_{jt}). Shocks to fundamental values, p^*_{jt}, are transferred to actual prices according to the product of this lag polynomial governing residual shocks and $\gamma - (\delta + \gamma)L$. At the estimated values of $\hat{\xi} = 0.50$ and $\hat{\delta} = -0.35$, the roots of $b(L)$ are complex and imply that the infinite order lag polynomial $a(L)$ has the damped, oscillating coefficients shown by the dashed line in the upper panel of Figure 3. A one-unit transitory innovation in ε_{jt} increases the logarithmic level of real house prices in the current and three subsequent periods, but thereafter the effect dampens down to close to zero. As shown by the solid line, a permanent change in the fundamental path of house prices (through $y^{net}_{m(j)t}$) is estimated to have two to three times as large an impact on actual prices in the short-run, but most of the convergence to the new long-run equilibrium level takes place within five years.

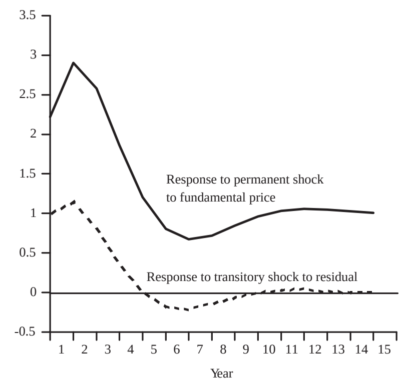
Thus, within the parameters of these dynamic response functions, the implied dynamics for actual prices depend on two unknowns: changes in the equilibrium values of housing in each county and the size of residual shocks to the system. The typical residual shock is relatively small. For example, the lower panel of Figure 3 shows the actual and predicted values of logarithmic real house price changes for Los Angeles County. The difference between the actual and predicted values, the residual ε_{jt}, is small relative to the overall variation in actual price changes.

The estimated current effects of changes in fundamental prices, $\hat{\gamma}\Delta p^*_{jt}$, shown by the thin solid line in the lower panel of Figure 3, generally explain a moderate proportion of the variation in actual price changes. For example, the immediate effect of changes in the fundamental housing price in Los Angeles County swung from about 2 percent in the mid-1980s to about –10 percent in the early 1990s. Furthermore, because changes in fundamental prices in one direction tend to be followed by changes in fundamental prices in the same direction, and the bulk of the cumulative responses to these shocks are spread over about five years (as shown in the upper panel of Figure 3), the changes

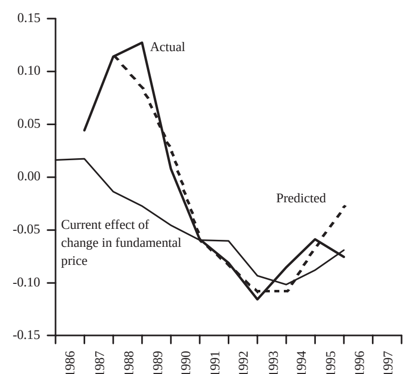
FIGURE 3

HOUSING PRICE MODEL CHARACTERISTICS

DYNAMIC RESPONSE FUNCTIONS FOR REAL HOUSING PRICES



ACTUAL AND PREDICTED HOUSE PRICE CHANGES FOR LOS ANGELES COUNTY



SOURCES: Dynamic response functions and predicted house price changes are calculated by the authors using parameter estimates described in the text. Real house prices are calculated from the Experian repeat sales home price indexes and the overall U.S. CPI as a deflator.

19. At $\hat{\gamma} = 0.18$, their estimated current period response of actual prices to changes in fundamental values is smaller than what we find. Our estimates of $\hat{\gamma}$ and of the other dynamic parameters are relatively precise; conventionally calculated standard errors imply rejection at the 0.01 significance level of individual hypotheses that the coefficients equal zero.

in fundamental prices contribute considerably to the overall explanatory power of the model.

With regard to the dynamics of the fundamental prices themselves, our model implies that these are completely determined by the dynamics of net migration for the CMSA, amplified to a lesser or greater extent by the (time-invariant) supply-side factors, S_j. The heterogeneity in dynamics induced by the supply-side amplification effects is notable and helps to explain the within-CMSA volatility of housing prices over the sample period. To see this, note that for most of the Los Angeles and San Francisco area counties, peak rates of real housing price growth occurred in 1988 or 1989, when net in-migration to these CMSAs also was near a peak. The troughs in real housing price growth generally were in 1993 or 1994, when net outmigration was bottoming out. The model predicts that real housing price growth would swing from positive to negative in each county over this peak to trough period, with the extent of the swing positively correlated with the level of the supply constraint index (Table 7).

The cross-sectional distribution of the actual swings in real house price growth rates was similar to the predicted distribution. For example, within the Los Angeles area, the actual and predicted dropoffs in real house price growth between 1988 and 1993 were near 20 percent in the most supply-constrained counties of Los Angeles, Orange, and Ventura, while, as predicted, real house prices experienced less volatility in Riverside and San Bernardino counties. In the San Francisco area, the actual and predicted dropoffs in real house price growth were near 20 percent in the supply-constrained counties of Marin, San Francisco and San Mateo, but notably less so in Contra Costa county.

Assessment of county-level house price dynamics is further informed by evidence on within-CMSA migration. In the Los Angeles CMSA, the largest outflows of population from the core to the periphery (Table 8) occurred during

TABLE 8

NET MIGRATION RATES
(PERCENT OF RESIDENTS AT AN AVERAGE ANNUAL RATE)

	BETWEEN AREA		WITHIN CMSA	
AREA	1986–1990	1991–1996	1986–1990	1991–1996
LOS ANGELES CMSA	–0.2	–1.6	—	—
Los Angeles	–0.3	–1.5	–1.2	–0.9
Orange	–0.2	–1.7	–0.3	0.4
Riverside	1.1	–1.3	5.4	2.6
San Bernardino	0.1	–2.3	4.6	2.3
Ventura	–0.6	–1.9	1.0	1.1
SAN FRANCISCO CMSA	–0.4	–0.9	—	—
Alameda	–0.8	–1.2	0.1	0.0
Contra Costa	0.1	–0.8	1.6	1.0
Marin	0.3	–0.6	–0.3	0.0
San Francisco	0.4	0.4	–2.9	–2.0
Napa	–0.6	–0.8	–0.6	–0.1
San Mateo	–1.1	–1.1	–0.5	–0.3
Santa Clara	–0.6	–0.8	–0.6	–0.1
Santa Cruz	–1.1	–1.1	–0.5	–0.3
Sonoma	0.5	–0.6	3.0	1.0
Solano	0.5	–0.6	1.7	1.1

SOURCE: Calculations by the authors using IRS county migration data.

the latter half of the 1980s, in the wake of the sharp acceleration in Los Angeles County house prices. A sizable portion of those within-Los Angeles CMSA movers migrated to the Inland Empire counties of Riverside and San Bernardino, areas characterized by a relatively elastic supply of housing, lower levels of housing quality and locational amenities, and, hence, more affordable housing. As anticipated by urban economic theory, another aspect of the within-Los Angeles CMSA migration was the flow of wealthier core area residents to Ventura County in pursuit of higher quality housing and more desirable locational amenities. Over the first half of the l990s, as house prices in Los Angeles County dropped back more substantially, the net outflows of population from Los Angeles County to the periphery slowed. Similarly, in the San Francisco area, the counties with the highest rates of net within-CMSA inmigration—notably Contra Costa, Solano, and Sonoma—also were those with the most elastic housing supply and the lowest levels of (quality-adjusted) housing costs. Moreover, as in the Los Angeles CMSA, the net outflows of population from the earlier developed counties to the periphery eased off some between the late 1980s and the early 1990s, as house prices in the urban core of San Francisco dropped back from the peak level. This pattern is broadly consistent with the predictions of between-area migration and urban development theory, which suggest that the between- CMSA moves primarily are driven by changes in area-wide job opportunities, whereas the within-CMSA moves are more heavily influenced by amenity and housing considerations.

IV. Conclusion

This paper has reviewed the literature on why local housing price differentials exist and change over time. We applied housing price theory, including models of compensating differentials, urban development, and short-run housing price dynamics, to explain recent housing price patterns in California's two largest metropolitan areas. We found that migration between metropolitan areas is important in explaining overall housing price dynamics for a given metropolitan area, and we showed that household mobility within each metropolitan area tended to attenuate price pressures in the most supply-constrained places. Longer-run, persistent housing price differentials can be partly explained by the distribution of housing quality and amenities within the areas, consistent with standard theories of urban development.

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APPENDIX

TABLE A1
AMENITIES, FULL IMPLICIT PRICES, AND CONTRIBUTIONS TO QUALITY-OF-LIFE INDICES FOR THE U.S. AND CALIFORNIA

		Contribution to Quality-of-Life Index		
		U.S.	California	
Static Amenity	Full Implicit Price	1981–1990 Avg.	1981	1990
Precipitation *35 inches per year*	–12 (24)	–420	-180	–180
Humidity *65.5 percent*	–51 (33)	–3340	–3536	–3536
Heating Degree Days *5091 per year*	–1.74 (0.19)	–8858	–3697	–3697
Cooling Degree Days *1215 per year*	–1.65 (0.31)	–2005	–1273	–1273
Wind Speed *9.36 miles per hour*	–216 (92)	–2022	–1772	–1772
Sunshine *59.4 percent of possible*	–54 (39)	–3208	–3947	–3947
Coast *0.52; 1 if coastal state*	27 (385)	14	27	27
Inland Water *2.7 percent of land area*	226 (62)	610	344	344
Federal Land *15.3 percent of land area*	34 (14)	520	1515	1515
Visitors to National Parks *148 per 100 population*	1.6 (0.9)	237	216	216
Visitors to State Parks *365 per 100 population*	–0.5 (0.6)	–182	–156	–156
Number of hazardous waste sites *25.2 sites per state*	–5 (7)	–126	–503	–503
Environmental Regulation Leniency *2200 on Green Policies Index*	0.0 (0.4)	0	18	18

(CONTINUED ON PAGE 22)

TABLE A1 (continued)
Amenities, Full Implicit Prices, and Contributions to Quality-of-Life Indices for the U.S. and California

		Contribution to Quality-of-Life Index		
		U.S.	California	
Time-Varying Amenity	Full Implicit Price	1981–1990 Avg.	1981	1990
Commuting Time *20.1 minutes*	–736 (74)	–14794	–16655	–18113
Violent Crime Rate *475 per 100,000 population*	0.4 (0.9)	190	384	465
Air Quality—Ozone *0.12 parts per million*	–26809 (5002)	–3217	–7265	–5071
Air Quality—Carbon Monoxide *8.2 parts per million*	–160 (46)	–1312	–2224	–1690
Student-teacher ratio *17.6 students per teacher*	–187 (90)	–3291	–4402	–4477
State and local taxes				
on income *$24 per $1000 of personal income*	–28 (10)	–672	–838	–986
on property *$32 per $1000 of personal income*	23 (15)	736	526	658
on sales and other *$51 per $1000 of personal income*	–3 (8)	–153	–116	–117
State and local expenditures				
on higher education *0.10 of general expenditures*	–3059 (7204)	–306	–340	–264
on public welfare *0.12 of general expenditures*	36455 (6063)	4375	6156	5830
on highways *0.09 of general expenditures*	46760 (8379)	4208	2070	2092
Memo: Quality-of-Life Index		–33016	–35646	–34615

Source: Calculations by the authors as described in Gabriel, et al. (1996).

Note: Conventional standard errors are in parentheses.