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Unaffordable Housing and Local Employment Growth

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Abstract

High housing prices have caused concerns among policy makers as well as the public in many U.S. regions. There is a general belief that unaffordable housing could drive businesses away and thus impede job growth. However, there has been little empirical evidence that supports this view. In this paper, we clarify how housing affordability is linked to employment growth and why unaffordable housing could negatively affect employment growth. We empirically measure this effect using data on California municipalities and U.S. metropolitan areas and counties. It is argued that for various reasons a simple correlation between unaffordable housing and employment growth should not be interpreted as causal. We therefore develop some empirical strategies and employ statistical techniques to estimate the causal effect of unaffordable housing on employment growth. Our results provide consistent evidence that indeed unaffordable housing slows growth in local employment. We discuss policy implications of these findings.

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Introduction

Housing prices and their growth rates vary substantially across regions in the United States. For example, the median sales price of single-family homes in the San Francisco area was $805,400 in 2007, compared with a median price of $130,000 in the Cleveland area.[1] According to the S&P/Case-Shiller Home Price Index, home values appreciated by 354 percent in San Francisco from January 1987 to January 2007, whereas they rose only 122 percent in Cleveland.[2]

In regions where housing prices are relatively higher or grow faster, there are always concerns that unaffordable housing could adversely affect local economic growth. (See Box 1 for quotes from newspaper articles reflecting widespread anxiety over high housing prices in California and other regions of the country.) There appears to be a general belief that high housing prices increase the costs of living and doing business, and make a region less attractive to workers and businesses, and therefore hurt the regional economy by slowing down employment growth. However, there is little empirical evidence that supports such a belief.[3]

Fast-growing housing prices until 2006 did inspire some recent studies on this topic. However, most focus on the supply side of local housing markets.[4] Saks (2008) investigates how housing supply regulations affect housing and labor market dynamics in metropolitan areas across the United States. She argues that land-use and other government regulations can lower the elasticity of housing supply, which in turn can change the geographic distribution of housing prices and alter the pattern of labor migration. As a result, employment growth will be lower in places where the

[1] See data on housing prices for U.S. metropolitan areas at http://www.realtor.org/research/research/metroprice (accessed June 12, 2008).
[2] See data on the S&P/Case-Shiller Home Price Index for many other metropolitan areas at http://www.data360.org/issue_group.aspx?Issue_Group_Id=12 (accessed June 12, 2008).
[3] Bluestone (2006) is perhaps the only study that directly addresses this concern. He examines the simple correlation between employment growth and housing cost at the metropolitan-area level. As we will argue, such simple regressions are subject to serious endogeneity and omitted-variables biases.
[4] The bulk of this literature focuses on how land-use regulations restrict land supply, leading to higher housing prices. See, for example, Glaeser 2006; Glaeser and Gyourko 2003; Glaeser, Gyourko, and Saks 2005a and 2005b; Glaeser and Ward 2009; Ihlanfeldt 2007; and Quigley and Raphael 2005. Hwang and Quigley (2006) examines how a broad range of economic conditions and regulations affect outcomes in local housing markets.

housing supply is more constrained. Saks presents some empirical evidence that supports that hypothesis.

In a related study, Glaeser, Gyourko, and Saks (2006) provide complementary evidence that in metropolitan areas with more stringent land-use regulations, positive labor demand shocks lead to slower population growth and faster housing price appreciation. Gyourko, Mayer, and Sinai (2006) show that inelastic land supply in some attractive locations, combined with the growing number of high-income families nationally, can partially explain the growing differences in house prices and incomes among cities. This line of research has helped us better understand why housing price varies so much across regions.

However, despite concerns voiced in the popular media, little research has been done to understand how high housing prices could affect a local economy. In this paper, we try to address this question. Our goal is twofold. First, we want to develop a simple model to clarify why housing affordability varies among cities, and under what conditions unaffordable housing could have negative effects on local employment growth. The model reveals two insights: (1) Different levels of amenities in different cities drive the variation in housing affordability; and (2) cities with unaffordable housing could experience slower employment growth, because land rents are so high in those cities that they have already reached the very inelastic portion of their land supply curves.

Second, we want to test whether unaffordable housing indeed negatively affects employment growth. We use data on California municipalities, U.S. metropolitan statistical areas (MSAs), and U.S. counties to empirically measure the effects of unaffordable housing on employment growth. Given the potential endogeneity and omitted-variables problems in OLS regressions, we use climate amenity variables to instrument for housing affordability, a solution suggested by our theoretical model.

We present the theoretical model in the next section, and discuss the empirical specification and identification strategies in the ensuing section. We then describe our data sources and present our empirical results before concluding.

Theoretical framework

This section presents a simple model to clarify thinking and motivate empirical research. We start with a simplified version of the well-known Roback (1982) model, which uses variations in amenities at the city level to explain differentials in land rents and income across cities.[5] We then make some explicit assumptions about land supply in different cities—which, within the Roback-type framework, implies a relationship between housing affordability and local employment growth.

Consider an economy that consists of many cities, each endowed with some amenity level a. One could think of the amenity as the total number of sunny days in a year, or the average daily temperature in winter.

City residents are all workers. A representative worker consumes a composite good x and land s (lot size, as part of housing) and enjoys the amenity a. He or she has the following utility maximization problem:

$$\text{Max } U(x, s, a),$$
$$\text{s.t. } x + rs = w + m, \tag{1}$$

where r is land rent; w is wage income; and m is non-labor income. The price of the composite good is determined on the international market. It is used as the numeraire and normalized to 1. To keep our notations cleaner, we do not index variables by city. However, it should be noted here that a, r, and w all vary across cities.

[5] Many researchers have adapted the Roback (1982) framework to measure quality of life or its effects. See, for example, Blomquist, Berger, and Hoehn 1988; Cragg and Kahn 1997; Gyourko and Tracy 1991; Shapiro 2006; and Chen and Rosenthal 2008.

Equation (1) defines the representative worker's indirect utility function $V(w, r, a)$.[6] Assume that workers can freely move from one city to another at no cost. In equilibrium, every worker would attain the same level of utility u:

$$V(w, r, a) = u. \tag{2}$$

V increases with a and w and decreases with r: that is, $V_a > 0$, $V_w > 0$, and $V_r < 0$.

There are also firms located in these cities. All firms have access to the same technology, which uses land and labor to produce the composite good. The production function is written as $f(n, d)$, where n is the number of workers and d is the quantity of land used in production.[7]

Assume that function f exhibits constant returns to scale. Therefore, we can describe the production technology can using the unit cost function $C(w, r)$, which gives the minimum cost of producing one unit of good x. Firms are free to enter or exit the market, and can move costlessly from one city to another. This implies that in equilibrium, firms everywhere have the same unit cost, which equals output price:

$$C(w, r) = 1. \tag{3}$$

Note that $C_w > 0$ and $C_r > 0$.

Workers consume land only as part of housing. Housing here refers to a physical structure attached to a piece of land. For the sake of simplicity, we assume that every worker lives in the same kind of physical structure, which is produced and assembled on the international market. Therefore, we consider the physical structure as part of the composite good x. Let b be the amount of the composite good that constitutes the physical structure of housing, and assume that in equilibrium, $b << x$ for any worker. A worker's spending on housing is therefore $b + rs$.

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[6] One could assume that the central government collects all the land rent and distributes it equally among all citizens in the form of non-labor income. Because non-labor income is the same for everybody, it does not show up explicitly in the indirect utility function.

[7] Following Roback (1982), we simplify our analysis by ignoring any capital used in production. Alternatively, one could admit the use of capital, but assume a fixed capital-to-labor ratio (such as one computer for each worker). In that case, as long as the price of capital is not determined locally, we can still write a production function this way without an explicit capital input.

Following common practice, we measure housing affordability using the ratio of housing price to labor income:

$$h = (b + rs)/w. \tag{4}$$

A higher h implies that housing is less affordable.[8]

We examine how h varies from one city to another. Differentiating equations (2) and (3) with respect to a, we obtain

$$dw/da = V_a C_r/(V_r C_w - V_w C_r) < 0, \text{ and} \tag{5}$$

$$dr/da = V_a C_w/(V_w C_r - V_r C_w) > 0. \tag{6}$$

These equations imply that in equilibrium, a city with a higher level of amenity has a lower wage rate and a higher land rent. It is an intuitive result. Because workers enjoy amenity, they are willing to accept a lower wage and pay a higher rent in a city with higher amenity. At the same time, firms' production is not affected by amenity. In a city with higher amenity, a firm can still break even: although it has to pay a higher rent, it offers a lower wage to workers, so its unit cost remains the same.

Further assume that a worker's demand for land is inelastic, so that an increase in land rent will never lower the worker's expenditure on land. That is, $d(rs)/dr > 0$. Together with equations (5) and (6), this assumption implies $dh/da > 0$, meaning that housing is less affordable in a city with a higher level of amenity.

We have now set up a modeling framework that we can use to examine how unaffordable housing affects local employment growth. Starting with an equilibrium, let's consider a change in the total number of workers in the national economy. One may imagine that a cohort of college graduates just entered the labor force, or that a group of immigrants just arrived.

[8] Many researchers and organizations use this simple housing affordability measure. For example, the World Bank uses this measure as a major indicator of urban development (see http://www.worldbank.org/html/opr/pmi/urban/urban006.html, accessed October 5, 2008). The central bank of New Zealand also uses this measure in its annual International Housing Affordability Survey (see http://www.demographia.com/dhi.pdf , accessed October 5, 2008). A more sophisticated and often-cited affordability index is the one used by the National Association of Realtors. It is defined as the ratio of median family income to the income needed to qualify for a mortgage on a median-priced, single-family house, which is simply median income divided by a function of the median housing price. See Fisher, Pollakowski, and Zabel (2008) for an attempt to build a theory-based housing affordability index that takes into account local amenities.

We ask the following question: Under what conditions will a city with less-affordable housing experience slower employment growth? Because the composite good is sold on the international market, we assume that the influx of workers to a city does not affect the price of x. However, in principle, a change in the number of workers (N) in a city would affect r and w, and thus a worker's utility in this city.

Differentiating equations (2) and (3) with respect to N and substituting for dw/dN, we obtain

$$(V_r - V_w C_r/C_w)(dr/dN)\Delta N = \Delta u. \tag{7}$$

Equation (7) shows that a change in N affects r, which in turn causes a change in a worker's utility through two channels. First, a change in r directly affects a worker's utility (by V_r). Second, the change in r also causes firms to adjust the wage rate so their unit cost remains the same, which in turn affects utility (by $-V_w C_r/C_w$).

We will try to illustrate our idea in the simplest way, by assuming that ($V_r - V_w C_r/C_w$) is constant across cities.[9] Note that under both the original equilibrium and the new equilibrium, indirect utility has to be the same everywhere after an influx of workers into the economy. Therefore, Δu will be the same in all cities. However, dr/dN may vary from one city to another, which implies that ΔN will be different in different cities. In particular, a city with a higher dr/dN will have a lower ΔN.

In each city, equilibrium land rent is determined by land supply and demand in the city. Land supply refers to the quantity of land available for industrial or residential uses as a function of land rent. Land demand refers to the quantity of land demanded by workers and firms as a function of land rent, which is ultimately determined by the number of workers who reside and work in the city.

We assume that the land supply function in each city has the following property: land is perfectly elastically supplied initially. As long as city residents and firms are willing to pay the opportunity cost of land in the agricultural sector, they can use more land and expand the city. However, this process cannot go on forever.

[9] We can derive this assumption by imposing conditions on the indirect utility function and the cost function. For example, we may assume the following: (1) in the indirect utility function V, a is additively separable from r and w; (2) V is linear in r and w; and (3) C is linear in r and w. Together these assumptions imply that ($V_r - V_w C_r/C_w$) is a constant everywhere.

After the city boundary reaches a certain limit, reflecting local land-use regulations or geographical constraints, land (for urban uses) can be supplied only at an ever-higher cost.[10]

More specifically, we assume that city *i* has an (inverse) land supply function, as follows:

$$r = \begin{cases} r_a & \text{if } q \leq \bar{q}_i \\ r_a + (q - \bar{q}_i)^{\rho} & \text{if } q > \bar{q}_i \end{cases}$$

where *r* is land rent in the city, and *q* is the quantity of land available for residential and industrial uses in the city; r_a is the cost of land in the agricultural sector, which, for simplicity, is assumed to be the same everywhere; and $\bar{q}_i$ is the maximum amount of land that can be supplied to the city at the opportunity cost in agriculture. We assume that $\bar{q}_i$ varies from one city to another because of local regulations and geographic conditions. We also assume that $\rho > 1$, so that dr/dq increases with *q* when *q* is higher than $\bar{q}_i$.

We are now ready to show that in the system of cities described above, employment growth is slower in cities with less affordable housing. Consider a simple example depicted in Figure 1: an economy with only two cities. City 1 has a higher amenity level than city 2. Suppose the initial equilibrium is attained when N_1 workers live in city 1 and N_2 workers live in city 2, and that $N_1 = N_2$. Note that equilibrium land rent in city 1 has to be higher, because city 1 has a higher level of amenity.

Imagine a small number of workers, ΔN, are now added to the economy. In equilibrium, these new workers will be absorbed by city 2, because the in-migration does not influence equilibrium land rent in city 2. More generally, given cities of the same size, we expect that the increase in the number of workers will be smaller in a city where the equilibrium land rent is already on the inelastic portion of the land supply curve.

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[10] See Saiz (2008) for a discussion of the factors that affect the local supply of land and housing.

In other words, in a city with unaffordable housing, employment growth is smaller because equilibrium land rent is already very high and land supply is more inelastic. An inelastic land supply implies that even a small increase in demand for land as a result of population growth pushes the city's land rent much higher and drives workers to other cities with lower rents. Therefore the city can accommodate only moderate employment growth.

In summary, the model presented above has two implications:

Housing is less affordable in cities with higher amenities. That is because higher amenities lead to lower wages and higher housing prices, which together imply less affordable housing. Higher housing prices in high-amenity cities are mainly driven by higher land rents.

Cities with less-affordable housing experience slower employment growth. That is because land supply in such cities is less elastic, and a small increase in land demand pushes land rent very high, to curb in-migration or spur out-migration of workers. Land supply is less elastic in those cities because equilibrium land rent is higher, and land supply becomes less elastic as land rent increases.

Empirical strategy

The main equation that we will estimate is the following:

$$y_{i,t} = \alpha + \beta h_{i,t-1} + \lambda X_{i,t-1} + \tau_t + \varepsilon_{i,t}, \qquad (8)$$

where the dependent variable $y_{i,t}$ is employment growth in city i and period t; $h_{i,t-1}$ is the key independent variable measuring housing affordability in city i and period $t-1$; $X_{i,t-1}$ represents a vector of control variables; τ_t is a year fixed effect; and $\varepsilon_{i,t}$ is the error term of the regression.

A simple OLS regression of equation (8) will likely produce a biased estimate of β. In the theoretical model, we assumed that the equilibrium was attained instantaneously after any shocks hit the system of cities—we ignored the adjustment process. In empirical work that is inappropriate, because the adjustment to a new equilibrium takes time, and data collected in out-of-equilibrium situations are likely to bias the coefficients in a simple OLS regression.

There are two types of potential biases. First, there may be some endogeneity bias. Conceptually, we want to investigate how unaffordable housing affects employment growth. However, a simple OLS regression may also pick up a reverse causal effect.

For example, rapid job growth in a city, resulting from exogenous shocks, can raise the land rent, and thus housing price, in the city in the short run (if the city has already reached the inelastic proportion of its land supply curve). Over time, workers and businesses will migrate to other cities to take advantage of the lower rents in those places, pushing land rent and housing price back toward their original equilibrium levels.[11]

If data are collected during this adjustment period, a simple OLS regression may show a positive relationship between unaffordable housing and employment growth, even if unaffordable housing leads to slower employment growth in equilibrium. See panel (a) in Figure 2 for an illustration of the shocks that may result in this type of bias.

The second matter of concern in estimating equation (8) is the problem of omitted variables. A simple OLS regression might fail to take into account some relevant but unobserved factors in some cities, and thus not properly control for their effects. For example, some cities have introduced zoning laws or other land-use regulations that would affect land supply as well as employment growth.

Consider a regulatory restriction on land use that pushes land rent, and thus housing price, higher in the short run. Again, over time, workers and businesses will migrate out, so the prices will move back toward their original equilibrium levels. During this adjustment period, both housing affordability and employment will change, although neither one is causing the other to change.

Again, data on housing affordability and employment growth may be collected in these out-of-equilibrium situations. If shocks to land supply are not

[11] This kind of transitional dynamics in out-of-equilibrium situations, although not the focus of our analysis here, has been studied in related work. See, for example, Sasser (2010) and Zabel (2009), both of which investigate how local economic (and especially housing market) conditions affect the flow of workers across U.S. states or cities.

observable or measurable, they will contaminate the estimated effect of unaffordable housing on employment growth that we intend to measure. See panel (b) in Figure 2 for an illustration of shocks that may lead to this type of bias.

We employ a few identification strategies to tackle the problems with simple OLS regressions. First, for part of our analysis, we conduct empirical research at the city level within a single state, California. That helps us avoid the potential bias caused by unobserved heterogeneities at the state or higher levels that we expect to confound empirical studies based on nationwide data.

Second, we always use predetermined affordability to predict employment growth in our empirical specifications. The idea is that if growth is not anticipated, it will not affect predetermined affordability measures. Thus the use of independent variables measured at the end of the last period should help mitigate the endogeneity biases.

Third, we add area (city, MSA, or county) fixed effects to the main equation, using within-area variations over time to identify the effect of unaffordable housing on local employment growth. This approach also helps mitigate the potential biases from unobserved heterogeneities across regions.

Our fourth strategy is to use the instrumental variables (IV) approach to correct for both the endogeneity and omitted-variables biases in simple OLS regressions. To identify the effect of housing affordability on employment growth in a city, we need a variable (or a set of variables) that affects local housing affordability but does not directly influence local employment growth. Our theoretical model predicts that housing affordability is a function of the amenity level in a city. Thus local amenity measures are natural candidates for instrumental variables used to isolate the effect of housing affordability on employment growth.

Specifically, we use weather variables, such as minimum January temperature and annual precipitation, to instrument for housing affordability. These weather variables qualify as valid instruments if (1) they are strongly correlated with housing affordability and (2) they can be excluded from the main equation.

Condition (1) is implied by our theoretical model, and, as we will show, is born out in the data. Condition (2) is a strong assumption we are making to attain model identification. Nice weather may affect employment growth by attracting residents or better-educated workers (Graves 1980; Poelhekke 2006; Rappaport 2007). To be cautious, we add some control variables in our regressions, including total population, the proportion of adult population with a bachelor's degree, and time variations.[12]

We estimate the impact of housing affordability on local employment growth using two-stage least squares (2SLS), treating housing affordability as an endogenous variable in equation (8). The first stage equation is given by

$$h_{i,t-1} = \gamma + \theta A_{i,t-1} + \delta Z_{i,t-1} + \mu_{t-1} + \eta_{i,t-1}, \qquad (9)$$

where, as before, the subscripts i and t index cities and years; $Z_{i,t-1}$ is a vector of city characteristics as controls; μ_{t-1} represents a year fixed effect; and $A_{i,t-1}$ is the set of instruments. The predicted value $(\hat{h})$ from this first-stage regression is used to estimate the employment growth equation in the second stage.

Although the instrumental variables method is used primarily to deal with endogeneity and omitted-variables problems, it can also be employed to correct for biases stemming from classical measurement errors in independent variables. In our case, if we suspect that our housing affordability variable is not precisely measured, the instrumental variables will also help correct biases introduced by such measurement errors.

Ideally, one would estimate fixed-effects models using instrumental variables, which presumably will produce the most convincing results. Unfortunately, the climate amenity variables that we use as instruments do not vary a lot within a small area, especially over a short period of time. Consequently, those instruments are sometimes not useful in fixed-effects models. Therefore, in some of

[12] The city population control is particularly important, given that early empirical research (e.g., Glaeser and Shapiro 2003; Glaeser and Gyourko 2005) has used weather variables to instrument for city population growth.

our empirical analyses, we try the IV approach and the fixed-effects approach separately.

Data and variables

We conduct empirical analyses at the levels of California cities, U.S. metropolitan areas, and U.S. counties.[13] For California cities, our analysis focuses on employment growth over two-year periods from 1993 to 2004. For U.S. metropolitan areas and counties, our analyses deal with employment growth over two 10-year periods, 1980–1990 and 1990–2000.[14] The choice of these time intervals is largely dictated by data availability. In this section, we describe the data sources and the variables we constructed for our empirical analysis.

Dependent variables

City-level employment growth in California: For California cities, we calculate employment growth using data from the state's Employment Development Department. This database contains average yearly employment at the city level, collected by the department's Labor Market Information Division in cooperation with the U.S. Department of Labor and the Bureau of Labor Statistics. California's official city-level employment statistics are based on these data.

U.S. metropolitan-area/county–level employment growth: We use data from U.S. Censuses to conduct analyses at the national level for the periods 1980–1990 and 1990–2000. We first obtain county-level employment data for the three Census years (1980, 1990, and 2000) from various editions of the *County and City Data Book*.[15]

[13] We chose California for our subnational analysis not only because it is the largest state economy, but also because it has the most diverse geography and climate. Its numerous microclimates provide enough variation in climate amenity variables to make them useful as instrumental variables.
[14] Although our outcome variable is employment growth—which seems most appropriate given our theoretical framework—we do not mean to suggest that it is the variable that policymakers should focus on. Some other variables, such as the employment-to-population ratio, might be a better measure of the welfare of local residents.
[15] The *County and City Data Book*, from the U.S. Census Bureau, provides demographic, economic, and governmental data from both the federal government and private agencies. We obtain our 2000 data from the 2000 edition of the *County and City Data Book*, our 1990 data from the 1994 edition, and our

Metropolitan areas are multi-county units, defined using the 1999 Census definitions of primary metropolitan statistical areas (PMSA) and New England county metropolitan areas (NECMA). The metropolitan-area employment data are aggregated from the county-level data using a consistent definition of geography over time, so changes in metropolitan-area boundaries do not affect any of the dependent or independent variables. The final panel consists of 3,146 counties and 317 metropolitan areas for the years 1980, 1990, and 2000.

Independent variables

California city-level housing affordability: We calculate this variable by dividing city-level median housing price by county-level median household income. We download data on median housing sales prices from the Business and Economic Statistic Division of RAND California.[16] RAND originally acquired these data from the California Association of Realtors. The price reflects both sales of new homes and resales. RAND has price data from 1991 to 2002, all measured in nominal dollars.

We obtain annual data on county-level median household income data from the Small Area Income and Poverty Estimates (SAIPE) program of the U.S. Census Bureau. The program provides estimates of key income and poverty statistics for small geographic areas in non-census years. Prior to 1998, the bureau produced county-level income data every two years, in odd-numbered years only, so data are not available for 1994 and 1996. We impute the missing data for those two years by taking the average of the preceding and the following year. Thus we are able to calculate the affordability ratio for each city in each year.

U.S. metropolitan-area/county–level housing affordability: Median housing price and median household income at the county-level are available from the *County and City Data Book*. For each county, the affordability measure is simply the ratio of the county's median housing price to its median household income. For each

1980 data from the 1988 edition (see http://fisher.lib.virginia.edu/collections/stats/ccdb/, accessed February 18, 2008).

[16] See http://ca.rand.org/stats/economics/houseprice.html (accessed June 12, 2008).

metropolitan area, affordability is similarly defined as the ratio of housing price to income, where housing price is a weighted average of county-level median housing price, and income is a weighted average of county-level median household income. The weight used for each county is the fraction of the metropolitan area's households living in that county.

Fraction of adult population with a bachelor's degree: For California, we obtain data on educational attainment from the SF-3 and STF-3 files of the 2000 and 1990 Census, respectively. These data give the share of the adult population (25 years and older) with a bachelor's degree in each city for the two census years. We impute the data for other years from 1992 to 2004, assuming a linear trend. For U.S. metropolitan areas and counties, we obtain these data from the SF-3 file for year 2000, the STF-3 file for year 1990, and the *County and City Data Book* for year 1980.

Population of California cities, U.S. metropolitan areas, and U.S. counties: We download population data on California cities from the website of the state Department of Finance, where they estimate the total population of each city each year based on 1990 and 2000 Census data.[17] For U.S. metropolitan areas and counties, we obtain population data from the *County and City Data Book*. We use log population as a control variable in all our regressions.

Other control variables: For analyses at the U.S. metropolitan-area and county levels, we use additional control variables, including population density, crime rate, and the percentage of the population that is black. We collect all these data from the *County and City Data Book*. We again use county-level data to calculate these variables for metropolitan areas, to keep geographic definitions consistent over time.

Instrumental variables

January temperature, July temperature, and annual precipitation: For cities in California, we obtain these weather variables from the National Climatic Data

[17] These city-level population estimates, and the methodology used for the estimates, are available at http://www.dof.ca.gov/HTML/DEMOGRAP/ReportsPapers/ReportsPapers.asp (accessed June 12, 2008).

Center's monthly surface data files (DS320).[18] The center's database includes monthly surface data from 18,000 stations, sited in major cities as well as some small towns. For our analysis, we extract data on the January minimum temperature, July maximum temperature, and monthly total precipitation for all available, active California stations. We use station names to generate city names, which we then use to match the weather variables with other data. In a few cases, when a single city has multiple weather stations, we use the simple average of the data recorded at those stations. The variables used as instruments in this paper are the January minimum temperature, January minimum temperature squared, and annual precipitation. We use July maximum temperature in an alternative specification for sensitivity analysis.[19]

For U.S. metropolitan areas, we obtain the climate variables from the *County and City Data Book*. These data are available only at the city level, so we take the values of the largest city in each metropolitan area and assign them to the entire metro area. All the climate variables in the *County and City Data Book* are 30-year averages, originally obtained from the U.S. National Oceanic and Atmospheric Administration and the National Climatic Data Center (NCDC). For 1990, they are average values for the 30-year period 1961–1990, while for 1980, they are average values for the 30-year period 1951–1980.

Empirical results

We now report our empirical results.

Analyses at the California city level

We start by using data from a single state: California. The main advantage of focusing on one state is that we will expect fewer unaccounted-for heterogeneities created by state policies, because all the jurisdictions within a state are subject to the

[18] See http://cdo.ncdc.noaa.gov/CDO/cdo (accessed June 12, 2008).
[19] We calculate January minimum temperature by averaging the daily minimum temperature over the month's 31 days. We calculate July maximum temperature similarly.

same regulations at the state level. However, a state may be too small to have wide regional variations. For that reason, we have chosen a large state where both housing prices and climate amenities vary drastically across regions. We conduct our analysis at the municipality level instead of the county or metropolitan-area level so we can have a reasonably large number of observations.

Descriptive statistics

There are 478 incorporated cities and towns in California, but the NCDC city list for California is much shorter, because many smaller cities have no weather stations. After matching all the variables from different sources, we find that our data cover 115 cities in the state for the period 1993–2004, including all the large cities.[20] See Table 1 for descriptive statistics for the dependent, independent/control, and instrumental variables.

The average California city in the sample has 140,295 residents, with an employment level of 64,014. Average employment growth is 2.0 percent over one year and 3.9 percent over two years. The key independent variable—the housing affordability ratio—averages 4.5. It varies substantially, ranging from a minimum of 0.78 to a maximum of 16.42. Table 2, which lists the housing affordability ratio for a selected group of cities in California, illustrates this variation. For example, the mean ratio in the inland city of Fresno is 2.97, while it is as high as 11.46 in the coastal city of Santa Monica.

The instrumental variables, shown in Table 1, also reveal a great deal of variation across cities. For example, the January minimum temperature ranges from a minimum of 9.9 degrees to a maximum of 52.4 degrees. Annual precipitation ranges from 72 to 10,197 hundredths of inches.

Figure 3 graphs the relationship between the housing affordability ratio and the instrumental variables. Panel (a) shows that January temperature is positively correlated with the housing affordability ratio. Housing is less affordable (with a higher affordability ratio) in cities where it is warmer in January. The relationship

[20] The housing price variable and the weather variables may be missing for certain years for some cities. Therefore we do not have a balanced panel.

appears to be nonlinear, which justifies the use of a squared term in addition to the January temperature variable in the first-stage regression. Panel (b) shows a positive relationship between the affordability ratio and annual precipitation, indicating that drier areas tend to have more-affordable housing.

OLS and IV estimates

Table 3 presents OLS and IV regression results for California cities. To focus on the independent variable of interest, we omit the coefficients of all the control variables. We report the standard errors clustered by county, allowing for both spatial and serial correlations among all observations within a county.

The OLS results are in the upper panel of Table 3. In the left column is the specification without city fixed effects. In this case, housing affordability has a negative coefficient, but its magnitude is small (-0.3 percent), and it is not statistically significant. The right column in the upper panel shows the estimate from the specification with city fixed effects. Here the coefficient is still negative but much larger (-2.5 percent), and it is statistically significant at the 1 percent level.

These results imply that if we simply compare different cities, we will not see slower employment growth in less-affordable cities. However, if we focus on within-city changes over time, we do see that slower employment growth tends to follow years with less-affordable housing.

The lower panel of Table 3 shows the IV estimates, without controlling for city fixed effects. We report three sets of IV estimates, depending on the specification of the first-stage equation. We tried to instrument for the housing affordability ratio using (1) January minimum temperature only, (2) January temperature together with annual precipitation, and (3) January temperature, its squared term, and annual precipitation.

When including both temperature and precipitation variables in the first stage, we are assuming that together they form a "comfortability index," and that housing should be less affordable in cities with more comfortable weather. All the IV estimates show a statistically significant negative relationship between the housing affordability ratio and city-level employment growth. In each case, the coefficient is slightly less negative (-2.0 or -2.1 versus -2.5 percent) than the OLS estimate with city fixed effects. The statistically significant IV estimates and the fixed-effects OLS estimate suggest that unobserved heterogeneity at the city level does indeed cause potential biases.

The magnitude of this negative effect on employment growth is surprisingly similar across different IV specifications. They are all close to -0.02. This implies that a one-unit (or about half-a-standard-deviation) increase in a city's housing affordability ratio leads to a two-percentage-point decrease in the two-year employment growth rate. This is a rather large effect, given that total employment in the average city grows by only 3.9 percent over two years (as shown in Table 1).

For our IV regressions, we also calculate the standard errors of the estimates, based on alternative clustering analyses, which are also presented in Table 3. Standard errors clustered on county-years, allowing for spatial correlations within a county in a single year, are shown in square brackets under the estimated coefficients. Standard errors clustered by city, allowing for serial correlations within the city over different years, are shown in curly brackets.

In general, clustering on county-year leads to smaller standard errors than in the baseline regressions, and clustering on city leads to larger standard errors. However, in both cases the standard errors change only slightly from our baseline results, and the coefficient of the housing affordability ratio remains statistically significant under all specifications.

Table 3 also presents some results regarding the validity of our instruments, and regarding the presence of endogeneity biases in the OLS estimates (without city fixed effects). We compute all these results by clustering standard errors by county.

Valid instruments must be correlated with the endogenous variable, and orthogonal to the error term. We use the F-statistics for the joint significance of the instrumental variables in the first-stage regressions to check the correlation between the instruments and the endogenous variable. This statistic ranges from 10.91 to 15.52 across the specifications for employment growth, and is consistently greater than 10, suggesting that the instruments used in our regressions have good explanatory power.[21]

In some specifications, we use both temperature and precipitation variables as instruments, although we have only one endogenous variable. One would naturally think of using the overidentifying test to check the validity of the instruments. It is worth noting here that all the instruments are based on a common foundation: climate amenity. As mentioned, when we include more than one weather variable in the first stage, we think of those variables as a single indicator. That is, together they constitute a "comfortability index," which we can use as an instrument for housing affordability. They should be either valid or invalid as a single index because they share common ground. For this reason, a failure of the overidentifying test should not be interpreted as strong evidence against our whole empirical approach.

Nonetheless, we conduct Hansen's J test for the null hypothesis that all instruments are proper instruments, and report the p-vales of this test in Table 3. In both cases where we use more than one instrumental variable, we cannot reject the null hypothesis. Given that the null hypothesis requires each instrumental variable to be valid separately, and that it is a requirement stronger than our need, we find these test results rather reassuring.

Although our conceptual discussion clearly suggested the potential endogeneity between employment growth and housing affordability, we still want to empirically test for the presence of endogeneity here. Table 3 shows the p-values of the statistics from the endogeneity tests. For all three specifications, we reject the null hypothesis that the OLS coefficient is unbiased. That is, our statistical tests suggest that when we measure the effect of unaffordable housing on employment growth, endogeneity is present, and can potentially lead to seriously biased estimates in OLS regressions. Therefore, an IV estimate is preferred in this case.

[21]A common problem in IV estimations is that of "weak instruments," even when the first-stage results are statistically significant and the sample is fairly large. The rule of thumb for a single endogenous variable is that the first-stage F-statistic must be greater than 10. An F-statistic below 10 is a reason for concern (Staiger and Stock 1997).

Our 2SLS regressions do not include county or city fixed effects. Presumably, such fixed-effects IV regressions would be the preferred specifications, because they would be the most conservative approach to dealing with unobserved heterogeneities among the cities. However, as noted, year-to-year variations in both housing affordability and the weather variables would be small within any small geographic region over a short period. Therefore the correlation between those two variables would be too weak for us to identify the effects of unaffordable housing in fixed-effects models.

Because our affordability ratio variable and city-level weather variables are observed in every year, we can certainly try to run the regressions with county or city fixed effects. Indeed, with county or city fixed effects, the first-stage F-statistics are small across all the specifications, confirming that the year-to-year correlation between weather variables and housing affordability within a county or a city is not strong enough to help identify the effects of unaffordable housing. The estimated coefficients under these fixed effects models blow up in some cases, and can never be precisely estimated. We therefore have to ignore these results and consider the baseline IV regressions without controlling for county or city fixed effects as our best-attainable results.

Table 4 reports results from some robustness checks. In all the specifications presented above, we include log city population and the percentage of adult population with a bachelor's degree in a city as controls. Here we try an alternative specification by adding another control variable: a dummy for coastal counties. The negative effect observed in the baseline IV regressions might result from the fact that housing is generally less affordable in coastal cities (refer to Table 2). In other words, our estimated coefficients might be picking up only this "coast effect." By introducing the coastal dummy, we identify the effects of unaffordable housing using only the variations within the coastal or inland areas.

Panel A of Table 4 shows the results from the specification with the coastal dummy. As with the baseline regressions, standard errors are clustered by county. The IV coefficients are all negative, and they are still similar across different specifications. Compared with results from our baseline IV specifications, the coefficient of the housing affordability ratio is somewhat higher, ranging from -2.5 to -2.7 percent. These results are still statistically significant under all specifications. That is, we still see a negative effect of unaffordable housing on employment growth, even if we try to identify this effect using only within-group variations in coastal or inland areas in California.

Panel B of Table 4 reports results from the use of alternative IVs. In particular, we interact the temperature variables with the price of electricity in the state to instrument for housing affordability.[22]

The primary reason for this exercise is that energy prices may affect climate (dis)amenities. For example, a cold winter or a hot summer may not be that unbearable if heating or air conditioning is cheap. Therefore an interaction between extreme temperature and electricity price may be a more accurate measure of the amenity that really matters.

We tried three different specifications, using the interaction of January minimum temperature with electricity price, the interaction of July maximum temperature with electricity price, and both interactions as instrumental variables. Results using these instruments are somewhat smaller than those from the baseline regressions, ranging from -1.2 to -1.9 percent. However, they are more or less of the same order. Coefficients from all three specifications are still statistically significant. The first-stage F-test statistics are much higher than before in two of the three specifications, suggesting that these amenity measures indeed better explain variation in housing affordability.

In panel C, we still use the alternative IVs as in panel B, but also add city fixed effects in the hope that the stronger first-stage correlations might allow us to identify fixed-effects models in this case. In all three cases, the coefficient is still negative but cannot be precisely estimated, and the first-stage F-statistics are all below 10. In one case, when the interaction with January temperature is used as the

[22] We thank John Brown for suggesting these alternative IVs. We obtained data on annual electricity prices for California from the Energy Information Administration (see http://www.eia.doe.gov/cneaf/electricity/st_profiles/sept08ca.xls, accessed February 6, 2009).

IV, the coefficient blows up and the first-stage F-statistic is very small. In the other two cases, when the IVs include an interaction with July temperature, the coefficient is more or less of the same magnitude as the baseline estimates.[23]

Overall, these different specifications using fixed effects and/or alternative instrumental variables rather consistently point to a negative effect of unaffordable housing on local employment growth in California. A one-unit increase in the housing-price-to-income ratio reduces city-level employment growth by 1.5–2.5 percentage points over two years.

Analyses at the U.S. metropolitan-area and county levels

Analysis at the municipality level, as presented above, is not ideal. Given that a typical municipality is very small, many workers could choose to work in one municipality but live in another, which could lead us to underestimate the effect of unaffordable housing on local employment growth.

We therefore conduct a parallel analysis at the metropolitan-area level, using nationwide data. We consider this level the best fit with our theoretical model, although we also report some results at the county level, mainly for comparison purposes.

Descriptive statistics

Table 5 shows descriptive statistics for the 317 U.S. metropolitan areas in our sample. The average employment in a metropolitan statistical area (MSA) is 299,436, and the average employment growth over two Census years is 14.5 percent. The average housing-price-to-income ratio is 2.75. The least-affordable metropolitan area in the sample is New York, where the affordability ratio is 9.22. The most-affordable metropolitan area is Decatur, Ill., where this ratio is only 1.58. Note that this affordability ratio varies within a narrower range than in the case of California cities, mainly because here we measure the ratio at a higher geographic level.

[23] This seems to make sense because in California, extreme summer temperatures are often the most unpleasant.

On average, an MSA has a population of 626,571, with an average density of 373 persons per square mile. Other demographic and social indicators show that the mean proportion of adult population with a bachelor's degree is 15 percent, 10 percent of the population is black, and on average 19,100 crimes (per 100,000 population) are reported in an MSA.

We again use the weather variables as instruments. The 30-year average January minimum temperature is 25.6 degrees, and varies from the lower extreme of -7.4 to the upper limit of 65.3 degrees. The 30-year average annual precipitation is 36.1 inches, and varies from 2.7 to 65.7 inches. In both cases, the range of variation is larger than in California cities, which is natural because we now include many other areas with more extreme weather.

In Figure 4, we again check whether the weather variables are closely related to our endogenous variable, the housing affordability ratio. Panel (a) shows a clear positive correlation between January minimum temperature and the housing affordability ratio. That is, a metropolitan area with a warmer winter tends to be less affordable. In panel (b), the correlation between affordability and annual precipitation is less clear. Beyond 25 inches, where most of the observations lie, there is a positive correlation between the two variables. However, below that point, housing affordability seems to have little to do with the level of precipitation.

OLS and IV estimates

Table 6 presents regression results at the U.S. metropolitan-area level. The upper panel shows the OLS coefficients. We again tried two specifications: with and without MSA fixed effects. We consider the specification with MSA fixed effects more appropriate, so we show the other specification mainly for comparison purposes.

If we do not control for MSA fixed effects, we find that the coefficient of the housing affordability ratio is positive, small, and statistically insignificant. The coefficient with MSA fixed effects, in contrast, is negative, large, and statistically significant. That is, focusing on variations within MSAs, we see that less-affordable housing is indeed associated with slower employment growth at the U.S.

metropolitan-area level. A one-unit (a little more than one-standard-deviation) increase in the housing affordability ratio leads to a 9.8-percentage-point decline in the 10-year employment growth rate. Note that this is remarkably consistent with the results estimated at the California city level, where a one-unit increase in the affordability ratio reduces employment growth by about two percentage points over two years.

The lower panel of Table 6 presents the IV regression results. As with the analysis of California cities, we again try three sets of instrumental variables, using January minimum temperature alone, January minimum temperature with annual precipitation, and January minimum temperature, its squared term, and annual precipitation as instruments.

Unlike in the analysis of California cities, here we also include the MSA fixed effects in the IV regressions. Because we use nationwide data to perform these analyses, we are much more concerned with unobserved heterogeneities. In particular, we suspect that some unobserved factors at the MSA level, such as land-use regulations and industry compositions, might be strongly correlated with our climate amenity variables. If that is the case, and if we do not include MSA fixed effects, then our instruments will be correlated with the error term in the main equation, and therefore they cannot be excluded from the main equation.[24]

Of course, adding MSA fixed effects to the IV regressions does not come without its cost. Our instrumental variables—although measured over a longer period of time than in the analysis of California cities—do not vary that much, and most of their effects are absorbed by the MSA fixed effects. Consequently, as Table 6 shows, the first-stage F-statistics show a relatively weak correlation between the endogenous variable and the instruments. The endogeneity tests also suggest that the IV coefficients are not statistically different from the OLS coefficient (with MSA

[24] We have checked whether the fixed effects estimated from our OLS regressions are correlated with our IVs. Indeed, at the metropolitan-area level, the correlation coefficient is -0.064 between the fixed effects and January minimum temperature, and -0.083 between the fixed effects and January minimum temperature squared. For California cities, these two correlation coefficients are 0.004 and 0.008, respectively—much closer to zero. That is why we feel comfortable excluding the fixed effects from the IV regressions for California cities but not for U.S. metropolitan areas.

fixed effects). In addition, the Hansen's J tests, after controlling for MSA fixed effects, show a rather strong correlation between the IVs and the error term in the main equation. Only one of the two specifications, using all three instruments, passed the test, and then only marginally.

Despite these weak results from the diagnostic tests, we still find these IV estimates informative. If we look at the coefficients of the affordability ratio variables, we see that they are still negative, statistically significant, and of roughly the same order across different specifications. Using January minimum temperature alone as the instrument, the IV coefficient is almost identical to the OLS coefficient from the fixed-effects specification. The other two IV specifications give slightly more negative coefficients.

Again, these results suggest that unaffordable housing hurts local employment growth. More specifically, a one-unit increase in the affordability ratio leads to a 10–14- percentage-point reduction in employment growth in a metro area over 10 years. This is again a very large effect, given that the average 10-year growth rate is only 14.5 percent in the sample period.

The weak instruments are perhaps the most worrisome concerns about these IV estimates. However, note that week instruments tend to produce IV estimates biased toward OLS estimates (Bound, Jaeger, and Baker 1995; Staiger and Stock 1997; Stock, Wright, and Yogo 2002). Given that our IV estimates are more negative than the OLS coefficient, we could think of these estimates as lower bounds of the actual negative effects. In this sense, we may still interpret these results as supportive of the hypothesis that unaffordable housing negatively affects local employment growth.

As a robustness check, we also try a similar analysis using U.S. county-level data. Because the weather variables are originally collected from stations located mostly in high-density urban areas, we do not have information on climate amenities for a large proportion of counties. As a result, we cannot instrument housing affordability using amenity variables, and therefore focus only on the OLS specification with county fixed effects.

Table 7 shows the results. Those from the specification with county fixed effects appear in the right column. The coefficient of the affordability ratio variable is again negative and statistically significant. That suggests that a one-unit increase in the affordability ratio leads to a decrease in county-level employment growth of 8.3 percentage points over 10 years. That is only slightly smaller than the results we found at the metropolitan-area level.

For comparison purposes, we also show the results without county fixed effects, which are in the left column. The coefficient from this specification is very different: it is positive and statistically significant, again indicating the presence of serious endogeneity and/or omitted-variables biases.

Overall, our empirical analyses—at both the California city and U.S. metropolitan-area and county levels—show that unaffordable housing negatively affects employment growth. Naïve cross-sectional OLS regressions tend to suggest no effects, or even positive effects. However, once we control for area fixed effects and/or use the instrumental variables approach, we do find negative effects from unaffordable housing. These effects are remarkably consistent across different specifications of our empirical model, different geographic levels, and different lengths of time.

Conclusion

Housing prices vary substantially across different areas of the United States. Persistently higher housing prices in certain regions always cause concerns in those areas, because unaffordable housing is expected to have negative effects on the local economy. Yet there is not much empirical evidence on such perceived effects. This paper attempts to study whether unaffordable housing impedes local employment growth.

We proposed a simple model to explain why housing affordability could affect employment growth in a regional economy. In the model, the variation of housing affordability is driven by heterogeneities in location-specific amenities. Cities with less-affordable housing tend to experience slower employment growth, because land rents are so high that the supply of land must have reached some limit. These land supply limits are the ultimate restrictions on local employment growth.

Potential endogeneity biases are a major problem in empirical studies of the effect of unaffordable housing. While housing prices may affect local employment growth, job growth could also make the local economy more prosperous, leading to an increase in housing prices. In addition, we are also concerned with omitted variables in the regression model. All of these can bias the estimates obtained through OLS regressions.

We used various identification strategies to correct for the potential endogeneity and omitted-variables biases. Most importantly, we took the instrumental variables regression approach. As suggested by our theoretical model, we used measures of climate amenities, such as January minimum temperature and annual precipitation, to instrument for the housing affordability measure.

Our findings show significant negative effects of unaffordable housing on local employment growth. For California cities, other things being equal, a one-unit increase in the housing affordability ratio reduces employment growth by about two percentage points over two years. For U.S. metropolitan areas and counties, a one-unit increase in the housing affordability ratio reduces employment growth by about ten percentage points over ten years. These empirical results—estimated at different geographic levels and using different data sources—turn out to be remarkably consistent.

We pursued this research because of local policymakers' concerns about the possible negative effects of unaffordable housing. Because our empirical analyses indeed show a relationship between unaffordable housing and employment growth, we ask whether these findings have policy implications.

We can address that question within the theoretical framework we developed. In our model, housing affordability is an endogenous variable: policymakers do not directly control it. However, they do have some policy levers for influencing housing affordability.

Interestingly, although we find a negative effect of unaffordable housing on local employment growth, that does not imply that any policy that makes housing more affordable will have a positive effect on employment growth. For example, a policy reducing local amenities will lead to more-affordable housing, but it will also make the region less attractive and drive people away. Such a policy will not stimulate employment growth. A policy relaxing constraints on land supply, in contrast, will help make housing more affordable in the short run. All else being equal, such a policy will make a region more attractive to both workers and firms, and will lead to faster employment growth during the transition to a new equilibrium.

Note that because amenity ultimately determines housing affordability, a policy that does not change the level of local amenity will have no effect on affordability in the long run. That also implies that not all policies aimed at unaffordable housing will affect real variables. For example, if policymakers aim to make housing more affordable by subsidizing rents or homeownership, they will induce residents to bid housing prices higher. Such a policy will eventually lead to even higher housing prices, and is unlikely to have a substantial effect on employment.

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Box 1: Media Excerpts on Concerns That Unaffordable Housing Will Undercut the Local Economy

Limits on immigration, rising global competition for skilled workers and California's high housing prices will impede the state's ability to meet its future economic demand, according to the study's author Hans Johnson and Deborah Reed. …… From 2000 to 2005, California lost more college graduates to other states than it gained, reversing a long trend of attracting them. The researchers said that the state's high housing prices were a prime cause. …… The outlook could change, the researchers said, if housing prices fall and wages rise, making California more attractive.

Los Angeles Times, May 24, 2007

A report being released today predicts robust job growth in Silicon Valley and the Bay Area economy over the next 10 years. But finding workers who are willing to put up with the area's high housing prices will be daunting.

San Jose Mercury News, February 16, 2007

High home prices are limiting the Boston area's ability to regain the jobs lost in the 2001 recession and sustain economic growth, according to two new studies being released today during a conference at Boston's Federal Reserve Bank. …… Massachusetts employers often cite high housing prices as a major reason they expand operations in other states, where costs and therefore, the wages they pay are lower.

Boston Globe, May 22, 2006

Over the past five years, the Bay Area's high housing prices have driven many residents to seriously consider leaving for less-expensive environs, according to a new poll. The numbers seem to illustrate what has long been a regional worry: that astronomical home price could eventually lead to a decline in competitiveness as talented workers move away looking for a better quality of life.

Contra Costa Times, February 27, 2006

Mayor Jerry Sanders pledged yesterday to place affordable housing and land-use issues on an equal footing with solving San Diego's many financial problems. …… "There's nothing I can promise as a mayor that's going to draw a company here because I can't give them housing at much cheaper cost than you can in Phoenix," he said.

The San Diego Union-Tribune, January 11, 2006

For the first time in more than three decades, the population of San Diego County declined last year, joining other Californian coastal counties that are losing their allure as high housing prices drive home-buyers to more affordable regions.

The San Diego Union-Tribune, March 16, 2006

Is the sun and surf of San Diego enough to lure choice recruits to local companies? After doing the math, many job candidates are scared off by S.D.'s high housing prices.

The San Diego Union–Tribune, September 5, 2004

Boston, like San Francisco and San Jose, finds its job growth constrained by the high cost of doing business, with sky-high housing prices front and center……

Boston Herald, December 3, 2005

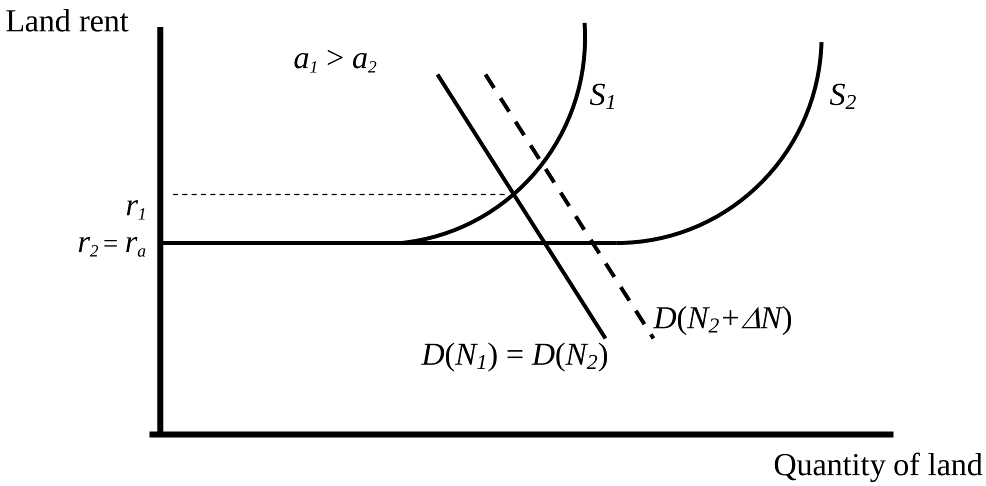
[W]hen housing costs outstrip wages, families start doubling up in homes intended for only one household or move farther from their jobs to find cheaper housing. They eventually tire of their long commutes and move away. When employers can't supply their labor needs locally, they, too, go elsewhere. Tampa Bay officials know that the local economy will soon feel the effects if they cannot find a way to boost the supply of affordable housing.

St. Petersburg Times, November 25, 2005

Moving in and moving on; Washington area is a 'funnel': people come for jobs, leave to find cheaper housing.

Washington Post, November 26, 2005

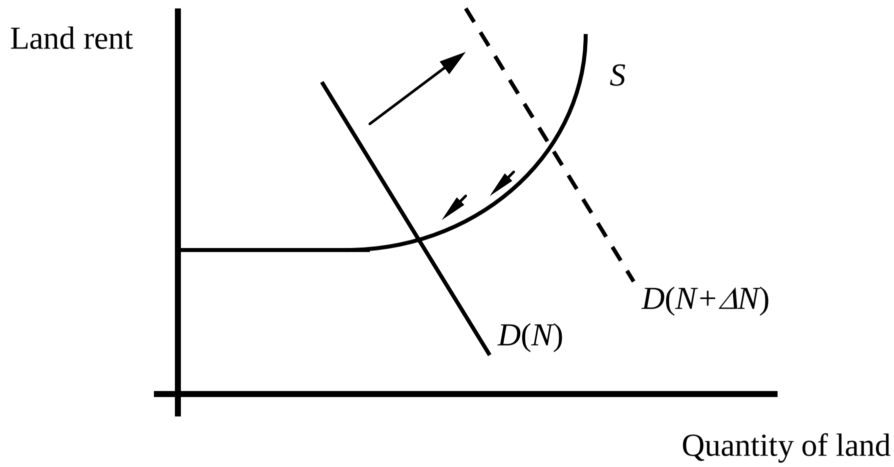
Figure 1: Land Market in Two Cities



Note: In this example, there are only two cities in the economy. S_1 and S_2 are land supply curves in the two cities. Each city's land is infinitely elastically supplied until the city boundary hits constraints imposed by land-use regulations or geography, beyond which urban land can be supplied only at an ever-higher cost. City 1 has a higher level of amenity: $a_1 > a_2$. Suppose that initially the number of workers living in city 1 is the same as that in city 2 ($N_1 = N_2$), and therefore that the two cities have the same land demand curve. The equilibrium land rent in city 1 is higher ($r_1 > r_2$) because of the higher level of amenity in city 1. As a result, housing price is higher and wage is lower in city 1. A small number of workers, ΔN, just entered the economy. In the new equilibrium, these workers are absorbed by city 2, because this in-migration does not alter the equilibrium land rent in city 2. Under the new equilibrium, the land demand curve in city 1 is unchanged, and the land demand curve in city 2 has moved to the right (the dash line). That is, employment growth occurs only in the city with more-affordable housing (city 2).

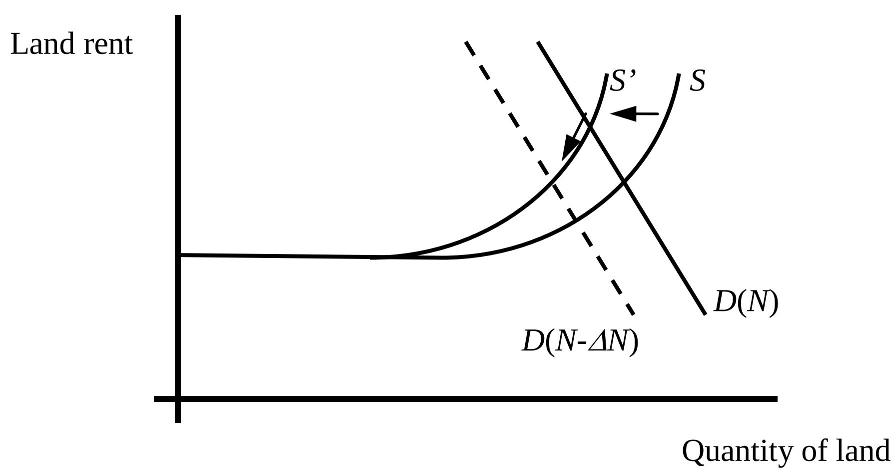
Figure 2: How Exogenous Shocks and Out-of-Equilibrium Data May Produce Biased Results

(a) An exogenous shock to employment growth that shifts demand for land



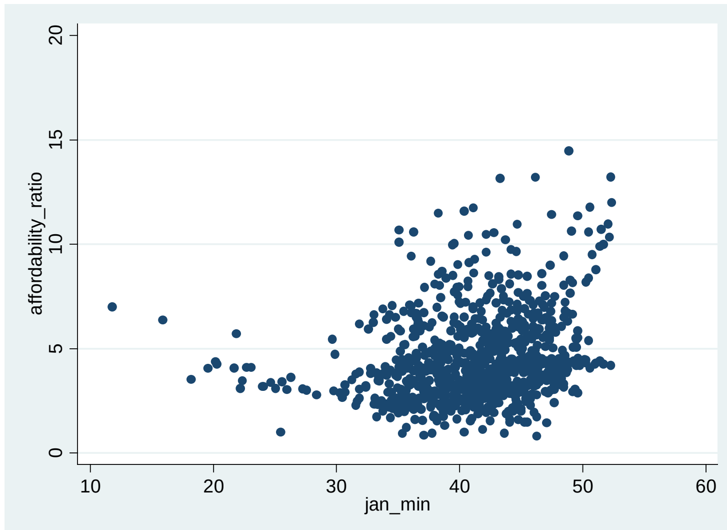
Note: The equilibrium land rent in the city is originally determined by S and D(N). An exogenous shock created ΔN more jobs. As a result, demand for land shifts to the right, and land rent and housing prices are higher in this city. Over time, workers and firms migrate to other cities because of the lower rents there, and demand for land moves back toward D(N). Any data collected during this adjustment period will show a positive relationship between unaffordable housing and employment growth.

(b) An exogenous shock that shifts land supply



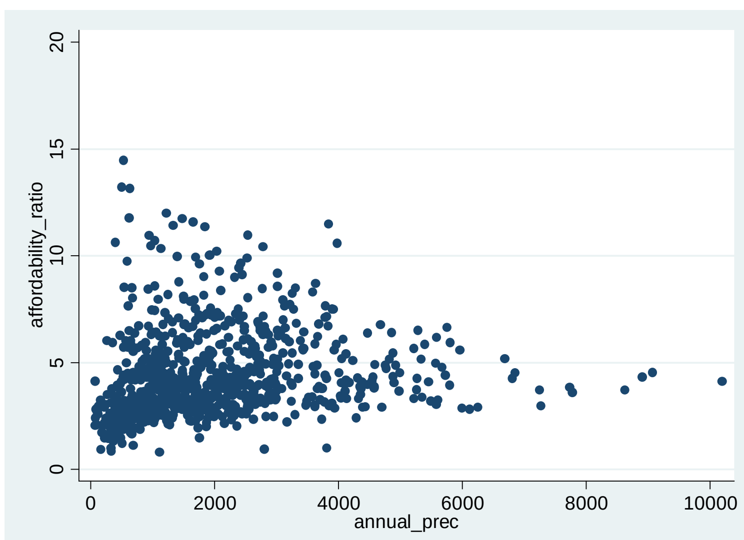
Note: The equilibrium land rent in the city is originally determined by S and D(N). An exogenous shock (say, a new land-use regulation) shifts the supply curve to S'. As a result, land rent and housing prices are higher in this city. Over time, workers and firms migrate to other cities, and demand for land shifts to D(N-ΔN). Any data collected during this adjustment period will show a positive relationship between unaffordable housing and employment growth.

Figure 3: Correlation between IVs and Housing Affordability in California Cities
(a) Housing affordability ratio vs. January minimum temperature



Note: This figure plots the housing affordability ratio against January minimum temperature in California cities (in degrees F). A higher housing-price-to-income "affordability ratio" means that housing is less affordable.

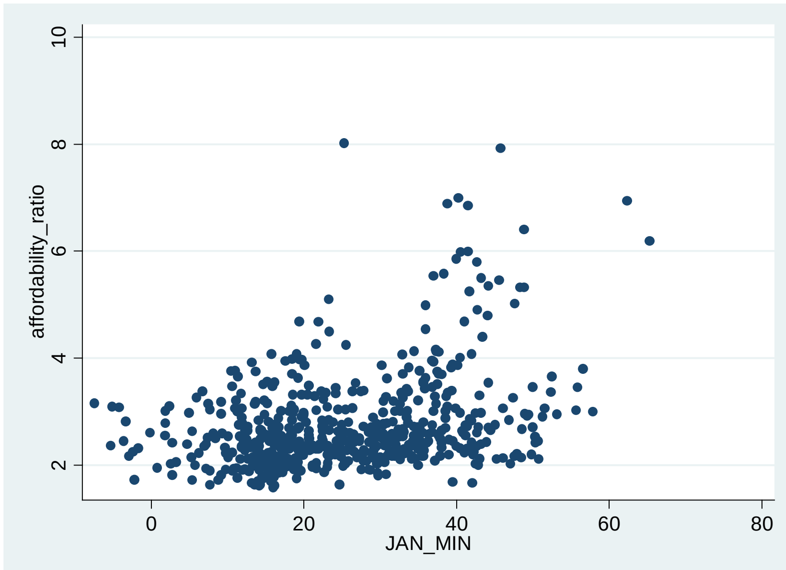
(b) Housing affordability ratio vs. annual precipitation



Note: This figure plots the housing affordability ratio against annual precipitation in California cities. A higher housing-price-to-income "affordability ratio" means that housing is less affordable.

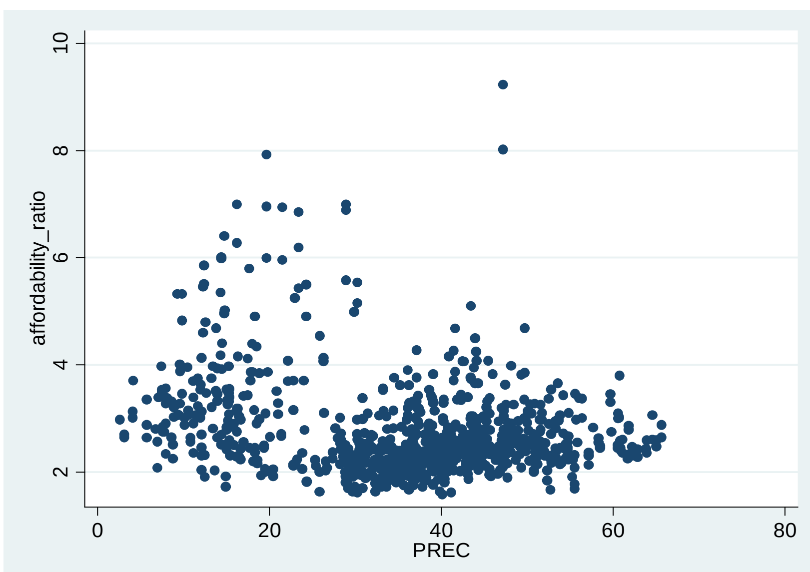
Figure 4: Correlation between IVs and Housing Affordability in U.S. Metropolitan Areas

(a) Housing affordability ratio vs. 30-year average January minimum temperature



Note: This figure plots the housing affordability ratio against 30-year average January minimum temperature for U.S. metropolitan areas. A higher housing-price-to-income "affordability ratio" indicates that housing is less affordable.

(b) Housing affordability vs. 30-year average total precipitation



Note: This figure plots the housing affordability ratio against 30-year average total precipitation for U.S. metropolitan areas. A higher housing-price-to-income "affordability ratio" indicates that housing is less affordable.

Table 1: Descriptive Statistics for California Cities

Variables	Variable Description	Mean	Std. Dev.	Min	Max
Dependent Variables					
total_emp	Total city employment in California	64,014	175,159	570	1,733,300
lmid_empg1	City-level employment growth over a one-year period in California	0.02	0.055	-0.684	0.488
lmid_empg2	City-level employment growth over a two-year period in California	0.039	0.078	-0.662	0.498
Independent/Control Variables					
affordability_ratio	Median home price in the city, divided by median household income in the county	4.49	2.11	0.78	16.42
percent_bachelor	Percentage of population 25 years and older in the city with a bachelor's degree	15.31	7.58	3.06	37.99
tot_pop	City-level annual population	140,295	389,261	1374	3,822,955
Instrumental Variables					
jan_min	January mean minimum temperature	40.99	5.73	9.9	52.4
jan_minsq	January mean minimum temperature squared	1,713.07	434.71	98.1	2,745.76
annual_prec	Annual total precipitation in the city	2,056.14	1,417.07	72	10,197

Note: Data on the percentage of the adult population with a bachelor's degree are from the 2000 and 1990 decennial Census. This variable is available only for the two Census years. We impute the figures for other years from 1993 to 2002 by linearly interpolating and extrapolating the Census data. Employment growth is defined as the difference in log employment.

Table 2: Summary Statistics on the Housing Affordability Ratio for Selected California Cities, 1993–2004

City Name	Housing-Price-to-Income Ratio			
	Mean	*Standard Deviation*	*Minimum*	*Maximum*
Anaheim	3.75	0.53	3.28	4.97
Bakersfield	2.88	0.31	2.42	3.40
Burbank	5.86	1.04	4.99	8.49
Fresno	2.97	0.37	2.52	3.48
Laguna Beach	9.32	2.10	7.08	13.16
Lodi	3.74	0.44	3.32	4.69
Long Beach	4.62	0.61	4.00	6.00
Los Angeles	4.81	0.76	4.05	6.49
Los Banos	4.57	0.87	3.84	5.92
Los Gatos	8.01	1.30	6.54	10.09
Madera	2.93	0.29	2.69	3.50
Merced	3.45	0.47	3.05	4.12
Modesto	3.22	0.57	2.75	4.38
Monterey	8.26	1.22	6.90	9.97
Newark	5.27	1.14	4.11	7.33
Oceanside	4.21	0.62	3.71	5.72
Sacramento	2.84	0.54	2.38	3.94
San Bernardino	2.20	0.23	1.94	2.64
San Diego	4.58	0.65	4.16	6.26
San Francisco	7.78	1.50	6.45	10.19
San Jose	4.60	0.86	3.82	6.23
Santa Barbara	8.71	1.68	7.15	11.73
Santa Cruz	6.69	1.59	5.14	9.17
Santa Monica	11.46	1.46	9.87	14.46
Stockton	3.19	0.61	2.57	4.45
Turlock	3.36	0.53	2.97	4.44
Victorville	2.59	0.29	2.26	3.03
Visalia	3.58	0.23	3.26	3.97
Vista	4.29	0.61	3.71	5.69

Table 3: Effects of Unaffordable Housing on City Employment Growth
in California
(Dependent variable: employment growth in a California city over two years)

Variables	**OLS Regressions**	
	(1)	(2)
Affordability ratio	-0.003 (0.002)	-0.025*** (0.008)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
City fixed effects	No	Yes
R^2	0.10	0.31
No. of observations	903	903

Variables (second stage)	**2SLS Regressions**		
	(1) IV: jan_min	(2) IV: jan_min & prec	(3) IV: jan_min, jan_minsq & prec
Affordability ratio	-0.020*** (0.007) [0.006] {0.010}	-0.020*** (0.006) [0.006] {0.009}	-0.021*** (0.007) [0.007] {0.010}
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
City fixed effects	No	No	No
First-stage F-statistic	15.52	10.91	15.37
Hansen's J test p-value	-	0.253	0.431
Endogeneity test p-value	0.025	0.015	0.015
No. of observations	903	786	786

Note: Standard errors clustered by county are in parentheses.
For the IV results, alternative standard errors are also reported. Standard errors clustered by county-year are in square brackets. Standard errors clustered by city are in curly brackets.
Levels of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Levels of significance, first-stage F-statistics, Hansen's J tests, and endogeneity tests are all based on standard errors clustered by county.
Although not reported in this table, we included an intercept and controlled for log city population and the percentage of adult population in the city with a bachelor's degree in all specifications.

Table 4: Effects of Unaffordable Housing on City Employment Growth in California: Alternative Specifications
(Dependent variable: employment growth in a California city over two years)

	A. IV Results on City Employment Growth: Specification with Coastal Dummy		
	IV: jan_min	IV: jan_min & prec	IV: jan_min, jan_minsq & prec
Affordability ratio	-0.026** (0.012)	-0.025* (0.014)	-0.027* (0.015)
First-stage F-statistic	5.41	2.98	4.53
No. of observations	903	786	786
	B. IV Results on CA City Employment Growth: Specification with Alternative IVs		
	IV: jan_min×elect_price	IV: jul_max×elect_price	IV: jan_min×elect_price & jul_max×elect_price
Affordability ratio	-0.019*** (0.007)	-0.012** (0.005)	-0.015*** (0.005)
First-stage F-statistic	15.70	38.35	22.68
No. of observations	903	902	870
	C. IV Results on CA City Employment Growth: Specification with Alternative IVs with City Fixed Effect		
	IV: jan_min×elect_price	IV: jul_max×elect_price	IV: jan_min×elect_price & jul_max×elect_price
Affordability ratio	-0.102 (0.123)	-0.026 (0.040)	-0.027 (0.038)
First-stage F-statistic	1.63	5.34	5.33
No. of observations	903	902	870

Note: Standard errors clustered by county are in parentheses.
Levels of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Levels of significance and first-stage F-statistics are based on standard errors clustered by county.
Although not reported in this table, we included an intercept and controlled for the year fixed effect, log city population, and the percentage of adult population in the city with a bachelor's degree in all specifications.

Table 5: Summary Statistics at U.S. Metropolitan-Area (MSA) Level

Variables	Variable Description	Summary Statistics			
		Mean	Std. Dev.	Min	Max
Dependent Variables					
tot_emp	Total MSA employment	299,436	520,476	20,815	4,506,104
empg	MSA employment growth over 10-year periods	0.145	0.127	-0.389	0.614
Independent/Control Variables					
affordability_ratio	Median home price divided by median household income in MSA	2.754	0.891	1.577	9.221
percent_bachelor	Percentage of population 25 years and older in MSA with a bachelor's degree	14.745	4.756	5.987	38.6
tot_pop	Total population in MSA	626,571	1,082,661	56,735	9,519,338
crime_rt	No. of crimes per 100,000 population in MSA	19,100	44,511	1,111	783,985
pop_mile	Total population divided by total land area in MSA	373.2	874.2	3.5	12,956.9
black_pct	Percentage of population in MSA that is black	10.32	10.31	0.05	50.98
Instrumental Variables					
jan_min	30-year average minimum January temperature in the MSA's central city	25.64	12.64	-7.4	65.3
jan_sq	Squared minimum January temperature in the MSA's central city	816.73	704.37	0.01	4,264.09
prec	30-year average annual precipitation in the MSA's central city	36.10	13.87	2.65	65.71

Table 6: Effects of Unaffordable Housing on Employment Growth in U.S. Metropolitan Areas
(Dependent variable: employment growth in a U.S. metropolitan area over 10 years)

Variables	**OLS Regressions**	
	(1)	(2)
Affordability ratio	0.011 (0.007)	-0.098*** (0.018)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
MSA fixed effects	No	Yes
R^2	0.12	0.75
No. of observations	591	591

Variables (second stage)	**2SLS Regressions**		
	(1) IV: jan_min	(2) IV: jan_min & prec	(3) IV: jan_min, jan_minsq & prec
Affordability ratio	-0.103* (0.055)	-0.127** (0.058)	-0.140** (0.052)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes
First-stage F-statistic	3.91	2.07	2.74
Hansen's J test p-value	-	0.053	0.117
Endogeneity test p-value	0.924	0.872	0.485
No. of observations	591	591	591

Note: Standard errors clustered by MSA are in parentheses.

Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Temperature and precipitation data for 1980 are the 30-year average from 1950 to 1980, while those for 1990 are the 30-year average from 1960 to 1990. Although not reported, we included an intercept and controlled for log MSA population, population density, percentage of adult population with a bachelor's degree, crime rate, and percentage of blacks in all specifications.

Table 7: Effects of Unaffordable Housing on Employment Growth in U.S. Counties
(Dependent variable: employment growth in a U.S. county over 10 years)

Variables	**OLS Regression**	
	(1)	(2)
Affordability ratio	0.050*** (0.007)	-0.083*** (0.014)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
County fixed effects	No	Yes
R^2	0.171	0.779
No. of observations	5,526	5,526

Note: Standard errors clustered by county are in parentheses.

Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Although not reported, we included an intercept in the regression and controlled for log county population, population density, percentage of adult population with a bachelor's degree, crime rate, and percentage of blacks.