Examining policies to reduce homelessness using a general equilibrium model of the housing market

Erin T. Mansur,[a,c] John M. Quigley,[a,b] Steven Raphael,[b,*] and Eugene Smolensky [b]

[a] *Department of Economics, University of California, 549 Evans Hall #3880, Berkeley, CA 94720-3880, USA*
[b] *Goldman School of Public Policy, University of California, 2607 Hearst Avenue, Berkeley, CA 94720-7320, USA*
[c] *School of Management and School of Forestry and Environmental Studies, Yale University, 135 Prospect Street, New Haven, CT 06520-8200, USA*

Abstract

In this paper, we use a general equilibrium simulation model to assess the potential impacts on homelessness of various housing-market policy interventions. We calibrate the model to the four largest metropolitan areas in California. We explore the welfare consequences and the effects on homelessness of three housing-market policy interventions: extending housing vouchers to all low-income households, subsidizing all landlords, and subsidizing those landlords who supply low-income housing. Our results suggest that a very large fraction of homelessness can be eliminated through increased reliance upon well-known housing subsidy policies. © 2002 Elsevier Science (USA). All rights reserved.

* Corresponding author.
  E-mail address: raphael@socrates.berkeley.edu (S. Raphael).

1. Introduction

The specter of homelessness is perhaps the most visible social problem in contemporary US metropolitan areas. Since the early 1980s, cities throughout the country have experienced sustained increases in the numbers of visibly homeless and in the numbers of individuals seeking temporary shelter in public and privately-run facilities. While estimates of the incidence of homelessness vary considerably, the most careful research (Burt [1] and Culhane et al. [2]) suggests that those who are homeless on any night account for one to two tenths of a percent of the total population (or roughly 250,000 to 500,000 people). Research on individual cities, however, indicates that a much larger population experiences a spell of homelessness over a given year (perhaps one percent of the population, or 2.5 million people), implying a dynamic homeless population with substantial turnover.

Discussions of the determinants of homelessness often emphasize explanations based on personal problems and changes in mental health policy at the expense of economic factors. The most popular explanation of homelessness posits that mental illness, alcohol abuse, drug use, and changes in their treatment by society are the principal determinants of homelessness (Jencks [3] and Rossi [28]). The alternative economic explanation argues that increases in housing costs relative to personal income drive low-income households out of the housing market and into the streets and shelters (O'Flaherty [4]). Assessing the relative importance of these distinct hypotheses is vital to designing policy responses to homelessness since the appropriate response to a problem originating in the housing market may differ considerably from the response to a problem caused by changes in mental health policy and patterns of drug use.

In a companion paper (Quigley et al. [5]), we analyzed statistical models relating the incidence of homelessness to metropolitan and regional measures of housing costs and availability, extending the empirical analysis of Honig and Filer [6] to more comprehensive data sets. The results confirmed the importance of housing-market conditions in affecting homelessness.

Those results motivate this paper that seeks to assess the effectiveness of policy interventions in the housing market in reducing homelessness. The evidence we present on this issue is purely theoretical, yet it can help illuminate the very ambiguous empirical evidence on the effects of policy interventions. Results reported by Cragg and O'Flaherty [7] suggest that the provision of homeless shelters may induce more homelessness. Regression estimates of the effects of housing subsidy policy on homelessness suggest that the availability of subsidized housing has no effect on homelessness (Early [8]); reduces homelessness if sufficiently targeted (Early and Olsen [9]); or actually increases homelessness (Troutman et al. [10]). None of these empirical findings are based upon a complete structural model of the housing market.

In contrast, we use a general equilibrium simulation of the housing market to investigate the sensitivity of homelessness to various changes in income conditions, population, and several policy interventions. The model we employ is an extended version of the simulation model introduced and developed in a series of papers by Anas and Arnott (A&A) [11–18]. This model describes the workings of a regional housing market in which dwelling units filter through a quality hierarchy (where quality is defined in discrete categories) and in which households of various income levels choose among these discrete types. One option in the stationary equilibrium is for households to opt out of the housing market and spend their entire incomes on "other goods." The proportion of households choosing this option provides an estimate of the incidence of homelessness. Changes in this outcome motivate our analysis. However, the general housing policies that we simulate have their principal effects upon those who are not homeless (since only a very small fraction of households are homeless). With this in mind, we also explore the broader and quantitatively more important implications of the simulated policies.

We calibrate the A&A model to the four largest metropolitan areas in California. Using data from the Census of Population and Housing for 1980 and 1990 and various years of the American Housing Survey, we conduct several simulations. First, we calibrate the model for each metropolitan area to observed housing market and income conditions in 1980 and assess the predictive power of the model. Lacking observations of homeless rates for 1980, we cannot test the power of the model in predicting this key aspect of behavior. Instead, we opt to measure how well the model predicts the changes in rents actually observed during the subsequent decade. We conclude that the model projects housing market conditions reasonably well in these four housing markets. We then calibrate the model to 1990 housing-market and income conditions. Following O'Flaherty's [4] theoretical arguments, we explore the effects on homelessness of changes in the income distribution similar to those that actually occurred during the 1980s and 1990s in these four markets. Finally, we explore the welfare consequences and the effects on homelessness of three housing-market policy interventions: extending housing vouchers to all low-income households, subsidizing all landlords, and subsidizing those landlords who supply low-income housing.

2. Homelessness and filtering in urban housing markets

While the homeless undoubtedly suffer from a confluence of personal problems (including rates of mental illness, substance abuse, and social isolation considerably higher than those for the general population), whether these problems are the principal causes of homelessness is a matter of much debate. The increase in homelessness during the 1980s did loosely coincide with the onset of

the crack epidemic and the tail end of the deinstitutionalization of the mentally ill. However, the spread of crack through American inner cities occurred relatively late in the decade, well after the noticeable increases in street populations recorded from 1979 to 1982. In addition, the lion's share of deinstitutionalization occurred prior to 1980, and research indicates that a substantial minority of those deinstitutionalized during the 1980s were reinstitutionalized in state prisons (O'Flaherty [4] and Raphael [19]) reducing the size of the population at risk.

Increased dispersion of the earnings and household income distributions coincided with the increase in homelessness. Moreover, the theoretical model offered by O'Flaherty [20] provides an avenue through which increased earnings inequality can affect the housing market so as to generate increases in the homeless population. O'Flaherty bases his argument on a model of urban housing markets where durable dwelling units filter through a quality hierarchy in a manner similar to that originally posited by Sweeney [21,22]. In this model, the supply of housing of a given quality is determined by several factors. First, the existing housing stock of a given quality level can either be maintained at that quality level or else be allowed to depreciate to lower quality levels. Thus, units may leak out of any quality category and filter down- to lower-quality levels while units that were previously of higher-quality may filter in. Above a certain quality threshold, new construction will also augment the housing stock. These new units are built on undeveloped land or on land that is cleared of existing low-quality units. This filtering of existing units and the recycling of land ties the price of housing of the lowest-quality units to the market conditions in all other points of the quality distribution.

Homelessness in such a model results from the choices of households bidding for housing of the lowest quality. Assuming homogeneous preferences, the homeless household with the highest income will be the household that is just indifferent between consuming conventional housing and paying a market determined positive amount for rent for housing of the lowest quality on the one hand, and being homeless and paying no rent on the other hand. To be sure, only the lowest-income households (for whom the minimum rent required would represent disproportionately large proportions of their budgets) will choose homelessness.

Changes in the distribution of income affect the level of homelessness by changing the price of the lowest-quality housing. An increase in earnings inequality around a stable mean (corresponding roughly to the course of income during the 1980s in the US) reduces the demand for middle quality housing and increases the demand for low-quality housing. Moreover, increases in demand for housing of the highest quality will increase the demand for developable land. Both factors will increase the price of low quality housing, thus implying a higher cutoff income level, below which homelessness is preferred by some to conventional housing.

The theoretical results presented here complement the available empirical evidence. We explore the relationship between homelessness and housing markets using a complete theoretical model and simulations calibrated to the housing markets of the four largest California metropolitan areas. Rather than focusing on *whether* housing market forces generate homelessness, we assess the extent to which policy interventions in the housing market can lower homelessness rates. In this section we first describe the A&A model in detail. Next, we present some base results from calibrating the model to the four California metropolitan areas.

2.1. The simulation model[1]

We extend and adapt the A&A model, a stationary representation of urban housing markets. Risk-neutral housing producers determine the supply of rental housing units for each level of quality k ($k = 1, \ldots, 4$) so as to equalize returns across housing types. With the exception of housing of the highest quality ($k = 4$ in our simulations), the supply of housing at each quality level is determined by the proportion of the stock of this quality in the previous period that is maintained plus the proportion that filters down from higher-quality levels. Maintenance and housing costs vary across but not within housing types. In addition conversion costs, as well as conversion possibilities (which we refer to as the conversion technology) differ between any two qualities of housing. There is also idiosyncratic dispersion in investment costs for all housing types and land. We restrict the conversion technology so that only housing of the highest quality is newly constructed.[2] We further restrict the conversion technology so that housing units do not "reverse filter" up the quality hierarchy, but either remain at the same quality or filter down to the next lowest-quality level. Housing of the lowest quality can be demolished at a cost, clearing the land for the construction of high-quality units. Hence, a change in the market conditions in higher quality submarkets may change the price of low-quality housing via competition for land.

Households fall into five income classes, $h = \{1, \ldots, 5\}$, and are heterogeneous with respect to their tastes for housing. Average incomes in each class, the distribution of households across income groups, and the total population are exogenous to the model. In addition, for each household there is an exogenously determined reservation utility at which they are indifferent between consuming rental housing and homelessness. This latter feature provides an exit option that can be interpreted as homelessness (or "doubling up") in response to high housing prices. The model assumes a specific form of the household utility function with

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[1] Here we present a verbal description of the stationary A&A model described in Anas [11]. In Appendix A we present a more detailed description of the model and the calibration process.

[2] As indicated below, this restriction is inconsequential empirically. For example, it restricts new construction to units renting for at least $850 to $900 per month in San Francisco, Los Angeles, and San Diego, and at least $650 in Sacramento.

idiosyncratic preferences, yielding a multinomial logit specification of household choice probabilities over the housing types, $k = 1, \ldots, 4$, and homelessness $k = 0$.

At stationary equilibrium in this model, housing stocks, the stock of vacant land, rents, and asset prices are constant from one period to the next. In this equilibrium, housing is filtering across quality levels, low-quality housing is being demolished, and high-quality housing is being constructed, all at constant rates. Four sets of market clearing equations must be satisfied. First, demand must equal supply in each of the housing quality submarkets. Second, suppliers must earn normal profits in each housing submarket. That is, for each housing type and for vacant land as well, the price of the asset must equalize the expected rate of return and the real interest rate. The third and fourth conditions are accounting identities. The third condition insures that the stock of housing of a given type equals the sum of those units that are newly constructed, those that filter in, and those maintained from the previous period minus those units that filter out. The final condition ensures that the sum of developed and undeveloped land equals the fixed quantity available in the metropolitan area. These identities impose some restrictions on the values of the equilibrium conversion probabilities. These properties of the model are described more precisely in Appendix A.

2.2. Calibration of the model and some diagnostic tests

Calibrating the model requires specification of the observed housing market conditions (rents, asset values, and stocks), populations, income levels, conversion and maintenance costs, and the real interest rate. In addition, we must assume values for the price elasticity of housing demand, and the price elasticity of short run stock adjustments. We must also specify housing unit conversion possibilities.[3] The model uses this information to calibrate the unobserved parameters of the structural equations so that these initial observed values represent a stationary equilibrium. "Calibration" is achieved when the structural equations of the model, combined with exogenous conditions, reproduce the observed market conditions (rents, stocks, and asset values). The calibrated model can then be used to simulate the effects of changes in any of the exogenous variables.

An important set of intermediate equations produced in the calibration process includes those that calculate the probability that a household of income class h chooses housing-quality type k. When k is equal to zero, this measures the probability that the household opts out of the housing market. Given fixed population sizes, this probability provides an estimate of homelessness in the housing market. Changes in this probability arising from changes in any of the exogenous variables are estimates of the effect of those changes on the size

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[3] A complete list of variables is provided in Appendix A.

of the homeless population. This variable, the homeless rate, is a key outcome analyzed in the policy simulations presented below.

We calibrate the model for four California metropolitan statistical areas (MSAs)—San Francisco, Los Angeles, San Diego, and Sacramento—using data from the 1989 and 1991 American Housing Surveys (AHS) and the 1990 Census of Population and Housing. Again, the model includes five household types (quintiles of the metropolitan income distribution for renters) and five housing types (land and the stock of rental housing segmented by rent quartile). We assume that renters in the lowest quintile never live in housing of the highest quality.[4] All other renters may occupy any type of housing. We do not include owner-occupied housing in the analysis. We thus assume that there is no interaction between rental and owner-occupied markets. Most owner-occupied housing is composed of single dwellings, which are far less likely to be in the rental stock. In addition, home ownership is an unlikely option for renters at the bottom of the income distribution, the population that is of particular interest here.

As discussed above, we restrict conversion technologies so that only highest-quality housing is newly constructed. We estimate construction costs of high-quality housing by capitalizing the equilibrium rent (calculated as the average annual rent observed for housing in this quartile in each market divided by the normal rate of return). Only the lowest-quality housing is demolished, and filtering is restricted to one level per period. We assume that maintaining a housing unit at the current quality level requires expenditures of one percent of market value plus the cost of utilities.[5] A unit depreciates to the next lowest-housing type if it is not profitable for the landlord to incur these maintenance costs. We assume that demolition costs of low quality units are equal to 20% of construction costs. Finally, we assume that all rental units have the same structural density.

In equilibrium, the housing quantity of any type that transitions to the next level, whether the transition is demolition, construction, or housing quality degradation, must equal the quantity flowing into that housing type. Using biannual MSA data from the American Housing Surveys (AHS), we compute the demolition rates by estimating the dwellings lost due to either demolition or mergers between adjoining housing units. The model is sensitive to reduced quantities of vacant land. To avoid erratic behavior, we assume that the city contains reasonable amounts of vacant land. Since demolition and construction *quantities* must be equal in equilibrium, this implies a slow transition out of vacancy. Therefore, we assume a slow *rate* of high-quality home construction,

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[4] Empirically, this is an inconsequential assumption. In these specific markets, the assumption implies that low-income renters never choose to spend more than approximately twice their annual incomes on housing.

[5] This is the widely used one-in-a-hundred rule (see Kain and Quigley [23] for an early discussion).

equaling half that of the demolition rate.[6] We assume filtering occurs at the same rate as the demolition rate. Since there are four types of housing and one type of land, the equilibrium amount of vacant land area is determined.[7]

We assume that the price elasticities of demand and short run stock adjustment are −0.67 and 0.50 for all cities, housing types, household types, and time periods (see Hanushek and Quigley [24] for empirical evidence). The real interest rate is assumed to be 8%. We test the robustness of the key economic parameters: demand elasticity, short run stock adjustment elasticity, and the interest rate. We find that homelessness is sensitive to demand elasticity, but we also find that the qualitative results of the analysis are unchanged even with substantial variations in these parameters (see Appendix C for details).

The choice probabilities for each household type are computed from the proportions reported in the 1989 and 1991 AHS for each metropolitan area. In addition, we use the AHS to compute conversion rates, mean rents for each quartile, mean incomes for each income quintile, mean rents of newly constructed units and utility costs by quartile. The number of rental households in each MSA comes from the 1990 Census. We estimate the homeless population for each MSA from several sources. This estimate is discussed in Appendix B.

Table 1 summarizes the conditions for the calibration for San Francisco for 1990. The table reports the joint frequency of income quintiles and housing quartiles, their numbers, annual rents, maintenance costs, demolition rates, and the costs of new construction. All these data come from the AHS and the Census. The table also reports demolition costs, homeless counts, and vacant land. Figure 1 indicates how the underlying distribution of renter incomes and housing quality was partitioned into the discrete categories reported in Table 1. Table 2 summarizes the analogous conditions for the calibration of the model for the Los Angeles, San Diego, and Sacramento housing markets for 1990.

While our principal results rely on models calibrated to the metropolitan housing markets in 1990, we also calibrated the model to 1980 using data from the 1979 and 1981 AHS and the 1980 Census. The methodology in calibrating the model to 1980 is identical to that used for 1990.[8] We use these supplemental calibrations to predict rents for each metropolitan area in 1990. That is, we use the 1990 values of populations and incomes to estimate rents for each type of housing using the 1980 calibrations. This simple test illustrates the extent to which the simulation model "tracks" the outcomes of the housing markets in the

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[6] The assumption that the construction rate is half that of demolition and filtering implies that there are twice as many units of land vacant to be built upon as there are in any one housing type.

[7] In fact, the amount of land and the construction rate are calibrated so that: the rental price of land is always less than the rent of the lowest-quality housing; and the rent computed for the lowest-quality housing is consistent with historical (census) data.

[8] In all cases, the models were calibrated so that the rent measures computed by the models were within 0.2% of the rents reported in the relevant census publications.

Table 1

Parameters of simulation model for San Francisco: households and dwellings (1990)

	Homeless	Housing type: quartile			
	0	1	2	3	4
	A. Annual costs				
Rents	0	$3489	$6259	$8102	$10,946
Maintenance cost	0	1153	1810	2284	3125

B. Numbers of households and dwellings

Household type

Income quintile	Mean income ($)					Total
1	5999	16,131	96,175	48,088	42,077	0	202,470[a]
2	14,362	867	61,697	53,442	54,311	32,152	202,470[a]
3	23,764	260	41,394	64,707	55,191	40,918	202,470[a]
4	33,562	69	22,437	48,614	75,257	56,093	202,470[a]
5	61,667	17	11,425	29,248	61,695	100,084	202,470[a]
Total	–	17,345[b]	233,128	244,099	288,532	229,246	1,012,350[a]

Cost of new construction $220,971
Cost of demolition $34,184[c]
Rate of demolition 5.2%
Total land 1,480,500[d]
Vacant land 485,860[d]

All parameters are taken from the 1989–1991 American Housing Survey (AHS) for San Francisco with the following exceptions. 1989 and 1991 AHS data on rents and income were averaged using the US consumer price index.
[a] Data from the 1990 US Census of Population and Housing.
[b] Data from special surveys reported in Appendix B.
[c] Demolition costs are assumed to be twenty percent of the cost of new construction.
[d] See footnote 6.

four metropolitan areas. Figure 2 summarizes the results of this exercise. The figure plots the percent change in rents observed between 1980 and 1990 against the percent change predicted by the model calibrated to 1980 using incomes and populations for 1990. Each data point represents the changes within one quartile within one of the four metropolitan areas (hence, there are 16 observations). As can be seen, the model performs well in terms of predicting relative changes in rents. A regression of actual changes on predicted changes yields a slope of 0.876 and is highly significant.[9]

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[9] While the model under-predicts actual changes in rents (as is evident by the positive intercept in the regression) changes in relative rents are predicted with a higher degree of accuracy. Of course, a great many things happened in these housing markets during the 1980s that are ignored in these simulations.
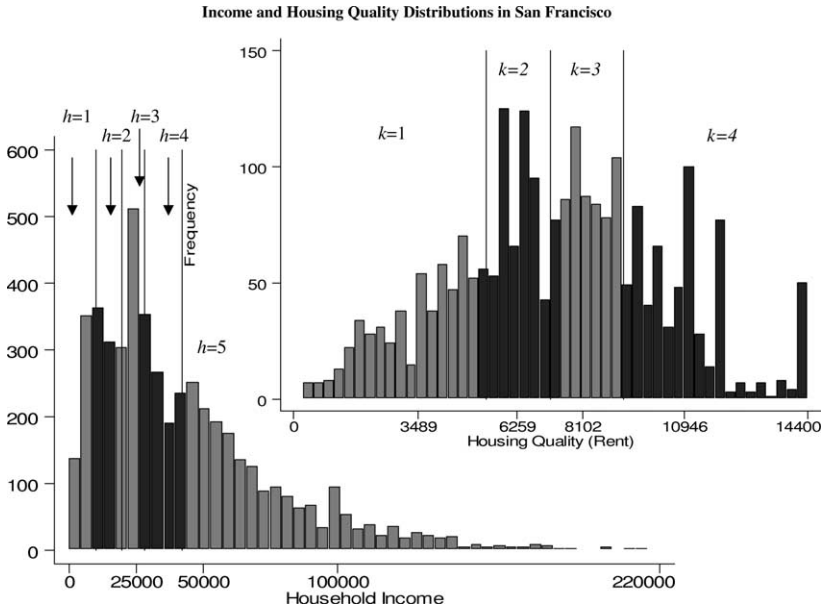
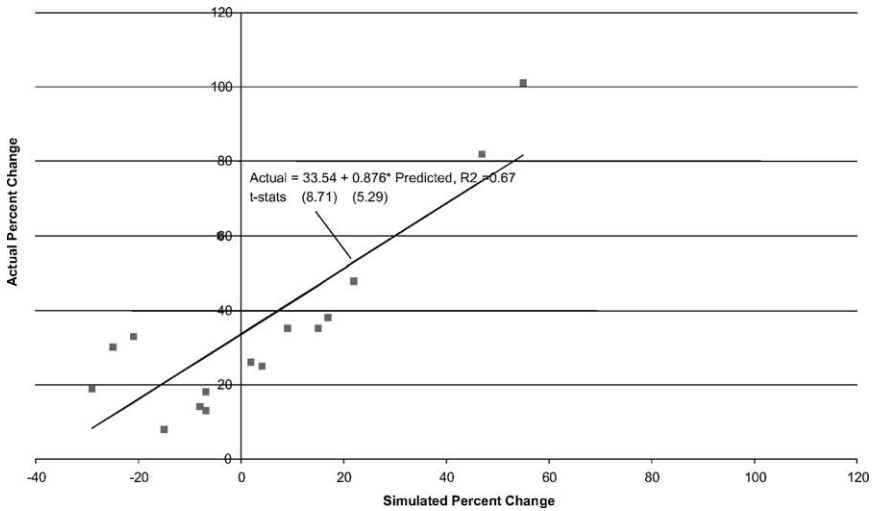Fig. 1. Income and housing quality distributions in San Francisco.

Fig. 2. Percent changes in actual rent for each housing type versus simulated changes for four California metropolitan areas (1980–1990).

Table 2
Summary of parameters of simulation models for Los Angeles, San Diego, and Sacramento (1990)

	Los Angeles	San Diego	Sacramento
A. Income and annual rents			
Household or housing type			
Income by quintile			
1	$5425	$7219	$5874
2	13,547	13,819	11,819
3	22,585	21,886	19,910
4	33,063	31,214	28,538
5	64,409	56,126	51,563
Rents by quartile			
1	4262	4666	3216
2	6415	6238	4944
3	7927	7477	5970
4	10,456	10,145	7745
B. Other variables			
Total population	2,255,720[a]	409,825[a]	228,342[a]
Number of homeless	14,400[b]	7098[b]	2427[b]
Demolition rate	3.3%	1.7%	1.5%
Maintenance cost by quartile			
1			
2	$1284	$1032	$1219
3	1753	1538	1566
4	1868	2009	1901
	2747	2788	2474
Total land	3,327,500[c]	591,500[c]	346,900[c]
Vacant land	1,086,217[c]	188,774[c]	120,986[c]

All parameters are taken from the 1989–1991 American Housing Survey (AHS) for each MSA with the following exceptions. 1989 and 1991 AHS data on rents and income were averaged using the nation consumer price index to adjust for inflation.

[a] Data from the 1990 US Census of Population and Housing.
[b] Data from special surveys reported in Appendix B.
[c] See footnote 6.

We also use the 1990 calibrations to simulate changes in homelessness caused by changes in the income distribution. This exercise illustrates the way in which external changes in labor market conditions affect competition in the housing market to cause some households to prefer homelessness. We perform three simulations using the 1990 calibrations for each MSA. First, we decrease the average income of households in the lowest quintile of the renter distribution by 20%. Second, we increase the average incomes of households in the top quintile by 20%. Finally, we redistribute twenty percent of the population in the third (middle) quintile equally into the bottom and top income quintiles.[10] This

[10] After this reallocation, the middle group has only 16% of the population and the bottom and top groups have 22% each.

Table 3
Simulated percentage changes in homelessness caused by various changes in the income distribution
(models calibrated to 1990)

Housing market	Percent change in homelessness caused by:		
	20% decrease in the income of the bottom quintile of the income distribution	20% increase in the income of the top quintile of the income distribution	Redistributing 20% of households equally from the middle quintile to the bottom and top quintiles
San Francisco	22.0	−0.1	8.6
Los Angeles	17.9	−0.1	8.8
San Diego	24.9	−0.1	8.8
Sacramento	29.1	−0.1	9.0

latter simulation greatly reduces the size of the middle class, but keeps average income constant.

Table 3 presents the results of these simulations. As should be expected, in each metropolitan housing market decreasing the incomes of the lowest quintile causes a sizable increase in the homeless population, while increasing the incomes of the highest quintile has essentially no effect on homelessness.[11] Note, however, that a reduction in middle-income households leads to a substantial increase in homelessness in all simulations. This arises in part because the price of low-quality housing increases, as predicted by O'Flaherty [4,20].

2.3. The policy simulations

We simulate the effects of three housing-market policy interventions. To the degree that subsidies (such as those under Section 8 of the housing Act of 1974) already exist in these markets, the data used in calibration (e.g., rents, homeless counts, and income) already take these subsidies into account. Therefore, our analysis examines the effects of additional policies on homelessness, rents, profits, and consumer well being.

First, we simulate the effects of rent subsidies for low-income households. We calculate the subsidy as the difference between the rent of the lowest-quality housing and thirty percent of the income of low-income residents (for those low-income residents who choose to be housed). This policy is similar to the current voucher program offered under Section 8 of the Housing Act of 1974.[12] Of course, the subsidy affects the equilibrium rents as well as the fraction of the low-income

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[11] Homelessness falls slightly as those very few rich homeless in the model opt for housing. The increases in rent caused by greater income for the top income quintile are inconsequential and therefore have no effect on homelessness.

[12] Under current tenant-based subsidy programs, participating households receive a voucher representing the difference between "fair market rents" (administratively calculated for each housing

population choosing homelessness. Thus, the aggregate amount of the subsidy is computed jointly with the other outcomes in the housing market. The general equilibrium model of the housing market is used to make these computations. While one may expect that homelessness will be greatly affected by such a policy, since preferences are heterogeneous, some households will opt to keep all of their incomes and be homeless rather than spend a third of their incomes on housing.

The second policy intervention provides a general maintenance subsidy to all landlords regardless of the quality of the unit supplied. The level of the subsidy is chosen so that the total budgetary cost of this program in each of the four markets is equal to the cost incurred under the rent subsidy program. Landlord subsidies are modeled by decreasing the landlord contribution to maintenance costs by the amount of the common subsidy for all housing types. The subsidy is equally distributed to the suppliers of each unit within each market.

The third policy targets the maintenance subsidy to those landlords that supply low-income housing. This policy is similar to the second, but the policy decreases maintenance costs for the lowest-quality units only. With the exception of Sacramento, the subsidy is large enough to offset completely landlord maintenance costs, thus resulting in a positive gross subsidy to landlords.

For all simulations, we assume that programs are funded from national taxes, that is, with resources from outside of the metropolitan area. Hence, we ignore the issue of the incidence and efficiency costs of the taxes needed to generate funding for the programs. For all programs, we simulate the change in homelessness, the changes in rents for housing of all types, and changes in transition rates. In addition, we compute the compensating variation for each policy for households of all types and for landlords. Since the model assumes that landlords are risk neutral, changes in profits identify changes in the well being of landlords.[13]

The program costs for each policy are $328 million for San Francisco, $1169 million for Los Angeles, $195 million for San Diego, and $64 million for Sacramento. These costs depend upon the incomes of the poor (i.e., those in the lowest quintile of the income distribution), their propensity to choose housing over homelessness, and the rents of low-income housing (i.e., units in the lowest quartile of the rent distribution). Rents of course depend on the general equilibrium effects of the subsidy. Program costs per household are lowest in Sacramento ($280 per renter household) and highest in Los Angeles ($518 per renter household).

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market) and 30% of income. Low-income households must live in dwellings that meet minimum quality standards to participate in the program. While our policy subsidizes all housing, most of the increased demand for housing is for that of the lowest quality.

[13] We elaborate on this issue below.

3. Results of the policy simulations

3.1. Changes in rents and homelessness

Table 4 presents the effects of these three policy interventions on the distribution of rents, the demolition rates of low-rent housing, and on homelessness. Panel A present the results from providing rent subsidies to all poor households equal to the difference between rents and 30% of mean household income for this group. The size of the annual subsidy to poor households is $1722 in San Francisco, $2642 in Los Angeles, $2507 in San Diego, and $1456 in Sacramento.

Table 4
Changes in annual rents, demolition rates, and homelessness caused by the alternative policy interventions

	San Francisco		Los Angeles		San Diego		Sacramento	
	$	%	$	%	$	%	$	%
A. Rent subsidies								
Low-rent units	32	+0.9	7	+0.2	6	+0.1	2	+0.1
Medium/low-quality units	48	+0.8	13	+0.2	13	+0.2	4	+0.1
Medium/high-quality units	62	+0.7	17	+0.2	19	+0.3	6	+0.1
High-quality units	67	+0.6	19	+0.2	23	+0.2	8	+0.1
Change in demolition rate of low-quality units	−0.09	−1.6	−0.02	−0.6	−0.03	−1.6	−0.01	−0.8
Change in homeless population	−4426	−25	−4727	−33	−2279	−32	−656	−27
B. General landlord maintenance subsidies								
Low-quality units	−322	−9.2	−519	−12.2	−481	−10.3	−283	−8.8
Medium/low-quality units	−318	−5.1	−518	−8.2	−480	−7.7	−283	−5.7
Medium/high-quality units	−315	−3.7	−517	−6.4	−478	−6.3	−282	−4.8
High-quality units	−314	−2.9	−517	−5.0	−477	−4.7	−282	−3.6
Change in demolition rate of low-rent units	−0.02	−0.4	−0.005	−0.4	−0.007	−0.04	−0.003	−0.2
Change in homeless population	−996	−5.6	−1164	−8.1	−542	−7.6	−154	−6.3
C. Targeted landlord maintenance subsidies								
Low-quality units	−1145	−32.8	−1696	−39.8	−1626	−34.8	−986	−30.7
Medium/low-quality units	−43	−0.7	−29	−0.5	−3	−0.1	−0.4	−0.01
Medium/high-quality units	−90	−1.0	−85	−1.1	−30	−0.4	−16	−0.3
High-quality units	−93	−0.8	−108	−1.0	−40	−0.4	−21	−0.3
Change in demolition rate of low-rent units	−0.59	−11.0	−0.51	−15.1	−0.27	−15.9	−0.18	−12.2
Change in homeless population	−1968	−11.1	−1677	−11.6	−877	−12.4	−262	−10.8

As expected from a program subsidizing the demand side of the market, annual rents increase for all quality levels. These increases, however, are quite small. All are below $70 a year and constitute less than 1% of base rents. These demand-side subsidies also reduce the demolition rate in all four cities (the reduction ranging from 0.01 percentage points in Sacramento to 0.09 percentage points in San Francisco). Again, the proportional reduction is small, ranging from 0.6 to 1.6% of the starting demolition rates. There are large effects of rent subsidies on the projected homeless population. In each metropolitan area, extending rent subsidies to all low-income households reduces the homeless population by at least 25% (San Francisco) and by as much as 33% (Los Angeles). Moreover, this large decrease in homelessness is achieved with relatively small increases in rents.

Panel B presents the comparable simulation results for the general landlord maintenance subsidies. Recall that the subsidies per unit are set so that the total cost of the program is equal to the total cost of the program providing rent subsidies to all low-income households. This yields annual subsidies to landlords equal to $329 per dwelling unit in San Francisco, $521 in Los Angeles, $483 in San Diego and $284 in Sacramento. The general maintenance subsidies cause substantial declines in equilibrium rents, on the order of 3 to 5% for high-rent units and 9 to 12% for low-rent units. The general maintenance subsidies yield small decreases in the demolition rates for low-rent housing, similar in magnitude to the changes in demolition rates caused by the rent subsidies. The declines in homelessness caused by the program are much smaller than the declines caused by the rent subsidy. These changes range from 6% in San Francisco to 8% in Los Angeles.

Finally, panel C presents the results from the simulations that provide maintenance subsidies to the suppliers of low-rent units only. Again, the subsidies are calculated so that the total cost of the program equals the total costs of the rent-subsidy program. This yields targeted subsidies equal to $1241 per unit annually in San Francisco, $1791 in Los Angeles, $1666 in San Diego, and $1010 in Sacramento. By comparison, the maintenance costs are $1153 in San Francisco, $1284 in Los Angeles, $1032 in San Diego, and $1219 in Sacramento. These subsidies are equal to roughly 55 to 72% of the market rents for low-rent units.

The most notable effects of the targeted subsidies are the large declines in the rents and demolition rates of low-rent units. For all four metropolitan areas, nearly all of the maintenance subsidy is passed through into a rent decrease for low-rent units (roughly 92 to 98% of the subsidy). The targeted subsidy also induces rent decreases for units in the other three quality levels. These latter declines are small, however, ranging from 0.01 to 1.1% of base rents. Unlike the other two policies, demolition rates decline considerably. These declines range from 11% in San Francisco to 16% in San Diego. In common with the general maintenance subsidy, the declines in homelessness caused by the targeted subsidies are moderate (either 11 or 12% in each city).

In summary, all three of these housing policies reduce homelessness, but to varying degrees. The largest decrease in homelessness comes from demand-side rent subsidies, ranging from 25 to 33%. The supply side programs (costing the same amount) also decrease homelessness, but by roughly one fourth the size of the decrease caused by the rent subsidies. The targeted maintenance program is most effective, however, in extending the useful life of the low-quality housing stock. This program causes decreases in demolition ranging from 11 to 16%, while the decreases caused by the general maintenance and the rent subsidies programs are equal to a fraction of these declines.[14]

3.2. The welfare effects of the three policy alternatives

The analysis summarized in Table 4 can also be used to make explicit welfare comparisons. In considering the welfare effects of government housing policies, however, it is important to recognize that the comparison is between two general equilibria that may take some time to achieve in response to subsidy policy. A more accurate welfare analysis would account for these policies along the dynamic path from the initial equilibrium to the equilibrium arising from the subsidy policy. Such calculations are well beyond the spirit of the general equilibrium analysis reported here.

With this caveat in mind, Table 5 presents estimates of the changes in well-being caused by the three policy interventions. Calculations indicate the benefits to low-income households, to all other households, to the providers of low-rent units, and to the providers of all other units. For low-income households and for all other households, the figures in the table are the within-group sum (in millions of dollars) of compensating variation associated with each program. For housing suppliers, the figures provided are the changes in rents and landlord subsidies caused by the program. For risk-neutral landlords, these changes in profits measure the change in landlord well being.[15] For each panel, the bottom row indicates the gross program benefits.[16]

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[14] Put another way, the targeted maintenance policy increases the useful life of the low-quality housing stock by 15% (from 18.6 years to 22.1 years) in San Francisco while the other policies increase the life of the low-quality stock by only 0.1 or 0.2 years. In Los Angeles, the targeted maintenance policy also increases the life span of low-income housing by 15% (from 30.3 to 35.9 years) while the other policies increase the life span by 0.1 or 0.2 years. The increases in the effective life of low-income housing associated with the targeted maintenance program are 18% in San Diego and 14% in Sacramento.

[15] Strictly speaking, these gains to landlords are not profits, since in general equilibrium, profits are zero. Rather, the entries in the table represent the aggregate changes in rents such that profits in the new equilibrium are zero. (Clearly, integrating along the dynamic path would be preferable, but this would require a dynamic model.)

[16] Here we abstract from the costs of the program. We simply assume that the program is financed with resources from outside of the metropolitan area.

Table 5
Effects of housing policies on welfare and homelessness

	San Francisco			Los Angeles			San Diego			Sacramento		
	Rent subsidies	General landlord subsidy	Targeted landlord subsidy	Rent subsidies	General landlord subsidy	Targeted landlord subsidy	Rent subsidies	General landlord subsidy	Targeted landlord subsidy	Rent subsidies	General landlord subsidy	Targeted landlord subsidy
A. Welfare effects (millions of dollars)												
Program costs	$327.8	$327.8	$327.8	$1168.8	$1168.8	$1168.8	$194.6	$194.6	$194.6	$64.15	$64.15	$64.15
Consumer benefits												
Low income	316.3	59.6	124.1	1157.7	227.1	337.1	191.1	36.3	61.3	63.53	12.30	21.74
All other	−44.2	256.3	219.6	−26.6	933.5	812.2	−5.4	156.7	122.0	−1.01	51.55	39.32
Landlord benefits[a]												
Low rent	7.6	1.7	25.3	4.0	1.0	61.8	0.6	0.2	4.6	0.13	0.03	1.55
All other	44.6	10.0	−55.6	27.8	6.8	−119.2	5.6	1.3	−7.1	1.05	0.25	−1.98
Gross benefits	$324.3	$327.7	$313.4	$1163.0	$1168.5	$1091.9	$192.0	$194.5	$180.9	$63.70	$64.12	$60.64
B. Effects on homelessness												
Change in homeless population	−4426	−996	−1968	−4727	−1164	−1677	−2279	−542	−877	−656	−154	−262
Percent change	−25.0	−5.6	−11.1	−32.7	−8.1	−11.6	−32.1	−7.6	−12.4	−27.0	−6.3	−10.8

[a] See text for explanation and discussion.

For all four metropolitan areas, the total benefits to consumers and landlords are largest from the general maintenance subsidy program, followed by the rent subsidy, and then by the targeted maintenance subsidy. The differences in total benefits across programs differ by at most 7%. The *distribution*, however, of the benefits does vary considerably among policies. For the rent subsidy policy, nearly all of the benefits accrue to low-income renters. There are small benefits for housing suppliers and moderate losses to all other renters for whom prices are higher. In contrast, the general maintenance subsidy allocates the benefits among all renters and suppliers of housing; in fact, all but those choosing to remain homeless benefit. Finally, the targeted maintenance subsidy again benefits all renters, provides slight benefits to the suppliers of low-rent housing, and imposes real costs on the suppliers of all other housing.

4. Conclusion

The results from this general equilibrium simulation of the housing markets in four California metropolitan areas suggest that the size of the homeless population is quite sensitive to changes in the income distribution and concurrent changes in housing costs. The results suggest that housing-market interventions that either reduce rents for low-rent housing or increase the incomes of low-income households can have substantial effects on the size of the homeless populations. Our results suggest that, in equilibrium, a universal Section 8 renter subsidy program would reduce homelessness in California housing markets by one quarter to one third. These findings are consistent with empirical research that indicates that homelessness is positively associated with measures of housing costs and negatively associated with measures of housing availability, such as vacancy rates.[17] The simulation models, however, define more explicitly the links between changes in housing and labor markets and the size of the homeless population.

The results from the policy simulations indicate that for the four metropolitan areas studied, demand-side subsidies cause larger declines in homelessness than do supply-side subsidies. The general maintenance supply-side subsidies cause slightly less deadweight loss, but do not achieve comparable reductions in homelessness. These simulations hold the total cost of each program constant, and this means that the demand-side programs yield the biggest "bang per buck" in reducing homelessness.

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[17] In particular, these results are consistent with our econometric evidence that modest changes in housing-market conditions (rent-to-income ratios, etc.) can reduce homelessness by a quarter or more. See Quigley et al. [5,25].

Acknowledgments

Appendix A. The General equilibrium model

The simulations we report are adapted from the general equilibrium model of the housing-market developed by Alex Anas and Richard Arnott. Here we present a terse description of the model which indicates its general structure and its limitations. A more detailed presentation of the model can be found elsewhere. (Anas [11] is a lucid and parsimonious presentation.)

The simulation solves for the static equilibrium conditions associated with an urban housing market. The housing stock (the rental housing market in our application) filters among discrete housing types along a hierarchy of housing quality, similar to the filtering model of Sweeney [21,22]. An exogenously determined fixed amount of common land is shared among $k = 1, \ldots, K$ housing types (four types of rental housing in our application) with the remainder reserved as vacant land. The housing types differ by construction costs, maintenance costs, demolition costs, conversion possibilities and structural density, i.e., the number of units of land needed to construct one unit of the housing type. (In our application, we assume that all rental units are of the same density.) The model avoids knife-edge solutions by including idiosyncratic uncertainty in costs. Risk-neutral, competitive investors own all rental units. They earn normal returns and invest with perfect foresight. Only frictional vacancies occur, since landlords with perfect foresight will build or maintain profitable rental units.

The model also incorporates consumer taste heterogeneity in each of the $h = 1, \ldots, H$ household types. (In our application, there are five household types, quintiles of the distribution of renters' incomes.) Households have distinct, exogenously determined incomes, populations, and outside utility (reservation utility) levels. The model assumes an open economy, allowing households to opt out of the rental market completely. As we shall see, this feature can be interpreted as choosing to be homeless. Households are myopic; they neither borrow nor save.

For a given set of initial conditions, the size of the stock, its rent and its asset price are all determined simultaneously for each type of housing. The stationary equilibrium is that state in which the stock, rents and asset prices reproduce the existing distribution of households and dwellings.

The solution is approached iteratively, using Mathematica's version of Newton–Raphson. Consumers receive income and pay rent at the start of each

iteration of the model; construction and conversions occur in response. In equilibrium, four market clearing conditions (described below) must be met. The economic parameters of the model—the marginal utility of income, taste premiums, non-financial costs to investors, and the dispersion parameter of idiosyncratic costs of investors—are calibrated so that the model reproduces the observed rents, asset values, and housing stock as an equilibrium. So calibrated, the model can be used for simulations by changing the exogenous parameters.

The model includes several exogenous variables that are determined from data for each city or from straightforward assumptions:

Y_h: Income of a consumer of type h,
E_{hk}: Maintenance expenditure on a type k housing unit by a type h occupant,
N_h: Number of type h consumers,
R_0: Unit rent on land,
$C_{kk'}$: Average cost of converting a type k unit to a type k' unit:
   When $k = k'$, then $C_{kk'}$ is the maintenance cost of k,
   When $k' = 0$ and $k > 0$, then $C_{kk'}$ is the demolition cost of k,
   When $k = 0$ and $k' > 0$, then $C_{kk'}$ is the construction cost of k',
$m_{kk'}$: Units of k needed to create one unit of type k' (this is assumed to be 1 everywhere in our application, simplifying subsequent notation),
   L: Total quantity of land (vacant plus occupied by housing).

The key economic parameters of housing markets include:

ζ_d: Price elasticity of demand,
ζ_s: Price elasticity of short run stock adjustment,
 r: Interest rate.

In Appendix C, we test the sensitivity of the results to these economic parameters. We indicate changes in estimates of homelessness when each of these parameters varies by 10%.

The expected value of housing type h consumers' indirect utility function for housing type j is of the form

$$W_{jh} = \frac{1}{\alpha_h} \log\left[\exp(U_{0h}) + \sum_j \exp\left[\alpha_h (Y_h - E_{hj} - R_j) + D_{jh}\right] \right], \quad \text{(A.1)}$$

where

α_h: Marginal utility of income of a type h consumer,
U_{0h}: Utility of the outside alternative for a type h consumer, and
D_{kh}: Constant subutility representing the taste premium which a type h consumer assigns to a type k housing unit ($k > 0$).

The form of the utility function insures that the consumers' choice probabilities across housing types ($k = 1, \ldots, K$) and homelessness ($k = 0$) are of the form

$$P_{hk} = \frac{\exp[\alpha_h (Y_h - E_{hk} - R_k) + D_{hk}]}{\exp[U_{0h}] + \sum_j \exp[\alpha_h (Y_h - E_{hj} - R_j) + D_{jh}]}, \tag{A.2}$$

for $k = 1, \ldots, K$

and

$$P_{h0} = \frac{\exp[U_{0h}]}{\exp[U_{0h}] + \sum_j \exp[\alpha_h (Y_h - E_{hj} - R_j) + D_{jh}]}, \quad \text{for } k = 0. \tag{A.3}$$

A landlord supplies housing of any type to maximize her utility derived from discounted net profits, a non-financial cost common to those supplying each housing type, and a landlord-specific random idiosyncratic cost. Assumptions are made about the form of the idiosyncratic cost[18] so that the probability of conversion from type k to type k', $Q_{kk'}$, is

$$Q_{kk'} = \frac{\exp\left[\frac{1}{1+r} \phi_k (V_{k'} - C_{kk'}) + K_{kk'}\right]}{\sum_s \exp\left[\frac{1}{1+r} \phi_k (V_s - C_{ks}) + K_{ks}\right]}, \quad \text{for each } k' \text{ and } k. \tag{A.4}$$

In expression (A.4):

ϕ_k: Dispersion parameter of idiosyncratic non-financial costs of owners of type k housing,

$K_{kk'}$: Non-financial cost (disutility) of converting housing of type k to k',

V_k: Asset price of housing of type k.

The left-hand side (LHS) variables in Eqs. (A.3) and (A.3) can be obtained from market data. In Eq. (A.3), the LHS is the observed proportion of households of type h living in housing of type k. In Eq. (A.3), the LHS is the fraction of housing of type k converted to type k' during a given time interval. In addition to Eqs. (2) and (3), market equilibrium conditions must be satisfied using these parameters in the model. First, the number of households living in each housing type (i.e., the population of each household type, n_h, times the fraction of that household type residing in each housing type P_{hk}) must equal the total stock of that type S_k available for occupancy

$$\sum_{h=1}^{H} (n_h P_{hk}) = S_k, \quad \text{for each of } K \text{ types of housing.} \tag{A.5}$$

For each type of housing, equilibrium rent R_k is a function of the asset price V_k, the dispersion parameter of idiosyncratic costs of landlords (ϕ), the interest rate r,

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[18] The specifics are discussed and derived in Anas and Arnott [12]. See specifically Eq. (2) and the associated discussion.

conversion costs c, the set of housing units to which a type k housing unit can be converted A and the non-financial costs of conversion K

$$V_k - \frac{1}{\phi_k} \log\left\{ \sum_{s=0}^{k} A_{ks} \exp\left[\frac{1}{1+r} \phi_k(V_s - C_{ks}) + K_{ks} \right] \right\} = R_k. \qquad (A.6)$$

The third market clearing condition is merely an accounting relationship, linking the stock of housing of each type S_k, investors' conversion probabilities Q, and the set of housing units that can be converted to a type k housing unit B.

$$\sum_{j=0}^{K} (B_{kj} S_j Q_{jk}) = S_k. \qquad (A.7)$$

Finally, an accounting for land usage requires that the total land L supply be equal to the sum of vacant land of the stock of each housing type

$$\sum_{k=0}^{K} (S_k) = L. \qquad (A.8)$$

Expressions (A.3)–(A.8) must hold in equilibrium. In our application, these expressions imply 20, 5, 25, 4, 5, and 5 separate equations, respectively: 64 equations in 64 unknowns.[19] The solution includes K market clearing rents, $K + 1$ asset prices (one for each housing type plus land) and $K + 1$ stocks, or a total of $3K + 2$ economic variables. Our application with four housing types solves for equilibrium values of 14 economic variables.

Appendix B. Homelessness data

Table B.1 presents the most reasonable estimates of homelessness in 1990 for the four housing markets analyzed in the text. For each MSA housing market, we use the median homeless count derived from three studies: US Census Bureau S-Night counts for 1990 [29]. Department of Housing and Urban Development's (HUD's) "Continuum of Care" estimates (Bonnewit [26]) and Urban Institute estimates produced by Martha Burt [1]. See Quigley et al. [25], for a detailed discussion of the sources and reliability of data reporting the incidence of homelessness in US metropolitan areas.

The number of homeless individuals is partitioned into households based upon estimates of the percentage of adult homeless households with children (15%) and the average number of children in those families (2.2) from the National Survey of Homeless Assistance Providers and Clients (Burt et al. [27]).

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[19] Excluding those conversion probabilities and choice probabilities which are zero yields 48 equations in 48 unknowns in our application.

Table B.1
Homeless counts and rates for california metropolitan areas 1990

Housing market	Homeless individuals	Household homeless rate (10,000)	Percent of low-income homeless	Source
San Francisco	23,068	60	8.0	Burt
Los Angeles	19,153	22	3.0	Burt
San Diego	9441	61	8.1	S-Night
Sacramento	3227	37	4.9	Burt

The model of household choice behavior is probabilistic. Thus, households in all parts of the income distribution have a nonzero probability of being homeless. Somewhat arbitrarily, we assigned the homeless to income groups in the following manner: 93% of the homeless were in the lowest-income quintile, 5% in the second lowest quintile and 1.5, 0.4, and 0.1% in the third, fourth, and fifth quintiles, respectively.[20] This assignment has no practical effect upon the estimates.

Appendix C. Sensitivity tests

Table C.1 reports the changes in the incidence of homelessness resulting from the three economic policies examined in this paper. We test the robustness of

Table C.1
Sensivity of reductions in homelessness to economic parameters

Housing market	Policy	Base case	Demand elasticity		Supply elasticity		Discount rate	
			−10%	+10%	−10%	+10%	−10%	+10%
Los Angeles	A	4727	4342	5096	4724	4730	4729	4726
	B	1164	1056	1272	1160	1167	1166	1162
	C	1677	1529	1821	1673	1679	1682	1671
Sacramento	A	656	599	710	655	656	656	656
	B	154	139	168	154	154	154	154
	C	262	238	284	261	262	262	261
San Diego	A	2279	2090	2460	2278	2280	2280	2278
	B	542	491	593	541	543	543	541
	C	877	801	952	876	879	879	876
San Francisco	A	4426	4065	4777	4398	4449	4441	4411
	B	996	933	1059	959	1027	1009	983
	C	1968	1822	2112	1932	1999	1987	1950

Base case: demand elasticity (−0.67), supply elasticity (0.50), and discount rate (8%).
A: rent subsidies, B: general landlord maintenance subsidies, C: targeted landlord maintenance subsidies.

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[20] This does mean that a few of the highest-income households do prefer homelessness to housing: 21 in San Francisco, 14 in Los Angeles, 8 in San Diego, and 2 in Sacramento.

the estimates to changes in the key economic parameters: the price elasticity of demand; the price elasticity of short run stock adjustment; and the interest rate. For each parameter, we examine how the homeless reductions associated with each of the three policies change as the parameters deviate by $\pm10\%$. The homeless estimates are sensitive to demand elasticities but not to the other parameters. Even with a 10% deviation in the price elasticity of demand, reductions in homelessness vary by less than 10%.

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