

NBER WORKING PAPER SERIES

DO RISING TIDES LIFT ALL PRICES? INCOME
INEQUALITY AND HOUSING AFFORDABILITY

Janna L. Matlack
Jacob L. Vigdor

Working Paper 12331
<http://www.nber.org/papers/w12331>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2006

Terry Sanford Institute of Public Policy, Box 90245, Durham, NC 27708. Email: jacob.vigdor@duke.edu. We thank Thomas Davidoff, seminar participants at the Federal Reserve Board of Governors and the University of Southern California School of Planning, Policy and Design, and conference participants at the 2005 American Real Estate and Urban Economics Association International Meeting and the 2005 North American Regional Science Council meetings for helpful comments on previous drafts. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

©2006 by Janna L. Matlack and Jacob L. Vigdor. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Do Rising Tides Lift All Prices? Income Inequality and Housing Affordability
Janna L. Matlack and Jacob L. Vigdor
NBER Working Paper No. 12331
June 2006
JEL No. D12, D31, I31, R21

ABSTRACT

Simple partial-equilibrium models suggest that income increases at the high end of the distribution can raise prices paid by those at the low end of the income distribution. This prediction does not universally hold in a general equilibrium model, or in models where the rich and poor consume distinct products. We use Census microdata to evaluate these predictions empirically, using data on housing markets in American metropolitan areas between 1970 and 2000. Evidence clearly and unsurprisingly shows that decreases in one's own income lead to less housing consumption and less income left over after paying for housing. The effect of increases in others' income, holding one's own income constant, is more nuanced. In tight housing markets, the poor do worse when the rich get richer. In slack markets, at least some evidence suggests that increases in others' income, holding own income constant, may be beneficial.

Janna L. Matlack
829 Spruce St, Suite 204
Philadelphia, PA 19107
jmatlack@urbanpartners.us

Jacob L. Vigdor
Terry Sanford Institute of Public Policy
Duke University
Durham, NC 27708
and NBER
jacob.vigdor@duke.edu

1. Introduction

Both recently and historically, debates over the progressivity of government tax and transfer policies have focused on arguments that increasing the incomes of wealthy individuals has an indirect “trickle-down” effect on those further down the income distribution. While the existence of these effects, to say nothing of their magnitude, have long been debated (Danziger and Gottschalk, 1986; Gottschalk and Smeeding 1997), recent advances at the intersection of economics and psychology suggest that the mere existence of trickle-down effects may be insufficient to raise the subjective well-being of the poor. When individuals assess their utility by comparing their own income to that of some reference group, policy changes that increase one's absolute income may not be favored if they simultaneously raise other's income by even more (Luttmer 2005).

This paper focuses on a more fundamentally economic concern regarding the potential for trickle-down effects to raise objective measures of welfare: the possibility that increases in income inequality raise the prices of the goods consumed by the poor. “Smoking gun” evidence of such a relationship is not difficult to obtain. Over the past twenty years, low-socioeconomic status (SES) households in the United States have witnessed both a decline in their relative incomes and adverse changes in housing outcomes. Figures 1 and 2 provide basic evidence of these trends. Figure 1 depicts a common income inequality measure, the ratio of family income at the 90th and 10th percentiles, and the average monthly rent paid by renter households headed by a high school dropout, using four Census microdata samples.¹ Both time series show similar trends: relatively stable patterns in the 1970s followed by increases in both measures after 1980.

¹ We focus on renter households in this paper, under the presumption that households purchasing housing on a spot market will face prices more clearly influenced by current market conditions. Low-SES owner households will in many cases be hedged against fluctuations in spot market prices, whatever their source (Sinai and Souleles, 2005).

Figure 2 replaces the price measure with an inverted quantity measure, the number of persons per room for renter households headed by a high school dropout. This time series bears a striking resemblance to trends in income inequality.

While Figures 1 and 2 bring only four data points to bear on this question, figures 3 and 4 present additional evidence, culled from a longitudinal dataset of metropolitan housing markets derived from Census microdata samples. Figure 3 shows the relationship between income inequality, as measured by the GINI coefficient, and the average residual income, defined as annual family income (in constant 2000 dollars) less annual gross rental payments, for renter households headed by a high school dropout. Figure 4 relates GINI coefficients to average persons per room for the same set of households. Both figures show a significant correlation.

The time-series and cross-sectional correlations between income inequality and housing affordability for low-SES households motivates this paper's basic research question: whether the former is at least partially to blame for the latter. This basic query can be decomposed into two component questions. The first, which is admittedly uncontroversial enough to be of limited interest, is whether housing outcomes worsen when a household's own income declines. The second, more pertinent to the general discussion that began this paper and to which we devote more attention here, is whether increases in another household's income worsen one's own consumption outcomes, holding own income constant.

The hypothesis that income inequality causes housing affordability problems is not novel. It is proposed by Rodda (1994) and discussed by Vigdor (2002). This paper contributes a more formal modeling of the potential relationship of the phenomena and more rigorous empirical tests using repeated cross-sectional and longitudinal data.

The answer to this question will be of interest to scholars and policy-makers concerned with both inequality and housing affordability. Evidence that inequality raises prices for the poor, even controlling for their own income, would argue against the “trickle-down” economic hypothesis. Evidence of a link between income inequality and housing affordability would also complement existing literature on the demand and supply-side determinants of housing prices (Glaeser and Gyourko, 2003; Greulich, Quigley and Raphael, 2004; Gyourko, Mayer and Sinai, 2004; Glaeser, Gyourko, and Saks, 2005a, 2005b; Quigley and Raphael 2004; Saiz 2003).

We begin the paper with a brief discussion of these two literatures in section 2. Section 3 presents two basic housing market models. In both models, consumers are disaggregated into two types, high- and low-SES. The first model, which considers the housing market in partial equilibrium, suggests that any increase in income inequality will lead to some combination of higher expenditures and lower consumption for the poor, so long as the supply of housing is less than perfectly elastic. The second model, which focuses on the housing market in general equilibrium, produces more ambiguous conclusions, particularly in the case where changes in production technology that lead to greater income inequality also influence the productivity of capital.

Given this theoretical ambiguity, we turn to empirical analysis to determine whether income inequality is associated with poor housing market outcomes for low-skilled workers, and whether this effect can more directly be attributed to reductions in the real earnings of those workers. Section 4 describes our data and methodology, and section 5 presents our results. Using Integrated Public Use Microdata Samples (IPUMS) from the 1970, 1980, 1990 and 2000 Census enumerations, we show that the total impact of income inequality on the housing

outcomes of the poor is significant and negative. Much of this total effect can be explained as the effect of own-income on housing consumption, however. Increasing others' income while holding one's own income constant appears to have a more nuanced effect. In tight housing markets, increases in others' income leads to a reduction in the quantity of housing consumed, to the point where the effect on total expenditures is negligible. In markets with high vacancy rates, increases in others' income may actually be beneficial, either because these changes are associated with reductions in the cost of capital or because some forms of housing are inferior goods.

Section 6 discusses these results and concludes the paper.

2. Housing affordability in the United States

In the half-century immediately prior to 1980, the American housing market underwent a remarkable transformation. Thanks in large part to innovation and increased Federal involvement in the mortgage market, homeownership rates increased by twenty percentage points. At the same time, the housing stock expanded rapidly, predominantly in suburban areas surrounding large and medium-sized cities (Jackson 1985; Stone 1993). Perhaps not coincidentally, the period between 1940 and 1950 witnessed a substantial compression in the American wage distribution, ushering in a period of relatively mild income inequality that persisted into the 1980s (Goldin and Margo, 1992; Piketty and Saez 2003). The tail end of this time period is represented in the leftmost datapoints of Figures 1 and 2. Households headed by individuals at the low end of the skill distribution generally paid rents that appear quite reasonable by more modern standards, and consumed a quantity of housing per household member that appears quite generous by these standards.

The rise of housing affordability problems after 1980, and the concurrent increase in income inequality, have attracted the attention of numerous researchers over the past fifteen years. Previous research has identified many possible causes of the increase in inequality. Skill premia have increased in the labor market, perhaps reflecting technological advances (Autor, Katz and Kearney 2005). Manufacturing employment, long a source of high-paying jobs for moderately skilled workers, declined (Bernard and Jensen, 1998). Labor unions declined in importance (Card, Lemieux and Riddell, 2003). International trade patterns and immigration have also been implicated by some studies (Feenstra and Hanson, 2001; Borjas, 2003).

The potential role of rising inequality as a *cause* of housing affordability problems has heretofore been only cursorily studied. The role of a household's own income in determining ability to afford housing is well supported by empirical evidence and not often disputed (Gyourko and Linneman 1997; Andrews 1998; Feldman 2002). The more nuanced question of whether an increase in other consumers' income adversely effects one's own housing outcomes has been addressed, to our knowledge, by only one empirical study, Rodda (1994). Using data from the Census enumerations of 1970 and 1980, Rodda finds a positive and significant relationship between the two measures. Using American Housing Survey data between 1984 and 1991, he also finds that when demand for higher quality housing increases, the best quality units from the low cost unit pool filter up and out of the low rent category.²

Analyses of the post-1980 growth of housing affordability problems has generally focused on financial factors such as inflation and high interest rates, or on supply-side factors

² Rodda's study is in many respects similar to our own. We expand on his study by using two additional Census enumerations, incorporating a broader array of household-level controls, and considering additional dependent variables. As will be revealed below, controls for a household's own income lead to conclusions opposite to those Rodda reaches.

(Gyourko and Linneman 1993). There is a strong case to be made that restricted growth in housing supply has played a role in the decline of housing affordability after 1980. The supply of subsidized and low-income housing has declined to pre-World War II levels, in part because of a general halt to construction during the Reagan era (Stone 1993). Older housing stock in many cities has been demolished or deteriorated beyond repair (Mulherin 2000). In many metropolitan areas, growth in the housing stock failed to keep up with population growth, leading to scenarios where the market price of housing units vastly exceeded the marginal cost of constructing those units. A considerable amount of recent research (Glaeser and Gyourko, 2003; Glaeser, Gyourko and Saks, 2005a, 2005b) suggest that zoning laws and other housing market regulations lie at the root of these trends.

Supply-side and demand-side explanations for the decline of housing affordability are not mutually exclusive. Indeed, they are complementary. Inelastic supply need not lead to price increases if demand is stable or declining. Similarly, the impact of demand growth on prices depends on the elasticity of supply. Given the recent explosion of papers associating housing price appreciation with inelastic supply, it seems appropriate to us to consider anew the potential for trends in the demand for housing – particularly the renewed interest in central-city housing on the part of affluent households (Vigdor 2002) – in reducing the affordability of housing units to less-affluent households.

3. Income inequality and housing prices in theory

This section begins by discussing housing markets in partial equilibrium. In this model, under reasonable assumptions, increases in income at the high end of the distribution lead to

higher housing costs and reduced consumption at the low end. We then present a simple closed-economy general equilibrium model, which suggests that the connection between income inequality and housing market outcomes is not universally clear. We conclude by considering the implications of moving to an open-economy model with (potentially costly) household mobility.

3.1 The partial equilibrium view

Figure 5 presents a simple representation of a housing market, where consumers can be disaggregated into two types, high- and low-SES. Panel (a) depicts the result of an increase in income in the high-SES group, presuming that housing is a normal good. Panel (c) shows the corresponding increase in the market demand curve. Assuming that the supply of housing is at least somewhat inelastic, this leads to an increase in the market price of housing.³ This price increase results in a decrease in the quantity of housing consumed in the low-SES population (panel b). Assuming income is unchanged in the low-SES population, agents must either consume less housing or devote a higher share of their income to housing consumption.

If an increase in income inequality can be attributed, at least in part, to a decrease in income among low-SES households, then the price effects depicted in figure 5 may be narrowed or reversed. The net implication for housing consumption of these households remains unchanged. Thus, regardless of the source of increasing income inequality, the partial equilibrium model unambiguously predicts worsened housing market outcomes for those at the bottom of the income distribution. The magnitude of the predicted effect varies inversely with

³ Inelastic housing supply in a market can be justified on the grounds that at least one input, land, is in finite supply in the long run.

the price elasticity of supply; in the special case where this elasticity is infinite, there is of course no impact of any change in demand on prices.

In this simple graphical model, housing is treated as an undifferentiated commodity. Allowing for product differentiation, particularly the creation of categories of housing with varying income elasticities, could potentially alter many of the model's predictions. As a simple example, suppose that each housing unit is a bundle of two subproducts, one an inferior good and the other with a positive income elasticity, with varying weights on the two subproducts. In equilibrium, low-SES consumers would be expected to consume a disproportionate amount of the inferior subproduct. Raising the income of high-SES consumers might well reduce market demand for the type of housing unit typically chosen by low-SES consumers.

Thus, in the partial equilibrium view, the question of whether higher incomes for the wealthy worsen housing outcomes for the poor hinges on the degree of product differentiation in the housing market. The question of whether housing is a differentiated product links to the traditional discussion in housing economics of whether “filtering” occurs (see Vigdor 2002 for a discussion). As the following subsection makes clear, however, general equilibrium considerations can introduce ambiguity even in the absence of product differentiation.

3.2 The general equilibrium view

The model presented in this section expands on the simple consumer model above to incorporate producers who potentially consume some of the same capital stock used in the production of housing. Consumers derive utility from a numeraire commodity X , and an asset A , best thought of as land, or more generically an asset that can be transformed costlessly into

housing. Firms use this asset in combination with labor to produce the numeraire commodity. Individuals supply labor inelastically. This labor is not of uniform quality: individuals are divided into high-skill and low-skill types, and firms treat their labor as unique factors of production. All markets are competitive, with agents treating the endogenously determined asset price p , and wages of high- and low-skilled labor, w_H and w_L , as given. The aggregate production function in the economy is Cobb-Douglas, with constant returns to scale:

$$(1) X = kH^\alpha L^\beta A^{1-\alpha-\beta}$$

where H and L refer to the total number of high- and low-skill workers in the economy, respectively. Individual utility also takes on a Cobb-Douglas functional form:

$$(2) U(X, A) = X^\gamma A^\delta.$$

Note that utility is assumed to be independent of type in this case. A standard budget constraint applies to the consumer's decision, and firms act to maximize profits. The aggregate amount of A in the economy is fixed at a level \bar{A} .

Equations (1) and (2), coupled with the fixed land constraint and consumer budget constraints, yield a system of eleven equations and eleven unknowns. Endogenous variables include land and numeraire consumption for each household type, the wage of each household type, the price of land, the aggregate amount of numeraire produced, the amount of land used in production, and two LaGrange multipliers associated with the budget constraints for each household type. This system of equations yields a solution for the equilibrium price of land:

$$(3) p = (1 - \alpha - \beta)kH^\alpha L^\beta \left[\left(\frac{(1 - \alpha - \beta)(\delta + \gamma)}{\delta + (1 - \alpha - \beta)\gamma} \right) \bar{A} \right]^{-\alpha - \beta}$$

Intuitively, the price of land equals the marginal product of land in production. Equation (3) is thus the derivative of (2) with respect to A , substituting in the term for the equilibrium amount of land used in production. The amount of land used in production is a set fraction of the total amount of land available. This fraction depends both on production technology and on relative consumer tastes for land. This fraction approaches one as consumers attach less value to land (i.e. $\delta \rightarrow 0$), to zero as the importance of land in production declines (i.e. $1 - \alpha - \beta \rightarrow 0$) and approaches $1 - \alpha - \beta$ as consumers attach increasing value to land. Similarly, the system of equations yields an expression for the equilibrium wage of low-skilled laborers:

$$(4) \quad w_L = \beta k H^\alpha L^{\beta-1} \left[\left(\frac{(1 - \alpha - \beta)(\delta + \gamma)}{\delta + (1 - \alpha - \beta)\gamma} \right) \bar{A} \right]^{1 - \alpha - \beta}.$$

Finally, as is universally true with Cobb-Douglas utility functions, low-skilled workers' expenditure on land is a constant fraction of income:

$$(5) \quad A_L = \frac{w_L}{p} \frac{\delta}{\delta + \gamma}.$$

Substituting (3) and (4) into (5) and rearranging terms yields the following solution for land consumption of low-skilled workers:

$$(6) \quad A_L = \frac{1}{L} \frac{\beta \delta}{[\delta + (1 - \alpha - \beta)\gamma]} \bar{A}.$$

In aggregate, low skilled workers consume a set fraction $\frac{\beta}{\alpha + \beta}$ of land not used in production.

Each individual low skilled worker consumes a share $1/L$ of this allocation.

In this model, changes in income inequality associated with differential productivity growth can be modeled as increases in α relative to β . The impact of changes in income

inequality on the land consumption of low-SES workers can thus be gauged by differentiating equation (6) with respect to these two parameters.

Consider first the scenario where the productivity of high-skilled workers increases, while the productivity of low-skilled workers remains the same. Note that in order to maintain the assumption of constant returns to scale, the productivity of land must be reduced in this scenario. In this case, the impact on land consumption of the low-skilled is given by equation (7), the derivative of A_L with respect to α .

$$(7) \frac{\partial A_L}{\partial \alpha} = \frac{\beta \delta \bar{A}}{L(\delta + (1 - \alpha - \beta)\gamma)^2}$$

This expression is unambiguously *positive*. Intuitively, the reduction in land productivity assumed in this scenario leads firms to employ less of it. Low-skilled workers receive a smaller share of land not used in production, but this reduction is more than offset by an increase in the total.⁴

The model's implications are quite different in the scenario where increases in productivity of the high-skilled are fully offset by decreases in the productivity of the low skilled. In this scenario, the net impact on land consumption of the low skilled is given by the difference in derivatives of A_L with respect to α and β ,

$$(8) \frac{\partial A_L}{\partial \alpha} - \frac{\partial A_L}{\partial \beta} = - \frac{1}{L} \frac{\delta \bar{A}}{\delta + (1 - \alpha - \beta)\gamma},$$

which is unambiguously negative. Income inequality thus leads to lower housing consumption only when it is associated with a decrease in the productivity of the poor. Holding this factor

⁴ This result should not be taken as evidence that low-skilled workers experience an increase in utility in this scenario. Lower land prices may be accompanied by reductions in the low-skilled wage. While the net effect is to increase housing consumption, reductions in numeraire consumption created by lower income can more than offset any welfare gains. Differentiating equation (4) with respect to a reveals a theoretically ambiguous effect.

constant, and assuming constant returns to scale, any negative impact on the earnings of low-SES households is more than offset by declines in the prices of production factors used to make housing.

3.3 Extensions to the model

The general equilibrium model presented above assumes a fixed population of workers. More realistic versions of the model would incorporate migration. Costless migration would impose the condition that utility for each household type would equalize across labor markets. In such a scenario, a positive shock to the productivity of high-SES households would lead to inflows of migrants. It is clear from equations (3) and (4) above that increasing H , other things equal, will lead to some combination of higher housing costs and lower wages for high-SES types, other things equal. The wages of low-SES types would also rise, producing ambiguous effects on housing and numeraire consumption. Depending on the direction of this impact, low-SES types would be expected to migrate into or out of the market in question. Net of migration responses, the impact of localized changes in production technology on the well-being of the poor would be exactly zero. A similar prediction holds in cases where income inequality results from a negative shock to the productivity of low-SES households; in this case outmigration would eliminate adverse impacts on living standards by raising wages and lowering housing prices.

To further increase the realism of the model, migration can be made costly. In such a scenario, an inflow of high-SES households brought about by a localized shock to production technology could reduce the living standards of the poor. Such an effect would not be guaranteed, however; there is at least the theoretical possibility that inflows of high-SES

households would increase the wages of low-SES households faster than housing prices. Localized negative shocks to the productivity of low-SES households in the presence of moving costs may lead to lower living standards for these households; the prediction is unambiguous in the case that lower productivity for low-SES households is matched by an increase in productivity for high-SES households.

A second reasonable extension to the model would allow multiple types of capital which may not perfectly substitute in the production of various types of goods. Land and lumber could certainly be used in a number of production processes, but many kinds of industrial equipment have little use in the production of housing. In the context of the general equilibrium model presented above, this implies that increases in the productivity of high-SES households, or decreases in the productivity of low-SES households, could be offset by changes in the productivity of factors that are irrelevant for the production of housing. In such a scenario, assuming mobility is at the very least costly, localized increases in the productivity of high-SES workers have positive impacts on both prices and the wages of low-SES workers, with an ambiguous net effect on the housing consumption and well-being of the poor. Localized decreases in the productivity of low-SES workers have unambiguous negative effects on their well-being.

In summary, simple partial equilibrium models of the housing market suggest that any increase in income inequality, regardless of its source, will have a negative effect on the housing outcomes of the poor, with an impact that varies inversely with the price elasticity of supply. Partial equilibrium models incorporating product differentiation can produce opposing

conclusions. General equilibrium models yield ambiguous predictions, and suggest that the nature of the increase in inequality is an important moderating factor.

4. Data and Methods

Our analysis uses the Integrated Public Use Microdata Series (IPUMS) dataset for the years 1970, 1980, 1990, and 2000. The IPUMS provides information on 1% of individuals and households drawn from the United States Census. While there are several caveats associated with these data, most notably a temporal dissociation between the reporting of income (previous calendar year) and housing information (April 1st of current year), the geographic detail and uniform timing make this dataset the most appropriate for our purposes.⁵ We focus on persons and households living in metropolitan statistical areas, using the MSA as our conceptualization of a housing market.⁶ While the Census Bureau uses different terminology throughout 1970 to 2000 to define MSAs, the basic definition is the same for all years.

Correctly defining low-SES to reflect those households without financial stability is critical to our research. In results reported below, we focus on the set of households headed by an individual without a high school diploma. It is important to note that the density of high school dropouts in the population has been declining over time, implying that we are analyzing a

⁵ Many previous studies researching housing affordability issues have used other datasets that have more information on housing characteristics, such as the American Housing Survey (AHS) or the Current Population Survey (CPS) (Somerville and Holmes 2001). While the higher frequency, greater detail on housing unit and neighborhood quality, and longitudinal aspects make the AHS attractive for many studies, the unavailability of reliable data to construct income inequality measures in non-Census years renders it less appealing for our purposes. The main shortcoming of the CPS for this study is its relatively coarse geographic identification, which would not permit us to use metropolitan areas as housing market constructs.

⁶ In Consolidated Metropolitan Statistical Areas (CMSAs), we use Primary Metropolitan Statistical Areas (PMSAs) as the unit of analysis.

systematically more-disadvantaged population in later years. Most of our regression specifications employ year fixed effects to address this concern.⁷

Table 1 presents summary statistics for the 234,345 households included in the sample. Unsurprisingly, households in this group tend to have low incomes, with a mean under \$25,000 in 2000 dollars. More than a fifth are headed by an African-American, nearly half are female-headed. Slightly more than half of households are “idle,” neither working nor in school.⁸ Over one-quarter are headed by an individual over 65 years of age, and over one-third are headed by a foreign-born immigrant.

We use three different variables as housing market outcomes. The ratio of rent to income is often used in policy contexts to delineate households experiencing affordability problems (Stone 1993). There are a number of methodological concerns with the measure, however, not least of which is that household income is generally not constrained to be positive, while rent usually is (Thalmann 1999). In spite of these concerns, the indicator is often promoted as easy to comprehend, calculate, and compare across areas and time periods (Bogdon and Can 1997). We exclude from analysis those households with ratios outside the interval [0,1].

While we use the rent-to-income ratio (RIR) in some specifications, we more frequently use an alternative indicator, which we term “residual income.” As the general equilibrium model presented in section 3.2 indicates, the share of income spent on housing is in many respects an unsatisfying measure of the burden placed on poor households. Increases in the rent-to-income ratio may mask situations where rent increases are matched more than dollar-for-dollar by

⁷ In alternative specifications, we employed different definitions of low-SES, including one based on householders’ occupation and one based on family income. Results using these alternative sample selection criteria were substantively similar to those reported here.

⁸ Our definition of “idle” follows that of Cutler and Glaeser (1997).

increases in income. Residual income, the simple difference between annual income and annualized monthly gross rent, is a superior measure of a households' welfare when housing is of uniform size and quality.⁹ For purposes of comparison with existing literature, we present some specifications using both residual income and the RIR.¹⁰ Table 1 reports means and standard deviations for these two variables. Residual income averages nearly \$19,000 in 2000 dollars, with a standard deviation of about \$24,000. Rent-to-income ratios average 0.313 with a standard deviation of 0.217.

Housing units are most assuredly not of uniform size and quality. If price increases are accompanied by increases in the size or quality of housing units, the residual income measure may incorrectly indicate a decrease in household welfare. To at least partially address this issue, we also analyze the impact of income inequality on an inverted measure of the quantity of housing consumed per person in a household – the number of persons per room. This is admittedly an imperfect measure of quantity, as room sizes and intended purposes may vary substantially, and does little to address construction quality or the value of land associated with the housing unit.¹¹ Nonetheless, consistency of specifications analyzing residual income and quantity consumed with theoretical predictions will assuage some concerns associated with either measure in isolation. Table 1 shows that the average persons per room in our sample is 0.863, with a standard deviation of 0.766.

⁹ The concept of residual income is at least somewhat related to the concept of 'shelter poverty' (Stone 1993). Shelter poverty is a sliding scale that measures the maximum proportion of income available for housing and varies that proportion with household size and type (Bogdon and Can 1997). While this indicator takes into account preference and other variables that RIR neglects, shelter poverty is often subjective and difficult to calculate over time.

¹⁰ To be consistent across observations, we compute both RIR and residual income using a measure of total family income. The total family income does not include income from any household members that are not related to the household head. While total household income includes income from all members of one household regardless of relationship to head and would be more appropriate, this variable was not calculated by the census until 1980.

¹¹ This variable is the best indicator for quantity given the data limitations of the IPUMS dataset.

Our primary measure of income inequality in each metropolitan area and year is the GINI coefficient, which quantifies the degree of deviation from an even distribution of income. In a population where the variance in income equals zero, the GINI coefficient will equal zero. In a population where only one individual collects all income, the GINI coefficient will equal one. We use total family income as reported by IPUMS households to construct this measure.¹² Table 1 shows that for the 812 MSA/year observations in the IPUMS sample, the average GINI coefficient is 0.411 with a standard deviation of 0.035.

The GINI coefficient can be skewed in datasets where income is topcoded, as is the Census. We feel that the topcoding is not a severe problem in our case, since it will be unlikely to change the rank ordering of communities. Nonetheless, we also report the results of alternative specifications where we control separately for three income quantiles in each metropolitan area and year: the 10th percentile, median, and 90th percentile. This methodology will also allow us some ability to distinguish among sources of change in income inequality.

5. Results

5.1 The total impact of inequality on housing outcomes

Table 2 presents the results of regression specifications examining the total impact of changes in income inequality on housing cost burdens, measured using either residual income or the more traditional rent-to-income ratio. That is to say, these regressions examine the effect of variation in income inequality operating both through variation in own and others' income. We will decompose this effect in Table 5 below. As described in the preceding section, the sample

¹² As our regressor of interest is a sample statistic, we weight all models by the square root of the sample size used to compute it.

consists of renter households headed by a high school dropout residing in metropolitan areas between 1970 and 2000.

The first regression specification controls for MSA and year fixed effects plus the MSA-by-year varying GINI coefficient measure of income inequality.¹³ The estimate derived here, which relies exclusively on within-MSA and within-year variation in income inequality, indicates that a one-standard deviation increase in inequality predicts a \$1,500 decrease in residual income for low-SES renters. This result corroborates the basic graphical evidence presented in Figures 1 and 3.

Some portion of the effect estimated in this first specification might be attributable to heterogeneity in the characteristics of low-SES renter households, possibly rooted in broad demographic changes or in changes in transitions to homeownership for this group. The second specification thus introduces a series of controls for individual household characteristics into the equation, as well as a control for the logarithm of MSA population. These household characteristics are themselves significant predictors of residual income. Smaller households, and those headed by African-American, female, unmarried, idle, immigrant, or younger householders tend to have less income available to spend after paying their housing costs. Controlling for these factors reduces the magnitude of the income inequality effect noticeably, to where a one-standard-deviation increase in the GINI coefficient predicts a \$1,000 decrease in residual income. The estimated coefficient continues to be statistically significant.

The last two specifications in Table 2 replicate the first, two replacing the residual income measure with the more traditional rent-to-income ratio. In general, household

¹³ Most regression specifications reported in this paper employ the Huber-White correction for clustered data, since the independent variable of interest varies at the MSA-by-year level and the unit of observation is the household.

characteristics predicting lower residual income also predict higher rent-to-income ratios. The impact of income inequality on rent-to-income ratios does not concord with the estimated impact of that variable on residual income.¹⁴ In the RIR specifications, these coefficients are of varying sign and statistically insignificant. This lack of concordance implies that those preferring the RIR as a measure of housing cost burden may wish to discount results derived with residual income, and vice versa. As we think of the residual income measure as more easily interpretable in the context of economic theory, we report results utilizing that measure in later tables and relegate discussion of results using RIR to footnotes.

The specifications reported in Table 3 use our inverted quantity measures, persons per room, as a dependent variable. Corroborating evidence shown in Figure 4, the both specifications display a positive association between income inequality and crowding for low-SES households. The estimated coefficient is statistically significant in the second specification, which incorporates household characteristics as well as MSA and year fixed effects. The point estimate indicates that a one-standard deviation increase in the GINI coefficient is associated with an 0.10 person increase in the number of persons per room. Household characteristics tend to have predictable effects on crowding: larger households are more crowded, as are households headed by males, by unmarried or idle individuals, and those headed by younger people. Crowding is significantly higher in larger cities.

Perhaps the strongest critique of the evidence presented to this point is that it controls only crudely for housing market characteristics other than income inequality. Metropolitan area

¹⁴ Specifications omitting MSA fixed effects yield significant positive coefficients on GINI in the RIR specification, and significant negative coefficients in the residual income specification. So the evidence in Table 2 could be considered something of a worst case scenario in terms of generating concordance across dependent variables. Nonetheless, the caveats stated in the text paragraph should be taken seriously.

fixed effects do eliminate any concerns regarding time-invariant market features, such as climate or topography, but do little to assuage concerns regarding time-varying characteristics. To more directly address these concerns, Table 4 presents the results of models where data have been collapsed to the metropolitan area/year level and first differenced, leading to an analysis that is truly longitudinal rather than repeat cross-sections. Each of the regressions reported here incorporate metropolitan area fixed effects, which have the effect of allowing MSA-specific time trends across the three decades studied here. Some specifications also introduce time-varying controls for the change in log population and change in log median income in each metropolitan area.¹⁵

The first reported specification, which resembles a first-differenced version of the second specification in Table 2, estimates a very similar relationship between inequality and residual income.¹⁶ This concordance is not mechanical in nature – many of the other coefficients do not match very closely across the two specifications, with signs switching in some cases. This lends further support to the notion that the estimates in Table 2 capture the true total impact of income inequality on the residual income of poor households.

As discussed in preceding sections, the total relationship between inequality and housing outcomes blends two potential causal pathways: the impact of own and others' income. The second specification in Table 4 begins the process of disentangling these effects, a process which will be carried much further in subsequent tables. Relative to the first column, the second adds two control variables, one for the change in population in an MSA, and the other for the change

¹⁵ The regressions in Table 4 continue weight observations by the number of observations used to compute the MSA/year-specific GINI coefficient in the end year of the decadal observation.

¹⁶ Comparable specifications examining the rent-to-income ratio reveal no significant relationship between change in the GINI coefficient and changes in the average RIR for low-SES households. This insignificance persists when we introduce controls for the change in log median income and change in MSA population.

in the logarithm of median income. The results show that the entire effect of inequality on residual income loads onto the control for median income. Controlling for the average income, then, this model suggests that changes in the distribution of income are of little consequence for housing outcomes of the poor. The estimated impact of increases in the GINI coefficient is positive and statistically insignificant.

Controls for median income are not sufficient to eliminate all the links between inequality and housing outcomes in these first-differenced specifications. The last two regressions in Table 4 replace the residual income measure with persons per room. While the inequality coefficients in these two specifications are smaller in magnitude than their counterpart in Table 3, the introduction of a control for change in median income actually increases the estimated magnitude. Both coefficients are statistically significant, indicating that raising inequality increases crowding among the low-income population. Controlling for changes in median income, then, increasing inequality appears to reduce the quantity of housing consumed while having little impact on residual income. While this is consistent with a model where households respond to increasing prices by reducing consumption, these results further motivate the specifications in the following section, which return to individual-level data in order to estimate the relationship between inequality and housing outcomes, holding own income constant.

5.2 Separating the effect of own income from other's income

The regression specifications in Table 5 return to the individual-level models, introducing controls for total family income in order to separately identify the impact of own income from

that of changes in others' income. These specifications confirm that a household's own income is a critical determinant of housing consumption. In the first specification, an increase of a dollar in family income raises residual income by roughly 98 cents. This coefficient is estimated precisely enough to be statistically distinguishable from one. It does indicate, however, that the marginal propensity to consume housing is very small in this segment of the population.¹⁷ This is not necessarily surprising, as housing is considered a necessity by most, but the magnitude is rather striking. In the second column, there is a statistically significant but weak relationship between own income and crowding. An increase of \$10,000 in family income predicts a decrease in persons per room of 0.1 – equivalent to moving a family of four from a six-room to a seven-room unit.

Controlling for family income, and the other household and MSA-level characteristics included in Table 5, the estimated impact of income inequality is no longer consistent across specifications. Increases in inequality, holding own income constant, actually increase residual income, albeit by a relatively small amount. A one-standard deviation increase in income inequality now predicts a \$300 increase in residual income. This sign reversal is nonetheless quite striking, as it argues directly against the simple partial equilibrium model of housing markets, supporting instead either a differentiated product model or the general equilibrium model.

Holding own income constant, an increase in income inequality continues to predict significantly greater crowding among low income households. As in Table 4, the results together

¹⁷ An alternative specification analyzing variation in the rent-to-income ratio shows a significant negative relationship between own income and the dependent variable, with a \$1,000 increase in income predicting a reduction in the ratio of 0.003. In this specification, the GINI coefficient continues to be an insignificant predictor of RIR.

suggest that poor renter households' response to increasing inequality is to reduce consumption, to the point where expenditures on housing actually decrease somewhat. The impact of a one-standard deviation increase in the GINI coefficient is a roughly one-seventh of a standard deviation on consumption per household member, coupled with a less than 2% of a standard deviation increase in residual income.

To further analyze this pattern, the specifications in Table 6 replace the GINI coefficient with income distribution quantiles, including the median, tenth percentile, and ninetieth percentile. The regressions continue to hold own income constant. The first specification, which analyzes variation in residual income, shows negative point estimates for each of the income quantiles, though only one is significant at the 10% level. The point estimates suggest, albeit weakly, that low-SES households are most negatively affected by increases in income at the bottom of the distribution.¹⁸ This suggests a natural interpretation for the estimated impact of the GINI coefficient in the preceding table: low-SES households do well when inequality increases, holding their own income constant, when other households with incomes similar to theirs are faring poorly. The income of individuals at higher points in the distribution is largely irrelevant. This result pattern points in turn to a differentiated product view of the housing market.

Results in the persons per room specification point to a slightly different conclusion. Here, the relationship between income inequality and crowding appears to operate through changes at the high end of the distribution. A one-standard-deviation increase in the 90th percentile of the local income distribution, roughly \$20,000 in 2000 dollars, predicts a 0.16 increase in persons per room – roughly equivalent to moving a family of four from a 6-room to a

¹⁸ An alternative specification using the rent-to-income ratio as the dependent variable confirms this notion: increases in income at the 10th percentile have the largest estimated positive impact on rent-to-income ratios, holding own income constant. This coefficient has a *p*-value of 0.127.

4-room unit. Lower quantiles of the income distribution show no significant relationship with crowding. These results imply a different pattern, one where increases at the high end of the distribution cause families at the low end to consume less housing per person.

Overall, there does not appear to be a uniform effect of increasing income inequality. Rather, there are different types of inequality increases, with differing effects. As an example of one type, consider the Boston area. Between 1970 and 2000, Boston's GINI coefficient rose from 0.391 to 0.487. This was driven largely by income increases at the high end of the distribution: the 90th percentile rose from \$90,354 to \$142,000 in constant 2000 dollars, while the 10th percentile remained steady in the \$9,000 to \$10,000 range. The models estimated here imply that in such an area, poor households respond by reducing the quantity of housing consumed, to limit any increases in total expenditures.

Metropolitan areas featuring pronounced decreases in the tenth percentile of the income distribution include Detroit, Gary, and other generally declining cities. Growing inequality in these areas would appear to accompany slack in the housing market, which could explain why residual income increases. The following subsection presents more rigorous evidence on the hypothesis raised by this comparison: that inequality worsens housing outcomes primarily in those areas with very little slack in the housing market.

5.3 The moderating effect of supply elasticity

Partial equilibrium analysis suggests that the impact of inequality on the housing outcomes of the poor depends critically on the price elasticity of supply in the market. To test the moderating impact of supply, we consider an indication of short-run supply elasticity, the

vacancy rate in the housing market. Markets with a large proportion of vacant units effectively have a flat supply curve linking the quantity currently consumed to the quantity available for consumption at the market price.¹⁹ Vacancy rates vary quite a bit across markets and over time; Table 1 shows that the mean vacancy rate in our sample is 6% with a standard deviation of 2%.

Table 7 presents the results of specifications that begin with those in Tables 5 and 6, adding controls for the vacancy rate in each metropolitan area and the interaction of that vacancy rate with income inequality measures, either the GINI coefficient or three income quantiles. Household level controls including income are included in each specification, but coefficients for these variables are excluded from the table.

The first specification shows statistically significant evidence that the impact of inequality on residual income is more benign when there is slack in the housing market. In a hypothetical MSA with a vacancy rate of zero, there is effectively no relationship between inequality and residual income. As the vacancy rate increases, this null relationship becomes positive, to resemble the specification reported in Table 5. The interaction term in this regression is statistically significant at the 10% level.

The second specification replaces the GINI coefficient with three income distribution quantiles. Here, unlike Table 6, the main effects indicate that the strongest impacts of other income on own residual income are at the 90th percentile of the distribution. In tight housing markets, an increase in income for the wealthy translates into a decrease in after-housing income for the poor. The interaction term, though insignificant, suggests that this effect moderates as vacancy rates increases.

¹⁹ For a discussion of the implications of slow downward adjustment of the housing stock to decreases in demand, see Glaeser and Gyourko (2005).

The third specification switches dependent variables, to examine persons per room. The main effect of the GINI coefficient on this measure suggests that inequality raises crowding significantly in housing markets with little slack. The interaction term is significant at the 10% level and suggests that inequality has little to no impact on crowding when vacancy rates are very high. A similar story appears in the final specification: increases in the 90th percentile of the income distribution, holding own income constant, have a detrimental impact in tight housing markets, which dissipates as vacancy rates increase, although once again the interaction term fails to attain statistical significance at conventional levels. Intriguingly, crowding also increases as the 10th percentile of the income distribution falls in tight housing markets. This suggests that both increasing poverty and increasing wealth can increase demand for housing in certain areas – a standard concern in the study of urban gentrification (Vigdor 2002).

6. Conclusion

Do rising tides lift all boats? If raising the income of the wealthy increases the prices that the poor must pay for certain necessities, then it becomes more difficult to argue in favor of policies that exacerbate inequality on the grounds that they at least do not lower the incomes of the poor. The notion that increases in the incomes of others can reduce an individual's subjective well-being has been long considered by psychologists and economists (Luttmer, 2005). To this point, less attention has been paid to the possibility that objective indicators of well-being, namely consumption levels, may suffer as well.

The theoretical discussion in this paper makes clear that the simple partial equilibrium take on this question can be quite misleading. Product differentiation in the housing market, or

general equilibrium impacts of increased productivity on the rich on the return to forms of capital used to produce housing, could easily break the simple link shown in Figure 5. Our empirical analysis confirms that the story is not always straightforward.

As expected, the findings in this paper confirm that decreases in one's own income have a negative impact on housing consumption. Presumably, the consumption of most other normal goods declines in such a scenario as well. Of greater interest from both a scientific and policy perspective is the question of whether increases in others' income, holding one's own income constant, influence consumption decisions.

In the end, the evidence on this question is mixed, and it seems relatively clear that the answer depends critically on the elasticity of housing supply. In this sense, the study of demand-side determinants of housing affordability problems should not be conducted in isolation from study of the supply side. In the United States, tight housing markets tend to be those where incomes are rising rapidly at the high end of the distribution, while incomes at the low end trend upward only slowly if at all. In these areas, the poor have experienced greater crowding, and there is at least some evidence that their expenditures on housing increase as well, though not in all specifications.

In housing markets with greater slack, or where increased inequality reflects declines at the low end more than increases at the high end, the impact of inequality appears more benign. Holding one's own income constant, a decline in the income of individuals like you appears to be a favorable thing.

Do price effects negate the impact of “trickle-down” effects? The answer appears to be “sometimes.” The key to making rising tides lift all boats appears to be ensuring that there are more than enough boats to go around.

References

- Andrews, Nancy O. "Housing Affordability and Income Mobility for the Poor." Meeting America's Housing Needs. April, 1998.
- Bogdon, Amy S. and Ayse Can. "Indicators of Local Housing Affordability: Comparative and Spatial Approaches." Real Estate Economics, Volume 25, Issue 1. Spring, 1997.
- Cutler, David and Edward Glaeser "Are Ghettos Good or Bad?" Quarterly Journal of Economics v.n. 1997.
- Danziger, S. and P. Gottschalk. "Do Rising Tides Lift All Boats? The Impact of Secular and Cyclical Changes on Poverty." American Economic Review v.76 n.2 1986.
- Feldman, Ron. "The Affordable Housing Shortage: Considering the Problem, Causes, and Solutions." September, 2002. <<http://minneapolisfed.org/pubs/region/02-09/feldman.cfm>> Accessed on February 20, 2004.
- Glaeser, Edward and Joseph Gyourko. "Urban Decline and Durable Housing." Journal of Political Economy v.113 n.2 2005.
- Glaeser, Edward and Joseph Gyourko. "The Impact of Zoning on Housing Affordability." Economic Policy Review v.9 n.2. 2003
- Glaeser, Edward, Joseph Gyourko and Raven Saks "Why is Manhattan So Expensive? Regulation and the Rise in House Prices." Journal of Law and Economics, 2005a.
- Glaeser, Edward, Joseph Gyourko and Raven Saks. "Why Have Housing Prices Gone Up?" Harvard Institute of Economic Research Discussion Paper #2061, February 2005b.
- Goldin, Claudia and Robert Margo. "The Great Compression: The US Wage Structure at Mid-Century." Quarterly Journal of Economics v.107 n.1 1992.
- Gottschalk, Peter and Timothy Smeeding. "Cross-National Comparisons of Earnings and Income Inequality." Journal of Economic Literature v.35 1997
- Greulich, Erica, John M. Quigley and Steven Raphael. "The Anatomy of Rent Burdens: Immigration, Growth, and Rental Housing." Brookings-Wharton Papers on Urban Affairs, 2004.
- Gyourko, Joseph and Peter Linneman. "The Affordability of the American Dream: An Examination of the Last 30 Years." Journal of Housing Research, Volume 4, Issue 1. 1993.

- Gyourko, Joseph and Peter Linneman. "The Changing Influences of Education, Income, Family Structure, and Race on Homeownership by Age over Time." *Journal of Housing Research*, Volume 8, Issue 1. 1997.
- Gyourko, Joseph, Christopher Mayer and Todd Sinai. "Superstar Cities." Zell/Lurie Real Estate Center Working Paper, July 2004.
- Gyourko, Joseph and Joseph Tracy. "A Look at Real Housing Prices and Incomes: Some Implications for Housing Affordability and Quality." *FRBNY Economic Policy Review*. September, 1999.
- Luttmer, E.F.P. "Neighbors as Negatives: Relative Earnings and Well-Being." *Quarterly Journal of Economics* v.120 n.3 2005.
- Mulherin, Stephen. "Affordable Housing and White Poverty Concentration." *Journal of Urban Affairs*, Volume 22, Issue 2. 2000.
- Quigley, John and Steven Raphael. "Is Housing Unaffordable? Why Isn't It More Affordable?" *Journal of Economic Perspectives*, v.18 n.1. 2004.
- Piketty, Thomas and Emmanuel Saez. "Income Inequality in the United States, 1913-1998." *Quarterly Journal of Economics* v.118 n.1 2003.
- Rodda, David T. 1994. "Rich Man, Poor Renter: A Study of the Relationship Between the Income Distribution and Low-Cost Rental Housing." Ann Arbor, MI: UMI Dissertation Services.
- Ryscavage, Paul. 1999. *Income Inequality in America*. Armonk, NY: M.E. Sharpe, Inc.
- Saiz, Albert. "Room in the Kitchen for the Melting Pot: Immigration and Rental Prices." *Review of Economics and Statistics* v.85 n.3 2003.
- Somerville, C. Tsurriel and Cynthia Holmes. "Dynamics of the Affordable Housing Stock: Microdata Analysis of Filtering." *Journal of Housing Research*, Volume 12, Issue 1. 2001.
- Stone, Michael E. 1993. "Shelter Poverty." Philadelphia PA: Temple University Press.
- Thalmann, Philippe. "Identifying Households which Need Housing Assistance." *Urban Studies*, Volume 36, Issue 11. October, 1999.
- United States House of Representatives. Subcommittee on Housing and Community Opportunity. "Housing Affordability and Availability." May 3, 2001.

Vigdor, Jacob “Does Gentrification Harm the Poor?” Brookings-Wharton Papers on Urban Affairs, 2002.

Figure 1: Income inequality and the housing outcomes of high school dropouts

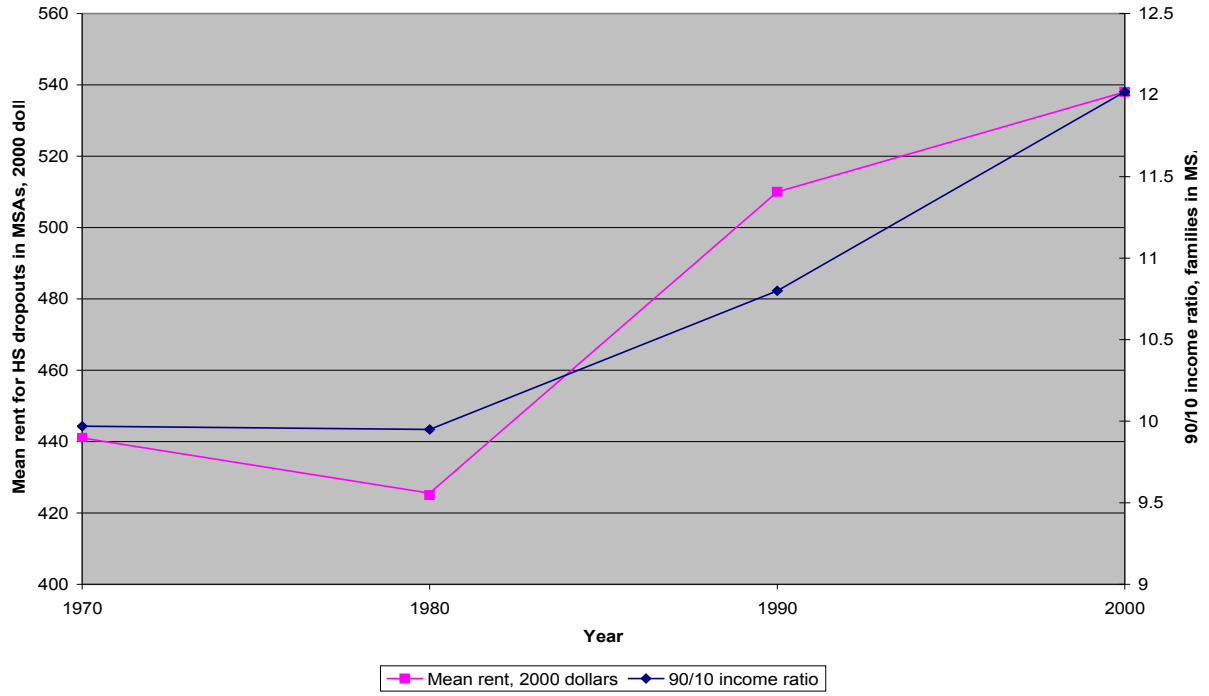
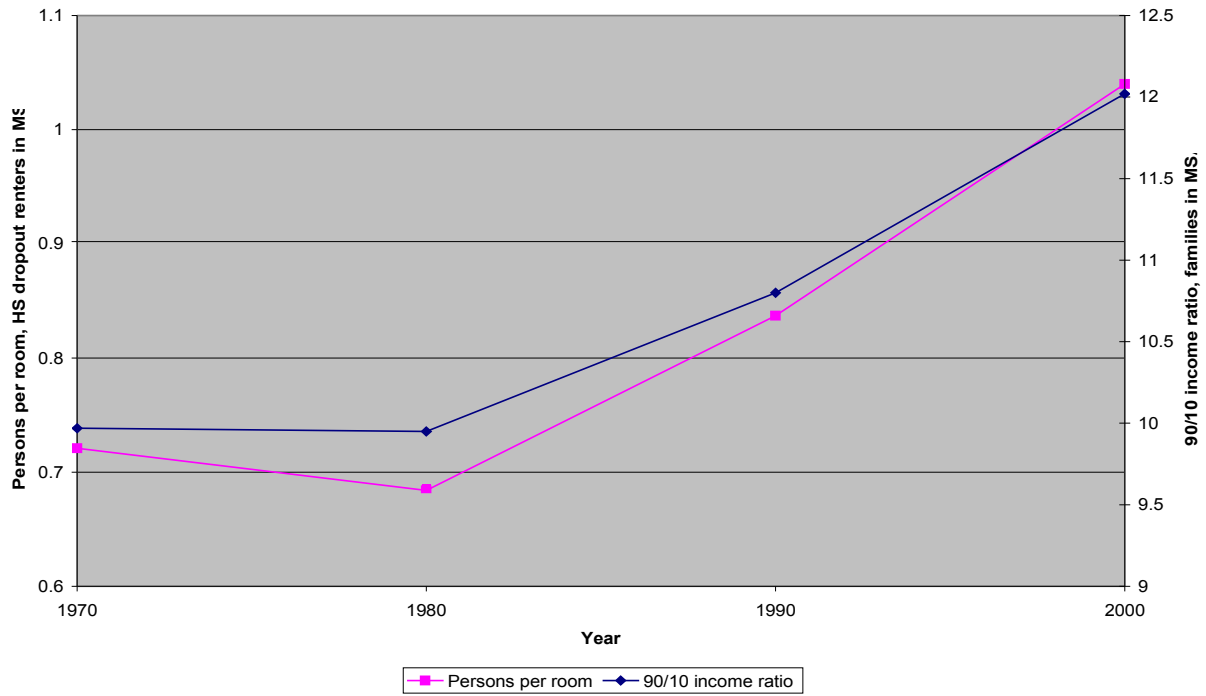


Figure 2: Income inequality and the housing outcomes of high school dropouts



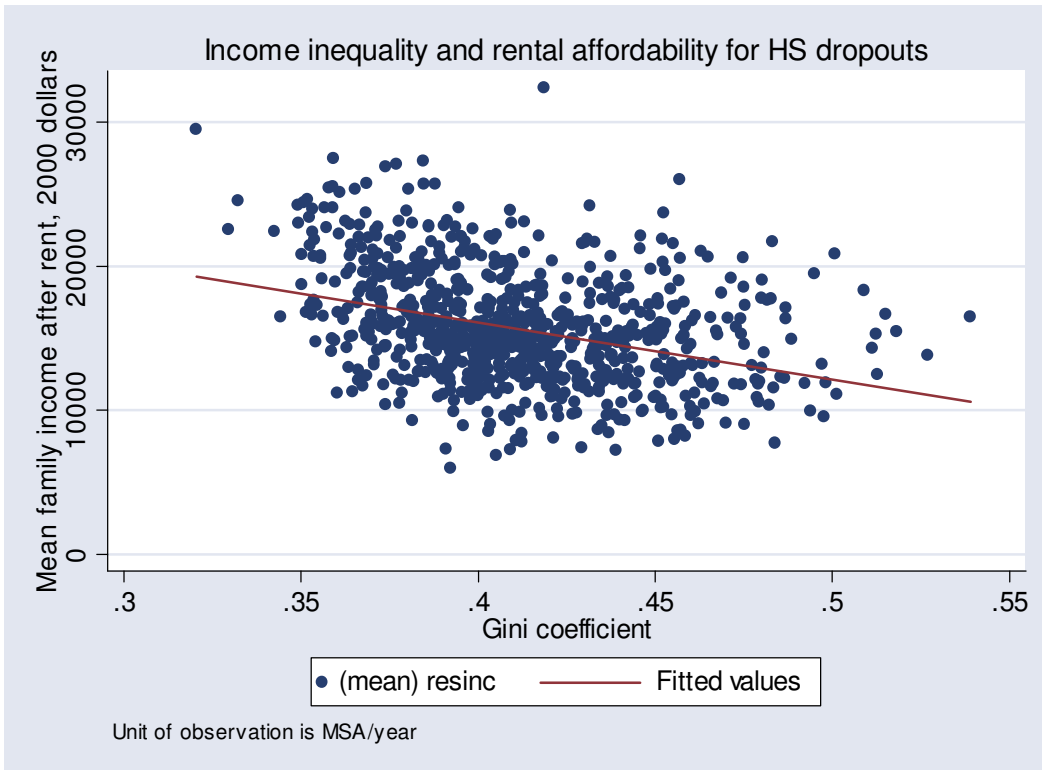


Figure 3

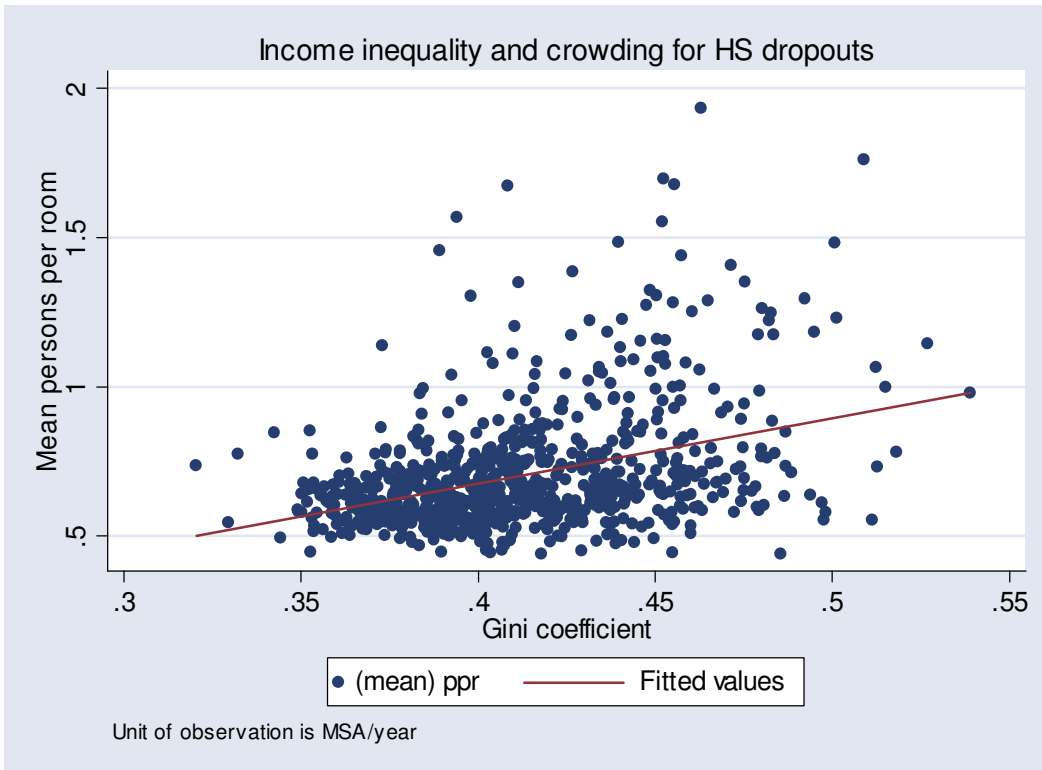


Figure 4

FIGURE 5: Partial Equilibrium Housing Market Model

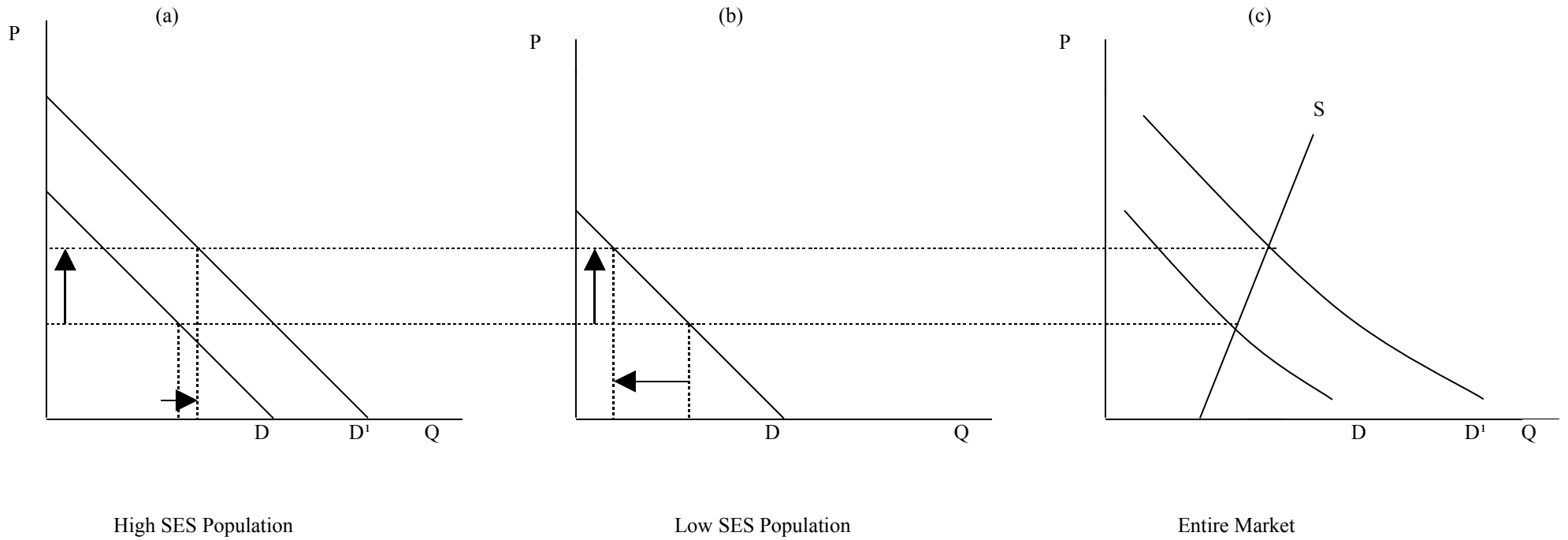


Table 1: Summary statistics for regression covariates

Independent variable	Mean	Standard deviation
Household variables (N=234,345)		
Residual income (2000 dollars)	18,648	23,985
Rent-to-income ratio (N=207,515)	0.313	0.217
Persons per room	0.863	0.766
Family income (2000 dollars)	24,662	24,643
Household size	2.82	1.94
Black householder	0.235	---
Female householder	0.441	---
Unmarried householder	0.478	---
Idle householder	0.520	---
Householder over 65	0.284	---
Householder under 30	0.180	---
Immigrant householder	0.379	---
MSA/Year level variables (N=812)		
GINI coefficient	0.411	0.035
10 th percentile of family income distribution	9,013	2,251
Median family income	37,218	7,179
90 th percentile of family income distribution	86,852	19,266
Log population	7.30	0.997
Vacancy rate	0.060	0.021

Table 2: The total effect of income inequality on cost burden
Sample consists of renter households headed by a HS dropout

Independent variable	Residual income		Rent-to-income ratio	
GINI coefficient	-49,916** (14,929)	-32,942** (12,954)	-0.006 (0.156)	0.158 (0.176)
Household size	---	2,070** (106)	---	-0.009** (0.001)
Black householder	---	-5,082** (519)	---	0.012** (0.004)
Female householder	---	-6,501** (310)	---	0.064** (0.004)
Unmarried householder	---	-4,329** (206)	---	0.033** (0.001)
Idle householder	---	-12,497** (811)	---	0.105** (0.009)
Householder over 65	---	2,062** (520)	---	-0.021** (0.010)
Householder under 30	---	-6,081** (289)	---	0.051** (0.004)
Immigrant householder	---	-4,442** (473)	---	0.145** (0.063)
Ln(MSA population)	---	-279 (828)	---	0.030** (0.011)
Year fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes
N	234,345	234,345	207,515	207,515
R ²	0.022	0.208	0.032	0.161

Note: Standard errors, corrected for clustering at the MSA/Year level, are in parentheses. Observations are weighted by the sample size used to construct the GINI coefficient variable. Data source is the IPUMS samples of 1970, 1980, 1990, and 2000. Residual income is equal to total family income for the year prior to the Census less twelve times reported gross rent. The rent-to-income ratio is equal to twelve times reported gross rent divided by total family income for the year prior to the Census. Households with zero income are excluded from the last two specifications.

** denotes a coefficient significant at the 5% level, * the 10% level.

Table 3: The total effect of income inequality on crowding
Sample consists of renter households headed by a HS dropout

Independent variable	Dependent variable: persons per room	
GINI coefficient	1.689 (2.244)	3.462** (1.312)
Household size	---	0.216** (0.012)
Black householder	---	-0.009 (0.010)
Female householder	---	-0.068** (0.005)
Unmarried householder	---	0.025** (0.007)
Idle householder	---	0.027* (0.015)
Householder over 65	---	-0.040** (0.014)
Householder under 30	---	0.109** (0.010)
Immigrant householder	---	0.213** (0.053)
Ln(MSA population)	---	0.229** (0.066)
Year fixed effects	Yes	Yes
MSA fixed effects	Yes	Yes
N	234,345	234,345
R ²	0.142	0.488

Note: Standard errors, corrected for clustering at the MSA/Year level, are in parentheses. Observations are weighted by the sample size used to construct the GINI coefficient variable. Data source is the IPUMS samples of 1970, 1980, 1990, and 2000. Dependent variable is equal to twelve times reported gross rent divided by total family income for the year prior to the Census.

** denotes a coefficient significant at the 5% level, * the 10% level.

Table 4: First-differenced models of income inequality and average housing outcomes

Independent Variable	Dependent variable: Change in residual income		Dependent variable: Change in persons per room	
	Change in GINI coefficient	-37,609** (10,726)	2,121 (11,570)	0.574** (0.275)
Change in average household size	1,300 (855)	778 (783)	0.345** (0.021)	0.342** (0.022)
Change in percent black [†]	-3,081 (3,061)	-2,255 (2,879)	-0.073 (0.079)	-0.055 (0.081)
Change in percent female head [†]	-9,087** (3,709)	-5,903* (3,408)	-0.132 (0.095)	-0.102 (0.096)
Change in percent unmarried [†]	-801 (3,612)	-2,252 (3,341)	0.129 (0.093)	0.110 (0.094)
Change in percent idle [†]	-6,741** (2,578)	-6,861** (2,361)	-0.006 (0.066)	-0.012 (0.066)
Change in percent over 65 [†]	4,740 (3,437)	975 (3,199)	0.111 (0.088)	0.086 (0.090)
Change in percent under 30 [†]	4,463 (3,700)	-2,508 (3,525)	0.068 (0.095)	0.005 (0.099)
Change in percent immigrant [†]	2,178** (3,046)	-706 (2,863)	0.460** (0.078)	0.446** (0.080)
Change in log(population)	---	355 (663)	---	0.013 (0.019)
Change in log(median income)	---	12,119** (1,816)	---	0.096* (0.051)
Year fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes
N	490	490	490	490
R ²	0.852	0.879	0.942	0.944

Note: Standard errors in parentheses. Unit of observation is the MSA/ten-year-interval. Observations are weighted by the sample size used to construct the GINI coefficient variable. Data source is the IPUMS samples of 1970, 1980, 1990, and 2000.

[†] denotes a variable measuring the characteristics of high school dropout renter householders.

** denotes a coefficient significant at the 5% level, * the 10% level.

Table 5: Separating the impact of own and others' income

Independent Variable	Dependent variable: Residual income	Dependent variable: Persons per room
GINI coefficient	10,147* (5,939)	3.405** (1.316)
Household size	-266** (26.79)	0.219** (0.013)
Black householder	802.8** (65.66)	-0.016 (0.010)
Female householder	2.839 (71.92)	-0.076** (0.006)
Unmarried householder	147.8** (22.38)	0.019** (0.006)
Idle householder	344.3** (81.99)	0.010 (0.018)
Householder over 65	242** (60.42)	-0.038** (0.014)
Householder under 30	-240** (58.62)	0.101** (0.010)
Immigrant householder	404.9** (74.09)	0.207** (0.052)
Log(MSA population)	-7.38 (304.6)	0.229** (0.066)
Family income	0.976** (0.003)	-1.31*10 ⁻⁶ ** (3.90*10 ⁻⁷)
Year fixed effects	Yes	Yes
MSA fixed effects	Yes	Yes
N	234,345	234,345
R ²	0.986	0.489

Note: Standard errors, corrected for clustering at the MSA/Year level, are in parentheses. Unit of observation is a renter household headed by a high school dropout. Observations are weighted by the sample size used to construct the GINI coefficient variable. Data source is the IPUMS samples of 1970, 1980, 1990, and 2000.

** denotes a coefficient significant at the 5% level, * the 10% level.

Table 6: Using alternative inequality measures

Independent Variable	Dependent variable: Residual income	Dependent variable: Persons per room
Tenth percentile of family income distribution	-0.167* (0.088)	-1.65*10 ⁻⁵ (2.12*10 ⁻⁵)
Median family income	-0.012 (0.043)	-1.77*10 ⁻⁵ (1.22*10 ⁻⁵)
Ninetieth percentile of family income distribution	-0.018 (0.016)	8.36*10 ^{-6**} (3.58*10 ⁻⁶)
Household size	-265** (26.7)	0.219** (0.013)
Black householder	805** (65.9)	-0.017 (0.010)
Female householder	0.675 (71.5)	-0.076** (0.006)
Unmarried householder	150** (22.8)	0.019** (0.006)
Idle householder	340** (81.8)	0.010 (0.018)
Householder over 65	247** (60.8)	-0.038** (0.014)
Householder under 30	-236** (59.8)	0.101** (0.010)
Immigrant householder	415** (74.6)	0.206** (0.052)
Log(MSA population)	-0.410 (277)	0.238** (0.069)
Family income	0.976 (0.003)	-1.31*10 ⁻⁶ (3.91*10 ⁻⁷)
Year fixed effects	Yes	Yes
MSA fixed effects	Yes	Yes
N	234,345	234,345
R ²	0.986	0.488

Note: Standard errors, corrected for clustering at the MSA/Year level, are in parentheses. Unit of observation is a renter household headed by a high school dropout. Observations are weighted by the sample size used to compute the income quantiles. Data source is the IPUMS samples of 1970, 1980, 1990, and 2000.

** denotes a coefficient significant at the 5% level, * the 10% level.

Table 7: The moderating impact of supply elasticities

Independent Variable	Dependent variable: Residual income		Dependent variable: Persons per room	
GINI coefficient	78.87 (7614)	---	6.48** (2.04)	---
Tenth percentile of family income distribution	---	-0.029 (0.093)	---	-5.66*10 ^{-5**} (2.71*10 ⁻⁵)
Median family income	---	0.035 (0.067)	---	-3.33*10 ⁻⁵ (2.15*10 ⁻⁵)
Ninetieth percentile of family income distribution	---	-0.048** (0.018)	---	1.71*10 ^{-5**} (6.13*10 ⁻⁶)
MSA vacancy rate	-64,780* (35,774)	-5,544 (16,950)	16.91** (8.297)	-3.691 (5.536)
MSA vacancy rate*GINI	155,769* (83,049)	---	-50.19** (20.58)	---
MSA vacancy rate*10 th percentile	---	-3.433 (2.354)	---	9.41*10 ⁻⁴ (6.72*10 ⁻⁴)
MSA vacancy rate*median	---	0.047 (1.091)	---	1.01*10 ⁻⁴ (3.09*10 ⁻⁴)
MSA vacancy rate*90 th percentile	---	0.340 (0.252)	---	-1.34*10 ⁻⁴ (8.45*10 ⁻⁵)
Table 6 control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes
N	230,284	230,284	230,284	230,284
R ²	0.986	0.986	0.490	0.490

Note: Standard errors, corrected for clustering at the MSA/Year level, are in parentheses. Unit of observation is a renter household headed by a high school dropout. Observations are weighted by the sample size used to compute the income quantiles. Data source is the IPUMS samples of 1970, 1980, 1990, and 2000.

** denotes a coefficient significant at the 5% level, * the 10% level.