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ABSTRACT

The Effect of Credit Standards on Urban and School Segregation*

This paper shows that the mortgage credit boom has significantly affected urban and school racial segregation from 1995 to 2007. We develop a model of urban segregation with credit constraints that shows that easier credit can either increase or decrease segregation, depending on the race of the marginal consumer who benefits from the expansion of credit. We then use the annual racial demographics of each of the approximately 90,000 public schools in the United States from 1995 to 2007, matched to a national comprehensive dataset of mortgage originations, linked to the neighborhood of the house, to show that higher leverage increases the segregation of African American and Hispanic students. Both segregation across schools and across school districts are higher when the leverage is higher. Higher leverage allows households to avoid interracial contact.

JEL Classification: H0, J15, R2 and R3
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1 Introduction

School segregation matters. There is abundant evidence that peers matter for educational achievement (Hoxby 2001, Sacerdote 2001, Goux & Maurin 2007, Kramarz, Machin & Ouazad 2008) for the formation of racial stereotypes (Chaudhuri & Sethi 2008), for health, smoking behavior (Nakajima 2007), crime (Glaeser, Sacerdote & Scheinkman 1996) and in a number of other dimensions. Segregated metropolitan areas experience higher black-white test score gaps (Card & Rothstein 2007), higher crime rates (Weiner, Lutz & Ludwig 2009), and analysis of school desegregation after *Brown v. Board of Education* (1954) shows that segregation explains part of the racial achievement gap (Hanushek, Kain & Rivkin 2009, Rivkin & Welch 2006). Students who attend more racially diverse schools also have access to a more diverse set of friendships and social networks that affect their lives.

The literature so far focused on the effects of active desegregation policies, such as busing (Angrist & Lang 2004)or school reassignment programs (Hoxby & Weingarth 2006).[1] But busing and school reassignment programs are constrained by the commuting distance. Also, since the *Milliken v. Bradley* (1974) Supreme Court decision, desegregation policies operate within the boundaries of school districts rather than across school districts; even though most of school segregation is across districts rather than within districts (Clotfelter 1999).

In the current paper, we look at whether the mortgage credit market can be as or more effective than active desegregation programs at improving racial diversity in schools and neighborhoods. The mortgage credit boom of the late 1990s until 2007 is a large-scale experiment on the housing market that led to a substantial fall of school segregation for white and black students. Figure 2 shows that the number of mortgage originations to hispanics was multiplied five-fold during the 1995-2007 period, and the number of mortgage originations to blacks doubled during the same period. Borrowers were allowed much higher loan-to-income ratios. In 1995, the average new homeowner borrowed on average 1.9 times

[1] A notable is Section 8 vouchers and the Moving To Opportunity program (Katz, Kling & Liebman 2001), which typically operates on a smaller scale (4,600 families) than active desegregation programs or than changes in the mortgage market.

his income, whereas in 2004 the average homeowner borrowed 2.4 times his income. Because this expansion of the supply of mortgage credit did not benefit all races equally, we expect it to change the patterns of racial segregation.

To illustrate the story linking credit conditions and school segregation, we look at the Houston-Sugar Land-Baytown (Texas) Metropolitan Statistical Area (Figure 3). The number of Hispanic students increased continuously from 26% of secondary school students in 1995 to 36% in 2007. The effect of this increase in Hispanic population on the segregation between Hispanic and non-Hispanic students was different in the early part of the period, and in the later part of the period. From 1995 to 2004, the median loan-to-income ratio of Houston borrowers climbed from 1.5 to 1.8. This increase in the loan-to-income ratio is in line with the national increase in the median loan-to-income ratio (+0.3 compared to +0.4 nationally). Interestingly, the isolation of Hispanics, our preferred measure of segregation which will be defined in section 3.2, followed the increase in Hispanic population up until the point at which the loan-to-income ratio started declining. The data suggests that Hispanic households were using leverage to avoid neighborhoods with high fractions of African American households. Note the sharp increase in the exposure of Hispanics to African Americans[2] when the loan-to-income ratio starts declining.

Should more leverage necessarily cause higher segregation? To show the effects of credit standards on racial segregation, we develop a model of residential choice (Benabou 1996, Epple, Filimon & Romer 1984) where households value neighborhoods differently based on the quality of housing and the quality of public goods, e.g. schools. We contribute to the literature by introducing liquidity constraints in residential choice. In our model, households need to borrow to buy a house, and banks base their lending decision on the loan-to-income ratio, the gender, and the race of the applicant. A relaxation of lending standards leads to a greater number of originated loans and higher loan-to-income ratios. This affects whites and minorities' ability to bid for houses in desirable neighborhoods. Hence, segregation could go

[2]The exposure index will be defined in section 3.2, and it measures the average fraction of African American peers at school for Hispanic students.

up or down depending on who benefits from an increased availability of mortgage credit and who values desirable neighborhoods. If whites value public goods much more than minorities, and if white-minority income gap is not too large, segregation will go up. If whites' valuation of public goods is lower or slightly higher than minorities' valuation of public goods, or if the income gap is high, more lenient credit standards will lead to lower segregation. The model is developed in section 2. A web appendix develops extensions of the model to include an elastic supply of housing and social interactions.

The paper then tests empirically whether a change in credit supply in a typical Metropolitan Statistical Area highers or lowers school segregation within that MSA. We obtain school demographics for every public and private school from the Common Core of Data. We match these data to the Home Mortgage Disclosure Act (HMDA), compiled by the Federal Financial Institutions Examination Council (FFIEC); the dataset contains more than 80% of all mortgage originations and applications, alongside their loan-to-income ratio, the income, race & gender of the applicant, and the location of the house.

We first document a signficant decline in the isolation of White students over the 1995-2007 period, due to an increased exposure to Hispanic students. We show that higher median loan-to-income ratios have increased the isolation of African-American students and the isolation of Hispanic students. An increase in the median loan-to-income ratio from twice borrowers' income to three times borrowers' income, conditional on borrowers' risk measures, increases the isolation of African-American students by 2.2 percentage points. An increase by 1 of the extreme (90th percentile) loan-to-income ratio, with a constant median loan-to-income ratio, increases the isolation of Hispanic students by 1.7 percentage points. We show that in Metropolitan Statistical Areas with high elasticity of housing supply, the effect of credit conditions on school segregation is particularly strong.

Schools are a useful source of information on racial segregation across neighborhoods. The census is only decennial, whereas the Common Core of Data (CCD) is an annual and comprehensive dataset. Moreover the CCD includes the latitude and the longitude of the school as well as its address. Furthermore, there is a tight link between urban segregation and school segregation. School composition explains 70% of the variance of census tracts nationally in the United States.

The paper is structured as follows. In section 2, we present the theoretical framework. In section 3, we present stylized facts, the identification strategy and the empirical results. Section 4 concludes.

2 A model of residential choice with credit constraints.

We present here a model where agents make locational choices based on neighborhood characteristics but also on the ability to secure mortgage credit. This model is to our knowledge the first that extends the standard neighborhood choice model to an environment where agents are credit constrained.[3] Segregation is expressed structurally as a function of credit conditions, household preferences, and neighborhood quality. The baseline model features two neighborhoods with housing in fixed supply and two ethnic groups with a fixed population size. Although excessively stylized, this model is enough to bring the core of our argument that relaxing lending standards can either increase or reduce the level of urban segregation.

The presentation of the model and model results follows five steps. First, we describe the model environment and the model equilibrium. Second, we derive several analytical results regarding the link between lending standards and urban segregation. Third, we simulate the model to analyze the consequences of a relaxation in lending standards under alternative scenarios. Fourth, we run counterfactual experiments: we compare the consequences on urban segregation of an increase in the share of minorities when accompanied (or not) by a contemporaneous relaxation of lending standards. Fifth, we present additional simulations results based on an extension of the baseline model to the case of variable housing supply.

[3]Benabou (1996) shows how small market imperfections are enough to cause segregation.

2.1 The environment

In this basic model, we consider a metropolitan area made of two neighborhoods indexed by $j = 1, 2$. Each neighborhood has a fixed continuum of mass 1 of dwellings. The total population of the metropolitan area is formed by a continuum of households of mass 2 belonging to two ethnic groups indexed by $r \in \{whites, minorities\}$. Minority ethnic groups represent a share s and white homeowners represent a share $1 - s$ of the population. Households have an infinite horizon. They make residential choices at the beginning of their life by borrowing against their future income. They have separable preferences over how much they want to consume and the neighborhood they want to live in. The lifetime utility of household i of race $r(i)$ living in neighborhood j can be expressed as:

$$V_{i,j} = \sum_{t=0}^{\infty} \beta^t U(c_{j,r(i),t}) + \nu_{j,r(i)} + \varepsilon_{i,j}$$

where $v_{j,r}$ represents the valuation of neighborhood j by agents belonging to the ethnic group r and ε_{ij} an idiosyncratic preference shock that we assume extreme-value distributed. For the sake of simplicity, U will be assumed isoelastic, $U(c) = \frac{1}{1-\gamma} c^{1-\gamma}$, but none of the mechanisms of the model rely on this specific functional form.

Households receive a constant wage income specific to their ethnic group ω_r. A time zero, they make the residential choice to live in the first or second neighborhood. They finance their purchased house by borrowing through a perpetuity mortgage loan issued by competitive lenders whose cost of funds is equal to the risk-free rate. We assume that mortgage loans are not defaultable and so do not carry a default risk premium. Borrowers are however screened out during an origination process that will be specified later in this section.[4] The intertemporal budget constraint of a household of race r leaving in neighborhood j is:

$$\sum_{t=1}^{\infty} \left(\frac{1}{1+\rho} \right)^t c_{r,j,t} = \sum_{t=1}^{\infty} \left(\frac{1}{1+\rho} \right)^t \omega_r - \sum_{t=1}^{\infty} \left(\frac{1}{1+\rho} \right)^t \rho D_j$$

[4] For now, we can just assume that origination probabilites are equal to 1 for all agents in all neighborhoods.

where D_j is the amount borrowed to buy a housing unit so $D_j = p_j$ where p_j is the price of a housing unit in neighborhood j ,and ρ is the risk-free rate. Assuming $\beta = \frac{1}{1+\rho}$, agents perfectly smooth consumption and the intertemporal budget constraint collapses to:

$$c_{r,j} = \omega_r - \frac{1}{1+1/\rho} p_j$$

which makes clear that the consumption level is determined by the choice of neighborhood. Substituting the budget constraint into the objective function, the maximization problem of a household is:

$$\text{Choose } J(i) \in \{1,2\} \text{ to maximize: } V_{i,j} = \underbrace{\frac{1}{1-\gamma}\left(\omega_{r(i)} - \frac{1}{1+1/\rho} p_j\right)^{1-\gamma} + v_{j,r(i)}}_{U_{j,r(i)}} + \varepsilon_{i,j}$$

where $J(i)$ is the neighborhood choice made by agent i.

Household i chooses neighborhood 1 if the utility it receives from this choice exceeds the utility it receives from the other neighborhood that is:

$$J(i) = 1 \Leftrightarrow V_{i,1} \geq V_{i,2} \Leftrightarrow U_{1,r} + \varepsilon_{1,i} \geq U_{2,r} + \varepsilon_{2,i} \Longleftrightarrow U_{1,r} - U_{2,r} \geq \varepsilon_{i,2} - \varepsilon_{i,1} \tag{1}$$

Because $\varepsilon_{i,2}, \varepsilon_{i,1}$ are drawn from an extreme-value distribution, we can follow McFadden (1974), and infer from the decision rule the probability to choose each neighborhood:

$$\Pr(J(i) = 1) = \frac{\exp(U_{j,r(i)})}{\sum_j \exp(U_{j,r(i)})} \tag{2}$$

The origination process.

The decision rule (1) implicitly assumes that all agents are eligible for a mortgage loan in both neighborhoods. We assume instead here that households need to apply for a loan and that their application can be rejected. The origination decision variable $O_{i,j}$ is equal to one if the application is accepted and to zero if the application is rejected. Since in this model, all households are home owners, we assume that the probability of origination is such as:

$$\Pr(O_{i,2} = 1) = 1$$

which implies that there is a "reservation" neighborhood in which all mortgage applications are accepted. The origination decision in the other neighborhood follows a logit latent variable model:

$$O_{i,1} = 1 \text{ if } y_{i,1} = \alpha_{r(i)} + \beta \text{Loan-to-income}_{j,i} + \eta_i \geq 0, \qquad O_{i,1} = 0, \text{otherwise}$$

where α_r is an ethnic group specific constant term, Loan-to-income$_{j,i} = p_1/\omega_{r(i)}$ is the loan to income ratio and η_i summarizes non-observable characteristics that determines creditworthiness. η_i is logistically distributed accross households and therefore the origination probability can be summarized as:

$$\Pr(O_{i,2} = 1) = 1 \text{ ; } \Pr(O_{i,1} = 1) = \frac{\exp(\alpha_{r(i)} + \beta p_1/\omega_{r(i)})}{1 + \exp(\alpha_{r(i)} + \beta p_1/\omega_{r(i)})} \tag{3}$$

The model assumes that the idiosyncratic terms $\varepsilon_{i,j}$ and $\eta_{i,j}$ are independent.

The parameters $\alpha_{r(i)}$ and β capture the severity of the lending standards that lenders choose to impose in order to insure repayment.[5]

Market Clearing Condition.

The supply of housing is fixed in each neighborhood and equals 1. In order to compute the demand for housing, we aggregate the unconditional individual probabilities of neighborhood choice. In order to do so, we aggregate the individual probabilities or neighborhood choice (equation 2), conditional on origination being approved, multiplied by the probabilities of

[5]We implicitly assume that lenders compete on loan pricing - so interest rate is equal to the risk-free rate - but apply the same lending standards.

origination (equation 3). The aggregate demand for housing in neighborhood 1 is thus equal to

$$d_1 = \int_i \Pr(O_{i,1} = 1 | J(i) = 1) \Pr(J(i) = 1) di$$

because the idiosyncratic terms $\varepsilon_{i,j}$ and $\eta_{i,j}$ are assumed to be independent. Using (2) and (3) and share of minorities in the population, we obtain:

$$\begin{aligned} d_1(p_1) = {} & s \frac{\exp(U_{1,\text{minority}})}{\sum\limits_{j=1,2} \exp(U_{j,\text{minority}})} \frac{\exp(\alpha_{\text{minority}} + \beta p_1/\omega_{\text{minority}})}{1 + \exp(\alpha_{\text{minority}} + \beta p_1/\omega_{\text{minority}})} \\ & + (1-s) \frac{\exp(U_{1,\text{white}})}{\sum\limits_{j=1,2} \exp(U_{j,\text{white}})} \frac{\exp(\alpha_{\text{white}} + \beta p_1/\omega_{\text{white}})}{1 + \exp(\alpha_{\text{white}} + \beta p_1/\omega_{\text{white}})} \end{aligned}$$

which yields the following neighborhood one market clearing relationship,

$$d_1(p_1) = 1$$

and implies by Walras law market clearing in neighborhood 2 as well.

Model Extension: the Case of Variable Housing Supply.

The baseline model has been specified with a fixed and equal supply of housing in each neighborhood, $H_1 = H_2 = 1$. We can instead assume variable housing supply by introducing housing developers whose marginal cost of developing any additional housing unit in neighborhood j is given by:

$$MC(H_j) = H_j^{1/\epsilon_j}$$

Under marginal cost pricing, we have $p_j = H_j^{\epsilon_j}$ where ϵ_j is the price elasticity of neighborhood j. The difference with the fixed supply environment is that the market clearing condition is now described by:

$$d_j(p_j) = H_j = p_j^{1/\epsilon_j}$$

for $j \in \{1, 2\}$.

The model with variable elasticity will be used in the simulation to understand how the elasticity of housig supply affect the relationship between lending standards and urban segregation.

2.2 The Equilibrium

The equilibrium concept in the economy is the one of a *sorting equilibrium* in which

- Households choose neighborhoods optimally.
- Supply of housing is fixed at 1 in each neighborhood.
- Lenders break even on loans originated.
- Neighborhod 1's housing market clears at price $p_1 = p_1^*$.

With these assumptions, neighborhood choice probabilities and origination probabilities are implicitly defined by the following fixed point mapping.

$$\begin{aligned} & s \Pr(J(i) = 1 | r = \text{minority}; p_1 = p_1^*) \Pr(O_{i,1} = 1 | r = \text{minority}; p_1 = p_1^*) \\ + & (1 - s) \Pr(J(i) = 1 | r = \text{white}; p_1 = p_1^*) \Pr(O_{i,1} = 1 | r = \text{white}; p_1 = p_1^*) = 1 \end{aligned} \tag{4}$$

The equilibrium, when it exists, is unique. The conditions for the existence of an equilibrium are presented in the appendix. In simulations of our model, we checked that this guarantees a single equilibrium, i.e. a single price that solves the market equilibrium 4.

2.3 Analytical Results.

In this section we present a set of analytical results that illustrate the basic mechanisms through which a relaxation of credit constraints affects the level of urban segregation in the economy. Since the model combined two stochastic distributions - one for the idiosyncratic valuations of neighborhood and one for the stochastic origination process - analytical results could only be obtained in some special cases. The simulation results presented in the next section will give a full account of the comparative statics of the model.

Two parameters - α and β - measure the severity of lending standards in the economy. An increase in α corresponds to a relaxation of *overall lending standards* while an increase in β captures more specifically a relaxation of *leverage constraints* as this parameter measures the sensitivity of the likelihood of origination to a change in the loan-to-income or price-to-income ratio. From now on, we set $\alpha = \alpha_{\text{minority}} = \alpha_{\text{white}}$ which means that our analysis abstracts from the role of racial discrimination in lending practices.

The two ethnic groups we consider - the whites and the minorities - differ along two dimensions: their income and their relative valuation of neighborhood. The propositions presented below consider each of them in turn.

The consequences of a relaxation of lending standards on segregation can be analyzed as the outcome of two effects. A *leverage effect* coming from a higher ability for a household of being originated at a given level of income and at a given price and *a general equilibrium effect* coming from an upward shift in demand and a resulting increase in the price of the most valued neighborhood. The two propositions show how depending on the specification the leverage effect of the general equilibrium dominates.

Proposition 1. *If whites and minorities have equal incomes, $\omega_w = \omega_m$, and if whites value neighborhood 1 more than minorities, any relaxation of lending standards - a higher α or a higher β - increases segregation.*

Proof. See Appendix. □

A relaxation of lending standards allow borrowers to enjoy a higher leverage without reducing their likelihood of origination. This channel affects the ability of each group to outbid the other in order to purchase in their most valued neighborhood. In the case of equal income but higher valuation by whites of neighborhood 1, a relaxation of lending standards allows white households to use more available credit to outbid minorities in neighborhood 1.

Proposition 2. *If whites have higher income than minorities, $\omega_w > \omega_m$, and if whites and minorities value neighborhood 1 equally:*

1. *A relaxation of leverage constraints - a higher β - reduces segregation.*

2. *If the probability of origination is insensitive to the loan-to-income ratio ($\beta = 0$), there is no segregation.*

   In addition, if the difference in the relative valuation of the two neighborhoods is not too large:

3. *A relaxation of overall lending standard constraints (a higher α) reduces segregation.*

Because minorities have a lower income, they are more constrained than whites in their access to housing credit. In order to buy in the same neighborhood as whites, they must have a higher leverage which reduces their likelihood of being originated. Therefore at a given price, they benefit more than the whites from the leverage effect. A relaxation of overall lending standards (a higher α) while not affecting directly the sensitivity to the loan-to-income ratio plays indirectly a similar role because it reduces the relative importance of leverage constraints in the origination process.

Because it allows for higher loan-to-income ratio and supply is fixed, a relaxation of credit standard results in an increase in the price of the most desirable neighborhood. This general equilibrium effect hurts the group with the lowest income the most. The change in the level of segregation depends on the relative strength of the leverage and the general equilibrium effect. Proposition 2 states that when neighborhood are equally valued by both group, the leverage effect dominates and segregation is reduced when leverage constraints are relaxed. A similar result holds for a relaxation of the overall lending standards if the difference between neighborhood valuations is not too large.

Under equal relative valuation of neighborhoods across groups, a relaxation of the borrowing constraints shifts upward the demand for the best neighborhood by both group but it does so by more for the minorities.

2.4 Simulation Results and Counterfactual Experiments.

We use the model to simulate the effect of a relaxation of the credit constraint on urban segregation for a plausible calibration of the economy. The simulations complement the analytical results by allowing to study more general cases, for example scenarios in which ethnic groups differ both in terms of income and in terms relative valuations of neighborhoods.

The simulations presented here are based on a relaxation of the leverage constraint, that is an increase in β. Very similar results are obtained with a relaxation of the overall lending standards - an increase of α - and are presented in the appendix.

We run simulations under two scenarios. In the first scenario, the two ethnic groups differ in terms income but have equal relative valuation of both neighborhoods. In this case, the simulations illustrate proposition 2: a relaxation of leverage constraints leads to a reduction of urban segregation. In the second scenario, the two group differ in terms of income and the whites value relatively more the first neighborhood than the minorities. In this case, the simulation shows how a relaxation of leverage constraints leads to a sharp increase in the level of segregation.

The counterfactual experiments are performed under the two same scenarios. In each case, we compare a baseline experiment, in which the growth in population and the increase in the share of minorities is accompanied by a relaxation of the leverage constraints, to a counterfactual experiment in which demographics change in the same way but the intensity of the leverage constraint is left unchanged. Comparing the results of the baseline and counterfactual experiments, we find a positive effect of a relaxation of the leverage constraint in the case of equal valuation of neighborhoods but a negative effect in the case of higher relative valuation of neighborhood 1 by the whites.

Model Calibration.

The simulation results that are discussed here are based on a 2-neighborhood economy composed by two ethnic groups: the "whites" which form the larger group and another group which consitutes the ethnic "minorities". In our baseline simulation, the minorities account for 20% of the population. The income of the whites is set at 60,000 USD per year and the one of the minorities at 40,000 USD. The group specific utility valuation of each neighborhood ($v_{j,r(i)}$) plays a key role here because it determines the average willingness to pay for each group. We consider two scenarios. In both, the first neighborhood is more sought after than the second for instance because it has better school quality. In the first scenario both group associate a utility value of 2,000 USD to live in the first neighborhood and of 10,000 USD to live in the second neighborhood. In the second scenario whites have a higher valuation of living in the first neighborhood than minorities (10,000 USD vs. 5,000 USD). The parameters of the model are kept constant accross the two scenarios and are summarized in the table below:

Parameter	Value	Definition
r	0.05	interest rate
s	0.2	share of minority
ω_w	$60,000$	whites' annual income
ω_b	$40,000$	minorities' annual income
γ	0.00	risk neutrality
$\alpha_w = \alpha_b$	2.5	no discrimination.
σ	1000	standard deviation of the idiosyncratic valuation $\varepsilon_{i,j}$

The two scenarios considered can be be summarized in the following table:

Scenario	$\nu_{1,\text{white}}$	$v_{2,\text{white}}$	$\nu_{1,\text{minority}}$	$\nu_{2,\text{minority}}$
1	10,000	2,000	10,000	2,000
2	10,000	2,000	5,000	2,000

Under each scenario, we look at the effect of an increase in the "looseness" of leverage constraints on the equilibrium variables with a special attention for its consequences on urban segregation. In order to so, we increase the parameter β that links the loan (or price) to income ratio to the origination probability in neighborhood 1 from -0.5 to 0.

Scenario 1: A Relaxation of Leverage Constraints reduces Urban Segregation.

This scenario illustrates proposition 2. Figure 4, panels (a) and (b), plots the the loan-to-income ratios and the denial rates (1-the probability of orginations) as a function of the severity of leverage constraints. Minorities have a lower income. In order for them to buy in neighborhood 1, they need to have a higher loan-to-income ratio than the whites and therefore are facing a higher risk of denial. When the borrowing constraint is relaxed, both groups can simultanuously enjoy higher loan-to-income ratios and lower denial probabilities. When $\beta = 0$, the denial rates becomes constant for both group as income does not play any role in the origination decision.

Figure 4, panel (c), plots the relative price of neighborhood 1. Because neighborhood 1 is more desirable than neighborhood 2, living there always requires to pay a premium but when leverage constraints are severe, high rate of loan denial *de facto* reduces the pool of agents that can buy in the first neighborhood. As credit constraints get relaxed, the buyer pool becomes more important and the price of neighborhood 1 increases. When $\beta = 0$, the first neighborhood commands a premium of 80% vs. 35% when $\beta = 0.5$.

Figure 4, panel (d), plots the probability of a minority household to live in neighborhood 1 and features our first key result. A probability inferior to 1/2 indicates that neighborhood 1 contains more whites than their share of the population and neighborhood 2 more blacks than their share of the population. When borrowing constraints are severe ($\beta = -0.5$), minority households have only one third of a chance to live in the best neighborhood. This probability increases gradually as credit conditions get relaxed and reaches half when $\beta = 0$ meaning that segregation has all but disapeared. As proved in proposition 2, when relative valuations are identical accross ethnic group, it is enough to relax the borrowing conditions to desegregate the city.

Figure 5 plots the change in standard measures of segregation, the isolation indexes and the exposure of each group to the other group. The reader is referred to empirical section of the paper for a full description of these measures. Consistently with the increase in the probability of minority to access neighborhood 1, whites and minorities isolation indexes are reduced and the interacial exposure increases.

Scenario 2: A Relaxation of Leverage Constraints increases Urban segregation.

In this scenario, the whites have a higher valuation of neighborhood 1 than the minorities. For example, they are able to benefit more from given school quality maybe because they are better educated themselves or they form a stronger network. As we will see, this simple difference in valuation is enough to completely reverse the previous result on the effect of leverage constraints on urban segregation. Whites households now use their additional leverage to outbid minorities and, as a result, isolates themselves further.

Figure 6 is the counterpart of Figure 4 for the second scenario. The plots exhibit a similar pattern in terms of loan-to-income, denial rate and neighborhood relative prices. Figure 6, panel (d), plots the probability of a minority household living in neighborhood 1 and points to a striking difference with scenario 1. As borrowing constraints get relaxed, minority household are gradually priced out of neighborhood 1. When $\beta = -0.5$, the probability for a minority to live in the good neighborhood is equal to 18%. When $\beta = 0$, this percentage falls to less than 2% and so both neighborhoods become almost fully seggregated, a result completely opposite to the one obtained in the first scenario. As before a relaxation of the borrowing constraints shifts the demand of both groups upwards but it now shifts the demand curve of the whites by much more. This reflects the stronger preference of the whites for this neighborhood. What happens is that a more relaxed *borrowing constraint gives more financial means to the white households to outbid the minority households.* In this case the general equilibrium effect through higher prices dominates the leverage effect. Figure 7 shows the consequences of this increase in urban segregation using standard measures.

Counterfactual Experiment: an increase in the share of minorities with and without a relaxation of leverage constraints

In order to contrast the predictions of our model with the data, we run the following experiment: we consider an increase in the population size by 25% along with an increase in the share of minorities in the population from 20% to 30%. This demographic change is designed to capture, for exemple, a population increase in an MSA which is largely driven by a large inflow of Hispanics (in our scenario 70% of the increase of the population is due to the inflow of minorities). The supply of housing increases equally in both neighborhoods and matches the increase of the population. To perform this, we introduce a non-zero elasticity of housing supply ϵ_1 in neighborhood 1.

In the baseline experiment, the demographic change is accompanied by a gradual relaxation of leverage constraints: the parameter controlling the looseness of the leverage constraint (β) is reduced from -0.5 to 0. In the counterfactual experiment, there is no change in the severity of the leverage constraint ($\beta = -0.5$). By comparing the baseline and the counterfactual experiments, we can assess how a decline in lending standards shapes the effect of a demographic change on urban segregation.

We compare the baseline and the counterfactual experiments under the two scenarios considered in previous simulation.

Scenario 3: As the share of minorities in the population increases, a reduction of the leverage constraint reduces urban segregation

Figure 8 and Figure 9 present the results when the relative valuation of neighborhoods is identical accross both groups. As the average income in the population decreases, the price of neighborhood 1 slightly declines but loan-to-income ratios and denial rates barely change. An effect of the decline in the price of neighborhood 1, the probability of minorites to live in neighborhood 1 rises modestly from 0.28 to 0.32. By contrast in the baseline scnenario, the price of neighborhood 1 increase sharply. Meanwhile loan-to-income ratios increase and denial rates fall. Urban segregation gets gradually reduced and fully disappear when leverage constraints are lifted. Figure 15 compare the evolution of isolation and exposure indexes in both scenarios. In the counterfactual scenario, as the share of minorities in the population increases, the isolation index of whites decreases and the isolation index of minorities increase. This is the mechanical effect of a demographic change - minorities (whites) become less (more) exposed to the other group. This feature underlines the crucial importance of controlling for demographic changes in the regression presented in section 3.6. In the baseline scenario, this mechanical effect is counteracted by the relaxation of leverage constraints. As a consequence the isolation of whites decreases by more and the isolation of minorities increases by less. The difference between the two scenario identifies the positive effect of a relaxation of leverage constraints on the level of urban segregation.

Scenario 4: As the share of minorities in the population increases, a reduction of the leverage constraint increases urban segregation

Figure 10 and Figure 11 present the results for the case of a higher relative valuation of neighborhood 1 by the whites. In this case, the counterfactual and the baseline scenarios yield very different results. In the counterfactual scenario, the probability of minorities to live in neighborhood 1 increases while it sharply decreases in the baseline scenario. In the baseline scenario, despite the demographic change, the isolation of whites do not change much and the isolation of minorities increases strongly. In the counterfactual scenario instead, the isolation of whites falls and the isolation of minorities increases far less. In this case the difference between the two scenarios illustrates the negative effect of a relaxation of leverage constraints on the level of urban segregation.

2.5 Effects of a relaxation of credit standards with higher or lower elasticity of housing supply.

In this section, we simulate the model extended to the case of variable housing supply. The parameters are the same as in the fixed supply case with the exception of the population size which is now set at 200,000. The elasticity of neighborhood 2 is set to unity. As in the previous two scenarios, changes in credit standards affect the population size of each neighborhood.

We run the experiment of scenario 1 - equal valuation of neighborhood 1 by whites and minorities - in the case of a relaxation of leverage constraints for two levels of price elasticities $\epsilon_1 \subset \{0.9, 0.75\}$. Results are summarized on Figure 12 and Figure 13. In the case of low elasticity, the price of neighborhood 1 is higher and increases by more when leverage constraints got relaxed than in the case of high elasticity. With low elasticity, the relative size of neighborhood 1 remains very small, absorbing less than 10 percent of the population.

By constrast, when elasticity is high, neighborhood 1 has a much higher relative size and absorbs a rapidly increasing probability of minority household (from 0.23 to 0.45 percent). When leverage constraint become irrelevant for the probability of origination ($\beta = 0$) neighborhood are fully deseggregated irrespectively of price elasticity. However because of their large different in size, the absorbion of minorities varies strongly with elasticity (8 percent for the case of low elasticity and 40 percent for the case of high elasticity). Furthermore changes in segregation measures along the transition from high to low leverage constraints are much more pronounced in the case of high elasticity: isolation measures decline more sharply and exposition of each group to the other increases more sharply.

The second experiment deals with the case of different valuation of neighborhood 1 by the whites and the minorities. The whites still value neighbordhood 1 at USD 10,000 but the black now value it at only USD 7,000. [6]

We analyze the effect of a reduction a leverage constraints for two level of price elasticities $\epsilon_1 \subset \{0.95, 0.75\}$. Resuts are presented on Figure 14 and Figure 15.

In the case of low elasticity, the combination of a high price of neighborhood 1 and higher relative valuation by whites of neighborhood 1 leads to an almost complete segregation. As leverage constraints are relaxed, neighborhood 1 remains small and fully segregated. Isolation

[6] Because the model with variable supply is more sensitive to parameter changes, we consider a smaller reduction of the valuation of neighborhood 1 by minorities than in the fixed suppl case

and exposure measures do not change.

The case with high elasticity is markedly different. Neighborhood 1 is much larger and less segregated when leverage constraints are severe. As leverage constraints are relaxed, whites are able outbid minorities and segregation increases sharply. The isolation of minorities increases from 0.3 to 0.38 and the isolation of whites from 0.826 to 0.845.

The main lesson from the extension of the model to variable supply is that the effects pointed out in the baseline model are still present but they are much more pronounced when price elasticity is high.

3 Descriptive Statistics

3.1 Dataset

The dataset gathers multiple sources. The main source on school segregation comes from the Department of Education's Common Core of Data, Public and Private School Universe , from 1995 to 2007. The Public School Universe is an annual dataset of virtually every public school in the United States. The Private School Universe is available every other year. In the paper we choose to focus on high schools. In order to study the dynamics of segregation at annual frequence, we first restrict the analysis to public schools. However in section 3.11 we consider the entire public and private school universe and analyze the effect of credit standards on sorting betwen public and private schools. Each school is identified by a unique number, its secondary or unified school district, its geographic position, latitude, longitude, and 5-digit zip code. We use the 5-digit zip code and the latitude and longitude to match schools with consistent Metropolitan Statistical Areas from 1995 to 2003.[7] We use the most recent definition of Metropolitan Statistical Areas, the 2008 Core Based Statistical Areas

[7] For zip codes, we used the geographical correspondence files provided by Geocorr 2K at the Missouri Census Data Center. Latitudes and longitudes are matched to CBSAs using ArcGIS and CBSA shapefiles provided by the Census Bureau. Latitude and longitude are not available prior to 2000, so we either use the post-2000 latitude and longitude if the school is still present in the dataset, or we match the school using the Geocorr file and the 5-digit zip code.

defined by the Census Bureau. In each MSA, we build variables of school demographics and measures of racial segregation across schools described in section 3.2.

The main source of data on mortgages is the Home Mortgage Disclosure Act (HMDA) data from 1995 to 2007.[8] The data is collected and made publicly available by the Federal Financial Institutions Examination Council (FFIEC). Banks, savings associations, credit unions, and other mortgage lending institutions submit information on mortgage applications and mortgage originations to various federal agencies which in turn report the information to the FFIEC. Reporting is mandatory for all depository insitution and for non-depository institutions, i.e. for-profit lenders regulated by the Department of Housing and Urban Development which either have combined assets above $10 million or originated 100 or more home purchase loans (including refinancing of home purchase loans) in the preceding calendar year. HMDA filings are estimated to cover close to 90% of all mortgage applications and originations (Dell'Arriccia, Igan & Laeven 2009). Each mortgage is fully documented with the loan amount, the income of the applicant, the race and gender of the applicant, and the census tract of the house.[9] The loan-to-income ratio is calculated by dividing the loan amount by the income of the applicant. We use the census tract to match mortgages to the corresponding 2008 Core Based Statistical Area,[10] and build MSA-level measures of credit conditions: median Loan-to-Income (LTI) ratio, 90th percentile LTI ratio, acceptance rate[11], and number of applications in the MSA.

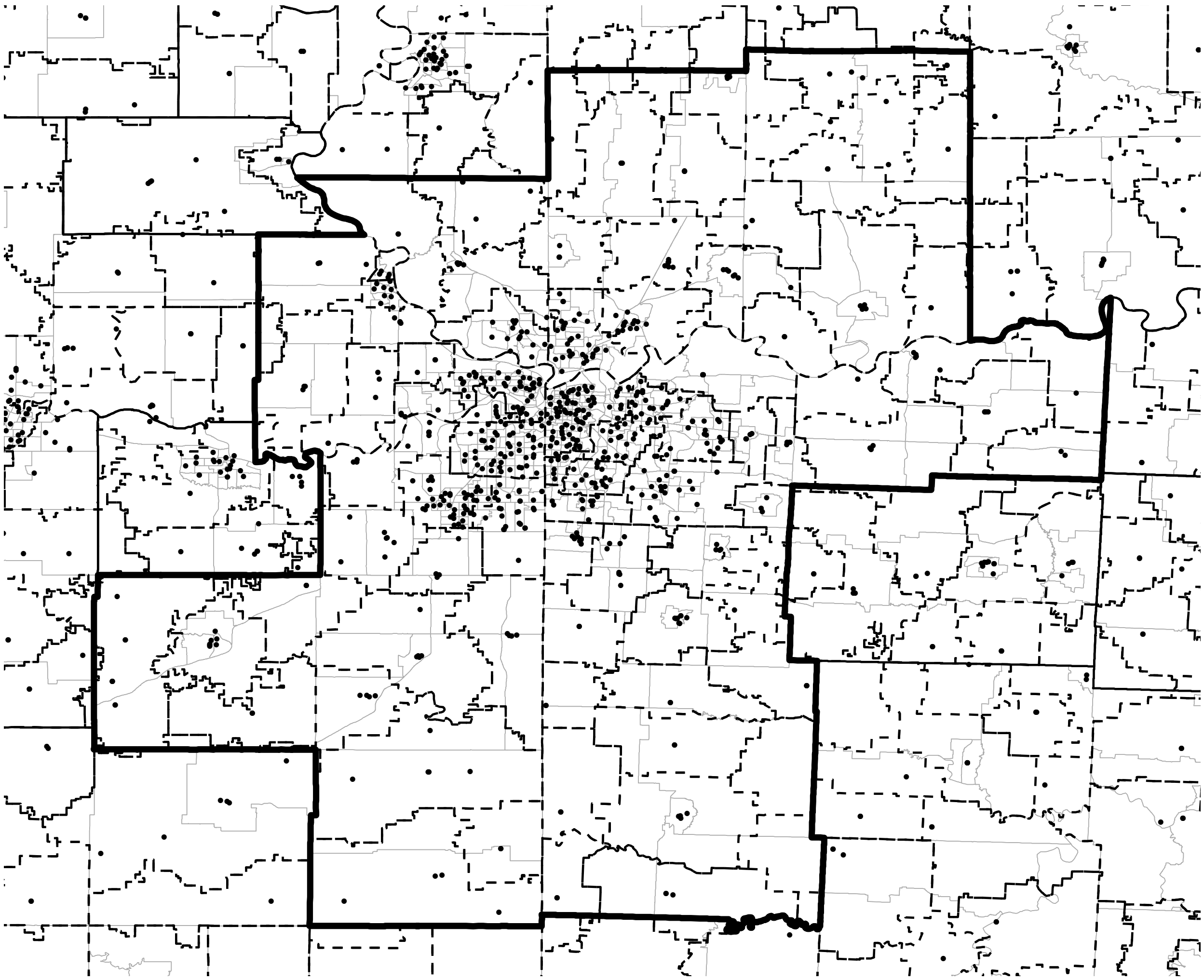
Additional county-level information are extracted from the County Characteristics file of the Interuniversity Consortium for Political and Social Research. For example, the growth of the housing stock between 2000 to 2007 is computed using the number of building permits issued by building type estimated by the Census Bureau.

[8]The Home Mortgage Disclosure Act (HMDA) was enacted by Congress in 1975 to collect information on mortgage lenders' practices, and among them discrimination and redlining against minority applicants.

[9]A census tract is an contiguous set of blocks with a few thousand inhabitants.

[10]Identical 2008 CBSA boundaries are used for schools and for mortgages. We used the geographical correspondence files provided by Geocorr 2K at the Missouri Census Data Center.

[11]The acceptance rate is the ratio of originations to applications.



Schools are represented by dots. Bold lines are the boundaries of Kansas City MSA. The thin lines are the boundaries of census tracts. The bold dashed lines are the boundaries of school districts.

Figure 1: Kansas City Metropolitan Statistical Area

3.2 Measuring School Segregation

There are several ways of measuring segregation (Massey & Denton 1988). We focus on one particular measure of segregation, the isolation index (Cutler, Glaeser & Vigdor 1999). The average fraction of peers of the same race is the isolation index, e.g. the isolation of white students is the average fraction of white peers for white students. There are several advantages in using the isolation index. This measure requires only minimal geographic and demographic information. In addition, the isolation index is a particularly relevant measure of peer composition when the effect of peers on educational achievement are considered, for instance in standard models with linear-in-means peer effects specification (Manski 1993, Hoxby 2001).[12]

The isolation of whites in each Metropolitan Statistical Area is calculated from the Common Core of Data as follows:

$$\text{Isolation}_j(whites) = 100 \times \sum_{s=1}^{S_j} \frac{whites_{s,j}}{whites} \cdot \frac{whites_{s,j}}{students_{s,j}} \tag{5}$$

where $whites_{s,j}$ is the number of white students in school $s = 1, 2, \ldots, S_j$ in MSA j, $whites$ is the overall number of white students, and $students_{s,j}$ is the number of students in school s in MSA j.

The isolation of white students goes down if they are more exposed to other racial groups, to African American students, Hispanic students, or students of other races. The exposure of white students to hispanic peers is:

$$\text{Exposure}_j(hispanics|whites) = 100 \times \sum_{s=1}^{S_j} \frac{whites_{s,j}}{whites} \cdot \frac{hispanics_{s,j}}{students_{s,j}} \tag{6}$$

where $hispanics_{s,j}$ is the number of hispanic students in school s. The same exposure index can be defined for any pair of races. The exposure of whites to whites is the isolation of white students.

From equations5 and equations 6, the sum of the isolation of a racial is one minus the exposure to other racial groups. Isolation increases as the exposure to other races decreases.

$$\begin{aligned} & \text{Isolation}_j(whites) \\ = \; & 100 - \text{Exposure}_j(blacks|whites) \\ & -\text{Exposure}_j(hispanics|whites) - \text{Exposure}_j(\text{other races}|whites) \end{aligned}$$

[12] Take for instance a peer-effects specification where the test score depends on peers' race, and other characteristics. Test Score$_i = x_i'\beta + \gamma$Peers' Race$+\varepsilon_i$. The isolation and exposure indices, multiplied by the relevant peer effect coefficient, measure the effect of segregation on educational achievement.

All specifications control for MSA fixed effects and for year dummies, which control for the average fraction of racial subgroups in the MSA, and for national trends in racial demographics.

3.3 Urban Segregation and School Segregation

The Department of Education's data provides us with an annual measure of the racial demographics of each school, and geographic information on the precise location of each school. Thus school segregation can be measured in-between census years, and schools can be geographically matched to neighborhood. Schools can therefore act as a proxy for the composition of census tracts and urban segregation.

We first compare urban segregation and school segregation for each Metropolitan Statistical Area with the 2000 Census. The scatter plots of figure 16 are suggestive of a strong link between urban segregation and school segregation. The top figure compares the isolation index for whites measured in 2001 using the School Universe, on the horizontal axis, to the isolation index for whites measured in 2000 using census tracts in the 2000 Census. 2000 data for private schools is not provided by the Department of Education, and we hence chose 2001 as the reference point for school segregation.

We then look at the number of schools within a reasonable distance of a house. For each mortgage, we observe the census tract of the purchased house. We calculate the centroid of the census tract using Geographic Information System software. Then, we determined, for each census tract, the 9 closest schools. [13] The match between schools and census tracts is accurate. The average distance to the closest school is 1.16 miles, the distance to the 9th closest school is 3.423 miles. Adding more than 9 schools did not significantly increase the explanatory power of school composition.

[13] We computed the centroid of each census tract and matched the census tract to the schools who are the closest to the census tract centroid, using Geographic Information System software. The centroid measures the center of the census tract. It is the center of gravity of the census tract represented as a polygon.

	Closest	2nd	3rd	4th	5th	6th	7th	8th	9th
Distance census tract									
to School (miles)	1.159	1.564	1.902	2.246	2.530	2.776	3.001	3.233	3.243

How well does school segregation reflect urban segregation? To see how much of census tract racial composition can be explained by the racial composition of nearby schools, we regressed census tract composition on school composition, interacted with the distance in miles between the school and the census tract.

$$\frac{\text{Race}_{r,j}}{\text{Population}_j} = \sum_{k=1}^{5} \frac{\text{Students}_{r,s(j,k)}}{\text{Enrollment}_{s(j,k)}} \cdot (a + b \cdot \text{Distance}_{s(j,k)}) + X_{r,j} \cdot \beta + \varepsilon_j$$

where $\text{Race}_{r,j}$ is the number of individuals of race r in census tract j, Population_j is the population of census tract j, $\text{Students}_{r,s}$ is the number of students of race r in school s, $s(j,k)$ is the k-th closest school from census tract j, Enrollment_s is the number of students in school s. $\text{Distance}_{j,s}$ is the distance in miles between school s and census tract j. $X_{r,j}$ is a set of controls for outliers – dummies for schools that are more than 15 miles and 30 miles from the census tract, county-level composition.

The controls do not significantly explain census tract composition. The single most important explanatory variable is the composition of the closest school. Also, the closer the school to the census tract, the more strongly it predicts census tract composition. A 10 percentage point increase in the fraction African American in the nearest school increase the fraction African American in the census tract by 3.5 percentage points if the school is one mile away from the census tract, and by 3.1 percentage points if the school is two miles away from the census tract. The predictive power of the school's demographics decreases with distance. The fraction African American in nearby schools explains up to 78% of the variance of the fraction of African Americans in census tracts.

In sum, the data show a strong correspondence between school-based and census-based measure of the racial composition of neighborhood.

3.4 School Segregation

In this paper we focus on secondary school segregation in Metropolitan Statistical Areas. Historically, segregation is more salient between central city and suburban districts than among students and schools within the central city district. Hence the Metropolitan Statistical Area is arguably the most relevant geographical unit when looking at segregation across schools. Overall, our results suggest a fall in the isolation of white students, a fall in the isolation of African American students, an increase in the isolation of Hispanic students, and an increase in the isolation of Asian students.

Table 2 shows a significant reduction in the exposure of White students to minority students over time between 1995 and 2007. In 1995, 80.3% of a white student's peers were white (Table 1). In 2007, this falls to 74.2%. Between 1995 and 2007, the measure of isolation of whites went down in all but 15 MSAs – small MSAs, with an average of 22,671 secondary school students. The median fall in the isolation of White students is 5 percentage points. The largest drops in the isolation of white students occured in California (10 MSAs with a drop larger than 5 percentage points), Florida (13 MSAs with a drop larger than 5 percentage points), North Carolina (10 MSAs), and Texas (13 MSAs). This drop is due to an increased exposure of white students to Hispanic and African American students (Table 1).

The isolation of African American students has also been reduced during the same period. Table 1 shows that African American students' peers were on average 51.9% African American in 1995 and 49.0% in 2007. This drop is mostly due to an increased exposure to Hispanic students in large Metropolitan Statistical Areas, and occurs despite the lower exposure to White students. MSAs in which the isolation of African Americans decreased are twice as large as the other MSAs. The drops were very substantial (larger than 3 percentage points) in large MSAs in Louisiana, Georgia, North Carolina, Pennsylvania, Oklahoma, Tennessee. The distribution of isolation trends accross MSAs is less uneven for African Americansthan for Whites: the isolation of African American students increased in 238 MSAs, and decreased in 114 MSAs. But the overall isolation decreases because of the larger number of students in MSAs of the latter group.

The isolation of African American students dropped by more in MSAs where their exposure to Hispanics increased by more (in MSAs where the isolation of African American students went down, the exposure to Hispanic students went up by 6.9 percentage points and the average MSA gained 6113 Hispanic students, while it only went up by 4.1 percentage points where the isolation of African American students went up, and the average MSA only gained 1833 Hispanic students).

The exposure of African American students to White students went *down*. This is a general trend, in 327 out of 352 MSAs. This fact cannot be explained by the increase in Hispanic population. A regression of the the 2007-1995 change in African American exposure to Hispanic students on the % increase in Hispanic population in the MSA explains only 1% of the change. It is the geographic mobility of African American or White households that explains the drop in African American exposure to White students rather than a pure mechanical effect due to the increase of Hispanic population.

Finally, the isolation of Hispanic students went up. The average secondary school Hispanic student had 48.4% of Hispanic peers in 1995 and 51.0% of Hispanic peers in 2007. There was a large increase in Hispanic population over the period; Hispanic secondary school student population grew 94% in the median MSA. But the growth of Hispanic population per se cannot explain why about 69 MSAs experienced a large influx of Hispanic students (+50.7%) but only a very modest - less than 1% - increase or even decreases in Hispanic isolation.

The isolation of Hispanic students went up. Indeed, the exposure of Hispanic students to African American students went up. The average Hispanic student had 12.2% of African American peers in 1995, and 13.2% in 2007. This means that the influx of migrants primarily happened in areas with a substantial fraction of Hispanic students and of African American students. On the other hand, the exposure of Hispanic students to White students went *down*; but this was not sufficient to make the exposure of Hispanic students go up.

3.5 Credit Constraints

Recent literature suggests that the increase in the number of originated mortgages can in large part be the result of supply-driven shocks. In a major contribution, Mian & Sufi (2009) showed that mortgage credit growth and income growth at the ZIP-code level were negatively correlated within MSAs during the credit boom; the authors argue that this negative correlation cannot be explained by a purely demand-driven increase in mortgage credit. Favara & Imbs (2010), moreover, showed that the branching deregulation reform of the mid-1990s, which allowed interstate branching, led to a higher number of mortgages and to higher volumes of originations. Dell'Arriccia et al.'s (2009) results suggest that there was a relaxation in credit standards during the credit boom. Other important contributions tend to suggest that low risk-free rates from 2001 to 2006 (Mian & Sufi 2009), together with the rise of mortgage securitization by private labels (Bernanke 2009), may have contributed to the largely supply-driven mortgage credit boom.

Overall, we observe a higher number of originations, higher acceptance rates, and higher loan-to-income ratios. In our dataset, the total volume of originations grew from 3,102,439 in 1995 to 4,370,320 in 2000, and to more than 6,000,000 originations in 2005. The volume declines after that, to about 3,875,000 originations in 2007. This large increase in mortgage activity benefited minorities disproportionately more than white households. Hispanic households got four times as many mortgages in 2005 as in 1995, while originations to Asians increased threefold, and originations to African Americans doubled. The volume of originations to white households increased only by about 50%. In 2007, the number of originations went back to its 2001 level for hispanics and Asians, to its 2002 for African Americans and to it 1995 level for whites. The increase in mortgage originations benefited different races differently and hence the table suggests that it may have affected the mobility of different races differently, lowering or higher school segregation.

As house prices increased, so did loan-to-income (LTI) ratios. LTI ratios grew substantially from 2000 to 2004. For Hispanics, African-Americans and Whites, the median loan-to-income ratio increased similarly by about 0.4. It increased more for Asians, by about 0.5; The appendix presents results and statistics on credit conditions in California, where a large share of the Asians live, and provides an explanation for the distinctive evolution of credit conditions of this population. The most leveraged households become even more leveraged, as we see a slight increase of the 90th percentile loan-to-income ratio, which went up by 1 percentage point for Asians, and by about 0.5 for the other racial groups.

3.6 Baseline Specification

The primary interest of this paper is to identify variations in segregation that are due to changes in credit conditions *beyond* changes in segregation that are due to migrations, national trends and idiosyncratic shocks.

MSA-level segregation is determined by racial demographics, national trends, MSA-specific effects, credit conditions, and other MSA-specific factors.

$$\begin{aligned} \text{Segregation}_{j,t} &= \text{Racial Demographics}_{j,t}\beta + \text{Year}_t + MSA_j \\ &\quad + \text{Credit Conditions}_{j,t}\gamma + \text{Other Factors}_{j,t} \end{aligned} \tag{7}$$

where j indexes MSAs, and t indexes years. In many MSAs there are large increases in Hispanic population over the period, and some MSAs, such as Austin-Round Rock, TX grow substantially (+40%) over the period 1995-2007 because of a large influx of Hispanic population. These changes have an impact on segregation independently of credit conditions. By taking the difference between segregation in year t and segregation in year $t+1$ (equation **7**), we see that changes in segregation are due to migrations, national trends, changes in credit conditions, and changes in other factors.

Changes in racial demographics - $\text{Racial Demographics}_{j,t+1} - \text{Racial Demographics}_{j,t}$- are due to migrations in and out of the MSA, differential birth rates, and differential mortality rates across racial groups. The national trend - $\text{Year}_{t+1} - \text{Year}_t$ - , common to all MSAs, captures secular declines or increases in segregation – which are described for instance in Cutler, Glaeser & Vigdor (2008).

Of course, racial demographics can be correlated with changes in credit conditions. We observe MSAs with large changes in racial demographics that experience substantial growth in mortgage originations and higher leverage, but we also observe MSAs with large changes in racial demographics that do not experience a large growth in mortgage originations and have had stable leverage.

To estimate the effect of credit conditions on segregation *conditional* on racial demographics, MSA effects, national trends, and idiosyncratic shocks, we regress measures of segregation – isolation and exposure – on measures of credit conditions, measures of creditworthiness, MSA fixed effects, racial demographics, and year dummies. Metropolitan Statistical Area fixed effects control for any MSA-specific effect that is correlated with credit conditions and has an effect on segregation. One of these unobserved factors is the elasticity of housing supply. Thus, by including an MSA fixed effect, we avoid the issue of non-time-varying confounders that may bias our estimate of the effect of credit conditions on school segregation. Also, we include measures of creditworthiness in the MSA: The fraction of subprime loans, the fraction of jumbo loans, and the fraction of delinquencies, 90+ days past due, and foreclosures four years from now. The rationale is that the creditworthiness of the borrowers will be revealed later during the credit crisis. Thus, by including measures of realized risk in the MSA, we proxy for applicants' creditworthiness now.

The main specification of the paper augments the specification of Cutler et al. (2008) with measures of credit conditions and controls for households' creditworthiness:

$$\text{Segregation}_{j,t} = \text{Credit Conditions}_{j,t}\gamma + \text{Racial Demographics}_{j,t}\beta \tag{8}$$

$$+\text{Creditworthiness}_{j,t}\delta + MSA_j + Year_t + \varepsilon_{j,t} \tag{9}$$

where $Segregation_{j,t}$ is a measure of segregation – isolation of Whites, Hispanics, African Americans and Asians, or the exposure of a racial group to another racial group. Segregation is, as before, measured across secondary schools. Credit Conditions$_{j,t}$ is the vector of estimates of credit standards. It includes the median Loan-to-Income ratio, i.e. our measure of leverage, the difference between the median leverage and the 90th percentile leverage, i.e. a measure of the ability for borrowers to obtain loans with abnormally high leverage, the acceptance rate from 0 to 100, and the log number of applications. γ_j is our vector of coefficients of interest. Racial Demographics$_{j,t}$ is a vector of the fraction of each racial and ethnic group in the MSA: fraction White Nonhispanic, fraction Hispanic Nonwhite, fraction African American (nonhispanic), fraction Asian, and fraction of other racial groups. Creditworthiness$_{j,t}$ is a vector that includes the fraction of subprime loans[14] , the fraction of jumbo loans[15] in year t, the fraction of delinquencies, foreclosures, and mortgages that 90+ days past due[16], in year $t+4$, and the fraction of high-risk loans.

To identify high-risk loans, we estimate the probability of denial for 1995 mortgages as a function of demographic characteristics (race, gender) and as a function of the characteristics of the loan (loan-to-income ratio, loan amound), as well as the interaction of the two sets of variables. We then use this prediction of risk to estimate the fraction of high-risk loans in year $t \geq 1995$ using the credit standards of 1995.

MSA$_j$ is the MSA fixed effect that controls for an MSA-specific level of segregation, $Year_t$ is a year dummy that controls for a national segregation trend, and $\varepsilon_{j,t}$ is the residual. Residuals are clustered at the MSA level, which accounts for autocorrelation, and shared unobservables. The MSA is likely to be the appropriate level of clustering. There are 355 MSAs overall, so the number of clusters is large, and there are 13 years of observations, hence

[14]We identify subprime loans as loans that have been originated by a subprime lender. The department of Housing and Urban Development provides a list of lenders that specialize in subprime or manufactured home lending.

[15]A jumbo loan is a loan whose amount is above the conformable loan limit. A loan above the conformable loan limit is typically not bought by the Government Sponsored Entreprises. We use the limits provided by the Department of Housing and Urban Development.

[16]This data comes from an MSA-level aggregation from Haver Analytics data.

13 points per MSA. Hence, clustering by MSA is likely to yield good estimates of standard errors (Wooldridge 2003).

The coefficients of interest γ should be interpreted as the effect of credit conditions as deviations from the trend implied by racial demographics and, in particular, migration flows. For instance, if we find that leverage positively affects segregation levels, that means that, in MSAs where there is a large increase in Hispanic population and thus a fall in White isolation, a higher leverage prevents isolation from falling as much as it would in MSAs with lower leverage.

The main regression (equation 8) is estimated using a Weighted Least Squares estimator weighted by the number of students of each race, i.e. when the dependent variable is African American isolation, the regression is weighted by the number of African American students in the MSA. This gives more weight to large MSAs, and less weight to very small MSAs. The rationale for the weighting is that, if the effect of credit conditions is different in small and large MSAs,[17] our estimator of the effect of credit conditions is the average effect of credit conditions on segregation, with weights equal to the size of the racial group in the MSA.

Finally, we checked that the results we obtained were robust by replicating the results dropping extreme observations, regressing on subsets of years, or dropping MSAs one by one. Thus no particular year or MSA is driving the results. We also performed multi-way clustering (Cameron, Gelbach & Miller 2006).[18] Results were not affected.

3.7 The Effect of Leverage

Table 3 presents the results of the baseline regression (Equation 8). 355 Metropolitan Statistical Areas are observed every year, for 13 years, and a few small MSAs are observed for

[17] We should expect the effect of credit conditions to be different across MSAs. The theory part of the paper emphasizes that the effect of credit conditions depends on households' valuations of housing, the elasticity of supply of housing, relative incomes, and other parameters. In the paper we measure the average effect of credit conditions on segregation.

[18] Consistent estimation of the standard errors requires a large number of clusters with a small number of observations per cluster. Hence we do not report results using multi-way clustering since 13 years of observation with 355 observations per year is far from the asymptotics.

some years, hence the overall number of 4,646 observations. We focus here on the effect of leverage as measure by the loan to income ratio. An increase in the media loan-to-income ratio in a MSA means that a larger fraction of borrowers are able to obtain credit with a higher leverage. [19] In the equilibrium of our model economy, a relaxation of lending standard is associated with higher loan-to-income ratios.

Higher leverage significantly increases the isolation of African Americans and the isolation of Hispanics. An increase of the median Loan-to-Income ratio by 1, e.g. from 2 to 3, increases the isolation of African Americans by 2.4 percentage points. This is substantial. Since the median LTI increased nationally by about 0.4, the effect is about 1 percentage point, or about a third of the decline in African American isolation from 1995 to 2007 (Table 1), reflecting the fact that a significant number of MSAs saw an increase in African American isolation, and another large set of MSAs saw a decline in African American isolation. MSAs in which the median LTI ratio was high saw increases in isolation. Table 4 shows that this effect stems from (i) the negative effect of the LTI ratio on the exposure of African Americans to Hispanics (ii) the negative effect of the LTI ratio on the exposure of African Americans to Whites. Thus, results indicate that the ability to purchase home using a higher leverage has helped White and Hispanic households to buy houses in areas close to schools with a lower fraction of African American students.

We now turn to the effect of leverage on the isolation of Hispanic students. A larger difference in loan-to-income ratios between the top decile and the median of the distribution of borrowers' leverage tends to increase the isolation of Hispanics. An increase in the difference between the median Loan-to-Income ratio and the 90th percentile loan-to-income ratio by 1 increases the isolation of Hispanics by 2.2 percentage points. From 1995 to 2007, the average difference P90-P50 increased from about 0.9 to 1.4. Such an increase would increase Hispanic isolation in a typical MSA by 1.1 percentage points, over and above the effect of migrations,

[19] The loan-to-income ratio is the product of the loan-to-value by value-to-income ratio. A reduction of the former means a lower downpayment - a standard measure of lending standard - and a reduction of the later denotes the ability for borrowers to buy a home worth a higher multiple of their current income.

MSA fixed effects, and national trends. This increase in the isolation of Hispanics is caused by a decline in the exposure of Hispanics to Blacks, Whites, and Asians. Hispanic borrowers generally exhibit higher leverage than borrowers from other ethnic groups (See Figure 2). As a consequence, they are more affected by the level of loan-to-income ratio at the top of the distribution. When leverage on top increases, Hispanics are less able to move to more mixed neighborhoods and instead settle in mostly Hispanic areas.

3.8 The Effect of Volume – Applications and Acceptance Rate

Between 1995 and 2004, acceptance rates grew by nearly 20 percentage points for African Americans, by 12 percentage points for Whites, and by 8 percentage points for Hispanics (Figure 2). At the MSA-level, increasing acceptance rates, conditional on year dummies and MSA fixed effects, reflect changes in credit standards, conditional on the measures of creditworthiness described in section 3.6.

An increase in acceptance rates by 10 percentage points causes a 0.1 percentage point increase in African American isolation and a 0.05 percentage point increase in Hispanic isolation. For African Americans, this is due to a lower exposure of African Americans to Whites. A 1 percentage point increase in the acceptance rate lowers exposure by 0.1 percentage point. Thus acceptance rates benefit White households who move to neighborhoods with lower fractions of African American students.

A higher acceptance rate *lowers* the exposure of Hispanics to Whites, which explains the effect of acceptance rates on the isolation of Hispanics. Note that a higher acceptance rate has no effect on the exposure of Whites to Hispanics.

To summarize, the results of Table and Table show our measures of credit standards relaxation are significantly associated with an increase in measure of isolation conditional on demographics, creditworthiness measures, MSA effects, and a national trend. This result means that if the trend implied by demographics was a reduction of segregation, this trend has been mitigated rather than amplified by the relaxation of credit standards.

3.9 Within- and Between School District Segregation

Court-ordered desegregation plans mostly occur within school districts rather than across school district boundaries. The *Milliken v. Bradley* 1974 Supreme Court decision held that a desegregation plan at the level of the Detroit Metropolitan Area was unconstitutional. Integration plans involving the reallocation of students across school district borders all but disappeared after the Supreme Court ruling. As a consequence, in most MSAs, parents wishing for their children to be educated in other school districts had to move geographically. The mortgage credit boom may have changed segregation patterns by allowing families to move to other school districts.

In this section, we control for the role of within school districts integration plans by focusing on between school districts measures of isolation.

In each metropolitan statistical area (MSA), we calculate between-school district segregation using the between school-district isolation index. For instance, the between school district isolation of White students is the average fraction of white peers for white students.

$$\text{Between School District Isolation}_j(Whites) = \sum_{k=1}^{K_j} \frac{whites_{k,j}}{whites_j} \cdot \frac{whites_{k,j}}{students_{k,j}}$$

where $k = 1, 2, \ldots, K_j$ indexes school districts in MSA j, $\text{whites}_{k,j}$ is the number of white students in school district k in MSA j and $\text{students}_{k,j}$ is the total number of students in school district k in MSA j. whites_j is the total number of white students in MSA j.

Segregation between school districts has broadly declined over the period. The between-school-district isolation of whites declined from 77.1% to 70.9%, the between-school-district isolation of African Americans declines from 44.7% to 42.6% and the between-school-district isolation of Hispanics stayed constant at 47.8%. This is remarkable, because there are fewer explicit desegregation plans in the years 2000 than in previous decades. Thus this change is likely to be mostly due to changes in household mobility.

Are these between-school districs changes parlty driven by the increase in mortgage credit supply? To answer this question, we regress between-school-district isolation and within-school-district segregation on credit conditions, MSA fixed effects, year dummies as in the main baseline specification 8 to control for a national trend.

$$\begin{aligned}\text{Between School District Segregation}_{j,t} &= \text{Credit Conditions}_{j,t}\gamma + X_{j,t}\beta \\ &+\text{Creditworthiness}_{j,t}\delta \\ &+MSA_j + Year_t + \eta_{j,t}\end{aligned}$$

where notations are as in the main specification 8, t indexes years from 1995 to 2007, j indexes MSAs, and Credit Conditions$_{j,t}$ is a vector that includes the median loan-to-income ratio, the difference between the median and the 90th percentile loan-to-income ratio, the acceptance rate, and the log of the number of applications. As before, $X_{j,t}$ includes controls for the racial demographics of the MSA in year t and applicants' income. Creditworthiness$_{j,t}$ is a vector of applicants' creditworthiness defined in section 3.6. Results are presented in table 5.

Most of the effects of credit conditions on between school district isolation are similar or stronger (table 5) than the baseline results. That strongly suggests that household mobility rather than integration plans are at play here and that households are using credit to afford housing in school districts with higher fraction of white students.

An increase in the median loan-to-income ratio by 1 increases the isolation of Blacks by 2.5 percentage points. This is very similar to the result of the main table, Table 3. The effects was 2.4 (Column 2, Table 3). Thus, for African-Americans, the increase in isolation due to an increase in leverage is mostly due to a change in between-school district isolation.

Table 6 is the equivalent of the exposure regressions (Table 6), for between school district segregation. For instance, the between-school district exposure of African American students to White students is the average fraction of White students in the school district for an average African American student. Table 6 shows that a higher median loan-to-income ratio lowers the between school district exposure of Blacks to Whites. This fully explains why the between school district isolation of African Americans goes up when the median loan-to-income ratio goes up: the coefficients on African American isolation (2.5, column 3 of Table 5) and exposure (-2.3, column 4, Table 6) are close and of opposite signs.

Table 5 shows that a higher median loan-to-income ratio increases the between school district isolation of Hispanics (+1.5, column 3, Table 5, significant at 95%), but that an increase in the highest leverages does not significantly affect Hispanic isolation. Also, the exposure table (Table 6) shows that this is due to a fall in the exposure of Hispanics to Whites. Overall, Hispanic households use that leverage to move to predominantly Hispanic school districts.

Higher acceptance rates have benefited Hispanic households who moved to school districts with more White and African American households. An increase of the acceptance rate by 10 percentage points increases the between school district exposure of African American students to White students by 0.2 percentage points, and hence lowers the between school district isolation of White households.

3.10 High and Low Elasticity MSAs

There is extensive evidence in the litterature that the elasticity of housing supply determines house prices, residential segregation and the effect of credit supply on house prices (see for instance Glaeser, Gyourko & Saks (2005), and specifically on segregation and the elasticity of housing supply, King & Mieszkowski (1973)). Our model has shown that the effect of credit supply on segregation can be larger when the elasticity of housing supply is higher.

Our dataset is matched to the elasticity measures calculated by Saiz (2010), which take into account both the geographic and regulatory constraints on housing. Elasticity is available for the 258 largest MSAs. The average elasticity is 2.8, the median elasticity is 2.5, the 90th percentile of the elasticity is 4.6. The dataset was split into the 40% MSAs with the lowest elasticity – housing supply there is constrained by geography or regulations – and the 40% MSAs with the highest elasticity – housing supply there can expand easily. That leaves us with 1,195 observations for the first subsample and 1,106 observations for the latter subsample.

Table 7 shows that the effect of the loan-to-income ratio is significantly stronger in MSAs where the elasticity of housing supply is higher. This is because in areas where there are high LTIs, the exposure of Whites to Hispanics and the exposure of Hispanics to Whites declines. Incidentally, the exposure of Hispanics to Blacks, and the exposure of Blacks to Hispanics declines. This effect is measured controlling for increases in Hispanic population.

Interestingly, the coefficient estimate does not change either when controlling for price increases using the price index of the OFHEO.[20]

3.11 Public and Private Schools

Finally, we look at the effect of credit conditions on sorting between private and public schools. We add data from the Private School Universe, which is only available every other year from 1995 to 2007. Table 1 shows that there has been little change in the fraction of students across public and private schools in the US over the period, for any racial group. Table 9 regresses the fraction of Whites in public schools, the fraction of African Americans in public schools, the fraction of Hispanics in public schools and the fraction of Asians in public schools on credit conditions. Overall there is little effect of credit conditions on public/private school sorting. This is good for the identification strategy of the main specification (Equation 8), since adding private schools to the dataset would have little impact on our conclusions.

[20]The Office of Federal Entreprise Oversight (OFHEO) publishes an annual and a quarterly house price index. We included the index in regression 8, and results on the loan-to-income ratio where not affected.

4 Conclusion

Mortgage credit tends to increase racial segregation across schools and neighborhoods – more specifically higher leverages tend to allow racial groups to sort into neighborhoods where schools are predominantly of the same race. The mortgage credit market appears to be a powerful driving force of segregation, mainly through its effect on leverage, which affects racial groups' ability to outbid other racial groups for housing in desirable neighborhoods.

The paper shows that the increased availability of mortgage credit, fueled by financial sophistication, banking deregulation, and supply of credit to lenders, has made segregation decline at a slower pace.

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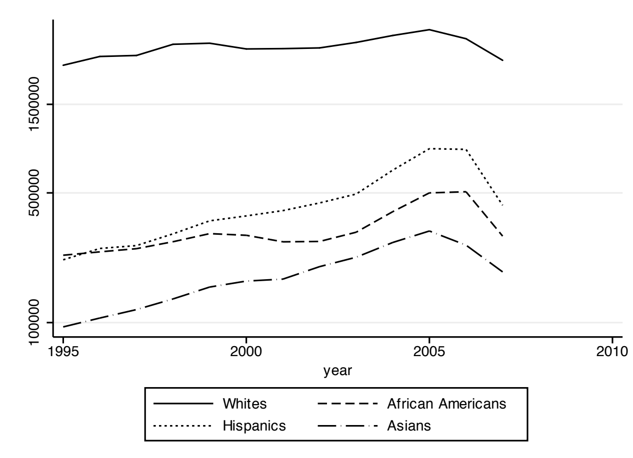
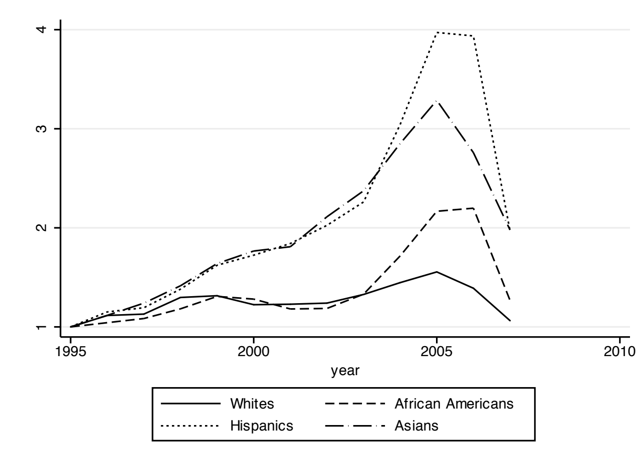
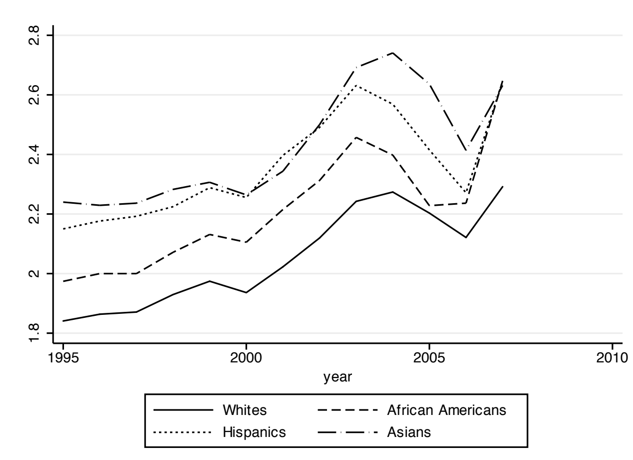


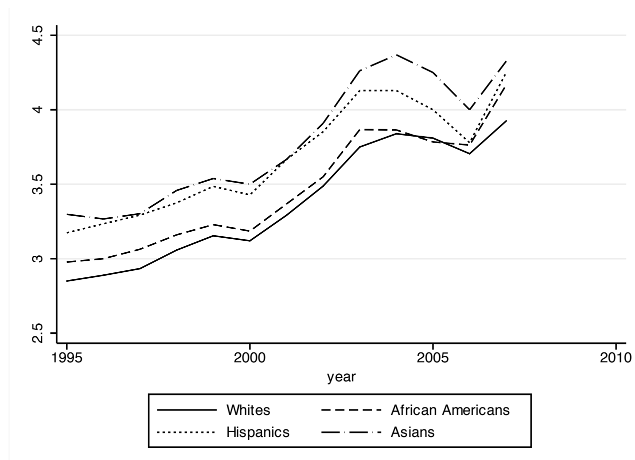
(a) Originations, log scale



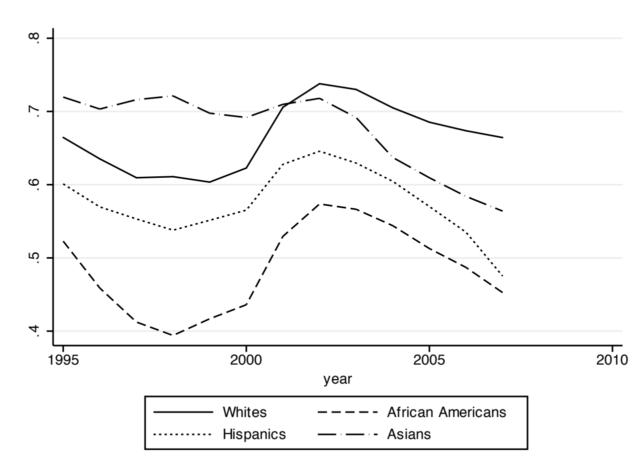
(b) Originations, Normalized



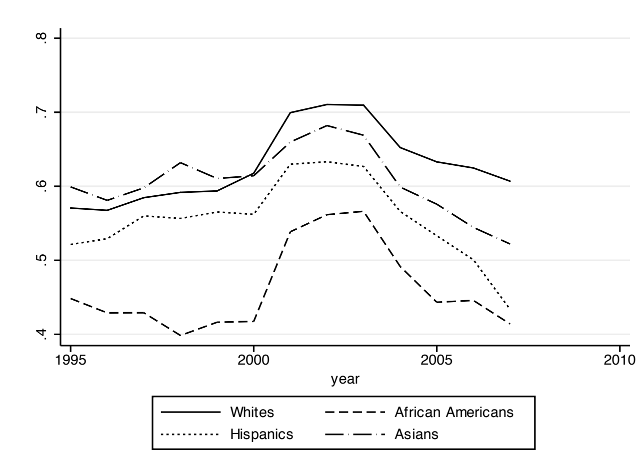
(c) Median LTI Ratio



(d) 90th Percentile LTI Ratio



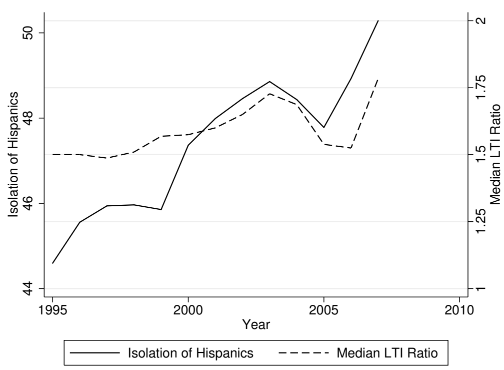
(e) Acceptance Rate



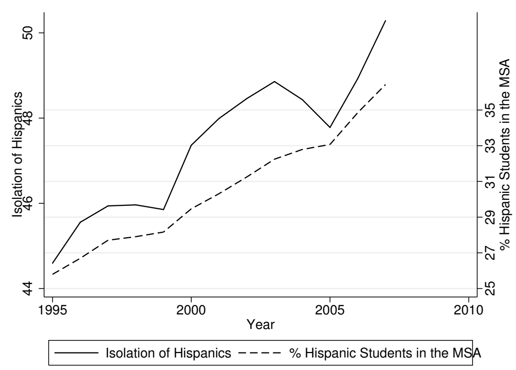
(f) Acceptance Rate for LTI above 3.5

LTI: Loan-to-income ratio. Source: Home Mortgage Disclosure Act data from 1995 to 2007. All racial groups are non-Hispanic members of those races. Hispanics are shown as a separate category.

Figure 2: Credit Standards – By Race



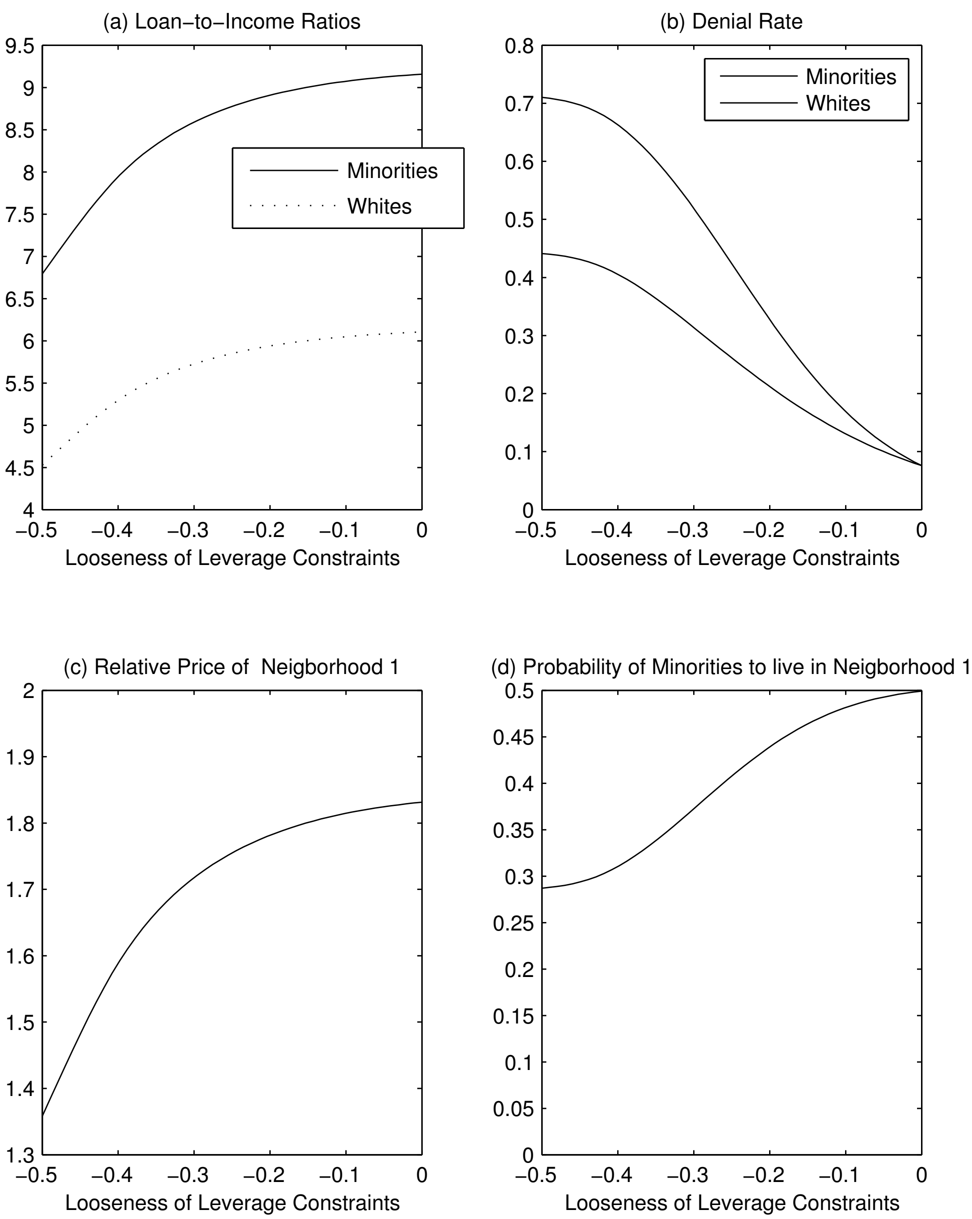
(a) Loan-to-Income Ratio



(b) Isolation and Fraction Hispanic

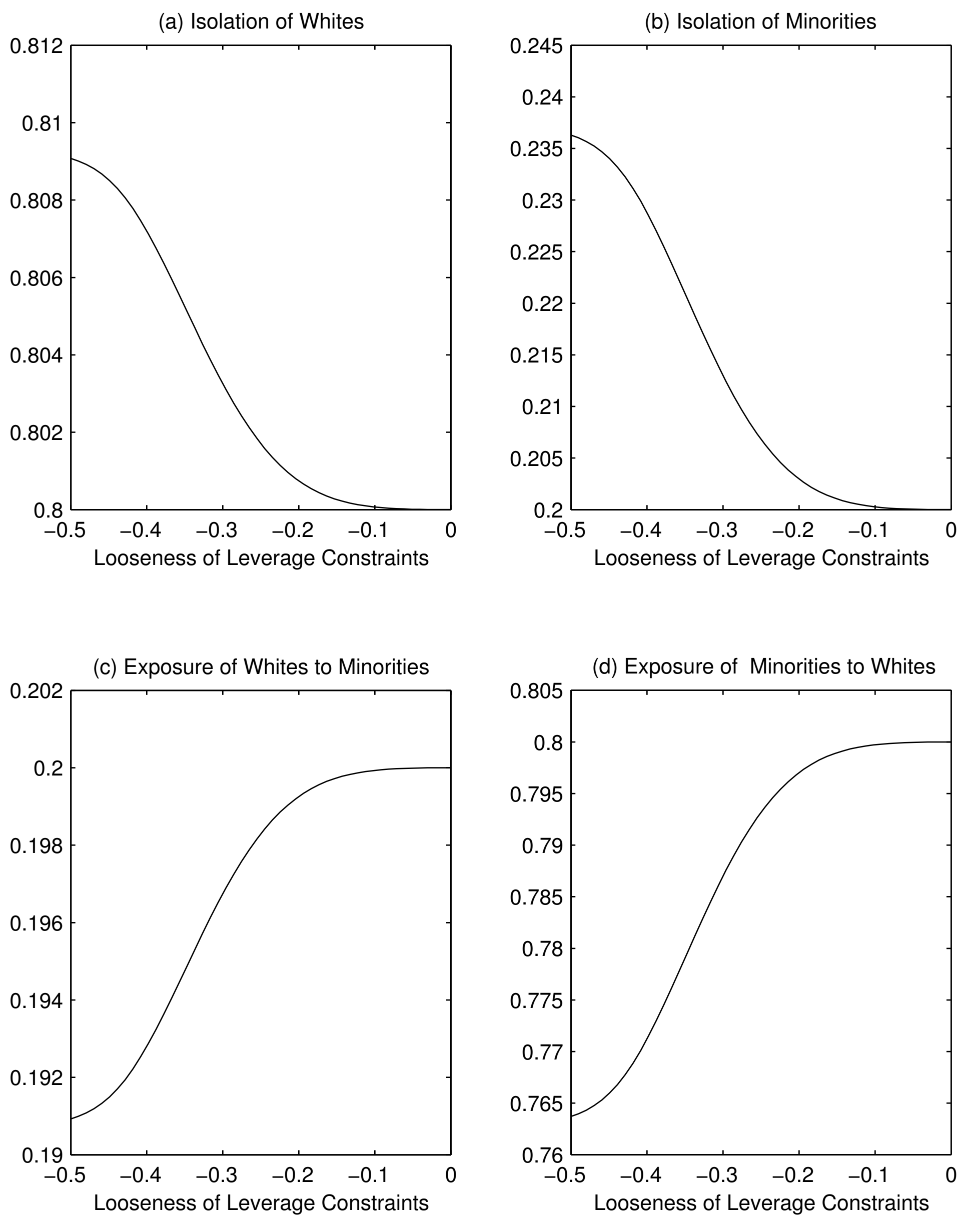
The isolation of Hispanics is the average fraction of Hispanic peers for Hispanic secondary school students (see section 3.2).

Figure 3: Houston-Sugar Land-Baytown (TX) Metropolitan Statistical Area



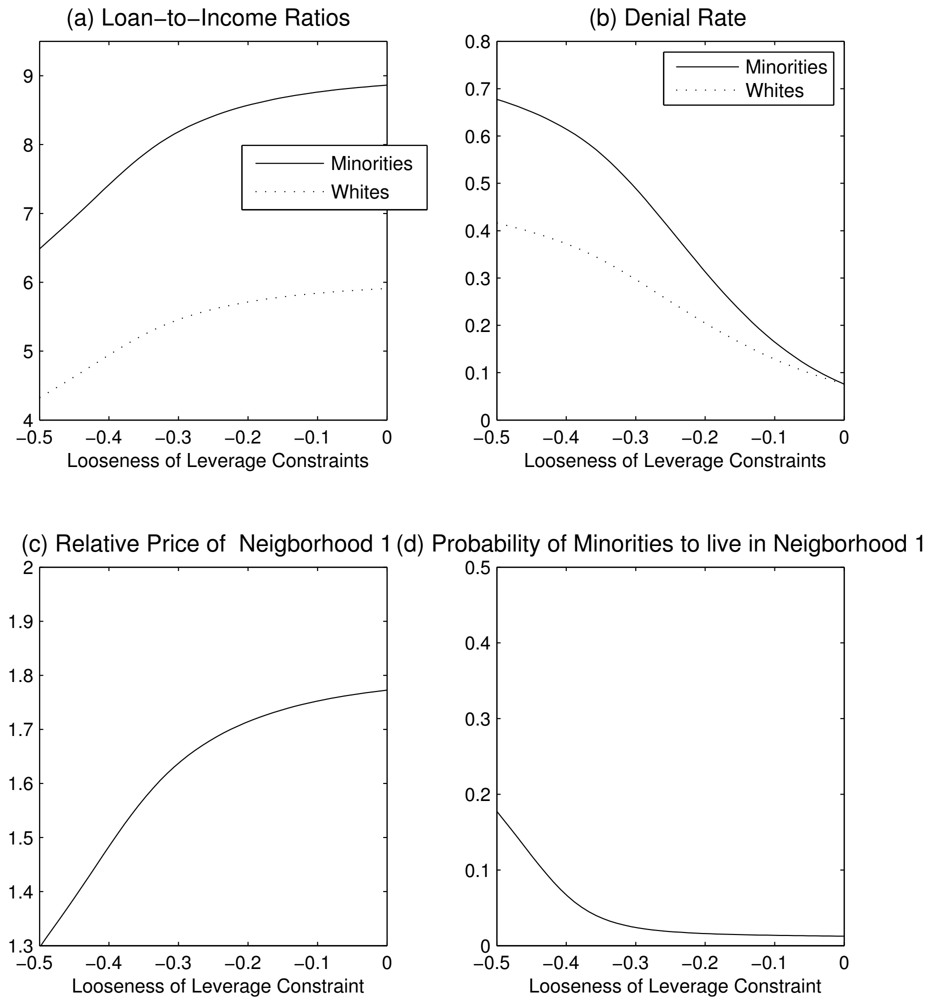
The looseness of the leverage constraint is the parameter β in the acceptance/rejection decision.

Figure 4: Scenario 1



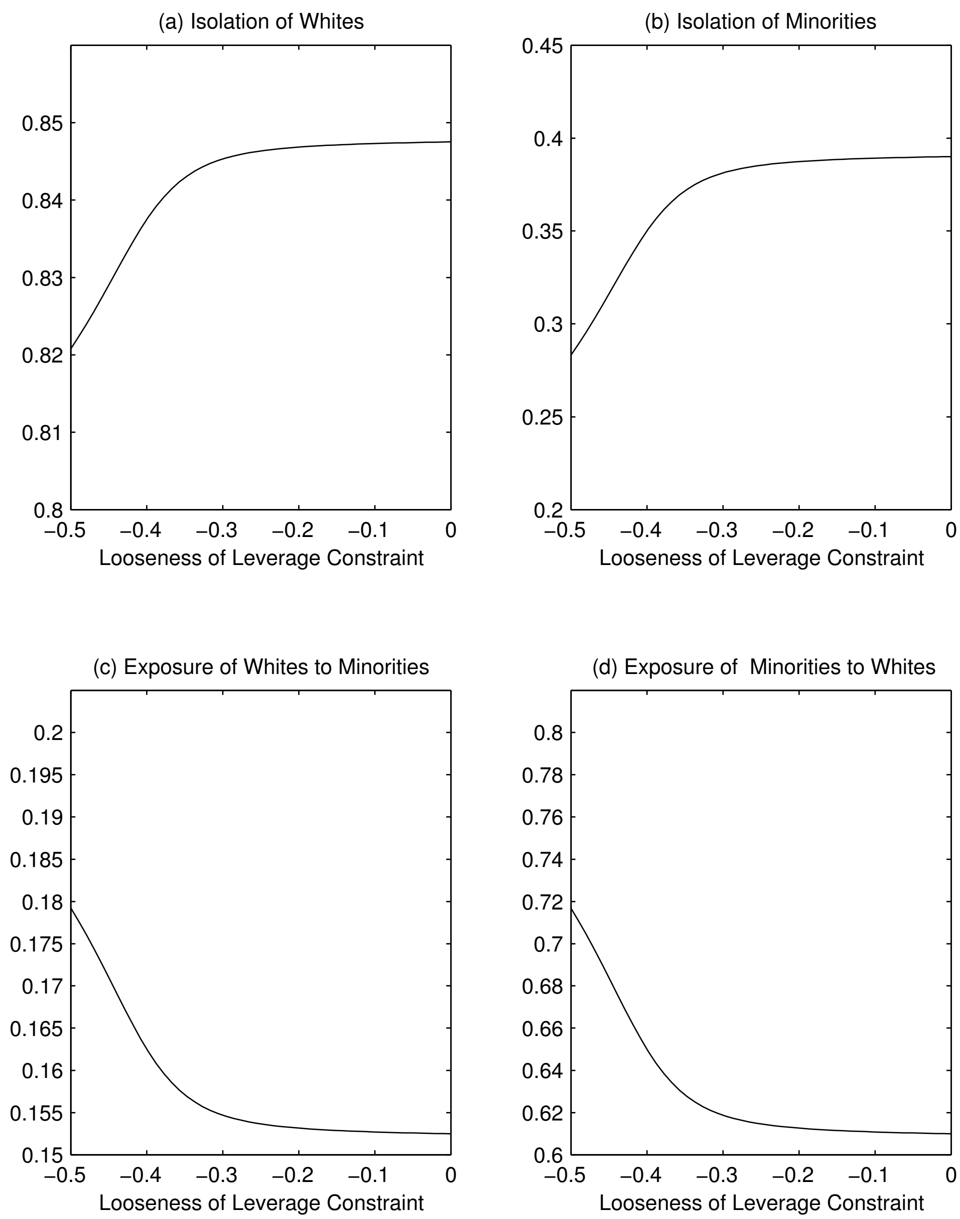
The looseness of the leverage constraint is the parameter β in the acceptance/rejection decision. For definitions of isolation and exposure, see section 3.2, equations 5 and 6.

Figure 5: Scenario 1 – Segregation and Credit Constraints



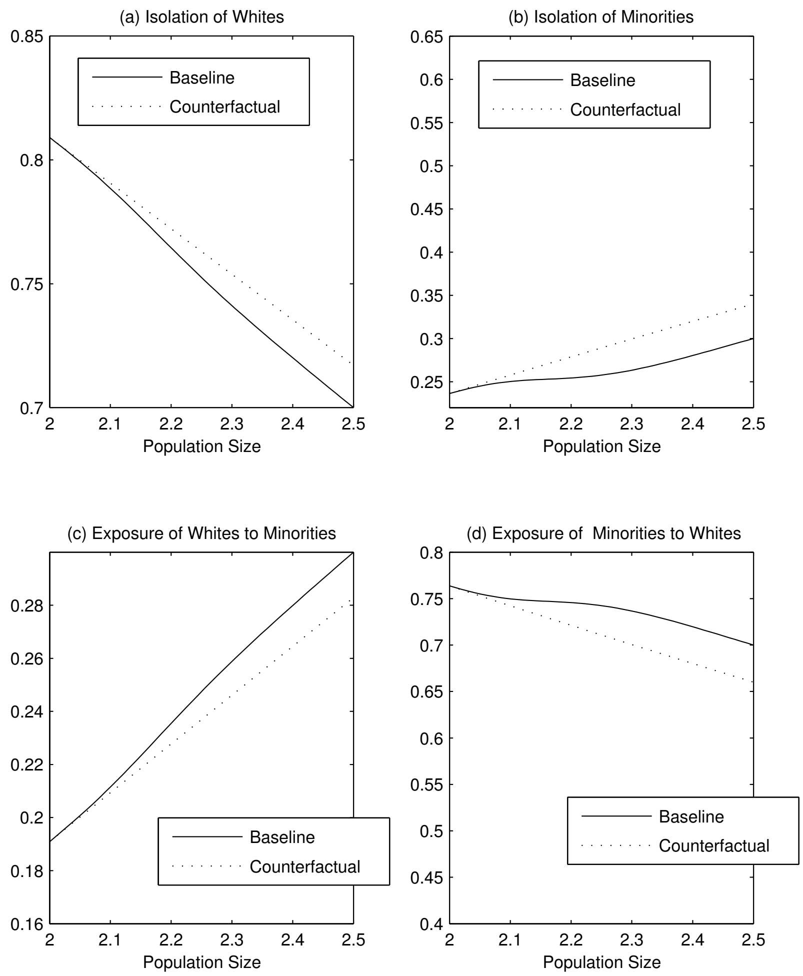
The looseness of the leverage constraint is the parameter β in the acceptance/rejection decision.

Figure 6: Simulation 2



The looseness of the leverage constraint is the parameter β in the acceptance/rejection decision. For definitions of isolation and exposure, see section 3.2, equations 5 and 6.

Figure 7: Simulation 2 – Segregation and Credit Constraints



The looseness of the leverage constraint is the parameter β in the acceptance/rejection decision.

Figure 8: Simulation 3

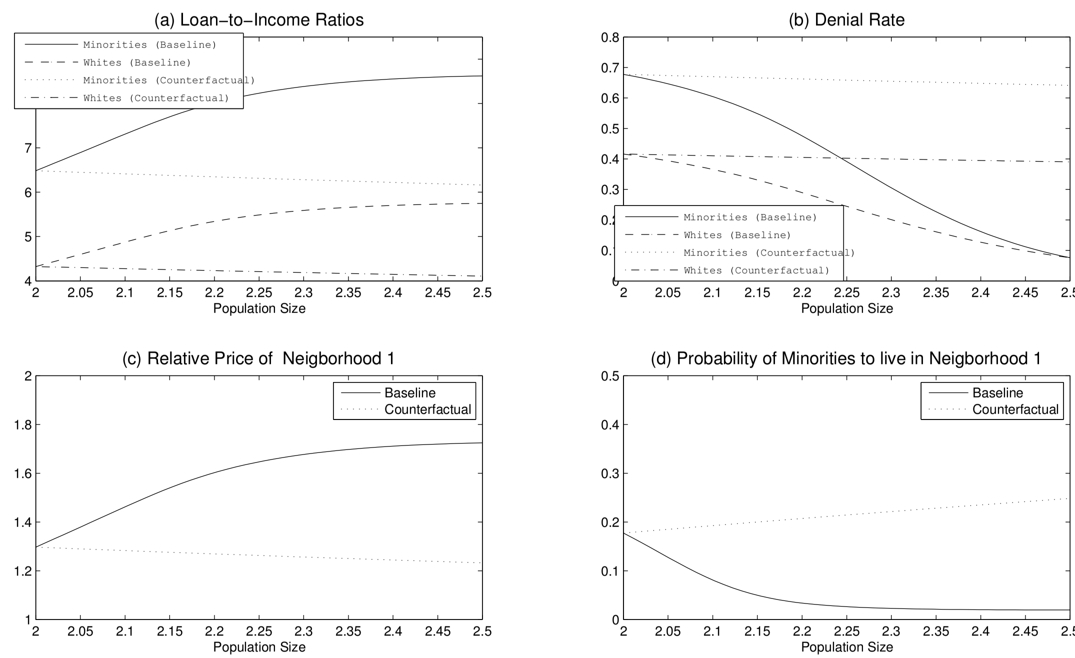


Figure 9: Simulation 3 – Segregation and Credit Constraints

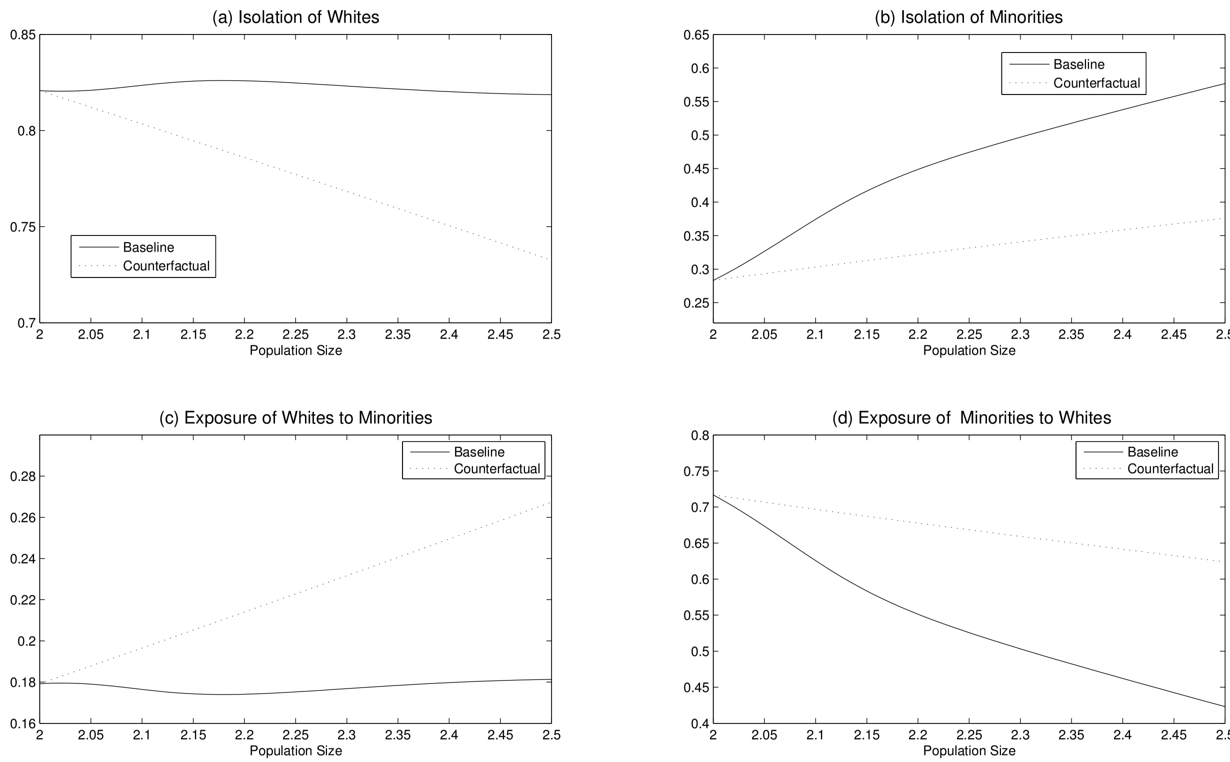


Figure 10: Simulation 4

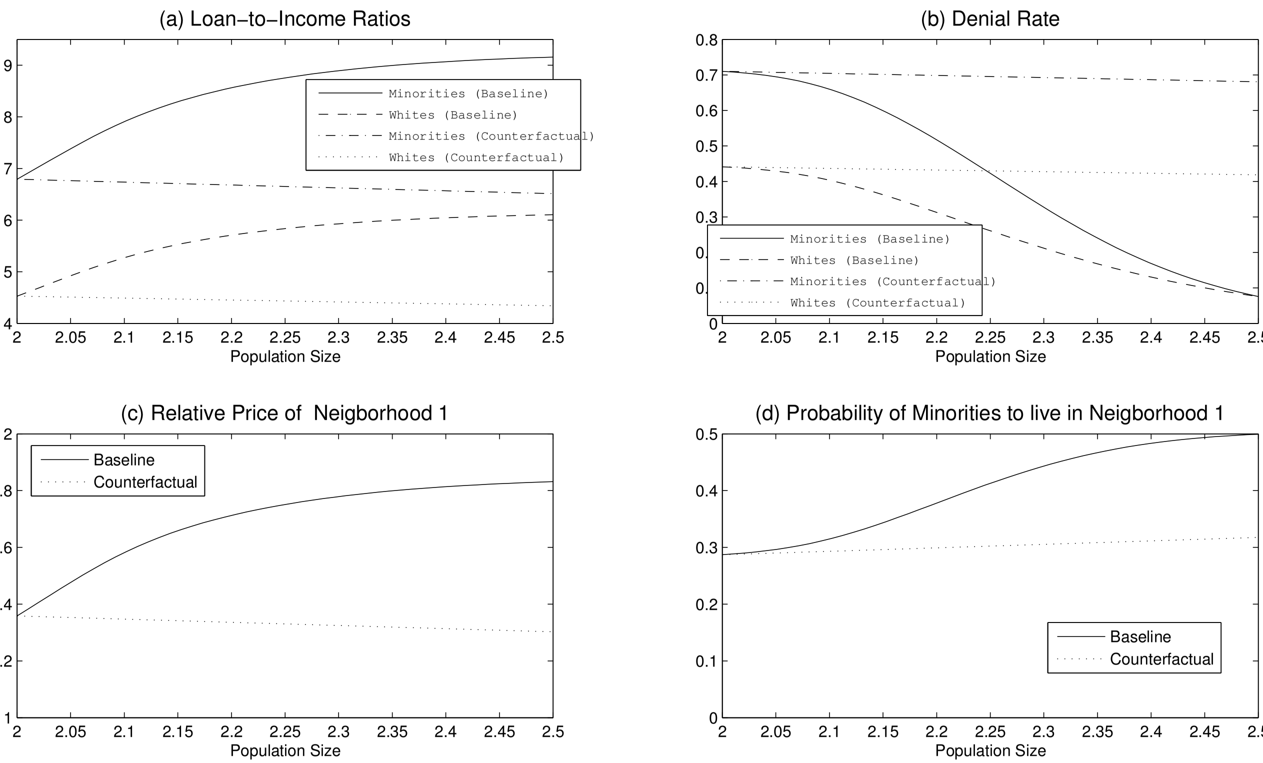


Figure 11: Simulation 4 – Segregation and Credit Constraints

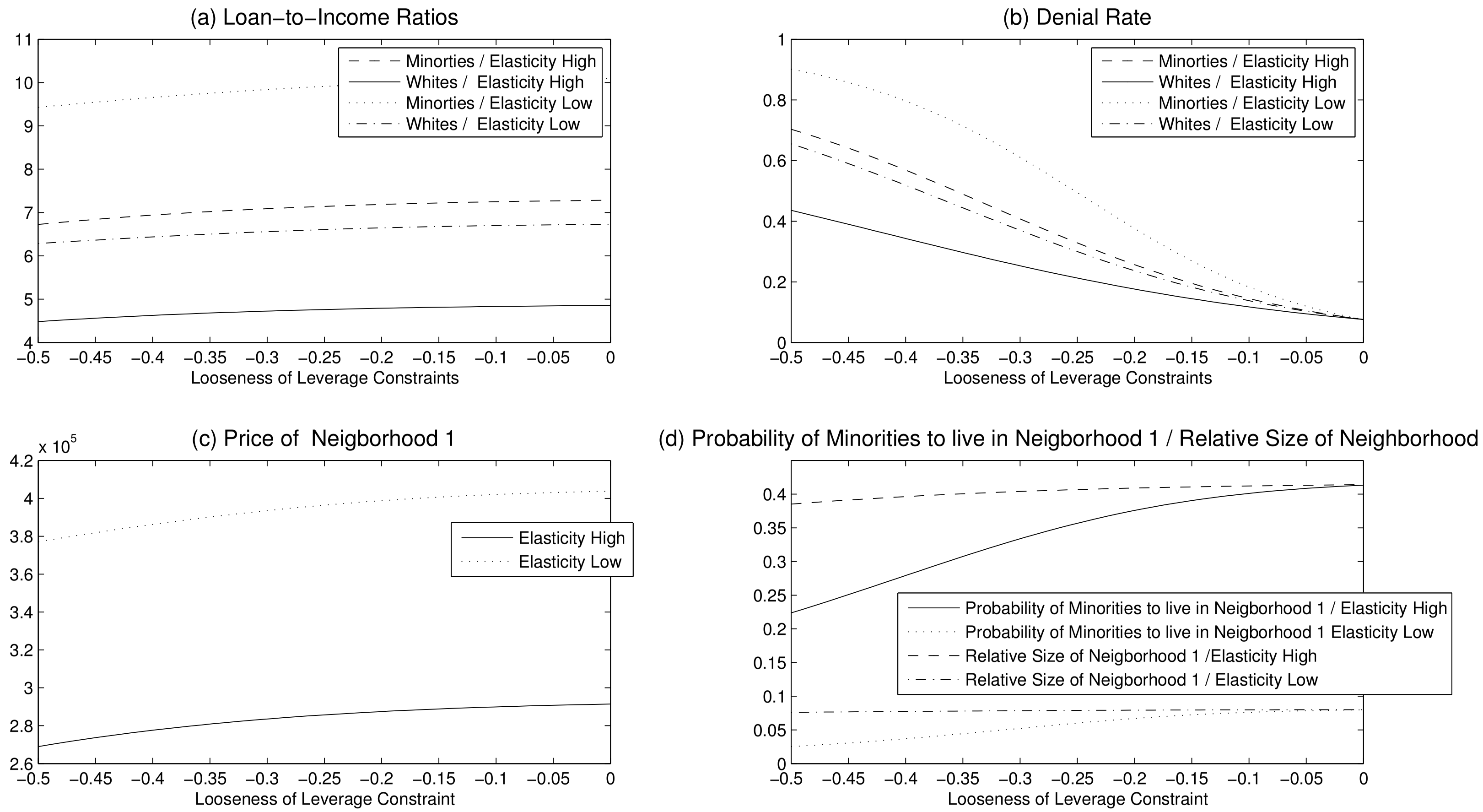


Figure 12: Simulation – Elasticity, Segregation and Credit Constraints

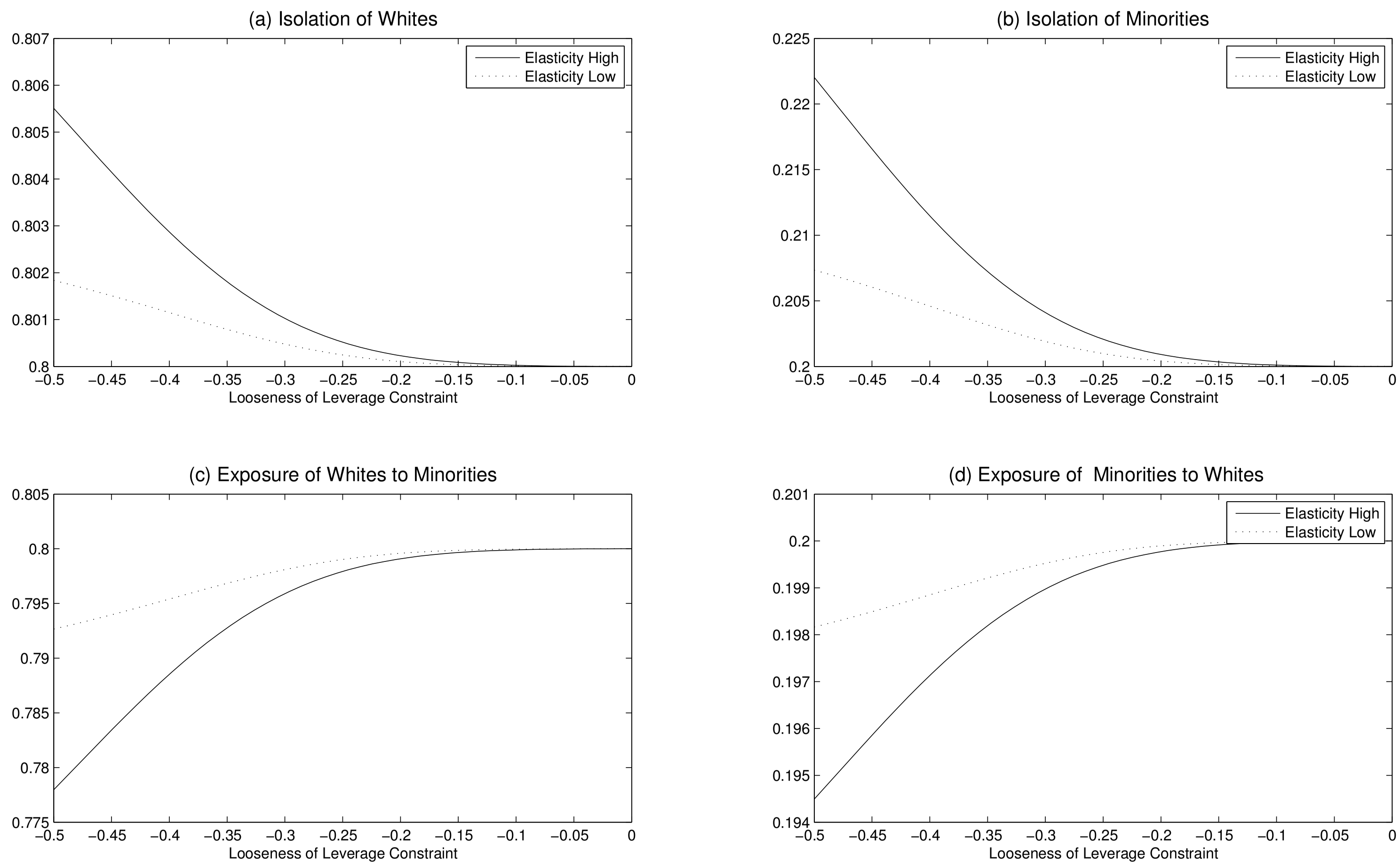


Figure 13: Simulation – Elasticity, Segregation, and Credit Constraints

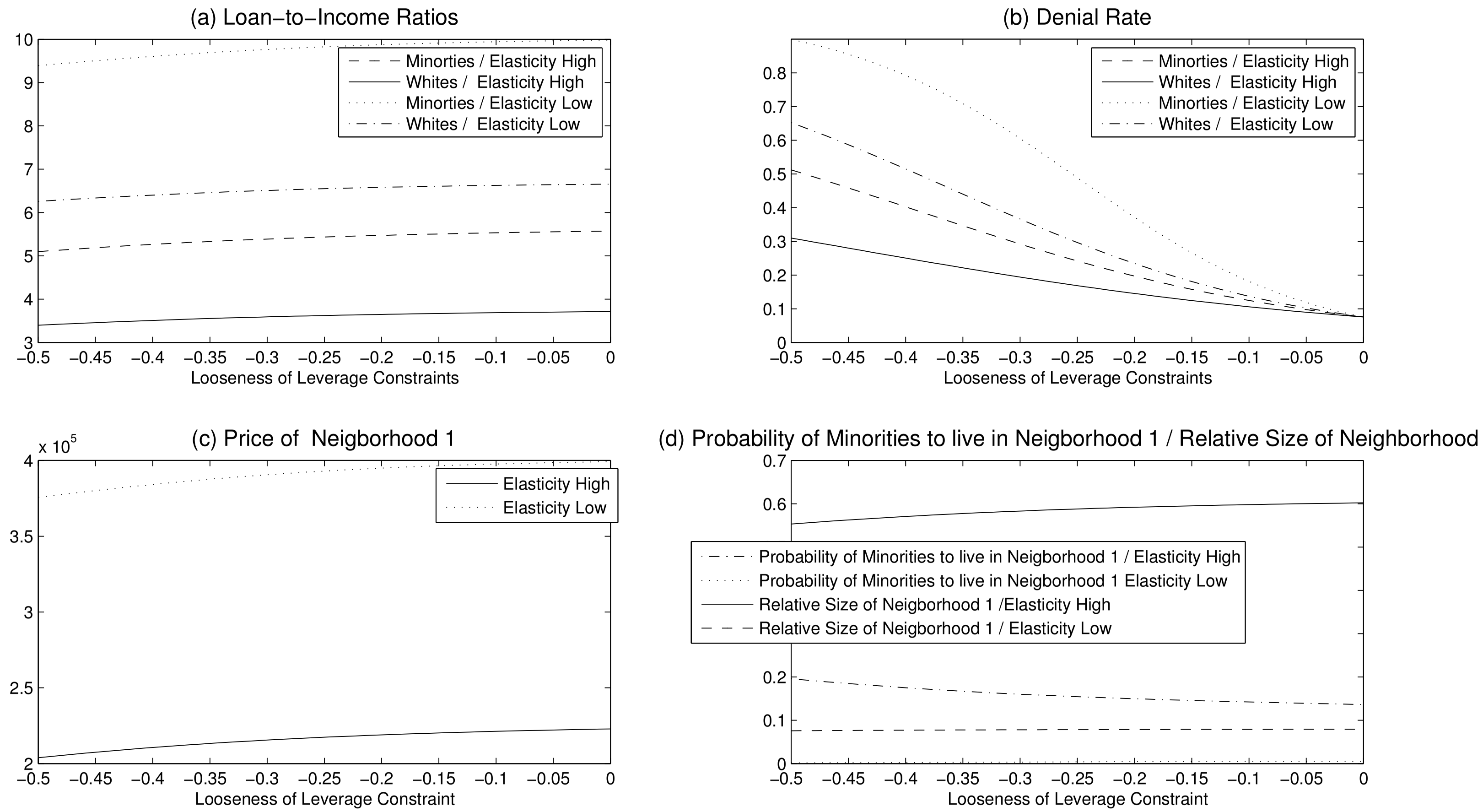


Figure 14: Simulation – Elasticity, Segregation, and Credit Constraints

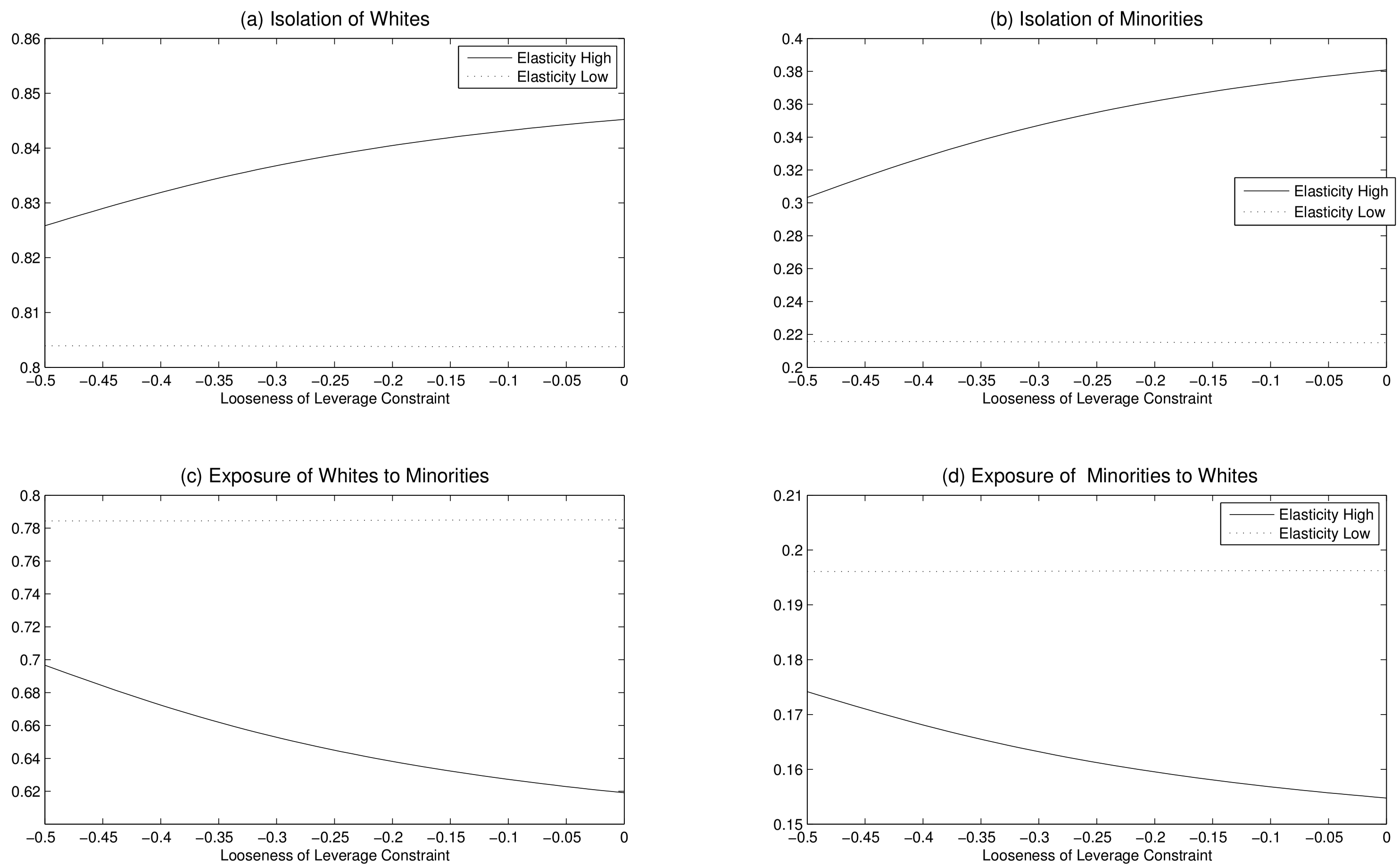
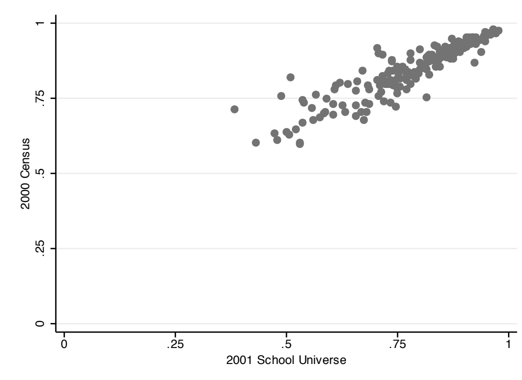


Figure 15: Simulation – Elasticity, Segregation, and Credit Constraints

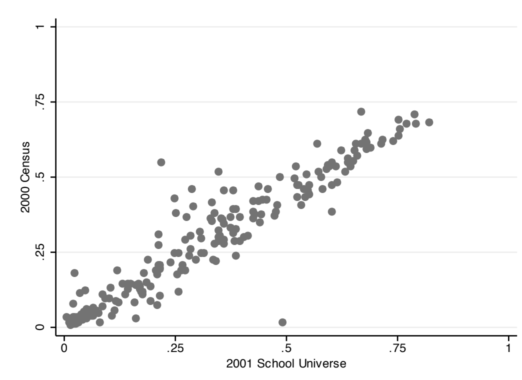
Year	1995	1997	1999	2001	2003	2005	2007
Isolation							
Isolation of Whites	80.3	79.8	79.2	78.2	76.8	75.6	74.2
Isolation of Blacks	51.9	50.5	50.8	50.4	50.2	50.1	49.0
Isolation of Hispanics	48.4	48.7	48.9	48.9	49.5	49.5	51.0
Isolation of Asians	21.1	21.7	21.9	21.3	21.5	21.6	22.1
Between School District Isolation							
Between LEA Isolation of Whites	77.8	77.4	76.7	75.5	74.0	72.7	71.1
Between LEA Isolation of Blacks	44.8	43.2	42.4	42.9	43.1	43.9	43.1
Between LEA Isolation of Hispanics	42.4	43.0	43.1	43.4	44.2	45.0	45.4
Between LEA Isolation of Asians	18.2	18.7	18.8	18.3	18.3	18.8	18.9
Exposure							
Exposure of Whites to Hispanics	6.6	6.9	7.6	8.2	8.9	9.4	10.3
Exposure of Hispanics to Whites	32.4	32.0	31.6	31.6	30.6	30.0	28.8
Exposure of Whites to Blacks	9.0	9.0	8.7	8.9	9.2	9.5	9.7
Exposure of Blacks to Whites	34.7	35.0	33.5	33.1	32.3	31.4	30.7
Exposure of Blacks to Hispanics	9.6	10.4	11.4	12.1	13.0	13.8	15.0
Exposure of Hispanics to Blacks	12.2	12.2	12.3	12.5	12.8	13.3	13.2
Fraction in Public Schools							
Overall	93.1	93.2	92.8	93.2	93.6	93.9	94.1
For Whites	90.9	90.8	90.1	90.6	90.9	91.1	91.3
For Blacks	97.2	97.1	96.8	96.9	97.0	97.1	97.0
For Hispanics	97.4	97.6	97.6	97.7	97.9	97.9	98.0
For Asians	94.1	94.4	94.4	93.9	94.7	96.0	95.0

Source: Public and Private School Universe, K12 schools.

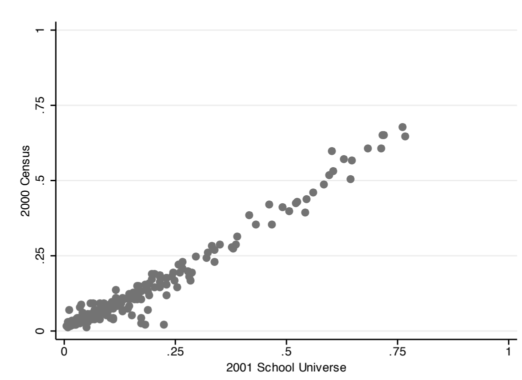
Table 1: School Segregation in Metropolitan Statistical Areas, 1995-2007



(a) Isolation of Whites



(b) Isolation of African Americans



(c) Isolation of Hispanics

Each point is a Metropolitan Statistical Area, defined using consistent 2003 boundaries of the U.S. Census Bureau. The horizontal axis is racial segregation across schools within the MSA, and the vertical axis is racial segregation across census tracts within the MSA. The 2001 Public and Private School Universe is used to compute school segregation.

Figure 16: School Segregation and Urban Segregation - Census 2000 and School Universe 2001

VARIABLES	(1) Fraction African American
Fraction African American in Nearest School	0.405**
	(0.017)
Fraction African American in 2nd Closest School	0.195**
	(0.019)
Fraction African American in 3rd Closest School	0.145**
	(0.018)
Fraction African American in 4th Closest School	0.050**
	(0.017)
Fraction African American in 5th Closest School	0.100**
	(0.016)
Fraction African American in 6th Closest School	0.048**
	(0.017)
Fraction African American in 7th Closest School	0.047**
	(0.016)
Fraction African American in 8th Closest School	0.016
	(0.015)
Fraction African American in 9th Closest School	0.019
	(0.015)
Frac. in Nearest School × distance	-0.039**
	(0.011)
Frac. in 2nd Closest School × distance	-0.048**
	(0.010)
Frac. in 3rd Closest School × distance	-0.033**
	(0.008)
Frac. in 4th Closest School × distance	-0.007
	(0.006)
Frac. in 5th Closest School × distance	-0.012*
	(0.005)
Frac. in 6th Closest School × distance	-0.008+
	(0.005)
Frac. in 7th Closest School × distance	-0.006
	(0.004)
Frac. in 8th Closest School × distance	-0.011**
	(0.004)
Frac. in 9th Closest School × distance	-0.001
	(0.003)
Observations	4,836
R-squared	0.782

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

The dependent variable is the fraction African American in each census tract. Controls include the distance with each school, dummies for schools further than 15 miles and 30 miles from the census tract. Source: Common Core of Data 2000, Public School Universe, matched with Census 2000.
Reading: An increase in the fraction of African American students in the nearest school by 10 percentage points predicts a 4 percentage point increase in the fraction African American in the census tract.

Table 2: Predicting Census Tract Composition with School Composition

VARIABLES	(1) Isolation of Whites	(2) Isolation of Blacks	(3) Isolation of Hispanics	(4) Isolation of Asians
Median LTI Ratio	0.331	2.448*	0.890	-0.404
	(0.329)	(1.174)	(0.597)	(0.771)
P90-P50 LTI Ratio	0.313	0.964	2.170**	0.187
	(0.379)	(1.360)	(0.620)	(0.907)
Acceptance rate	0.004	0.112*	0.046*	0.011
	(0.012)	(0.047)	(0.021)	(0.028)
log Applications	-0.329+	0.046	-0.012	-0.888+
	(0.170)	(0.642)	(0.226)	(0.481)
% White in MSA	0.778**	-0.085	-0.505**	-0.311
	(0.101)	(0.165)	(0.133)	(0.203)
% Hispanic in MSA	0.000	-0.003+	0.005**	-0.004+
	(0.001)	(0.002)	(0.001)	(0.002)
% Black in MSA	0.460**	0.923**	-0.241	-0.333
	(0.116)	(0.160)	(0.173)	(0.225)
% Asian in MSA	-0.100	-0.353	-0.136*	0.500**
	(0.076)	(0.264)	(0.061)	(0.056)
Observations	4,646	4,646	4,644	4,639
R-squared	0.997	0.993	0.997	0.997

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$, + $p<0.1$

Controls include MSA fixed effects, racial demographics of the MSA (that capture MSA-specific demographic trends), year dummies, measures of applicants credit worthiness (fraction jumbo, fraction subprime, fraction 90+ overdue and foreclosures 4 years after the year of observation, fraction of high risk loans as measured by 1995 credit standards). LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Acceptance rate is from 0 to 100%. Clustered by MSA.

Reading: If the median LTI ratio increases from 2 to 3, the isolation of black students increases by 1.1 percentage points. If the acceptance rate to Hispanics increases by 10 percentage points, the isolation of Hispanic students increases by 0.2 percentage points.

Table 3: Credit Standards and Segregation - Isolation

VARIABLES	(1) Whites to Hispanics	(2) Blacks to Hispanics	(3) Hispanics to Whites	(4) Blacks to Whites	(5) Whites to Blacks	(6) Hispanics to Blacks
Median LTI Ratio	0.318*	-1.218+	-0.735	-1.635	-0.417	-0.447+
	(0.157)	(0.626)	(0.653)	(1.015)	(0.317)	(0.257)
P90-P50 LTI Ratio	-0.112	-0.678	-0.949	0.466	-0.125	-0.452+
	(0.263)	(0.503)	(0.660)	(1.252)	(0.321)	(0.263)
Acceptance rate	0.003	-0.003	-0.031+	-0.111*	-0.012	-0.011
	(0.005)	(0.012)	(0.016)	(0.049)	(0.011)	(0.007)
log Applications	0.179*	0.252	-0.019	-0.175	0.082	0.072
	(0.073)	(0.229)	(0.180)	(0.696)	(0.102)	(0.088)
Observations	4,646	4,646	4,644	4,646	4,646	4,644
R-squared	0.999	0.998	0.996	0.989	0.995	0.996

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$, + $p<0.1$

Clustered at the year level. Controls include MSA fixed effects, and year dummies. LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Applicant Income is in $1,000.

Reading: If the median LTI ratio increases from 2 to 3, the exposure of white students to hispanic students goes up by 1.35 percentage points. If the volume of African American applications doubles, the exposure of blacks students to white students goes up by 1.79 percentage points.

Table 4: Exposure

	(1)	(2)	(3)	(4)
VARIABLES	Isolation of Whites	Isolation of Blacks	Isolation of Hispanics	Isolation of Asians
Median LTI Ratio	0.582	2.456*	1.515*	0.785
	(0.418)	(0.960)	(0.667)	(0.542)
P90-P50 LTI Ratio	-0.013	-0.746	1.167	0.051
	(0.518)	(1.660)	(0.902)	(0.477)
Acceptance rate	-0.026*	0.019	-0.025	-0.009
	(0.012)	(0.035)	(0.021)	(0.022)
log Applications	-0.309*	0.706	-0.202	-0.425+
	(0.143)	(0.694)	(0.143)	(0.253)
Observations	4,594	4,592	4,592	4,586
R-squared	0.996	0.992	0.997	0.997

Robust standard errors in parentheses
** $p<0.01$, * $p<0.05$, + $p<0.1$

Controls include MSA fixed effects, racial demographics of the MSA (that capture MSA-specific demographic trends), year dummies, measures of applicants credit worthiness (fraction jumbo, fraction subprime, fraction 90+ overdue and foreclosures 4 years after the year of observation, fraction of high risk loans as measured by 1995 credit standards). LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Acceptance rate is from 0 to 100%. Clustered by MSA.

Table 5: Credit Standards and Segregation - Segregation between School Districts Across MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Whites to Hispanics	Blacks to Hispanics	Hispanics to Whites	Blacks to Whites	Whites to Blacks	Hispanics to Blacks
Median LTI Ratio	-0.033	-0.235	-1.505*	-2.314*	-0.468	0.109
	(0.146)	(0.314)	(0.591)	(0.966)	(0.345)	(0.535)
P90-P50 LTI Ratio	-0.015	1.070*	-1.084	0.211	-0.056	0.626
	(0.272)	(0.506)	(0.740)	(1.341)	(0.365)	(0.575)
Acceptance rate	0.018**	0.016	-0.026	-0.044	0.011	0.048**
	(0.006)	(0.010)	(0.027)	(0.034)	(0.008)	(0.018)
log Applications	0.151*	-0.159	-0.007	-0.438	0.084	0.243*
	(0.066)	(0.158)	(0.145)	(0.715)	(0.100)	(0.097)
Observations	4,594	4,592	4,592	4,592	4,594	4,592
R-squared	0.999	0.998	0.996	0.989	0.994	0.995

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$, + $p<0.1$

Clustered at the year level. Controls include MSA fixed effects, racial demographics of the MSA (that capture MSA-specific demographic trends), year dummies, measures of applicants credit worthiness (fraction jumbo, fraction subprime, fraction 90+ overdue and foreclosures 4 years after the year of observation, fraction of high risk loans as measured by 1995 credit standards). LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Applicant Income is in $1,000.

Reading: If the median LTI ratio increases from 2 to 3, the exposure of white students to hispanic students goes up by 1.35 percentage points. If the volume of African American applications doubles, the exposure of blacks students to white students goes up by 1.79 percentage points.

Table 6: Segregation between School Districts Across MSAs - Exposure

VARIABLES	(1) Isolation of Whites	(2) Isolation of Blacks	(3) Isolation of Hispanics	(4) Isolation of Asians
Median LTI Ratio	0.319	2.214*	0.311	-0.165
	(0.334)	(1.098)	(0.482)	(0.773)
P90-P50 LTI Ratio	0.324	0.497	1.770**	0.345
	(0.385)	(1.407)	(0.553)	(0.883)
Median LTI Ratio × Elasticity	0.022	0.045	0.565*	-0.256
	(0.186)	(0.510)	(0.257)	(0.340)
P90-P50 LTI Ratio × Elasticity	-0.153	1.339	0.851+	-0.742
	(0.274)	(0.894)	(0.484)	(0.507)
Acceptance rate	0.004	0.112*	0.039+	0.012
	(0.012)	(0.043)	(0.021)	(0.028)
log Applications	-0.341*	0.127	-0.052	-0.880+
	(0.173)	(0.572)	(0.232)	(0.470)
Observations	4,646	4,646	4,644	4,639
R-squared	0.997	0.993	0.998	0.997

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$, + $p<0.1$

Controls include MSA fixed effects, racial demographics of the MSA (that capture MSA-specific demographic trends), year dummies, measures of applicants credit worthiness (fraction jumbo, fraction subprime, fraction 90+ overdue and foreclosures 4 years after the year of observation, fraction of high risk loans as measured by 1995 credit standards). LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Acceptance rate is from 0 to 100%. Clustered by MSA.

Table 7: Credit Standards and Segregation - Elasticity Interactions

VARIABLES	(1) Whites to Hispanics	(2) Blacks to Hispanics	(3) Hispanics to Whites	(4) Blacks to Whites	(5) Whites to Blacks	(6) Hispanics to Blacks
Median LTI Ratio	0.300+	-1.097+	-0.114	-1.557	-0.394	-0.381
	(0.161)	(0.570)	(0.525)	(0.985)	(0.321)	(0.249)
P90-P50 LTI Ratio	-0.122	-0.586	-0.518	0.813	-0.127	-0.405
	(0.263)	(0.463)	(0.575)	(1.283)	(0.320)	(0.268)
Median LTI Ratio × Elasticity	0.035	-0.149	-0.540*	0.146	-0.042	-0.037
	(0.075)	(0.135)	(0.230)	(0.561)	(0.150)	(0.119)
P90-P50 LTI Ratio × Elasticity	0.049	-0.071	-1.088**	-1.244	0.086	-0.171
	(0.100)	(0.218)	(0.418)	(0.985)	(0.211)	(0.179)
Acceptance rate	0.003	-0.002	-0.024	-0.113*	-0.012	-0.010
	(0.005)	(0.012)	(0.016)	(0.047)	(0.010)	(0.006)
log Applications	0.188*	0.211	0.023	-0.203	0.085	0.076
	(0.076)	(0.217)	(0.192)	(0.636)	(0.103)	(0.088)
Observations	4,646	4,646	4,644	4,646	4,646	4,644
R-squared	0.999	0.998	0.996	0.989	0.995	0.996

Robust standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Controls include MSA fixed effects, racial demographics of the MSA (that capture MSA-specific demographic trends), year dummies, measures of applicants credit worthiness (fraction jumbo, fraction subprime, fraction 90+ overdue and foreclosures 4 years after the year of observation, fraction of high risk loans as measured by 1995 credit standards). LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Acceptance rate is from 0 to 100%. Clustered by MSA.

Table 8: Credit Standards and Segregation - Exposure - Elasticity Interactions

VARIABLES	(1) Whites	(2) Blacks	(3) Hispanics	(4) Asians
Median LTI Ratio	-0.127	-0.695	-0.042	-0.699
	(0.735)	(0.791)	(0.897)	(0.969)
P90-P50 LTI Ratio	0.418	-1.390	0.892	0.768
	(1.222)	(1.636)	(1.458)	(1.997)
Acceptance rate	-0.011	0.014	0.024	0.010
	(0.015)	(0.018)	(0.023)	(0.024)
log Applications	0.356	0.471	-0.172	0.352
	(0.392)	(0.477)	(0.257)	(0.334)
Observations	2,559	2,559	2,559	2,558
R-squared	0.874	0.577	0.730	0.775

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$, + $p<0.1$

Controls include MSA fixed effects, racial demographics of the MSA (that capture MSA-specific demographic trends), year dummies, measures of applicants credit worthiness (fraction jumbo, fraction subprime, fraction 90+ overdue and foreclosures 4 years after the year of observation, fraction of high risk loans as measured by 1995 credit standards). LTI: Loan-to-Income Ratio. MSA: Metropolitan Statistical Area. Acceptance rate is from 0 to 100%. Clustered by MSA.

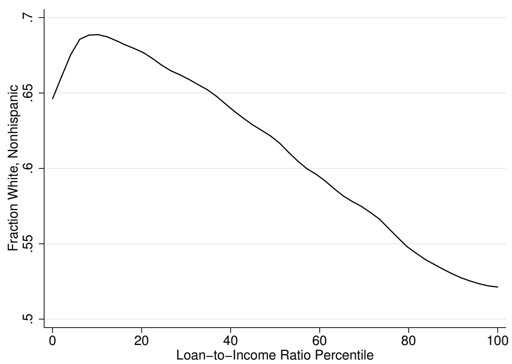
Table 9: Public/Private

Appendix

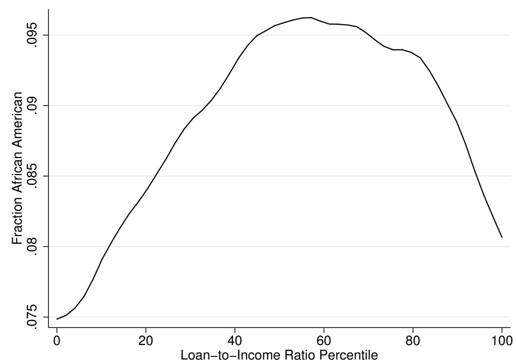
The distribution of leverages accross ethnic group.

Section 3.7 presents results that show the strong effect of leverage on the segregation of Whites and on the segregation of Hispanics.

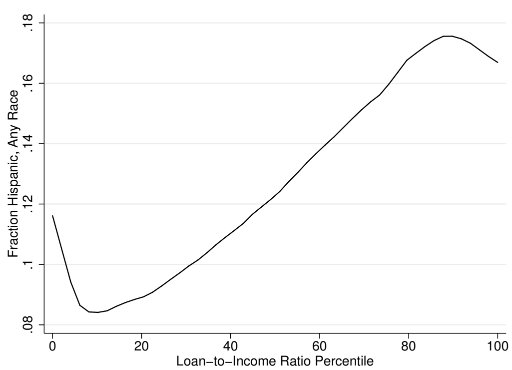
Figure 17 shows the fraction of each racial group at each percentile of the Loan-to-income distribution in 2004. The graph shows that Hispanics are overepresented among highly levered borrowers, and African American among borrowers with median leverages. The fraction of African American borrowers is highest at the median leverage. Interestingly, there are twice as many Asian borrowers for the highest Loan-to-income ratios (between 8 and 9%) than for the lowest Loan-to-Income ratios (between 3 and 4%).



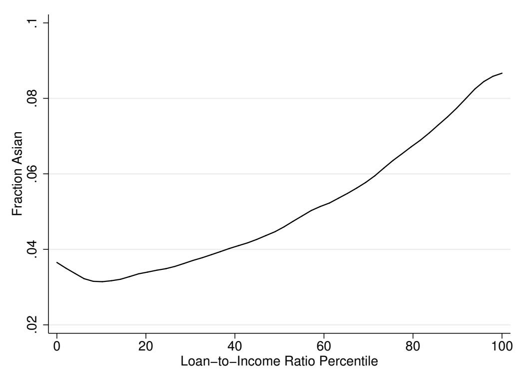
(a) White



(b) African American



(c) Hispanic



(d) Asians

Figure 17: Distribution of Races at Percentiles of the Loan-to-Income Ratio