GENTRIFICATION AND RETAIL CHURN: THEORY AND EVIDENCE

By

Edward L. Glaeser[1], Michael Luca[2]

Harvard University and NBER

and

Erica Moszkowski [1,3]

Harvard University

April 15, 2022

Abstract

How does gentrification transform neighborhood retail amenities? This paper presents a model in which gentrification harms incumbent residents by increasing rental costs and by eliminating distinctive local stores. While rising rents can be offset with targeted transfers, the destruction of neighborhood character can – in principle – reduce overall social surplus. Empirically we find that gentrifying neighborhoods experience faster growth in both the number of retail establishments and business closure rates than their non-gentrifying counterparts. However, we see little evidence that gentrification is associated with changes in retail mix or prices – suggesting limited welfare losses.

---

[1] Glaeser and Moszkowski have no competing interests.

[2] Luca has done consulting for tech companies, including Yelp, but his compensation and ability to publish not tied to the results of this paper.

[3] Moszkowski gratefully acknowledges support from the National Science Foundation Graduate Research Fellowship. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Abstract

How does gentrification transform neighborhood retail amenities? This paper presents a model in which gentrification harms incumbent residents by increasing rental costs and by eliminating distinctive local stores. While rising rents can be offset with targeted transfers, the destruction of neighborhood character can – in principle – reduce overall social surplus. Empirically we find that gentrifying neighborhoods experience faster growth in both the number of retail establishments and business closure rates than their non-gentrifying counterparts. However, we see little evidence that gentrification is associated with changes in retail mix or prices – suggesting limited welfare losses.

I. Introduction

Does gentrification destroy neighborhoods and generate negative externalities for existing neighborhood residents? Vigdor (2002 and 2010) defines gentrification as an increase in demand to live in a formerly high poverty neighborhood. Rising rents will cause long-term tenants to lose and landlords to gain, but there is no larger welfare gain from preventing neighborhood change. According to this view, if renters were compensated for rising rents, through community land trusts or other social programs, then gentrification could benefit everyone.

Yet protesters argue that the adverse impacts of gentrification go beyond higher rents and include the destruction of community assets, such as ethnic restaurants and social cohesion.[1] This view suggests that gentrification might generate harmful externalities that more than offset the benefits that accrue to landlords.[2] In this paper, we present a model in which gentrification can reduce overall social welfare through an endogenous change in retail amenities. As higher paid residents enter, stores enter that specialize in time-saving services for them, like providing hot

[1] Newman and Wyly (2006) discuss the displacement created by gentrification and community opposition that the gentrification process. Betancur (2011) identifies a negative effect of gentrification on "community fabric" in Chicago.

[2] Sullivan (2007) finds a generally positive view of gentrification using survey data, but renters and minorities are more negative than the average respondent. These findings are compatible with the view that rising rents are a primary negative effect of gentrification.

coffee, and these replace idiosyncratic stores that generate more consumer surplus. The key distinction is that a reduction in the number idiosyncratic stores is like a drop in the number of product varieties, while an increase in the number of generic service stores provide the same goods but at a lower time cost.

The model shows how welfare-reducing gentrification could happen, but does not imply that welfare is actually being reduced. The model also examines the (slightly different) implications of another driver of retail closures that is important during our time period. In the model, improvements in e-commerce will also lead to business closures, as shops that sell tradable goods are replaced by shops that sell both generic and idiosyncratic services. The model predicts that the key empirical distinction between a gentrification shock and an e-commerce shock is that gentrification increases the number of stores and e-commerce reduces the total number of stores. We indeed find that, in our 5 cities, gentrification is associated with a modest increase in establishments at the zip code-category level.

The model also predicts that gentrification is associated with more exit of idiosyncratic goods-selling stores and an increase in the number of generic service-supplying stores. We use data from Yelp to analyze whether gentrification is associated with a greater number of retail closures or a shift from idiosyncratic services to generic services (as measured by the presence of chain stores). We find only modest empirical evidence, in both OLS and IV analyses, that gentrification in our 5 cities is associated with higher closure rates. We also find modest evidence that chains are more likely to move into the vacant storefronts left behind.

We focus on the three largest U.S. cities (New York, Los Angeles, and Chicago) and two smaller cities that are known for their high levels of education and limited local housing supply (San Francisco and Boston). We use Yelp data from 2012 to 2017 to measure store closings and changes in prices, as measured by the number of dollar signs on Yelp listings. We define gentrifying areas as places with high initial poverty, relative to the city as a whole, and a large increase in the share of the population with a college degree between 2012 and 2017.

While the average closure rates in four of our five cities are higher in poor areas that do not gentrify than in gentrifying areas, our regressions find that closure rates increase with growth in the share of the population that is college educated and that this effect is stronger in places that were initially poor. The magnitude of the effect, however, is modest. A four-percentage point growth in the college-educated share is associated with a 2.4 percentage point increase in the closure rate in an initially poor area. Rent growth is also associated with higher closure rates in initially poor places, but the effect is also modest.

We also find that gentrification is associated with increases in the total number of establishments. A four-percentage point increase in the share of the population with a college degree is associated with a 2.5-percentage point increase in the total number of establishments in places that are initially poor. As the model predicted, gentrification is associated both with an increased rate of closure and growth in the total number of stores.

To address causality, we follow the logic of the model and choose instruments which are likely to be correlated with an increased influx of gentrifiers. Our instruments are the share of college graduates in nearby zip codes, past housing price growth in nearby zip codes, and the interaction between the two. The key assumption is that the instruments only impact local retail detail through their impact on neighborhood change. As gentrifying neighborhoods are typically not in the city center, it is less likely that local retail demand is driven by customers outside of the zip code. Our tests of the exclusion restriction do not reject this assumption. Our instrumental variable results identify a significant effect of increase in the college educated share on store closures, but there is little difference between initially rich and initially poor areas in the impact of education.

We examine retail churn by looking at whether gentrification is particularly associated with either the closure of idiosyncratic stores or whether stores that close are likely to be replaced (in the same storefront) by more generic chain stores. We do not find that gentrification is more likely to lead non-chain stores to close. We do however find that franchisees, but not franchisors (corporate-owned chain stores) are less likely to close as education in an initially poor area increases. Non-chain stores which Yelp assigns one dollar sign correspond best to idiosyncratic stores in the model, but we do not find that they are more likely to shut down in gentrifying areas.

We find that stores are overall less likely to be replaced by chains in areas with increases in the level of education, but the effect is reduced in initially poor, gentrifying areas. We do not find that gentrification is significantly linked to increases in dollar signs. Taken together, these results suggest that gentrification is correlated with slightly higher store closure rates, but little change in the composition or price point of retail stores.

Our results do not imply that gentrification comes without costs. Residents of poorer areas who are used to long-run stability may be understandably surprised and troubled by the rate of change. One definition of gentrification we explore is rising rental costs, which are likely to hurt most long-term renters. Moreover, the Yelp data is coarse and it is certainly possible that some stores are subtly changing their character in important ways. However, the Yelp data does not suggest the sort of retail Armageddon that is sometimes suggested by anti-gentrification advocates. While our model admits the possibility that strong planning controls that limit change could be welfare improving, our results suggest that the losers from gentrification are more likely to benefit from standard income redistribution rather than from retail related restrictions aimed at preserving neighborhood character.

Our paper provides novel insight into the endogenous response of retail amenities to gentrification. Our model demonstrates that gentrification has the potential to create a welfare loss driven by shifts in the mix of businesses in an area. To our knowledge, our model is the first to shed light on this aspect of the economics of gentrification. Moreover, our model guides our empirical strategy, including our instrument, and also helps to guide our interpretation of the empirical results.

While existing work has shown that shifts in the small business landscape are early predictors of gentrification (e.g. Behrens et al forthcoming, Glaeser, Kim and Luca 2018), there is a less clear picture of the impact of gentrification on business outcomes. Meltzer (2016) finds no impact of neighborhood-level gentrification on store closure and turnover in New York City between 1990 and 2010. In contrast, our results look at 5 cities from 2013-2017, a period marked by rapid growth of e-commerce. During our period, gentrification is associated with higher closure rates. Our data, which includes storefront level data with precise location, and a rich set of business attributes, provides us with a compelling opportunity to explore these issues.

Our results also relate to a recent literature on neighborhood choice, which has found that college graduates' location choices are responsive to the prevalence of local non-tradable services (Couture and Handbury 2020). One strand of this literature endogenizes retail responses to gentrification in structural models (for example, Su 2022), but employ an assumed amenity supply curve to match more aggregate data on retail amenities. While we do not write a structural model integrating amenity provision and neighborhood choice, we are able to exploit establishment-level microdata in our analysis.

Finally, though Baum-Snow and Hartley (2020) emphasize the importance of racial differences in valuations of local amenities in driving urban gentrification, relatively few papers in the gentrification literature expressly allow for variation in preferences. Even the structural papers we reference here primarily use a logit model rather than a random coefficients logit model that would allow different demographic groups to have different preferences. By contrast, our model proposes a microfoundation for differences in retail demand between poor incumbent residents and the richer “gentrifiers”: the rich have a higher value of time, leading them to demand more generic services (e.g. coffee shops) that help them save time. This assumption is consistent with other results in the literature, especially Su (2022), who argues that an increase in the time premium for the rich is the driving force behind gentrification. We focus on the implication of this assumption on retail mix, and specifically map generic services to chain retailers. In our data, while 11.5% of stores in rich neighborhoods are chains, only 7.32% of stores in poor neighborhoods which don’t gentrify during our study period are chains. Neighborhoods that start out poor but subsequently gentrify over the 2013-2017 period have a chain share of 7.29% in 2013, which is comparable to the poor neighborhoods which don’t gentrify. Our model predicts that as the share of rich residents rises (which we call gentrification), rich residents’ demand for generic services crowds out other types of retail stores.

The paper proceeds as follows. In section 2, we present our model of gentrification, which makes several empirical predictions we test in subsequent sections. In section 3, we describe our measure of gentrification and show summary statistics for gentrifying, poor but non-gentrifying and rich areas. In section 4, we introduce the Yelp data and benchmark it against the County Business Patterns. We use the County Business Patterns to provide context on the overall amount of establishment growth in our 5 cities, before turning to our closure analysis in section 5. In section 6, we discuss the impact of gentrification on retail mix, focusing on within-storefront turnover. Section 7 concludes.

II. Gentrification and Retail: A Model of Redistribution and Externalities

Individuals allocate their time between working or producing generic services, and choose amounts of traded goods, generic services, and idiosyncratic services, to maximize:

$$(1)\quad U_T(Traded\ Goods) + U_G(Generic\ Services) + \sum_j U_j(Idiosyncratic\ Services) + \theta_i^k$$

where θ_i^k represents individual i's preference for neighborhood k. Traded goods act as the numeraire good and can be purchased online at a price of one. Traded goods can also be bought locally at an endogenous price. Idiosyncratic services, such as ethnic food or specialized hair salons, must be bought locally and cannot be produced at home. Generic services, such as a hot coffee, can either be bought locally at no time cost, or made at home for a cash cost of p_h and a time cost of q. For example, an espresso can either be bought at Starbucks or made in your kitchen, as long as you have purchased a machine and espresso beans. Each individual has one unit of time that can be allocated either to working for a wage of Y_i or to producing generic services.

If the price of traded goods is p_t (which will equal 1 if goods are bought online), then the total budget constraint is:

$$(2)\ Y_i(1-\omega G) = p_t T + G\big(\omega p_h + (1-\omega)p_g\big) + \sum_j P_j Q_j + R^k,$$

where G and T refer to the quantity of generic services and traded goods respectively, ω represents the share of generic services that is made at home, p_g is the endogenous local price of the generic services, P_j and Q_j are the price and quantity consumed of idiosyncratic service j, and R^k represents the rent in neighborhood k.

Within this framework we will focus on a single neighborhood, which we refer to as the community. There is a fixed number H of identical homes in this community and each home houses exactly one individual. We will refer to $R^k H$ as the "property value" of the neighborhood. We assume individuals can have one of two income levels, $\underline{Y}$ and $\overline{Y}$, where $\overline{Y} > \underline{Y}$. We assume that neighborhood preference $\theta_i^k = 0$ for the rich individuals in community k and $\theta_i^l = 0$ for all other neighborhoods $l \neq k$ for the poor. For a poor individual i, the taste for living in the community θ_i^k is drawn from a uniform distribution with mass H on the interval $[0, \theta_0]$. Therefore, if the share of the community that is rich equals r (and so there are $(1-r)H$ poor people in the community) then the marginal poor resident has a taste for living in the community of $r\theta_0$. We are concerned with welfare defined as the sum of property value and total utility of the inframarginal poor.

We make the following functional form assumptions on consumer utility. Utility for traded goods is linear, $U_T(X) = X$. Utility for generic services is linear up to a limit, $U_G(X) = \delta Min[X, q_G]$, and utility from idiosyncratic services is quadratic $U_j(X) = \frac{1}{\beta}(AQ_i - .5Q_i^2)$, with AH>1. We also assume that $\delta > p_G + q_G\,\overline{Y}$, which ensures that everyone will always consume q_G units of the generic service. The reservation utility of the poor outside the community is $\underline{Y}(1-q_G) - p_G q_G + \delta q_G + \underline{U}$, and the welfare of the rich outside the community equals $\overline{Y}(1-q_G) - p_G q_G + \delta q_G + \underline{U} + \Delta$. Δ denotes the difference in reservation utilities between the poor and the rich.

The community contains stores that sell traded goods, generic services and idiosyncratic services, and the cost of opening up a store is $k_0 + k_1 S + \underline{Y}$, where S is the total number of stores. All stores are capacity constrained to sell at most one unit of goods or services.

Goods stores purchase, produce and sell goods at a cost of $1 - \tau + \varphi_T N_T$, where N_T refers to the number of traded goods stores in the community. We assume costs are increasing in the number of traded goods stores to capture congestion in transportation at the local level. The parameter τ reflects the edge the brick-and-mortar retail enjoys over e-commerce, and we interpret improvements in e-commerce as reductions in τ.

Generic services have a marginal cost of $p_G + q\underline{Y} + \varphi_G N_G$, where N_G refers to the number of generic service stores in the community, and $\varphi_G > 0$. If the number of firms in the community have total capacity equal to exactly $q_G rH$, then we assume that the equilibrium price will generate zero profits. The marginal cost of supplying idiosyncratic services is $\varphi_I N_I$. The providers of idiosyncratic services have the capacity to set monopoly prices.

Given the linearity of this model, we must make a set of additional parameter assumptions to guarantee interior solutions to the number of stores of different varieties and the number of rich people in the neighborhood. To ensure that there are idiosyncratic service providers and traded goods in equilibrium, we assume that $Min\left[\frac{AH-1}{\beta H}+\frac{k_1}{\varphi_T}\left(\frac{AH-1}{\beta H}-\tau\right), \tau+\frac{k_1}{\varphi_I}\left(\tau-\frac{AH-1}{\beta H}\right)\right] > \underline{Y} + k_0 + k_1 q_G H$. Intuitively, this condition requires that the returns to selling traded goods and the return to idiosyncratic services are reasonably similar, which means that $\left|\frac{AH-1}{\beta H}-\tau\right|$ cannot be too large, and these returns outweigh the costs of opening a store. To ensure that the idiosyncratic service providers sell their full capacity, we assume that $\frac{k_1}{\varphi_T}\frac{AH-1}{\beta H}+\frac{k_1\tau}{\varphi_T}+\underline{Y}+k_0 > 1+\frac{k_1(\varphi_I+\varphi_T)}{\varphi_I\varphi_T}$. To ensure that the equilibrium share of the rich is less than one, we assume that $\frac{\theta_0+\Delta}{q_G} > \overline{Y}-\underline{Y}$, which means that there are some poor people who really care about living in the community. Finally, to ensure that equilibrium share of the rich is positive and that there are exactly enough generic service providers to cover the demand from the rich, we assume that $\left(1+\frac{k_1(\varphi_I+\varphi_T)}{\varphi_I\varphi_T}\right)\left(\overline{Y}-\underline{Y}\right)$ is greater than $\frac{k_1}{\varphi_I}\left(\frac{AH-1}{\beta H}\right)+\frac{k_1\tau}{\varphi_T}+\underline{Y}+k_0+\left(1+\frac{k_1(\varphi_I+\varphi_T)}{\varphi_I\varphi_T}\right)Max\left[-\frac{\Delta}{q_g}, q_G H\left(\varphi_G+\frac{k_1\varphi_I\varphi_T}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\right)\right]$. This assumption requires that the value of time is much higher for the rich than for the poor.

We characterize the equilibrium and prove the following propositions (we relegate the proofs to Appendix A).

Proposition 1: Suppose

- Δ denotes the reservation utility of the rich
- $\underline{Y}$ and $\overline{Y}$ denote the incomes of the poor and the rich, respectively
- S denotes the total number of stores, N_T denote the number of tradable goods stores, N_G
- $k_0 + k_1 S + \underline{Y}$ is the cost of opening a store, where S is the number of stores and
- the cost of selling tradable goods is $1-\tau+\varphi_T N_T$ for brick-and-mortar stores and $1+\varphi_T N_T$ for e-commerce
- the marginal cost of selling generic services is $p_G + q\underline{Y} + \varphi_G N_G$, where $\varphi_G > 0$
- the marginal cost of supplying idiosyncratic services is $\varphi_I N_I$.
- q_T, q_G, q_I denote quantities of tradable goods, generic services, and idiosyncratic services
- H is housing supply

- R^k denotes rent in neighborhood k
- $1/\beta$ is the weight on idiosyncratic services in the consumer's utility function
- The poor have a preference for the neighborhood which is drawn from Uniform[0,θ_0]

A gentrification shock that causes Δ to decrease will cause (1) the share of the community that is rich and the number of generic service stores to increase, and (2) the number of stores that sell idiosyncratic services and traded goods to decrease. A decrease in Δ will cause property values to fall if and only if $\frac{k_1\varphi_T q_G}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)} > 2\beta H\theta_0$ and will cause welfare to fall if and only if $\frac{k_1\varphi_T q_G}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)} > 2(1-r)\beta H\theta_0$.

In Proposition 1 a downward shift in the reservation utility of the rich (Δ) leads to an increase in the share of rich people in the community or gentrification. Since we have assumed that the poor have idiosyncratic preferences for the neighborhood but the rich do not, this shift causes a loss of welfare. As long as long-term residents have heterogeneous tastes for remaining in that community while newcomers are simply looking for cheap space, then the replacement of long-time residents with in-migrants will cause some welfare loss.

The more important empirical prediction of the model is that gentrification leads generic service providers to crowd out both stores that sell traded goods and stores that sell idiosyncratic services. Overall, post-gentrification stores will cater more to the rich and the number of stores will increase. We will test for these outcomes later in the paper. The generic services can be made at home, but the value of the time of the rich is so high that they are willing to pay for these services, while the poor provide them at home. The generic service providers crowd out the traded goods stores, which doesn't impact welfare, and the idiosyncratic service providers, which does reduce welfare. The willingness to pay for both the rich and poor declines when there are fewer shops selling idiosyncratic services, since each shop creates inframarginal welfare for consumers.

The overall impact on rent and welfare from a gentrification shock is ambiguous. Property values go up because of increased demand from the rich, but down because of the elimination of idiosyncratic service providers. Overall welfare can go down, even if property values go up, because of the lost inframarginal welfare among the poor long-term residents. This proposition motivates our empirical focus on the changing retail composition of gentrifying neighborhoods.

Proposition 2 focuses on an e-commerce shock, which also hit American cities during the 2010s:

Proposition 2: An e-commerce shock that causes τ to decrease will cause the number of total stores and the number of traded good stores to decrease, but the number of idiosyncratic and generic service stores will increase, as will the number of rich residents, total property values and total welfare.

The model predicts that e-commerce leads traded goods shops to close and be replaced by a mix of stores selling idiosyncratic and generic services. Those generic services will attract the rich, so gentrification can actually be increased by a negative shock to tradable good stores. The model predicts that this negative shock to brick-and-mortar retail will increase both property values and welfare, but those predictions could easily be reversed in a model with vacancies or upward sloping labor supply.

Propositions 1 and 2 suggest that a key difference between gentrification and e-commerce is that an e-commerce shock will cause the overall number of stores to decline, while a gentrification shock will have the opposite effect. As we turn to the data, we will test this prediction. Then we will focus both on overall changes in closure rates and changes in price points. We will also look at whether transitions appear to primarily represent the replacement of local stores with more expensive ones, which is the process predicted by gentrification, or the replacement of stores that sell tradable goods with stores that sell non-tradable services, which is the process predicted by the technological march of electronic commerce.

III. Gentrification and Establishment Growth

Our model is static, but we interpret the comparative static results on a shift in gentrification or e-commerce costs as helping us to understand neighborhood dynamics. Indeed, if a neighborhood was an equilibrium in one period, and then there was a shock to one of these parameters, and everyone could freely re-optimize after the shock, then the model does describe the change between the two periods. Consequently, the model generates predictions about the change in the number of establishments, which we can test using County Business Patterns, and business closures, which would occur when shops that sell generic services replace idiosyncratic or traded good shops.

In particular, our model generates the following empirical question: in areas where gentrification is occurring, is there a corresponding and contemporaneous change in the nature of neighborhood retail stores? Answering this question requires us to measure which neighborhoods within a city are gentrifying, and then to measure the correlation between the degree of gentrification and different forms of retail change. There are almost as many ways to measure gentrification as there are papers about the subject, and we cannot hope to use every definition. In this section, we introduce our measure of gentrification, and discuss the extent and geography of gentrification in our five cities: Boston, Chicago, Los Angeles, New York, and San Francisco. We then assess the impact of gentrification on overall establishment growth using the County Business Patterns.

Measuring Gentrification in the Five Cities

Our measure of gentrification in this paper is based on data from the American Community Survey (ACS). These data are only available at the Census ZIP Code Tabulation Area (ZTCA) level in 5-year windows. We will refer to ZCTAs as "zip codes" throughout the paper. To take advantage of the most recent data possible, we compare zip codes across the 2008-2012 and 2013-2017 vintages of the ACS.

In all five cities, we define the set of neighborhoods that *could* gentrify as those zip codes with poverty rates greater than the city's median poverty rate in the 2008-2012 ACS. We made this restriction because the term gentrification is generally associated with a rapid inflow of wealthier residents who push out poorer long-term residents, and wanted to specifically look at neighborhoods where there was a significant share of poor residents that could be displaced. This classification gave us thirteen potential gentrifying zip codes in San Francisco and fifteen in Boston. The same definition implied that there were thirty zip codes that could gentrify in Chicago, fifty-four in Los Angeles and sixty-seven in New York City.

Glass (1964) coined the term gentrification to refer to population changes that were happening in the London neighborhood of Islington, where more educated urban professionals were replacing the area's historically working-class population. "Gentry" and "college educated" may not be synonymous, but they are as close as is possible within the heterogeneous American population.[3] The first question we ask is whether poorer neighborhoods that see increases in share of the population that is college educated also experience increase in property values. Specifically, we take the same set of zip codes that *could* gentrify and order them by percentage-point increase in share college educated rather than rent growth. For our descriptive work, as pictured in Figure 1, we will define the zip codes in top half of this group as gentrifying. In our regressions, we will use a continuous measure of change in the share of the population with a college degree, interacted with a dummy for whether the zip code's poverty rate is above the city median.

zip code level changes in the proportion of adults who are college educated is correlated with other measures of demographic change that are highlighted by the Urban Displacement Project (2019). We control for other demographic variables in the ACS, including median income, share of the population which is white, Black, and Asian, and the share of the population aged 25-34. We supplement these controls with the share of the zip code land area devoted to parks, distance to city hall, and the density of retail establishments in the zip code.

Table 1 looks at how gentrifying neighborhoods, defined on the basis of initial poverty and change in the share of college graduates, differ along demographic, housing market and retail market dimensions from other initially poor areas that experienced less gentrification Our definition of gentrification split the higher poverty zip codes into two equal groups based on rent growth. We use one, two, and three stars to denote cases in which the gentrifying and non-gentrifying poorer areas differ in a way that is statistically significant at 10, 5, and 1 percent level. These differences are quite rare in the small cities, even though magnitudes may differ, because the overall number of zip codes is quite small.

The first panel of Table 1 shows that the only demographic variable that shows sharp differences between gentrifying areas and non-gentrifying areas is the change in the share of the population with a college degree, which reflects our definition of gentrification. In fact, gentrifying and poor non-gentrifying areas are surprisingly similar on other demographic and housing market characteristics, at least prior to 2013. Gentrifying neighborhoods are always closer to the city

[3] McKinnish, Walsh and White (2010) find that gentrification often takes the form of better educated minorities replacing older residents.

center than non-gentrifying neighborhoods, but (as the maps suggest) the differences are only statistically significant in New York and Los Angeles. The only city with significant differences between poor and gentrifying areas is Los Angeles, which has the most zip codes and therefore the most power to identify statistically significant differences.

We measure changes in housing value with growth in the median zip code rents in the between the 2008-2012 and 2013-2017 American Community Survey (ACS). Initial rents are lower in the gentrifying areas of Los Angeles and San Francisco, but not in the other cities. Rent growth is larger in the gentrifying areas of the big cities, but lower in the gentrifying areas of the small cities. This pattern is compatible with the model if $\frac{k_1 \varphi_T q_G}{\varphi_I \varphi_T + k_1(\varphi_I + \varphi_T)} > 2\beta H \theta_0$ holds in the small cities, but not in the big cities, perhaps because the costs of opening new stores (captured by k_1) is particularly high in those places. There is little difference, outside of Los Angeles, in the share of homes that are single family, the share of homes with two or fewer bedrooms and the share of the population taking public transportation to work.

The third panel shows that there are more retail establishments in the gentrifying areas in all five cities, but the difference relative to non-gentrifying areas is only significant in Los Angeles. The last two columns show little difference in the retail diversity between the two types of neighborhoods. We look at growth in the number of establishments by city and gentrification status in Table 3.

We now look at maps of gentrification in our five cities and at the connection between gentrification and price changes. Figure 2 provides maps of gentrification based on change in the share of the adult population that has a college degree. For each city, the lightly colored zip codes show areas that were above the median city-wide poverty rate in 2012, the dark red zip codes show gentrifying areas, and the orange areas show areas that are poor but not gentrifying. A black circle surrounds the centroid of the zip code containing city hall. Next to each map showing gentrification, we place a second map showing median residential rent growth.

In our large cities (New York, Los Angeles, and Chicago), gentrification occurs close to the city center, but also in certain pockets farther from the city center. In the smaller cities, this is not the case, primarily because they are also smaller places geographically and have only a modest number of zip codes. The correlation between the change in the college share and rent growth varies across our 5 cities. In most cities, areas closer to downtown are also more likely to see rents rise. We discuss these patterns in each of our cities in detail in Appendix B.

Overall Establishment Growth and Gentrification in the Five Cities

In this section, we answer our model's primary empirical question: did the total number of establishments in gentrifying areas grow during our time period? In Table 2, we show the growth rates in the number of establishments across categories in all five cities, using the establishment counts from the County Business Patterns. To match the Yelp data we will use later, we include only establishments in food-related retail and hair salons.

In the first two regressions, we look at the basic relationship between gentrification and the change in the number of establishments at the zip code level. In the first column, we control for county fixed effects and nothing else. In the second column, we add zip code level controls. In regressions (3) and (4), we repeat the analysis but rather than looking at establishment growth by zip code, we look at establishment growth by industry within the zip code.

In general, in the first 4 columns of Table 2, the coefficient on the change in the college share is negative, but imprecisely estimated. By contrast, gentrification (as measured by the interaction between initial poverty and the change in the college share) does not shrink the number of businesses. If anything, gentrification appears to be associated with positive growth in the number of establishments, though the estimated coefficient is imprecise. This effect holds both with and without controls, and is consistent with existing research showing that initially poor neighborhoods which experience income growth also experience a modest increase in retail employment (Schuetz, Kolko and Meltzer, 2012).

In column (2), we find that the initial poverty rate has a positive but statistically insignificant coefficient. Growth in college share has a negative coefficient, but the interaction between the high-poverty dummy and growth in the college share is positive if statistically indistinct from zero. As our model predicts, gentrification is associated with an increase in the total number of stores.

In regressions (3) and (4), we run our regressions at the zip code-industry level. This enables us to control for any broad industry trends that might be shaping growth. In this case, the coefficient on the interaction between growth of college share and initial poverty rate is significant and positive. Regression (3) shows that a one-percentage point increase in the college share in an area that was initially high poverty is associated with 2.3 percent higher growth in the number of establishments relative to a non-poverty area that experienced a one-percentage point increase in the college share. The correlation between change in college share and establishment growth is negative in low-poverty areas, meaning that the net effect of increasing college share is indistinguishable from zero.

Regressions (5) through (8) repeat the same analysis, but substitute rent growth for the increase in college share. We view rent increases as another proxy for gentrification, although the model predicts that we should only expect to see rent increases associated with gentrification if the negative impact of store closures is limited. As it is, we find little to no significant correlation between rent increases and the overall growth in establishments.

In Appendix Table A2, we repeat this analysis for the fifty most populated counties in the United States. The results are broadly similar. We also run regressions at the county-industry level, including both county and industry fixed effects.

IV. Measuring Retail Closures with Yelp

We now turn to the connection between gentrification, rent change and changes in neighborhood retail mix. This work follows the earlier analysis of Baum-Snow and Hartley (2020), Meltzer (2016), Meltzer and Capperis (2017), and Meltzer and Schuetz (2012), who all provide analysis of how different measures of demographic change correlate with retail turnover. To investigate the nature of retail change in a given neighborhood, we use establishment-level data from Yelp.

Our primary outcome of interest is a binary variable indicating, for each establishment that was present in 2012, whether that establishment closed between 2013 and 2017. Our dependent variables of interest include the establishment's industry (restaurant, café, grocery store, etc.), price level on a scale of $ (least expensive) to $$$$ (most expensive) and average numerical rating. We can also see the establishment's name, address, and the number of reviews posted each year.

Our dataset includes a sample of establishments within each city's political boundaries, up through the end of 2018. Yelp obtains its listings either directly from platform users (either business owners or consumers) or by acquiring listing data from other companies and data partnerships. As a result, industry categorization does not follow any particular protocol and does not directly correspond to industry categorizations used by the Census Bureau or retail trade groups. Our dataset contains 235 different categorizations, which are not mutually exclusive (for example, "restaurant" and "French restaurant" are both categories reported in the data) and vary tremendously in popularity (some categories, such as "rotisserie chicken", list only one establishment, but others, like "restaurant", list over ten thousand).

To simplify analysis and improve power, we aggregate these fine-grained business types into broad, mutually exclusive and comprehensive categories for most of the analysis. These broad categories are sit-down restaurants, cafés and coffee shops, dessert places (including bakeries and ice cream shops), hair salons/barbers, fast food (including "fast casual" establishments and chains), bars, groceries (including supermarkets, butchers, vegetable stands, etc.), and convenience stores. These categories represent the most popular categories on Yelp, so while we do not observe every retail establishment, they are likely to have the most representative coverage within our dataset.

In order to incorporate zip code-level information from the American Community Survey, our analysis focuses on the nature of retail change over the 5-year period from 2012-2017. Therefore, we need to know whether the establishment opened before 2013, and whether it closed between 2013 and 2017. Since Yelp does not monitor every storefront at all times, the data we observe about the timing of openings have limited precision. We observe the date that an establishment was added to Yelp's database, not the date it first opened its doors. This introduces some measurement error, but since we are looking at the nature of retail change over a 5-year period, the precise date on which an establishment opens should have minimal influence our estimates.

We drop establishments that Yelp adds via data partnerships and acquisitions, because in that case our proxy for establishment entry is not accurate. Therefore, our analysis relies only on crowdsourced data, and there is reason to be concerned that these establishments constitute a selected sample. To address these concerns, we perform a number of exercises to validate our dataset in Appendix C.

V. Is Gentrification Associated with Higher Closure Rates?

As we discussed in Section IV, the Yelp data is reasonably good at identifying businesses that once existed and that now have closed, although there will be some stores that have closed that have not been reported. As the Yelp data can also measure store replacements at the same address, we can see whether a new store opens and classify the new store's industry and price level. In this section we focus on store closures. We will focus on replacement in the next section.

We perform three exercises within this section. First, for all five cities separately, we compare closure rates and establishment change rates between poor gentrifying, poor non-gentrifying and non-poor areas for each retail category.

Second, we perform regressions at the store level, and we regress closing rates on changes in rental price level at the zip code level and the interaction between that rate and the initial poverty level. For these regressions, we treat gentrification as a continuous variable and focus on the interaction between a dummy variable indicating a high initial poverty rate and the growth in both share college educated and rental prices. Our results are largely unchanged when we perform regressions with discrete gentrification measures.

Third, we instrument for changes in the college share and changes in rent levels with instruments that are motivated by our model: the initial share of the four closest zip codes that is college educated and the rise in housing prices in those zip codes between 2009 and 2012 and the interaction between those two variables. In our model, gentrification occurs as a result of options elsewhere becoming relatively worse. Rising housing prices are often cited as the reason why wealthier individuals move into previously poor communities. We use this variable also as an instrument for rent change, with the interpretation that this is not a causal effect of rent growth on its own, but on rent growth that results from gentrification. Unfortunately, these instruments are not powerful enough to identify the interaction between initial poverty and growth in the college share, and they do not work in our small cities (San Francisco and Boston). Consequently, we run these regressions just on the sample of zip codes that is initially poor in our three larger cities.

Before proceeding to the regressions, we return to the interplay between e-commerce and gentrification that we highlighted in the model. We do not have data on local e-commerce, but Nielsen shopping surveys do capture the share of e-commerce at the national level as a share of total purchases. The black line in Figure 4 (right axis) shows that there is essentially a linear trend in this share from under four percent in 2008 to over nine percent in 2018. Next to this trend line, we show the change in closure rates average across our five cities in non-poor, gentrifying and poor non-gentrifying areas. Units for closure rates are on the left axis.

While closure rates are distinctly lower in the initially poor areas than in the initially rich areas, the closure rates in three groups essentially move upward in parallel from 2008 to 2016. After that point, the closure rates in the three groups converge. We interpret these trends as indicating that the e-commerce shock is happening at the same time as the gentrification shock. Not only is the rise of e-commerce likely to directly increase closures of traded goods stores, but it may also increase the impact of gentrification since e-commerce was disproportionately used by the well-educated. In our empirical work, we will follow our model's predictions and attempt to distinguish between e-commerce and gentrification shocks by looking at the changes in the total number of establishments and at the changing nature of retail.

Closures in Gentrifying and Non-Gentrifying Areas

In Table 3, we show establishment growth rates across the five cities for gentrifying poor areas, non-gentrifying poor areas and rich areas. In Table 4, we show the comparable business closure rates across the five cities and the three types of areas. The closure rate is defined as the share of establishments open before 2013 that closed between 2013 and 2017. As discussed above, gentrification is defined as having experienced an increase in the college share of the zip code than was larger than the city as a whole. The stars continue to capture statistical significance, with the stars in the middle column indicate statistical difference between gentrifying and stable poor areas, and the stars in the left column indicate statistical difference between gentrifying and rich areas.[4]

Panel A of each table shows our results for Chicago, Los Angeles and New York. Panel B results for the smaller cities of Boston and San Francisco. The gentrifying parts of Chicago experienced faster establishment growth (or slower establishment decline) than the poor areas of Chicago in every store category, though not always significantly so.

Table 4 shows Yelp closure rates for each city and neighborhood type. Closure rates are generally higher in gentrifying areas than poor non-gentrifying neighborhoods, but lower than in rich neighborhoods. In our large cities, the differences between gentrifying and rich areas are generally statistically significant. The differences between gentrifying and poor non-gentrifying areas are significant for some cities and some categories.

The first three columns show our results for Chicago. In every category, closure rates are higher in gentrifying areas than in poor non-gentrifying areas. In all but two categories (bars and convenience stores), the differences are statistically significant. In all but one category (restaurants), the closure rate is rate is twice as high in gentrifying areas than in non-gentrifying poor areas. In most cases, gentrifying areas do not have more closures than rich areas, and overall the closure rates are higher in rich areas.

In Chicago and Los Angeles, closure rates are higher in gentrifying areas than in non-gentrifying poor areas for almost all of the categories. Anecdotally, poor areas in these cities have particularly low commercial rents, and this may keep businesses in operation for long periods of time. Consequently, residents of poorer parts of these cities may have had an expectation of permanence that broke down when gentrification occurred. Yet when poor areas gentrify, the closure rates converge to the city-wide norm, not to some exceptionally high level. The third panel shows the weaker results for New York City. In general, in New York, differences in closure rates between gentrifying and poor neighborhoods are not statistically significant. Once again, the rich areas experience more closures than the poor areas.

[4] These differences in statistical significance was established using a city-by-city linear probability models including only stores in initially poor areas where closure was regressed on a dummy variable indicating gentrification.

The bottom panel shows our results for Boston and San Francisco. In these smaller places, there are almost no statistically distinct differences in either the establishment growth rates or the closure rates between the three types of areas. There are, of course, fewer areas and so we should expect to see less statistical significance, but the point estimates for the closure rates are also generally close. In San Francisco, establishment growth is higher in the gentrifying areas. We expected to see more closures in gentrifying areas in these cities, as generic service providers crowd out everything else because of their paucity of land. The establishment growth data for Boston, but not for San Francisco, can be interpreted in that way as the number of convenience stores increased dramatically and there was a decline in the number of bars and grocery stores. However, we see essentially the same pattern for poorer areas that did not gentrify.

Regression Analysis of Closure Rates

We now turn to our regression analysis of closure rates across all five cities. Our basic regression treats a business as a unit of observation and the model predicts whether a business that was open on December 31, 2012 closes between January 1, 2013 and December 31, 2017. Our key independent variable is the interaction between the demeaned growth in college share between 2012 and 2017 and an indicator variable that equals 1 if the business is in a zip code with a poverty rate that his higher than the median in the city. We demeaned to ease the interpretation of our controls for the initial poverty rate and the growth in rents.

More formally, our main probit specification is:

$$\begin{aligned}
&\Pr(Closed_{iz}^{2013-2017}) \\
&\qquad = \Phi(\beta_0 + \beta_1 Change\ in\ College\ Share_z^{2012-2017} + \beta_2 High\ Poverty_z^{2012} \\
&\qquad + \beta_3 (HighPoverty_z^{2012} \times Change\ in\ College\ Share_z^{2012-2017}) + \delta X_{iz})
\end{aligned}$$

where *i* indexes establishments and *z* indexes zip codes. As we have chosen to define gentrification as high college share growth in initially poor areas, we are primarily interested in the effect of the interaction between initial poverty and subsequent rent growth on closure probability. This effect is captured by the parameter is β_3. The interaction term will be high for areas which have high initial poverty and high rent growth over the study period) and low for both rich areas (which have low poverty rates) and poor non-gentrifying areas (which have low rent growth).

The expression X_{iz} denotes a vector of controls. We control for the initial density of Yelp establishments in the zip code and the density of that category of establishment in the zip code, as well as initial percent college educated, the initial share of the population aged between 25 and 34, the initial median income and the initial percent white. We also include fixed effects for the different retail sectors, different cities and the price level of the establishment as it is categorized in the Yelp data. All standard errors are clustered at the zip code level.

Table 5 presents the results of a Probit model following this specification. The first regression shows the impact of gentrification on the overall closure rate for our entire sample of establishments with no other controls, except for county dummies. In all regressions, we cluster standard errors at the zip code level. The basic interaction is positive, meaning that gentrification is associated with more closures, but it is not statistically significant. The overall impact of growth in college share is positive as well.

In the second regression, we add controls for city and category fixed effects as well a number of store- and zip code-level variables which are likely to be correlated with gentrification and closure. At the store level, we control for ownership type (whether the store is a chain, franchise, or part of a chain which franchises some of its stores) because different types of retailers may face different strategic challenges which affect their exit behavior. For example, franchisees may have less ability to negotiate their way out of a lease than a large chain retailer. We control for zip code population and demographics, to account for the fact observed in Table 1 that richer areas have higher closures. We also control for the number of dollar signs Yelp gives the establishment, since retail firms choose where to locate and what price point to target based on who lives an area. To control for the degree of local competition, include the spatial density of establishments in the zip code. We control for the share of zip code area occupied by parks, to capture non-retail amenities that might make some zip codes more susceptible to gentrification. Finally, we control for the distance to city hall, since previous literature shows gentrification is most likely to occur in low-income neighborhoods closer to the city center (Su 2022).

These controls serve two functions: they soak up variation (tightening our standard errors) and correct for omitted variables bias. The controls most responsible for the change in the magnitude of the gentrification coefficient are category fixed effects and the initial college share. Category fixed effects are important to include because retail mix differs across poor non-gentrifying, gentrifying and rich neighborhoods. For example, Table 3 shows restaurants are among the most likely to close, and represent a higher share of stores in rich areas relative to initially poor areas. The initial college share is negatively correlated with the change in the college share, since areas that start with a high college share are less likely to see significant further increases. Therefore, when we include the initial college share in regression (2), the estimated coefficient increases in magnitude.

The coefficient on initial education suggests that this fact should not surprise us. Closure rates are higher in better educated neighborhoods, just as we saw that closure rates were higher in richer neighborhoods in Table 4. As poor places become better educated, closure rates rise to the levels that are typically associated with a higher share of college-educated residents.

In the third regression, we display the estimated coefficients from a linear probability model which has the virtue of producing coefficients that are easy to interpret. For example, the coefficient of .54 on the gentrification interaction means that a four-percentage point increase in the college share, which is about the mean change in gentrifying areas in New York and Los Angeles, is associated with a 2.16 percentage point increase in the probability of closure. This is a significant effect, but it approximately one-tenth of the sample mean in initially higher poverty areas. It is dramatically smaller than the impact of being in a mall or being a franchisee, which reduce closure probabilities by five and fifteen percentage points respectively.

Regressions (4)-(6) reproduce these results interacting residential rent growth, as measured with the American Community Survey, with initial poverty rates. These specifications should be interpreted as a test of whether business closures are higher when rents go up in high poverty areas, not as a direct test of gentrification itself. In regression (4), we find a positive but insignificant coefficient on the interaction between rent growth and initial high poverty status. Rent growth itself also has a positive and insignificant coefficient.

Regression (5) shows a Probit regression with more controls, in which the interaction becomes statistically significant. Regression (6) shows the results for a linear probability model. The interaction between initial poverty and rent growth is significant and positive, but again small in magnitude. A ten-percentage point increase in rents is associated with 2 percentage point increase in the probability of store closure in poor neighborhoods relative to rich neighborhoods. Both our direct measure of gentrification and rent growth modestly increases the closure rates for businesses located in initially high poverty areas.

Table 6 shows the robustness of our effects to finer fixed effects, in the spirit of a matching estimator. We start by regressing the closure indicator on the same controls as in Table 5, but replacing the separate fixed effects for city, category, and chain/non-chain status with a single fixed effect for each possible combination of the original three fixed effects. This ensures that we are comparing closure rates for stores in the same city, the same retail category, and the same chain/non-chain status but which are located in neighborhoods which experience different amounts of gentrification. However, partitioning stores in this way means that we are comparing stores at different price points: for example, a McDonald's (which has 1 dollar sign on Yelp) and a Panera (which has two dollar signs) which are both in Chicago would be in the same category. Furthermore, a McDonald's in a mall food court and a McDonald's in a regular storefront are also in the same category, though they may face very different exit incentives. Therefore, in columns (2) and (5), we further refine the cells by comparing closure rates within city-category-chain-dollar sign-mall/freestanding categories. Finally, to allow for the fact that McDonald's locations near the city center may differ from locations far from the city center, in columns (3) and (6) we control for the decile of the establishment's distance to city hall. As in Table 5, the first three regressions focus on the interaction between initially high poverty and change in the college share. The last three regressions look at the interaction between initial poverty and rent growth.

Between the first, second and third regressions, the coefficient on the college share interaction falls from .53 to .48 to .47. Between the fourth, fifth and sixth regressions, the coefficient on the rent interactions falls from .21 to .20 to .18. The rent growth interaction loses statistical significance with the extra fixed effects, but the magnitude of the coefficient remains essentially unchanged. These basic interactions seem quite robust to including or not including these types of control variables.

The model suggested that the welfare costs from shutting highly idiosyncratic non-tradable businesses might be significant but that closures of stores that focus on ordinary tradable goods might have little welfare effect. The model also noted that we might confuse the impact of gentrification, which should replace idiosyncratic non-tradable service stores with generic service stores, and electronic commerce, which should replace all tradable goods stores with non-tradable service stores.

To look at these issues, Table 7 examines whether gentrification shocks have a differential impact on chain stores, franchises or non-chain, non-franchise stores that have only one dollar sign on Yelp. We will interpret the one-dollar sign, non-chain variable as suggesting a low cost, local provider. The first three regressions look at the education change interaction with initial poverty. The last three focus on the rent growth interaction.

The first and fourth columns look at interactions with being a chain store. None of the interactions are statistically significant. In general, being a chain store blunts the positive impact that change in college share has on closure rates, and there is not much of a difference in initially rich or initially poor places. Consequently, gentrification is slightly less likely to be associated with chain stores closing, or conversely slightly more likely to be associated with non-chain stores closing, which is compatible with the model. Rent growth does not have any particular interaction with chain store status.

The second and fifth columns look at franchisors and franchisees. Franchisors are corporate-managed locations of chains that have both franchised and corporate locations. Increases in college share are much less likely to lead to closures of franchisees and that fact is even stronger in places that are initially poor. Increases in the college share are less likely to be associated with franchisor closures in initially rich neighborhoods, but the double interaction between college share growth and franchisor and initially poor neighborhoods is positive and more than offsets this effect in poorer places. None of the interactions between franchisee or franchisor with rent growth are close to significant.

The third and sixth columns focus on one dollar sign, non-chain stores, which our model predicts would be most vulnerable to gentrification. In initially non-poor places, growth in the college share has a slightly larger impact on closure rates. In initially poorer places, growth in college share is actually less likely to lead to closure for these stores, but the interactions are small and statistically insignificant. These patterns are reversed for rent growth in regression six, where rent growth is less likely to lead to closures of one-dollar sign non-chain stores in rich neighborhoods, but not in poor neighborhoods.

Taken together these interactions show few clear patterns. We cannot reject the hypothesis that gentrification has the same impact on closures for all types of stores. While the results in the first column are compatible with the model, there are also compatible with the view that neighborhood change disrupts everything equally.

Appendix Table A4 calculates different gentrification coefficients in the five cities separately, to test if any one city is driving our results in Table 5. The interaction between growth in college share and initial poverty has the strongest impact on store closures in Los Angeles, which has a coefficient over three, and the weakest impact in Chicago, where the coefficient is essentially zero. The effect on closures of interaction between growth in rents and initial poverty is strongest in New York and Chicago, and weakest in Boston, where the effect is negative.

Instrumental Variables Estimates

One challenge with interpreting the previous results is that the changing mix of establishments could itself change rent levels and influence gentrification. Consequently, we turn now to a linear instrumental variables strategy that relies on well-known spatial patterns in gentrification. Our instruments build on our model, where gentrification resulted from high skilled individuals being "pushed" into the community. We take our push factors to be the presence of nearby skilled individuals, measured as the average percent of the population with a college degree in the nearest four zip codes, price growth in the nearest four zip codes between 2009 and 2012 as measured by the Federal Housing Finance Agency's repeat sales index and the interaction between the two.

Our instrumental variables strategy leverages two well-known facts about neighborhoods and housing markets: short-term housing price momentum (Case and Shiller, 1989, Cutler, Poterba and Summers, 1991) and neighborhood invasion (Burgess, 1925, Schelling, 1979, Naik et al., 2017). Momentum implies that past housing price growth in an area predicts future housing price growth. Invasion, a term coined by urban sociologists, describes transitions in neighborhood racial or social status driven by an influx of newcomers from a different socioeconomic group than the incumbent residents.

These two phenomena motivate two instruments for the change in a given zip code's college share. Our first instrument is the average housing price growth in the 4 nearest zip codes. In the context of our model, housing price growth in nearby areas represents a decrease in Δ (the value of the outside option to the rich), which we interpret as a gentrification shock. Our second instrument is the average college share of the 4 nearest zip codes. This follows Burgess' invasion hypothesis and identifies zip codes which are more likely to gentrify due to their proximity to areas that already have a high college share. The interaction of our two instruments (neighboring college share and past housing price growth) acts as a shift-share instrument. Gentrification is likely to be furthest along in neighborhoods with high neighboring college share and high pre-period price growth.

The validity of these instruments requires them to impact restaurant closures only through the gentrification channel. One concern is the possibility that instruments might be correlated with demand from outside the neighborhood. In this case, closures might be correlated with demand from non-residents rather than residents. However, our gentrifying areas are generally peripheral rather than core zip codes, which means that they are unlikely to be retail or restaurant destinations for neighboring residents. Indeed, if we drop establishments within two miles of the city center, our results are qualitatively unchanged. Similarly, we think that high-priced establishments are also more likely to be visited by non-neighborhood residents. If we drop these establishments, our results are also qualitatively unchanged. While not definitive, these tests suggest that changes in external demand is not primary driver of differences in closure rates across neighborhood types.

While these instruments do significantly predict growth in college share, they are not strong enough to separately identify an interaction effect. Consequently, we restrict our sample to initially poor areas and we will exclude the two smaller cities of Boston and San Francisco. Our instruments do a substantially worse job there, partially because there are so few zip codes. When data is missing for a particular zip code, we replace it with the city-level average.

Regression (1) of Table 8 shows our ordinary least squares results when we restrict ourselves to this sample. As controls, we include our store level variables and the share of adults in the area with a college degree in 2012. The estimated coefficient is .80 which is comparable to the .60 total effect of growth in college share in Table 5 (the sum of the direct effect of change in college share and its interaction with the high poverty dummy).

Regression (2) shows our instrumental variable estimate of 1.36. This estimate is larger than the OLS estimate, which would be compatible with the view that places with fewer closures attracted more skilled people. While this point estimate is larger and implies that a four-percentage point increase in the college share is associated with a 5.44 percent increase in the closure rate. Our third regression adds in the initial poverty, and the coefficient remains above one and statistically significant. In our fourth regression, however, we add our full range of area level controls and the coefficient shrinks to .44 and loses statistical significance. We therefore view this is as suggestive, but not definitive, evidence that gentrification leads to higher closure rates among incumbent businesses.

In regressions (5) and (6), we repeat regressions (1) and (2) for zip codes that were initially rich. In regression (5), the ordinary least squares coefficient is much smaller than in regression (1). This is compatible with the robust interaction between growth in college share and initial poverty rates that we found in our earlier ordinary least squares results. In regression (6), we find that the coefficient rises to over one, which is statistically indistinguishable from the coefficient in regression (2). One interpretation of these results is that our earlier interactions reflected the fact that the reverse causality, from shop closures to reduced growth in college share, was much larger in initially rich places than in initially poor places. However, one limitation of this analysis is that our sample size and instruments limit our ability to detect interaction effects with precision.[5]

Overall, our instrumental variables results largely corroborate the results found using ordinary least squares. There does appear to be a positive impact of neighborhood change on closures,

[5] Table 8 includes both the traditional F statistic and the Kleibergen-Paap F statistic. We also include the Kleibergen-Paap rk statistic to test for underidentification. As noted by Andrews, Stock, and Sun (2018), in heteroskedastic settings like ours, the Kleibergen-Paap F statistic is not a formal gauge of instrument strength.

both in rich and poor areas. Moreover, these point estimates are larger than the ordinary least squares estimates, although they are more sensitive to the inclusion of other neighborhood characteristics.

VI. Gentrification and Retail Mix

We now turn to gentrification and the changing mix of retail businesses. Our model suggests that gentrification could yield inefficiencies and large welfare losses if idiosyncratic stores are replaced by generic service providers. We have so far looked at closure rates. We now look at the stores that open following a closure.

In Table 9, we include all closures for which we observe another establishment enter the same space between the closure and the end of 2017, and look at three types of transitions. As we mentioned in the data description, our data may be missing some stores that replace a previous store but are not uploaded to the Yelp platform by users. However, given that for this transition analysis, we are conditioning on storefronts that have had a store that was on Yelp in the past, we think this concern is somewhat mitigated. In regressions one and four, we look at the probability of becoming a service provider. Regressions two and five examine the probability of becoming a chain store. In regressions three and six, the probability of moving up a dollar sign is the dependent variable.

Columns one and four show that neither increasing college share nor increasing rents have a statistically significant impact on the probability of transitioning to a service provider. The point estimate on college share in non-poor areas is .26, meaning that a four percentage point increase in college share is associated with a one percent increase in the transition rate. The interaction between change in college share and initial high poverty is even closer to zero.

Both rising college shares and rising rents reduce the probability of switching to a chain store in areas that were initially not poor. A four percentage point increase in college share is associated with a four percentage point decrease in the probability of becoming a chain in a non-poor area. The interaction between change in college share and initial poverty is positive, however, so the same four percentage point increase in college share would only reduce the probability of becoming a chain by two percentage points in an area that was initially poor. Similarly, there is almost no link between rent growth and switching to a chain store in places that had been poor.

Somewhat surprisingly, neither growth in college share nor growth in rents seems to lead to dollar sign increases. In the third and sixth regressions, the coefficients on the interactions between the change variables and initial poverty status are small in magnitude and statistically insignificant. This data does not support the notion that gentrification leads to a quick increase in the price of local services. However, since Yelp's dollar signs are fairly course categories, it is a rather imprecise proxy for actual prices and this may be obscuring some real effects of gentrifiction.

All told, there is little evidence here that links gentrification with changing retail mix. Closures seems to be slightly more common in gentrifying areas, but there is no sense in which gentrification means that these closures produce more expensive or less idiosyncratic stores. The evidence is more compatible with slightly higher levels of churn in places where education levels are rising.

VII. Conclusion

Gentrification creates winners and losers. When rents rise in poorer areas, landlords benefit and long-term tenants lose. While the distributional effect of gentrification have been long understand, the model in this paper clarifies the conditions under which changing neighborhood character can cause poorer incumbents to lose even more than their rent increases would suggest. The key condition for these added welfare losses is that the local retail stores, favored by the poor, generate more inframarginal consumer surplus, then the up-market chain stores, favored by the rich. This mechanism is inspired by neighborhood activists who claim that gentrification destroys the local character that is particularly valued by long-time residents. The central difference between high surplus stores and low surplus stores is that the high surplus stores are unique while the low surplus stores have an identical alternative a few blocks away.

While it seems reasonable to expect that the influx of the rich will generate demand for stores that mainly serve to save the time of the rich, we do not claim that the assumptions needed for gentrification to decrease welfare apply universally or even broadly. We see the model's larger contribution as generating empirical predictions for testing when neighborhood change is likely to have welfare impacts that go beyond housing price changes. Moreover, the mechanism in our model is relevant with any neighborhood change, not just gentrification. The welfare impacts of new subway station or a large business closure will be shaped partially by whether these events are accompanied by the change in the number of idiosyncratic local residents.

We tested the model using Yelp data, by examining whether gentrification is associated with high closure rates and shifts in the nature of local retail. Closure rates are indeed higher in poorer areas that are experiencing increases in education levels than in areas that are poor and static. In a regression framework with closures as the dependent variable, we find a statistically significant, albeit small, interaction between initial poverty and the growth in the college share. When we instrument for change in college share with the skill level and past price growth of neighboring communities, we estimate a somewhat larger fact.

The key fact is not that stores close so much more quickly in gentrifying areas, but they close much less in poorer areas that have stable education levels, especially in our larger cities. A natural explanation for this fact is that stores in poor neighborhoods may just subject to much less competition than stores in rich neighborhoods. Gentrification is also associated with an increase in the number of retail establishments.

There is little evidence for extreme changes in the character of the retail stores. Most stores that close are replaced by restaurants in all areas. Stores are no more likely to become service providers in gentrifying areas and they are no more likely to increase their dollar signs. Rising education levels do make it less likely that stores will convert into chains, although that relationship is weaker in initially poor places.

The limitations on our data means that it can support a variety of interpretations, but our conclusion is that gentrification's impact on retail mix is modest, at least over our short five-year window. Nonetheless, we believe that the model can serve as a guide for analyzing the impact of many different forms of neighborhood change, especially as as more granular data on local stores becomes available.

References

Andrews I, Stock J, Sun L. Weak Instruments in IV Regression: Theory and Practice. Annual Review of Economics. 2019; 11:727-753

Austin, Peter C. Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharm Stat.* 2011 Mar-Apr; 10(2): 150-61.

Baum-Snow, Nathaniel and Daniel Hartley. "Accounting for central neighborhood change, 2980-2010." *Journal of Urban Economics*, no. 117 (2020).

Behrens, K., Boualam, B., Martin, J., & Mayneris, F. (forthcoming). Gentrification and Pioneer Businesses. *The Review of Economics and Statistics*.

Betancur, John. "Gentrification and community fabric in Chicago." *Urban Studies* 48, no. 2 (2011): 383-406.

Burgess, E. (1925). *The Growth of the City*. University of Chicago Press.

Case, K. E., & Shiller, R. J. (1989). The Efficiency of the Market for Single-Family Homes. *The American Economic Review*, *79*(1), 125–137.

Couture, V., & Handbury, J. (2020). Urban revival in America. *Journal of Urban Economics*, *119*.

Cutler, D. M., Poterba, J. M., & Summers, L. H. (1991). Speculative Dynamics. *The Review of Economic Studies*, *58*(3), 529–546. https://www.jstor.org/stable/2298010

Dragan, Kacie, Ingrid Ellen, and Sherry A. Glied. *Does gentrification displace poor children? New evidence from New York City Medicaid data*. No. w25809. National Bureau of Economic Research, 2019.

Ellen, Ingrid Gould, and Katherine M. O'Regan. "How low income neighborhoods change: Entry, exit, and enhancement." *Regional Science and Urban Economics* 41, no. 2 (2011): 89-97.

Ellen, Ingrid Gould, and Katherine O'Regan. "Gentrification: Perspectives of economists and planners." In *The Oxford Handbook of Urban Economics and Planning*. Oxford University Press, 2012.

Ellen, Ingrid Gould, Keren Mertens Horn, and Davin Reed. "Has falling crime invited gentrification?." *Journal of Housing Economics* 46 (2019): 101636.

Freeman, Lance, and Frank Braconi. "Gentrification and displacement New York City in the 1990s." *Journal of the American Planning Association* 70, no. 1 (2004): 39-52.

Freeman, Lance. "Displacement or succession? Residential mobility in gentrifying neighborhoods." *Urban Affairs Review* 40, no. 4 (2005): 463-491.

Glaeser, Edward L., Jed Kolko, and Albert Saiz. "Consumer city." *Journal of economic geography* 1, no. 1 (2001): 27-50.

Glaeser, Edward, Hyunjin Kim and Michael Luca. "Measuring Gentrification: Using Yelp Data to Quantify Neighborhood Change." No w24952. National Bureau of Economic Research. 2018.

Glass, Ruth. "Aspects of change." *The gentrification debates: A reader* (1964): 19-30.

Hipsman, Nathan. "Housing Price Changes within the City." Harvard University. 2017.

Kleibergen F, Paap R. 2007. "Generalized reduced rank tests using the singular value decomposition." Journal of Econometrics 133:97–126

McKinnish, Terra, Randall Walsh, and T. Kirk White. "Who gentrifies low-income neighborhoods?." *Journal of urban economics* 67, no. 2 (2010): 180-193.

Meltzer, R. (2016). Gentrification and Small Business: Threat or Opportunity? *Cityscape*, *18*(3), 57–86.

Meltzer Rachel, and Sean Capperis. Neighbourhood differences in retail turnover: Evidence from New York City. *Urban Studies* 54, vol. 13 (2017): 3022-3057.

Meltzer R, and Jenny Schuetz. Bodegas or Bagel Shops? Neighborhood Differences in Retail and Household Services. Economic Development Quarterly 26, no. 1 (2012): 73-94.

Naik, N., Kominers, S. D., Raskar, R., Glaeser, E. L., & Hidalgo, C. A. (2017). Computer vision uncovers predictors of physical urban change. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(29), 7571–7576. https://doi.org/10.1073/pnas.1619003114

Newman, Kathe, and Elvin K. Wyly. "The right to stay put, revisited: Gentrification and resistance to displacement in New York City." *Urban studies* 43, no. 1 (2006): 23-57.

Schuetz, Jenny, Jed Kolko, and Rachel Meltzer. 2012. "Are Poor Neighborhoods 'Retail Deserts'?" Regional Science and Urban Economics 42(1-2):269-285

O'Sullivan, Arthur. "Gentrification and crime." *Journal of Urban Economics* 57, no. 1 (2005): 73-85.

Su, Y. (2022). The Rising Value of Time and the Origin of Urban Gentrification. *American Economic Journal: Economic Policy*, *14*(1), 402–439.

Sullivan, Daniel Monroe. "Reassessing gentrification: Measuring residents' opinions using survey data." *Urban Affairs Review* 42, no. 4 (2007): 583-592.

Urban Development Project. *Rising Housing Costs and Re-Segregation in the San Francisco Bay Area*. Report. 2019.

Vigdor, Jacob L., "Does gentrification harm the poor?." *Brookings-Wharton papers on urban affairs* (2002): 133-182.

Vigdor, Jacob L. "Is urban decay bad? Is urban revitalization bad too?." *Journal of Urban Economics* 68, no. 3 (2010): 277-289.

Appendix A: Model Proofs

Appendix: Characterization of Equilibrium and Proof of Propositions

Community demand for the idiosyncratic service depends on the share of the community that is poor and equals $H(A - \beta P)$. As long as $AH > \beta\varphi_I N_I H + 2$, the store sells to capacity. This is guaranteed by The price and revenues equals $\frac{1}{\beta}\left(A - \frac{1}{H}\right)$. The gross profits from a store equal $\frac{1}{\beta}\left(A - \frac{1}{H}\right) - \varphi_I N_I$, and that must equal $k_0 + k_1 S$ in equilibrium. The surplus utility, measured in units of the traded good, that each local resident receives from an idiosyncratic store is $\frac{1}{2\beta H^2}$

As $\varphi_G > 0$, generic services are only consumed locally by the rich and the poor will always "pay" $p_G + \underline{Y}$ for these services. If $(\overline{Y} - \underline{Y}) < k_0 + k_1 S + \underline{Y}$ then no generic service providers will enter, because the maximum net profit in this case is negative. If $k_0 + k_1 S + \underline{Y} < q(\overline{Y} - \underline{Y}) < \varphi_G q_G rH + k_0 + k_1 S + \underline{Y}$, then $N_G < q_G rH$, will enter and the price will be $p_G + q\overline{Y}$. Firms will sell to capacity, and earn zero profits. If $(\overline{Y} - \underline{Y}) > \varphi_G q_G rH + k_0 + k_1 S + \underline{Y}$, then exactly $q_G rH$ generic service firms will enter. We have assumed that in this case, the price will be set to generate zero profits in equilibrium, and hence the price will equal $p_G + \varphi_G q_G rH + (1+q)\underline{Y} + k_0 + k_1 S$.

Our assumptions focus on the case where local demand for traded goods is not met entirely by local shops, and so the market price for traded goods will be 1. This implies that $\tau - \varphi_T N_T = k_0 + k_1 S + \underline{Y}$.

We now describe the equilibrium in the retail market, treating "r" as exogenous. We focus on the case where $(\overline{Y} - \underline{Y}) > \varphi_G N_G + k_0 + k_1 S + \underline{Y}$, so that the number of generic service stores equals $q_G rH$. In this case, the retail market equilibrium is characterized by

(A1) $\frac{1}{\beta}\left(A - \frac{1}{H}\right) - \varphi_I N_I = \tau - \varphi_T N_T = k_0 + k_1(N_I + q_G rH + N_T) + \underline{Y}$

This implies that:

(A2) $S = \frac{\varphi_T\left(\frac{AH-1}{\beta H}\right)+\varphi_I\tau+\varphi_I\varphi_T q_G rH-(\varphi_T+\varphi_I)(\underline{Y}+k_0)}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}$,

(A3) $N_I = \frac{(k_1+\varphi_T)\left(\frac{AH-1}{\beta H}\right)-k_1(\varphi_T q_G rH+\tau)-\varphi_T(\underline{Y}+k_0)}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}$, and

(A4) $N_T = \frac{(\varphi_I+k_1)\tau-k_1\left(\frac{AH-1}{\beta H}\right)-k_1\varphi_I q_G rH-\varphi_I(\underline{Y}+k_0)}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}$

The utility earned by the poor in the community equals: $\underline{Y}(1-q_g)-p_g q_g-R^k+\frac{N_I}{2\beta H^2}+\delta q_g+\theta_0 r$, which implies that $R^k=\frac{N_I}{2\beta H^2}+\theta_0 r-\underline{U}$. The utility earned by the rich in the community equals $\overline{Y}-\left(p_G+\varphi_G q_G rH+2\underline{Y}+k_0+k_1 S\right)q_g-R^k+\frac{N_I}{2\beta H^2}+\delta q_g$, which implies that $R^k=q_g\left(\overline{Y}-2\underline{Y}-(\varphi_G q_G rH+k_0+k_1 S)\right)+\frac{N_I}{2\beta H^2}-\underline{U}-\Delta$.

Together these imply that

$$\text{(A5)}\qquad r=\frac{q_g\left(\overline{Y}-\underline{Y}-\frac{k_1\varphi_T\left(\frac{AH-1}{\beta H}\right)+k_1\varphi_I\tau+\varphi_I\varphi_T(\underline{Y}+k_0)}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\right)-\Delta}{\left(\varphi_G+\frac{k_1\varphi_I\varphi_T q_G}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\right)q_G H+\theta_0}$$

Differentiating yields $\frac{dr}{d\Delta}=\frac{-1}{\left(\varphi_G+\frac{k_1\varphi_I\varphi_T q_G}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\right)q_G H+\theta_0}<0$, and the number of generic service firms is proportional to the number of rich individuals, so it also declines with Δ. For the other retail establishments: $\frac{dN_I}{d\Delta}=\frac{-k_1\varphi_T q_G H}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\frac{dr}{d\Delta}>0$, $\frac{dN_T}{d\Delta}=\frac{-k_1\varphi_I q_G H}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\frac{dr}{d\Delta}>0$, and $\frac{dS}{d\Delta}=\frac{\varphi_I\varphi_T q_G H}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\frac{dr}{d\Delta}<0$. The impact on rents is ambiguous, where $\frac{dR^k}{d\Delta}=\frac{1}{2\beta H^2}\frac{dN_I}{d\Delta}+\theta_0\frac{dr}{d\Delta}=\frac{1}{2\beta H^2}\frac{-k_1\varphi_T q_G H}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\frac{dr}{d\Delta}+\theta_0\frac{dr}{d\Delta}$, and this is negative if and only if $\theta_0>\frac{1}{2\beta H}\frac{k_1\varphi_T q_G}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}$.

Total surplus in the city combines total rents ($R^k H$) and the inframarginal surplus enjoyed by low income individuals $.5(1-r^2)\theta_0 H$. The derivative of the sum of these two quantities $.5(1-r^2)\theta_0 H+R^k H$, equals $\frac{1}{2\beta H^2}\frac{-k_1\varphi_T q_G H}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}\frac{dr}{d\Delta}H+(1-r)\theta_0 H\frac{dr}{d\Delta}$, which is negative if and only if $(1-r)\theta_0>\frac{1}{2\beta H}\frac{k_1\varphi_T q_G}{\varphi_I\varphi_T+k_1(\varphi_I+\varphi_T)}$.

Differentiating yields $\frac{dr}{d\tau} = \frac{-q_g k_1 \varphi_I}{k_1\varphi_I\varphi_T q_G q_G H + (\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T))(\theta_0+\varphi_G q_G H)} < 0$, and the number of generic service firms is proportional to the number of rich individuals, so it also declines with τ. For the other retail establishments: $\frac{dN_I}{d\tau} = \frac{-k_1\left(\varphi_T q_G H \frac{dr}{d\Delta}+1\right)}{\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T)} =$

$\frac{-k_1}{\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T)}\left(\frac{(\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T))(\theta_0+\varphi_G q_G H)}{k_1\varphi_I\varphi_T q_G q_G H + (\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T))(\theta_0+\varphi_G q_G H)}\right) < 0$, $\frac{dN_T}{d\tau} = \frac{(\varphi_I + k_1) - k_1\varphi_I q_G H \frac{dr}{d\Delta}}{\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T)} > 0$

and $\frac{dS}{d\tau} = \frac{\varphi_I + \varphi_I\varphi_T q_G H \frac{dr}{d\tau}}{\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T)} = \frac{\varphi_I}{\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T)}\left(\frac{(\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T))(\theta_0+\varphi_G q_G H)}{k_1\varphi_I\varphi_T q_G q_G H + (\varphi_I\varphi_T + k_1(\varphi_I+\varphi_T))(\theta_0+\varphi_G q_G H)}\right) > 0.$

The impact on rents is negative where $\frac{dR^k}{d\tau} = \frac{1}{2\beta H^2}\frac{dN_I}{d\tau} + \theta_0\frac{dr}{d\tau} < 0$,

Total surplus in the city combines total rents ($R^k H$) and the inframarginal surplus enjoyed by low income individuals $.5(1-r^2)\theta_0 H$. The derivative of the sum of these two quantities $.5(1-r^2)\theta_0 H + R^k H$, equals $\frac{1}{2\beta H}\frac{dN_I}{d\tau} + (1-r)\theta_0 H\frac{dr}{d\tau} < 0$, which is also negative.

Appendix B: Description of Gentrification in the 5 Cities

In this Appendix, we look at maps of gentrification in our five cities and at the connection between the change in the share with a college degree and median residential rent growth. As discussed in the main text, Figure 2 provides maps of gentrification based on change in the share of the adult population that has a college degree. For each city, the lightly colored zip codes show areas that were above the median city-wide poverty rate in 2012, the dark red zip codes show gentrifying areas, and the orange areas show areas that are poor but not gentrifying. A black circle surrounds the centroid of the zip code containing city hall. Next to each map showing gentrification, we place a second map showing median residential rent growth.

In Chicago, the two primary areas of gentrification, as measured by change in the share of the population with a college degree, are two strips of zip codes heading west and south from the central business district. The area closest to downtown have also gentrified, as have most of the previously poor zip codes in the north. The areas that did not gentrify are those that are closer to Lake Michigan.

The gentrification patterns bear only a slight resemblance to the rent change patterns. Chicago's rent growth was sharpest close to the downtown and in the north. The south and western areas that were changing their educational mix were not experiencing rent growth. The overall correlation between changes in log median rent and changes in the share of the population with a college degree across zip codes that were initially poor is .38. The model's explanation of this positive relationship might be either that Chicago's gentrifying areas did not lose a lot of idiosyncratic stores or that the long-term residents of Chicago's West and South Side have strong ties to their communities.

There are two major pockets of poverty in Los Angeles, both of which have experienced education-based gentrification. The northern poor area is centered around Van Nuys, and gentrification has occurred on the edges of the other, which abut wealthier neighborhoods. The southern area is larger and includes both African-American neighborhoods, such as Watts, and Latino neighborhoods, such as Boyle Heights. In these areas, education has increased in the core not on the periphery, perhaps because metro stations tend to be located in centers, such as Boyle Heights' Mariachi Plaza.

In the northern cluster, rent increases are highest in the center of the initially poor cluster of zip codes, not on the edges. This partially reflects the fact that those central areas had the lowest initial rent levels. In the southern poverty cluster, the rent changes are more spatially connected to the changes in the education share. Across initially poor Los Angeles zip codes, the correlation between changes in log median rent and changes in the share of the population with a college degree is .66.

New York has the most straightforward patterns of both gentrification and rent growth. Both phenomena occur in the areas that were initially poor, including the South Bronx, Harlem and Queens that were closest to midtown Manhattan. Whether or not gentrification was associated with loss of neighborhood character in New York City, the demand from wealthier New Yorkers for this space appears to have been more important. In New York, the correlation between the change in college educated share and the change in log median rents is .38.

The last two sets of maps show patterns for Boston and San Francisco. Although both cities are known for their gentrification, they are also smaller places and have only a modest number of zip codes. Boston has a pattern where the sharpest change in percent college graduate occurs further away from the city center, possibly because those areas have larger homes. Rent growth, however, was higher in the inner areas. In San Francisco, gentrification occurs in the north-south strip and excludes the most central areas, such as the Tenderloin District and Chinatown. Rent growth, however, is highest at the city center. Over the past 20 years, price increases have concentrated close to the urban core (Hipsman, 2017) presumably because rising incomes have increased the demand for short commutes (Su, 2018) and because of increased demand for urban amenities (Glaeser, Kolko and Saiz, 2001). As gentrification in Boston and San Francisco occurred further away from the city center, unsurprisingly the correlation between gentrification and rent increases is negative in both cities.

Appendix C: Validating the Yelp Dataset

To address concerns about selection onto Yelp platform, we benchmark our Yelp data against the County Business Patterns (CBP). The County Business Patterns uses the North American Industrial Classification System (NAICS) to classify businesses, which is standard but does not correspond exactly to the classification given in Yelp. To effectively compare the Yelp data and the CBP data, we use a crosswalk from Yelp categories to NAICS industry categories which is similar to the crosswalk used in Glaeser, Kim and Luca (2018). Our crosswalk is displayed in Appendix Table A1.

Overall, the correlation between the number of Yelp establishments and the number of CBP establishments is quite high. Figure 3 shows the correlation between the number of listings on Yelp and the number of corresponding businesses in the County Business Patterns. The correlation coefficient is 0.801 and the estimated coefficient from a regression line is 0.99.

In Appendix Table A3, we disaggregate zip code retail establishment counts by year and gentrification status. The average of the ratio of number Yelp establishments to number of CBP establishments is usually less than one. After all, the County Business Patterns count all businesses while Yelp's establishments are mostly crowdsourced. Sometimes, however, the ratio is greater than one, which we attribute to variation in the classification method between Yelp and NAICS (for example, a coffee shop which serves a small menu of hot foods may be considered a restaurant in the CBP but a café in the Yelp data, or vice versa). We expect Yelp's restaurant coverage to be more comprehensive than its coverage of other categories, and indeed we see that the Yelp establishment count to CBP establishment count ratio is very close to 1 in all cases. Appendix Table A3 also shows that in most categories and for most neighborhood types, Yelp coverage improves between 2013 and 2017. This makes sense, since the platform itself was growing over time as mobile expanded.

While the overall Yelp coverage is good, the correlation between Yelp establishment counts and CBP establishment counts is lower for poor, non-gentrifying neighborhoods relative to gentrifying and rich neighborhoods. There are a few reasons this might be the case. It could be that Yelp measurement is more accurate for non-tradable services establishments than for retailers of tradable goods, and we do find a stronger correlation between the number of Yelp and County Business Patterns establishments in a given zip code for these categories. It could also be that "gentrifiers" (new, more educated or higher-income residents) are more likely to add businesses to Yelp than long-term residents. If this is the case, then gentrification of a particular neighborhood could improve Yelp's coverage in that area. For this reason, all of our analysis with the Yelp data focuses on establishment closures, rather than on openings or on the net change in number of establishments.

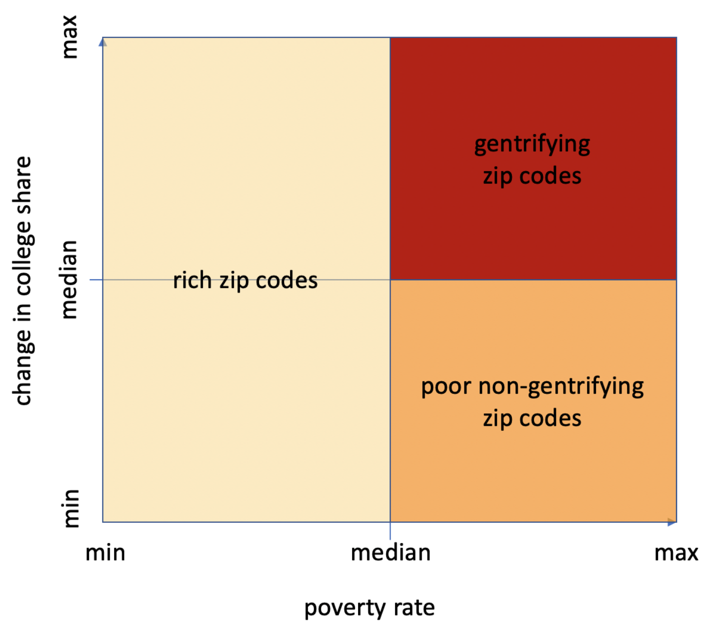
We examine the impact of gentrification on the total number of establishments of different types in a zip code using the County Business Patterns. However, the County Business Patterns does not track individual establishments over time. It reports only the total number of establishments in each NAICS category in a given year at the zip code level, and is not suitable for separately analyzing opening and closing rates.

Exhibits for
Gentrification and Neighborhood Change: Evidence from Yelp

December 30, 2022

1 Figures

Figure 1: Discrete definitions of rich, gentrifying, and non-gentrifying zip codes

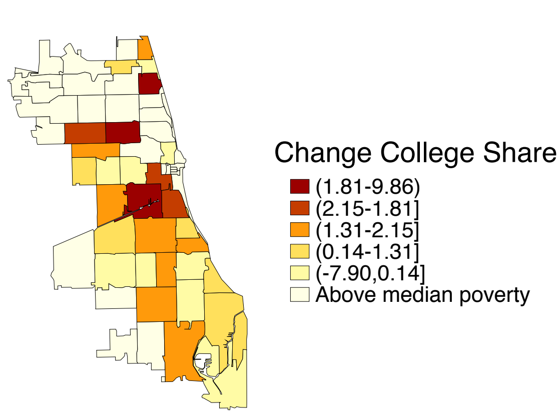


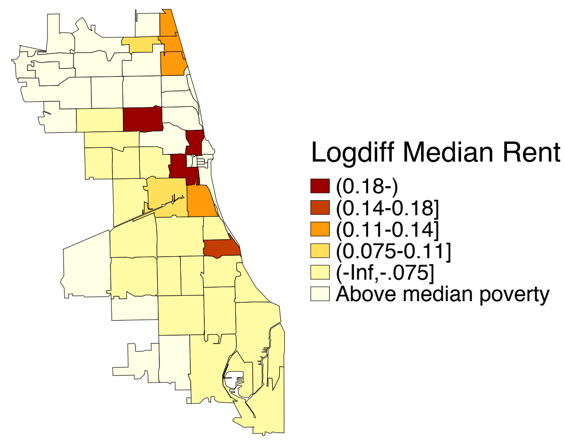
This diagram illustrates how we classify zip codes as rich, gentrifying, or poor but non-gentrifying. Zip codes with a 2012 poverty rate less than the city median are classified as “rich”. Zip codes with a 2012 poverty rate higher than the city median are then classified as “gentrifying” if their rent growth over the 2013-2017 period is above the median.

Figure 2: Spatial Distribution of Gentrification

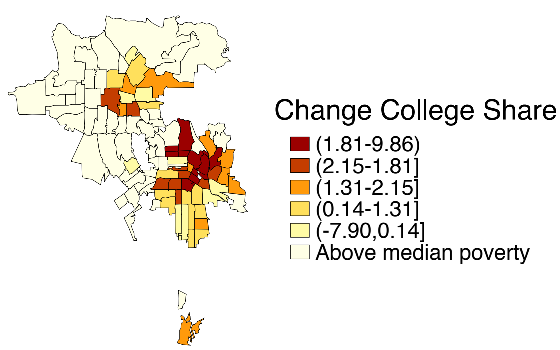
(a) Large cities

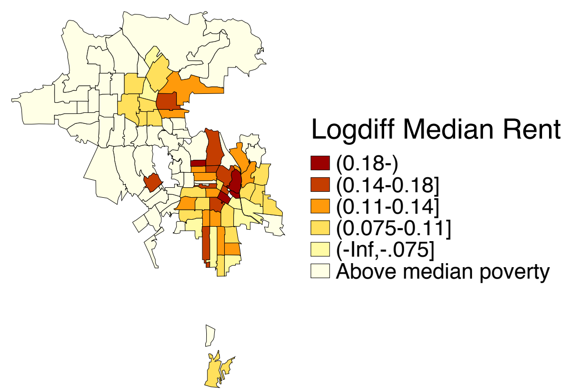
	Change college share	Log change median rent



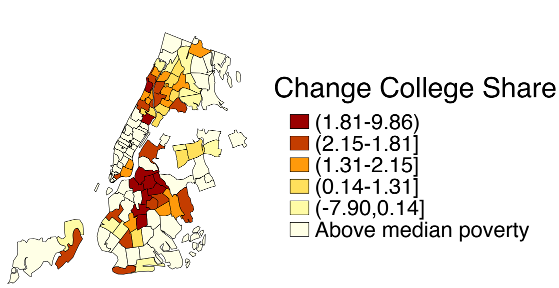


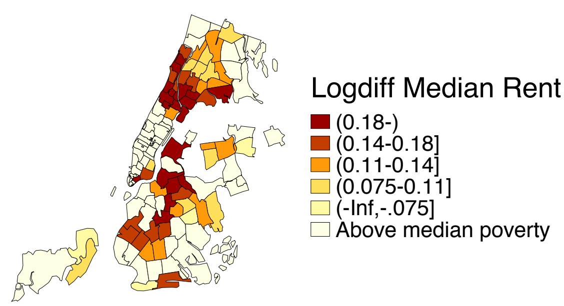
Chicago





Los Angeles



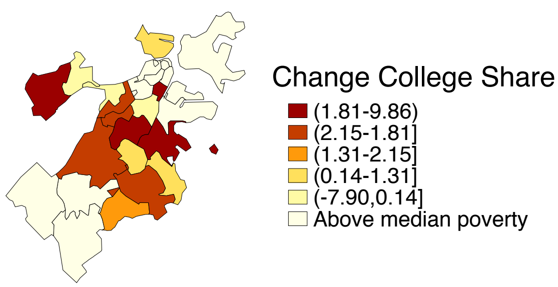


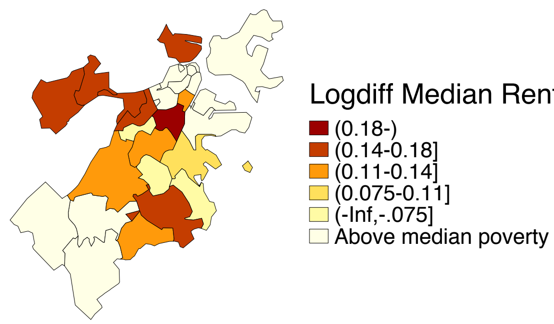
New York

In the left column, we shade poor zip codes according to the change in the college share between 2013-2017. In the right column, we perform the same exercise but show the log difference in median rents between 2013 and 2017.

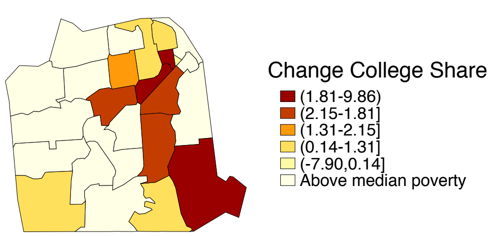
(b) Small cities

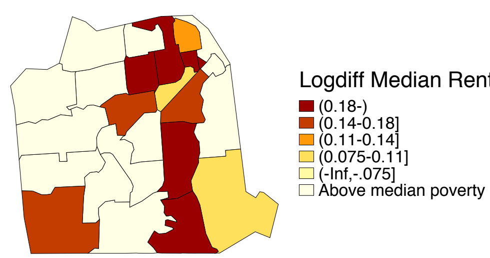
	Change college share	Log change median rent





Boston

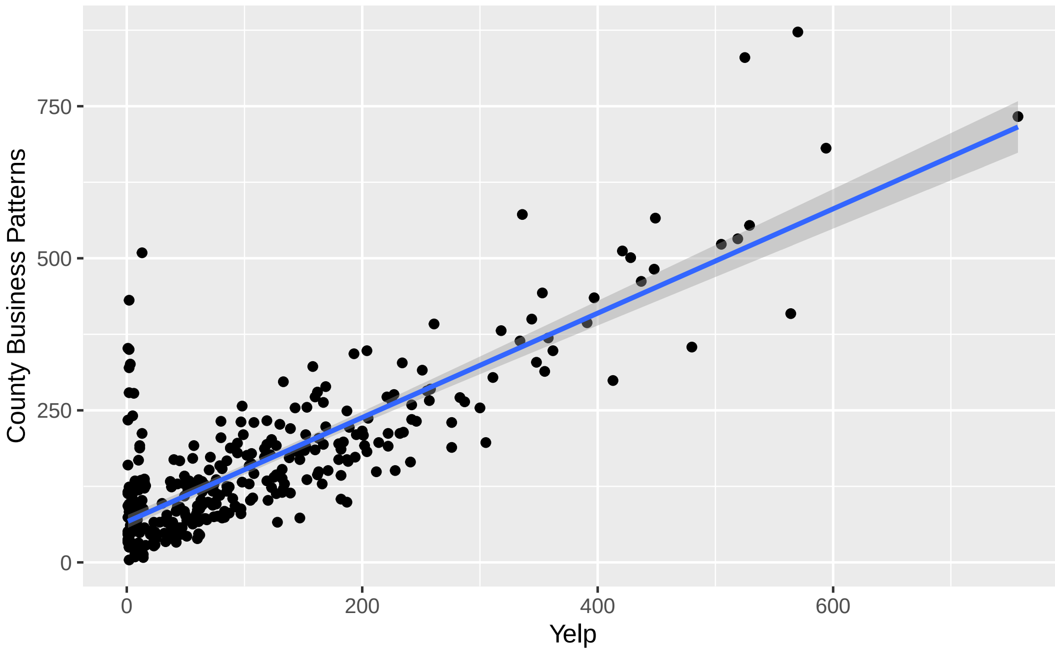




San Francisco

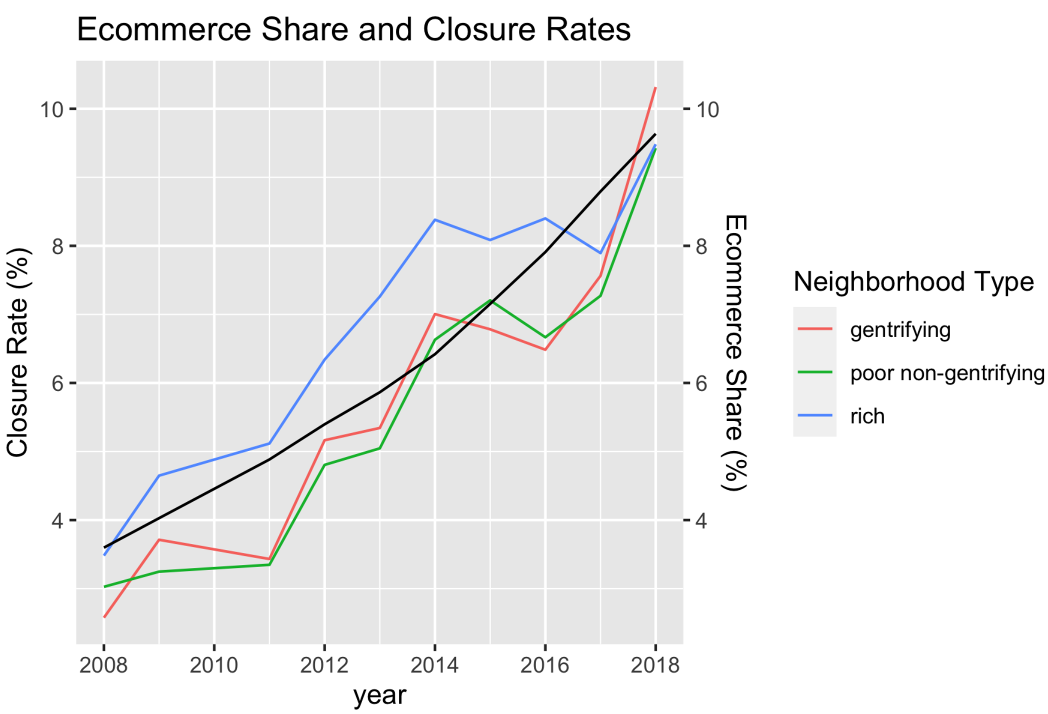
In the left column, we shade poor zip codes according to the change in the college share between 2013-2017. In the right column, we perform the same exercise but show the log difference in median rents between 2013 and 2017.

Figure 3: Yelp and County Business Patterns Establishment Counts



This figure plots, for each zip code, the number of establishments as measured by Yelp and by the County Business Patterns.

Figure 4: National Ecommerce Share and Closure Rates by Gentrification Category



The black line shows the national e-commerce expenditure share as a share of total purchases, from the Nielsen Consumer Panel. The colored lines show closure rates in rich, gentrifying, and poor non-gentrifying zip codes in our sample.

2 Tables

Table 1: Demographic summary statistics by city and gentrification status

	Chicago		Los Angeles		New York		Boston		San Francisco	
	gentrify	poor	gentrify	poor	gentrify	poor	gentrify	poor	gentrify	poor
N. Zip Codes	15	14	26	26	30	30	8	7	7	6
Demographic information (2012 level and percentage change 2012-2017)										
share college	15.74	14.91	14.76	11.35	15.08	15.18	21.78	24.17	27.89	31.16
change (p.p.)	2.37	0 ***	3.98	0.23 ***	3.89	0.22 ***	3.72	-0.64 ***	4.84	-0.46 ***
share 25-34	18.24	15.72	18.41	15.74 **	17.82	16.47	18.91	22.31	25.63	18.33
change (p.p.)	0.65	1.05	0.7	0	1.77	0.71 *	3.52	2.23	2.03	3.92
share white	33.16	30.79	42.35	43.49	32.79	31.6	47.37	45.84	46.87	47.39
change (p.p.)	1.4	1.48	-0.09	-0.63	-1.11	-1.54	-2.05	-1.71	-1.78	-5.13
median income	39,053.93	37,227.79	33,555.69	39,491.04 *	37,474.1	36,653.87	42,871.12	47,616.43	54,640.14	55,568.17
% change	8.45	4.7	14.69	7.37 **	17.42	9.61 **	16.43	20.89	47.92	38.27
Housing market variables										
miles to city hall	6.07	7.74	4.77	9.87 ***	6.33	8.75 ***	3.38	3.46	1.62	2.44
median rent	894.87	891.71	945.19	1050 **	1031.53	1021.97	1209.25	1167.86	1114	1204.5
% change	8.87	5.69	16.25	9.8 ***	17.93	15.07 *	10.91	13.47	16.32	28
share single-family	19.19	27.74	27.38	44.92 ***	3.23	4.51	7.3	8.63	9.06	14.33
share 0-2 bedrooms	62.19	56.75	80.46	65.07 ***	74.65	74.99	67.26	69.04	80.53	76.57
share public transit	29.23	27.77	18.87	12.72 **	64.58	62.31	35.42	33.62	36.23	28.97 **
Retail summary statistics (2012 level and percentage change 2012-2017)										
# Establishments	136.64	101.92	105.45	74.71 **	188.43	228.1	89.5	79.5	218.67	113
# Cats > 10 Estabs	2.14	2	2.05	1.87	2.5	2.7	2	2	2.33	1.67
% change	7.14	0	2.5	-4.17	8.33	5.83	11.11	8.33	16.67	33.33

Stars indicate statistically significant differences between the gentrifying and poor non-gentrifying areas within the city at the 10 (*), 5 (**), and 1 (***) percent levels. For retail summary statsistics section, we include establishment counts from the County Business Patterns with NAICS codes corresponding to our Yelp categories. # Cats > 10 Estabs refers to the average number of 3-digit NAICS codes with more than 10 establishments in the zip code.

Table 2: Impact of Gentrification on Overall Establishment Growth, County Business Patterns, Our Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	%Δ Stores	%Δ Stores	%Δ Stores	%Δ Stores	%Δ Stores	%Δ Stores	%Δ Stores	%Δ Stores
2012 college share		0.43**		0.86**		0.16		0.79*
		(0.16)		(0.29)		(0.17)		(0.32)
2012 share age 25-34		0.52*		0.50		0.52**		0.44
		(0.23)		(0.28)		(0.17)		(0.33)
2012 share white		-0.15		-0.48**		-0.16		-0.51**
		(0.10)		(0.16)		(0.10)		(0.16)
2012 share Black		-0.20*		-0.07		-0.17*		-0.08
		(0.09)		(0.15)		(0.09)		(0.15)
2012 share Asian		0.01		-0.37*		-0.07		-0.46**
		(0.13)		(0.17)		(0.10)		(0.17)
2012 log median income		-21.3		-55.2		57.2		-25.7
		(49.3)		(77.7)		(54.9)		(89.9)
park area		-0.28**		-0.32*		-0.18**		-0.28*
		(0.08)		(0.13)		(0.06)		(0.13)
2012 population (000s)		-0.0008*		-0.001*		-0.0009*		-0.001*
		(0.0004)		(0.0006)		(0.0004)		(0.0007)
2012 poverty rate		0.34		0.24		0.44*		0.37
		(0.19)		(0.30)		(0.20)		(0.32)
log(establishments / sqmi)		-0.07***		-0.09***		-0.04***		-0.07***
		(0.02)		(0.02)		(0.01)		(0.02)
high poverty	-0.02	-0.03	0.01	-0.04	0.007	-0.01	0.05	-0.04
	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)
Δ college share	-0.09	-0.18	-0.37	-0.04				
	(0.34)	(0.36)	(0.51)	(0.50)				
high poverty x Δ college share	1.8*	1.7*	2.3*	1.5				
	(0.89)	(0.73)	(0.97)	(0.98)				
rent growth					0.05	-0.15	-0.45	-0.61*
					(0.20)	(0.22)	(0.27)	(0.30)
high poverty x rent growth					0.14	0.31	0.50	0.84*
					(0.31)	(0.27)	(0.37)	(0.38)
Level of Analysis	Zip	Zip	Zip-NAICS	Zip-NAICS	Zip	Zip	Zip-NAICS	Zip-NAICS
Fixed-Effects:								
county	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
naics	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R^2	0.07	0.21	0.10	0.11	0.03	0.11	0.10	0.11
Within Adj. R^2	0.04	0.19	0.003	0.02	-0.006	0.08	0.001	0.02
Observations	285	285	3,012	3,012	261	261	2,806	2,806

We regress the establishment growth rate from the County Business Patterns on our two measures of gentrification. Columns 1-4 show the regression results when we use the interaction between the high-poverty dummy and the change in the college share, and columns 5-8 show the same regressions but substitute rent growth for the change in the college share. We select only NAICS codes associated with food-related retail and hair salons, in order to select the sample most similar to our Yelp sample, and include only zip codes in the counties which contain our 5 cities. In columns 1, 2, 5, and 6, each observation is a zip code. In columns 3, 4, 7, and 8, each observation is a zip code × NAICS code. Standard errors are clustered at the county level.

Table 3: Percentage change in number of establishments

Panel A: Large Cities

	Chicago			Los Angeles			New York		
	gentrify	poor	rich	gentrify	poor	rich	gentrify	poor	rich
all	8.4	-13.78 ***	5.31 *	7.63	0.12	7.8	15.1	11.23	1.57 ***
bar	15.73	-29.75 ***	-2.76	7.25	-18.54 *	-12.21	12.7	-5.32	6.48
cafe	26.47	22.16	19.71	21.45	12.86	17.52	19.03	17.87	21.9
convenience	-2.05	-20.09	-0.82	-11.33	-7.72	27.14 ***	43.65	10.26 *	16.3 *
fastfood	20.07	-0.5 **	11.28	11.45	9.53	14.14	14.08	14.58	7.18 *
grocery	-17.96	-21.33	-23.47	-25.79	-19.68	-24.01	0.32	-0.39	-16.2 ***
hair	29.28	-0.03	-0.14 **	11.93	10.22	8.17	19.93	20.66	5.13 **
restaurant	33.92	17.74 *	16.01 **	18.64	19.07	10.46	34.09	26.3	16.44 ***

Panel B: Small Cities

	Boston			San Francisco		
	gentrify	poor	rich	gentrify	poor	rich
all	4.71	2.16	2.03	25.26	1.25	6.95
bar	-29.51	-20.2	-16.63	5.15	-1.08	17.67
cafe	-1.06	21.79	3.97	28.66	32	21.29
convenience	22.6	32.76	15.97	80	NA	NA
fastfood	14.27	8.32	0.26	18.68	13.72	20.44
grocery	-12.61	-37.66 ***	-24.19	-16.4	-19.09	-16.62
hair	-5.57	-11.15	-0.99	20.19	28.03	9.29
restaurant	13.48	24.15	27.32	8.11	-6.35 **	5.36

This table presents the percentage change in the number of establishments in different retail categories in gentrifying, poor non-gentrifying, and non-poor areas . Stars in the poor non-gentrifying and rich columns indicate that the average outcome in gentrifying neighborhoods is statistically significantly different from the average outcome in poor non-gentrifying or rich neighborhoods, at the 10% (1 star), 5% (2 stars), or 1% (3 stars) level.

Table 4: Closure Rates by Retail Category (%)

Panel A: Large Cities

	Chicago			Los Angeles			New York		
	gentrify	poor	rich	gentrify	poor	rich	gentrify	poor	rich
all	24	24	27 ***	24	19 ***	26 ***	21	23 ***	28 ***
cafe	27	23	29	24	31 *	29 *	25	25	30 *
grocery	19	17	28 ***	18	9 ***	28 ***	11	10	24 ***
hair	24	18	27	23	9 ***	15 **	13	17	23 ***
liquor and convenience	11	8	23 **	15	13	13	7	9	11
other	27	0	3 **	5	14	6	0	30 ***	10
restaurant	27	28	27	26	21 ***	27	28	28	30

Panel B: Small Cities

	Boston			San Francisco		
	gentrify	poor	rich	gentrify	poor	rich
all	25	27 *	21 **	23	24	24
cafe	27	21	17	30	25	26
grocery	17	25	23	24	22	24
hair	18	32	25	17	20	19
liquor and convenience	0	11	11	15	27	12
other	0	0	0	6	19	0
restaurant	28	29	23	24	25	25

This table presents the closure rate of Yelp establishments in different retail categories in gentrifying, poor non-gentrifying, and non-poor areas . Stars in the poor non-gentrifying and rich columns indicate that the average outcome in gentrifying neighborhoods is statistically significantly different from the average outcome in poor non-gentrifying or rich neighborhoods, at the 10% (1 star), 5% (2 stars), or 1% (3 stars) level.

Table 5: Analysis of Store Closure, 2013-2017, All Establishments

	Dependent variable:					
	Indicator for closure					
	probit		*OLS*	*probit*		*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
log(establishments/mile)		−0.02	−0.01		−0.03*	−0.01
		(0.02)	(0.01)		(0.02)	(0.01)
distance to city hall		−0.002	−0.001		−0.01	−0.003**
		(0.005)	(0.001)		(0.01)	(0.001)
college share (2012)		1.04***	0.36***		0.86***	0.30***
		(0.26)	(0.06)		(0.27)	(0.06)
log median income (2012)		−0.06	−0.02*		−0.11*	−0.04*
		(0.06)	(0.01)		(0.06)	(0.02)
mall		−0.15***	−0.05***		−0.15***	−0.05***
		(0.04)	(0.01)		(0.04)	(0.01)
chain		−0.22***	−0.07***		−0.22***	−0.07***
		(0.03)	(0.02)		(0.04)	(0.02)
franchisee		−0.54***	−0.15***		−0.61***	−0.16***
		(0.08)	(0.01)		(0.09)	(0.02)
franchisor		0.08**	0.03		0.05	0.01
		(0.04)	(0.02)		(0.05)	(0.02)
share park area		−0.25**	−0.09**		−0.24**	−0.09**
		(0.11)	(0.04)		(0.10)	(0.04)
high poverty	−0.06*	−0.03	−0.01	−0.05*	−0.003	−0.001
	(0.03)	(0.04)	(0.01)	(0.03)	(0.04)	(0.01)
Δ college share	0.27	0.17	0.06			
	(0.47)	(0.47)	(0.14)			
Δ college share $\times$ high poverty	0.54	1.59**	0.54***			
	(0.73)	(0.63)	(0.09)			
rent growth				0.10	−0.27	−0.09
				(0.19)	(0.21)	(0.07)
rent growth $\times$ high poverty				0.42	0.58*	0.20**
				(0.28)	(0.31)	(0.08)
Constant	−0.57***	−0.37***	0.36***	−0.54***	−0.25**	0.40***
	(0.05)	(0.12)	(0.05)	(0.06)	(0.12)	(0.06)
Observations	27,042	27,042	27,042	23,969	23,969	23,969
R^2			0.01			0.02
Adjusted R^2			0.01			0.01

Note: We regress an indicator for store closure on our measures of gentrification, using our Yelp sample. *Additional zip code level controls:* share white, share Black, share Asian, 2012 population, share age 25-34. *Additional store level controls:* city, category, Yelp dollar signs.

Table 6: Store Closure Analysis within Narrow Categories

	reg_out1	reg_out2	reg_out3	reg_out4	reg_out5	reg_out6
Dependent Var.:	1(Closure)	1(Closure)	1(Closure)	1(Closure)	1(Closure)	1(Closure)
high poverty	-0.009	-0.007	0.007	-0.001	0.0003	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Change college share	0.06	0.10	0.11			
	(0.16)	(0.16)	(0.16)			
high poverty x Change college share	0.53*	0.48*	0.47*			
	(0.22)	(0.21)	(0.22)			
rent growth				-0.10	-0.10	-0.04
				(0.07)	(0.07)	(0.09)
high poverty x rent growth				0.21	0.20	0.18
				(0.11)	(0.11)	(0.13)
Fixed Effects:	——–	——–	——–	——–	——–	——–
City,Category,Chain	Yes	No	No	Yes	No	No
+Dollar Sign,Mall	No	Yes	No	No	Yes	No
+Miles to City Hall Decile	No	No	Yes	No	No	Yes
--	----------	----------	----------	----------	----------	----------
Adj. R2	0.01	0.01	0.01	0.01	0.01	0.01
Within Adj. R2	0.005	0.004	0.003	0.005	0.004	0.003
Observations	27,042	27,042	27,042	23,969	23,969	23,969

We include all the same controls as in columns 2, 3, 5 and 6 of table 5, but suppress coefficients for brevity. Within each group of three regressions, we divide the observations into finer and finer cells and estimate the coefficeints on the gentrification variables within each cell. For example, in the first column, we look within city-category-chain/not chain cells. In the second column, we further split these cells by the store's price point and whether or not it is located in a mall. Standard errors are clustered at the zip code level.

Table 7: Heterogeneity Analysis of Store Closure, 2013-2017, All Establishments

	Dependent variable:					
	Closure Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
poor	-0.17^{***}	-0.21^{***}		-0.19^{***}	-0.21^{***}	
	(0.05)	(0.04)		(0.06)	(0.04)	
change	-0.61^{***}	-0.46^{***}	-0.73^{***}	-0.61^{***}	-0.50^{***}	-0.74^{***}
	(0.09)	(0.08)	(0.08)	(0.09)	(0.12)	(0.08)
chain	0.05	0.13^{**}	-0.09^{**}	0.05	0.06	-0.09^{**}
	(0.05)	(0.06)	(0.04)	(0.05)	(0.07)	(0.04)
franchisee	0.004	0.01	-0.01	0.004	0.003	0.01
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
franchisor	1.00^{*}	1.28^{**}	0.84	-0.26	-0.30	-0.05
	(0.59)	(0.60)	(0.73)	(0.21)	(0.20)	(0.30)
$, non-chain			0.07^{*}			0.10^{***}
			(0.04)			(0.04)
poor × change	1.06	0.70	1.39	0.44	0.53^{*}	0.39
	(0.71)	(0.71)	(0.93)	(0.31)	(0.31)	(0.40)
chain × poor	-0.07			-0.10		
	(0.08)			(0.08)		
chain × change	-0.75			-0.002		
	(1.26)			(0.68)		
chain × poor × change	0.11			1.16		
	(2.04)			(0.89)		
franchisee × poor		-0.23			-0.40^{**}	
		(0.20)			(0.20)	
franchisor × poor		-0.18^{*}			-0.10	
		(0.09)			(0.10)	
franchisee × change		-4.34			-0.35	
		(3.03)			(1.78)	
franchisor × change		-3.17^{**}			0.62	
		(1.49)			(0.91)	
franchisee × poor × change		-3.09			1.67	
		(5.70)			(2.50)	
franchisor × poor × change		4.48^{*}			0.41	
		(2.42)			(1.14)	
$, non-chain × poor			0.01			-0.03
			(0.06)			(0.05)
$, non-chain × change			0.22			-0.60
			(1.13)			(0.53)
$, non-chain × poor × change			-0.56			0.56
			(1.43)			(0.61)
Constant	-0.22^{*}	-0.22^{*}	-0.28^{**}	-0.16	-0.16	-0.24^{**}
	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.12)
Observations	23,969	23,969	23,969	23,969	23,969	23,969

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7: Heterogeneity Analysis of Store Closure, 2013-2017, All Establishments

In the first 3 columns, "change" refers to the difference in college share between 2012 and 2017. In the second 3 columns, it refers to rent growth (log difference in median rent) between 2012 and 2017. This regression includes all the same controls as the main probit specification.

Table 8: IV Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable:					
	Indicator for closure					
	OLS	*IV*	*IV*	*IV*	*OLS*	*IV*
change college share	0.80**	1.36*	1.49*	0.44	0.08	1.17
	(0.24)	(0.56)	(0.71)	(1.66)	(0.23)	(0.93)
chain	-0.04*	-0.04*	-0.04*	-0.04*	-0.08***	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
mall	-0.02	-0.02	-0.02	-0.03	-0.06**	-0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
franchisee	-0.22***	-0.22***	-0.22***	-0.22***	-0.13***	-0.12***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
franchisor	-0.06**	-0.06**	-0.06**	-0.06**	0.04	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
2012 share college	38.46***	38.81***	37.03***	35.66	10.27	18.64*
	(7.20)	(7.38)	(8.29)	(25.59)	(7.23)	(9.46)
2012 poverty rate			-0.00	-0.00		
			(0.00)	(0.00)		
Constant	0.33***	0.32***	0.32***	0.37***	0.35***	0.32***
	(0.02)	(0.02)	(0.02)	(0.11)	(0.02)	(0.03)
Zip-level controls	No	No	No	Yes	No	No
Sample	Poor	Poor	Poor	Poor	Rich	Rich
Observations	7769	7769	7769	7769	13079	13079
KP rk LM Statistic		13.08	7.18	4.36		4.52
KP F Statistic		7.48	4.05	1.22		0.76
1st Stage F	19.28	17.83	17.73	14.99	10.35	9.18

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table uses data from Los Angeles, New York City and Chicago only. City, category, and dollar sign fixed effects are included in all regressions. Additional zip-level controls include all controls from table 5. Standard errors are clustered at the zip code level.

Table 9: Within-storefront retail type change

	Dependent variable:					
	To service	To chain	Increased $	To service	To chain	Increased $
	(1)	(2)	(3)	(4)	(5)	(6)
high poverty	0.02	-0.05^{***}	0.01	0.02	-0.03^{***}	0.02
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)
Δ college share	0.26	-1.00^{***}	-0.30			
	(0.42)	(0.24)	(0.39)			
high poverty x Δ college share	0.02	0.54^{**}	0.55			
	(0.47)	(0.27)	(0.53)			
rent growth				-0.10	-0.21^{**}	0.03
				(0.12)	(0.09)	(0.15)
high poverty x rent growth				-0.01	0.17	-0.12
				(0.16)	(0.11)	(0.20)
Constant	0.84^{***}	0.05	0.33^{***}	0.85^{***}	0.05	0.31^{***}
	(0.05)	(0.04)	(0.08)	(0.05)	(0.04)	(0.08)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Category FEs	Yes	Yes	Yes	Yes	Yes	Yes
Dollar Sign FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,277	9,277	3,861	9,277	9,277	3,861
R^2	0.07	0.04	0.31	0.07	0.04	0.31
Adjusted R^2	0.06	0.04	0.30	0.06	0.04	0.30

Additional zip code level controls: 2012 share white, Black, and Asian, 2012 population, share age 25-34, 2012 log median income, log(establishments/mile), 2012 poverty rate,
Additional storefront level controls: distance to city hall

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A Appendix

Table A1: NAICS to Yelp Crosswalk

2017 NAICS Code	2017 NAICS Title	Yelp Category
311811	Retail Bakeries	cafe
312120	Breweries	restaurant
445110	Supermarkets and Other Grocery (except Convenience) Stores	grocery
445120	Convenience Stores	liquor and convenience
445210	Meat Markets	grocery
445220	Fish and Seafood Markets	grocery
445230	Fruit and Vegetable Markets	grocery
445291	Baked Goods Stores	grocery
445292	Confectionery and Nut Stores	grocery
445299	All Other Specialty Food Stores	grocery
445310	Beer, Wine, and Liquor Stores	liquor and convenience
722330	Mobile Food Services	restaurant
722410	Drinking Places (Alcoholic Beverages)	restaurant
722511	Full-Service Restaurants	restaurant
722513	Limited-Service Restaurants	restaurant
722514	Cafeterias, Grill Buffets, and Buffets	restaurant
722515	Snack and Nonalcoholic Beverage Bars	cafe
812111	Barber Shops	hair
812112	Beauty Salons	hair

Table A2: Impact of Gentrification on Overall Establishment Growth, Top 50 Counties

	(1)	(2)	(3)	(4)
Dependent Variable	%Δ Stores	%Δ Stores	%Δ Stores	%Δ Stores
2012 college share	0.48**	0.26*	0.36**	0.24*
	(0.15)	(0.11)	(0.13)	(0.12)
2012 share age 25-34	0.72***	0.36**	0.77***	0.29*
	(0.17)	(0.12)	(0.17)	(0.13)
2012 share white	0.02	-0.07	0.06	-0.06
	(0.08)	(0.07)	(0.07)	(0.07)
2012 share Black	0.0007	0.03	0.03	0.04
	(0.07)	(0.07)	(0.07)	(0.07)
2012 share Asian	0.34**	0.09	0.28**	0.05
	(0.12)	(0.10)	(0.10)	(0.09)
2012 log median income	-34.6	-12.3	-30.5	-6.1
	(50.9)	(37.6)	(45.9)	(39.9)
park area	-0.25***	-0.18***	-0.22***	-0.16**
	(0.06)	(0.05)	(0.06)	(0.05)
2012 population (000s)	-0.0003	-0.002***	-0.0004	-0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
2012 poverty rate	0.10	0.10	0.07	0.11
	(0.16)	(0.13)	(0.15)	(0.13)
log(establishments/mile)	-0.10***	-0.08***	-0.09***	-0.07***
	(0.01)	(0.006)	(0.009)	(0.006)
high poverty	-0.01	-0.04*	0.0004	-0.02
	(0.02)	(0.02)	(0.02)	(0.01)
Change college share	0.28	-0.52		
	(0.35)	(0.32)		
high poverty x Change college share	1.2	1.4***		
	(0.66)	(0.42)		
rent growth			0.19	0.008
			(0.13)	(0.08)
high poverty x rent growth			-0.10	0.22
			(0.16)	(0.12)
Level of Analysis	Zip	Zip-NAICS	Zip	Zip-NAICS
Fixed-Effects:	———	———	———	———
county	Yes	Yes	Yes	Yes
naics	No	Yes	No	Yes
______________________________	___________	___________	___________	___________
Adj. R2	0.20	0.11	0.20	0.11
Within Adj. R2	0.17	0.02	0.17	0.02
Observations	2,885	17,958	2,768	17,441

Standard errors clustered at the zip code level.

Table A3: Correlation between Yelp and CBP establishment counts

Panel A: Gentrifying Zip Codes

	2013			2017		
category	avg # Yelp estabs	corr	mean Yelp/CBP ratio	avg # Yelp estabs estabs	corr	mean Yelp/CBP ratio
all	127.09	0.83	0.76	154.72	0.83	0.86
cafe	9.11	0.83	0.83	11.73	0.78	0.80
grocery	8.17	0.70	0.49	10.00	0.70	0.68
hair	11.44	0.49	1.37	13.29	0.37	1.23
liquor and convenience	2.46	0.04	0.97	2.85	0.30	0.51
other	2.70	0.65	0.64	3.50	0.68	0.49
restaurant	37.42	0.72	1.05	44.99	0.78	1.02

Panel B: Poor, Non-Gentrifying Zip Codes

	2013			2017		
category	avg # Yelp estabs	corr	mean Yelp/CBP ratio	avg # Yelp estabs estabs	corr	mean Yelp/CBP ratio
all	73.62	0.62	0.54	94.89	0.60	0.70
cafe	6.15	0.71	0.74	8.17	0.71	0.72
grocery	7.67	0.60	0.44	9.24	0.54	0.73
hair	6.24	0.22	1.35	7.95	0.21	0.85
liquor and convenience	2.54	0.07	1.28	3.13	0.15	0.61
other	2.51	0.61	0.81	3.51	0.48	0.70
restaurant	22.88	0.68	1.09	29.14	0.64	1.09

Panel C: Rich Zip Codes

	2013			2017		
category	avg # Yelp estabs	corr	mean Yelp/CBP ratio	avg # Yelp estabs estabs	corr	mean Yelp/CBP ratio
all	122.82	0.87	0.63	148.09	0.86	0.75
cafe	11.45	0.81	0.84	14.66	0.80	0.84
grocery	7.82	0.77	0.45	9.01	0.76	0.62
hair	12.56	0.61	0.87	14.97	0.65	0.82
liquor and convenience	2.62	0.47	0.69	3.15	0.50	0.59
other	2.85	0.50	0.46	3.67	0.50	0.47
restaurant	41.16	0.88	0.78	47.50	0.86	0.80

Table A4: Heterogeneity Analysis of Store Closure, 2013-2017, All Establishments

	Dependent variable:	
	Closure Indicator	
	(1)	(2)
Chicago	0.10^{**}	0.06
	(0.04)	(0.06)
Los Angeles	-0.09	-0.05
	(0.06)	(0.06)
New York	0.11^{**}	0.08
	(0.05)	(0.07)
San Francisco	-0.08^{*}	-0.12^{*}
	(0.05)	(0.06)
poor	-0.003	0.003
	(0.04)	(0.04)
Boston × rich × change	0.53	-0.96^{***}
	(1.83)	(0.35)
Chicago × rich × change	0.64	-0.72
	(0.66)	(0.47)
Los Angeles × rich × change	3.51^{**}	-0.30
	(1.55)	(0.85)
New York × rich × change	-0.18	-0.06
	(0.96)	(0.25)
San Francisco × rich × change	-0.63^{**}	0.16
	(0.31)	(0.54)
Boston × poor × change	0.59	-1.33
	(1.59)	(1.27)
Chicago × poor × change	-0.02	0.42
	(1.09)	(0.58)
Los Angeles × poor × change	3.83^{***}	0.37
	(1.00)	(0.41)
New York × poor × change	1.70^{*}	0.55
	(0.89)	(0.45)
San Francisco × poor × change	1.31^{*}	0.09
	(0.67)	(0.26)
Constant	-0.37^{***}	-0.25^{**}
	(0.12)	(0.12)
Observations	27,042	23,969

*p<0.1; **p<0.05; ***p<0.01

Note: In the first 3 columns, "change" refers to the difference in college share between 2012 and 2017. In the second 3 columns, it refers to rent growth (log difference in median rent) between 2012 and 2017. This regression also includes all the same controls as the main probit specification, but we suppress their coefficients for brevity.

Table A5: IV First Stage Regressions

Table 8 Column	(2)	(3)	(4)	(6)
	Dependent variable:			
	Change college share			
neighboring college share x HPI growth	-0.34	-0.35	-0.16	0.39
	(0.26)	(0.26)	(0.26)	(0.61)
neighboring HPI growth 09-12	0.15*	0.12*	0.03	0.16
	(0.06)	(0.06)	(0.06)	(0.10)
neighboring college share 2012	-0.08	-0.07	0.01	0.05
	(0.04)	(0.04)	(0.04)	(0.07)
chain	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
mall	0.01	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
franchisee	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
franchisor	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2012 share college	-2.69	-0.10	-15.21*	-13.65*
	(5.63)	(5.86)	(6.31)	(6.71)
2012 poverty rate		0.00	-0.00	
		(0.00)	(0.00)	
miles to city hall			-0.00	
			(0.00)	
2012 share 25 to 34			0.00***	
			(0.00)	
2012 share white			0.00*	
			(0.00)	
2012 share black			0.00*	
			(0.00)	
2012 share asian			-0.00	
			(0.00)	
2012 log(median income)			-0.03	
			(0.02)	
log(establishments/mile)			0.00	
			(0.01)	
2012 population			-0.00	
			(0.00)	
share park area			-0.01	
			(0.02)	
Constant	0.01*	0.01	0.02	0.03***
	(0.01)	(0.01)	(0.04)	(0.01)
Sample	Poor	Poor	Poor	Rich
Observations	7769	7769	7769	13079

First stage results for IV regressions

This table uses data from Los Angeles, New York City and Chicago only.

Clustered SEs (at the zip code level) in parentheses.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$