Does Demand Lead Supply? Gentrifiers and Developers in the Sequence of Gentrification, New York City, 2009-2016

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Abstract

Consumption-side theorists of gentrification examine the flow of middle-class White people into previously working-class neighborhoods and argue their demand for housing stimulates gentrification. In contrast, production-side theorists emphasize the movement of capital into previously disinvested neighborhoods and contend that profit-seeking development increases property values and sparks gentrification. Hybrid theorists argue consumption and production occur simultaneously. This paper operationalizes arguments made by each approach and asks: Do gentrifiers precede rising home values or do rising home values precede gentrifiers? To answer this question of sequence, we build a dataset of census and property tax assessment data for 2,192 New York City census tracts between 2009 and 2016. Using cross-lagged regression models with tract and year fixed effects, we find neighborhoods experiencing an increase in White, middle-class residents experienced related housing price spikes in each of the following two years. A 1% increase in gentrifiers was associated with a subsequent 2.7% increase in property values. However, housing market growth did not predict future increases in gentrifiers. This suggests consumption leads production during neighborhood gentrification and suggests developers are reactive, not proactive, in their investment decisions. Focusing on the sequence of gentrification’s subsidiary elements enables city officials, non-profits, and social movements to better anticipate gentrification and develop more targeted policies.

Key Words
gentrification, property tax assessment data, supply and demand, real estate investment, longitudinal methods

Introduction

In the 1980s, gentrification scholars divided into two schools of thought: one stressing gentrification’s consumption dynamics, and one its production elements. The former emphasized the role of new middle-class residents in initiating gentrification with their retail and housing demands. By their account, wealthy, credentialed, usually White gentrifiers moved into previously poor and working-class neighborhoods, thereby driving up housing prices (Ley, 1996; Zukin, 1989). Production theorists emphasized how landlords and real estate developers initiate gentrification by changing the supply of housing. Investors seek profit in previously disinvested neighborhoods by “redeveloping” them. Real estate elites buy properties, evict long-term tenants, renovate old units, and build new units to increase rents and attract wealthier tenants (Hackworth, 2002; Hammel, 1999; Smith, 1979).

Today, after several decades of gentrification research, the consumption-production dichotomy is often resolved by synthesizing the two theories. A group we call “hybridists” argue “gentrification involves both a change in the social composition of an area and its residents, and change in the nature of the housing stock” (Hamnett, 1991: 176). Exclusive supply-side or demand-side explanations describe different aspects of the same phenomenon the way the blind men in Aesop’s fable each touched a different part of an elephant and failed to grasp its whole (Hamnett, 1991). Embodying this approach, Hwang and Sampson (2014) argue the “social processes of neighborhood selection interact with political and economic forces to *simultaneously* shape both the supply and demand for potential neighborhood reinvestment” (728, emphasis added). Hybridists see consumption and production dynamics as conterminously shaping one another and call for the integration of research on middle-class demand and developer investment.

This hybrid explanation is appealing. No one wants to describe a rope when they are holding an elephant’s tail. What’s more, both demographic and economic changes are readily observable during gentrification. Yet, hybridists set aside an important question about the consumption and production of gentrification: which comes first? Do the gentry move into a neighborhood and *then* housing investment spikes, or is the reverse true? The present study seeks to reveal gentrification’s leading edge by sequencing its subsidiary elements. We collect data from New York City between 2009 and 2016 and model supply- and demand-side dynamics in longitudinal, cross-lagged regressions to gauge whether a neighborhood's new residents predict future housing investment, vice versa, or whether they occur simultaneously.

Understanding the sequence of gentrification enables city officials, non-profits, and social movements to anticipate gentrification and develop more targeted solutions to address housing unaffordability. Our project answers the Urban Institute's call to develop better early warning systems that can anticipate gentrification by providing a method with "more current and frequently updated data that cover a broad range of indicators" (Greene and Pettit 2016:7). To this end, we use New York City property tax assessment data to capture housing market change at a more granular level and with more frequent measurement than the typical measures of home price that use census or sales data. New York City's active housing market, pronounced gentrification, demographic diversity, and large sample of neighborhoods make it a useful research site for developing this tool. Municipalities around the world can apply our flexible methodology to identify early signs of gentrification in their cities and develop more targeted policy and action.

Theories and Research on the Sequence of Gentrification

Consumption-side explanations of gentrification emphasize how the flow of middle-class, often White, professionals into previously working-class and poor neighborhoods precipitates housing price growth. Ley (2003) argues the cultural status of early gentrifiers "brings followers richer in economic capital" (2541). He emphasizes how middle-class "pioneers" lead reinvestment because their housing consumption represents a "demand base for housing re-investment in the inner city" (Ley, 1986: 532). Increases in home value are then a *consequence* of the demands for housing by "small middle-class households" (Ley, 1996: 23). Zukin (1989) traced a similar a pattern in lower Manhattan in the 1970s, where gentrification was sparked by new residents with cultural capital. Middle-class professionals and artists presided over the early stages of gentrification, but then "real estate development reassert[ed] its dominance over the arts economy" (Zukin, 1989: 121).

Empirical research supporting consumer-led explanations of gentrification has focused on the consumption patterns and the race of gentrifiers. Such research has not explicitly examined gentrification's sequence, but has instead assumed demand leads supply (see, e.g., Blasius et al., 2015; Cameron and Coaffee, 2005; Zukin, 2010). In one quantitative study, Galster and Tatian (2009) estimate models to predict when housing price appreciation starts in disadvantaged neighborhoods. They find an influx of better-off home buyers is a key predictor of rising housing prices (Galster and Tatian, 2009). However, they do not model the inverse: whether housing price appreciation predicts future gentrifiers.

This literature has not agreed on the role of race in gentrification (Brown-Saracino, 2017). Many quantitative scholars find in-moving gentrifiers are likely to be White (Baum-Snow and Hartley, 2017; Ellen et al., 2019; Freeman, 2005; McKinnish et al., 2010). Other researchers have noted that middle-class Black people also participate in gentrification (Bostic and Martin, 2003; Pattillo, 2008). Yet other researchers have focused more exclusively on the class of gentrifiers (Landis, 2015; Vigdor, 2002). Some studies have found a neighborhood's preexisting racial composition shapes the likelihood it will gentrify (Hwang and Sampson, 2014; Timberlake and Johns-Wolfe, 2017). The demand-side literature is clear, however, that no matter the race of gentrifiers, they precede supply-side forces during gentrification.

Unsatisfied with “consumer sovereignty” explanations of gentrification, production-side theorists emphasized capital’s role in producing gentrification (Smith, 1979: 538, 1996). Such theorists describe how landlords and developers reinvest in neighborhoods with the highest potential rate of profit (Stein, 2019). As Smith wrote, “gentrification is a back-to-the-city movement all right, but of capital rather than people” (1979: 547, 1996). Lees and colleagues (2016) echo this sentiment, writing, “planetary gentrification is a capital-led colonization of urban space related to globalization and neoliberalization” (87). Supply-side proponents see "banks, real estate developers, small-scale and large-scale lenders, retail corporations, [and] the state, [as having] generally gone before” new residents (Smith, 1996: xvii). This includes state-led gentrification where “government involvement signals to the market that it is safe to proceed” (Chapple and Loukaitou-Sideris, 2019: 47) and new-build gentrification that includes new construction led by large corporate developers. In short, production-side theorists expect developers to be active pioneers, not passive reactors to gentrifiers.

Empirical investigations into production-side explanations document how capital speculation spurs gentrification. Studying Swiss cities using mixed methods, Rérat and colleagues (2010) found new housing construction best explained middle- and upper-class attraction to core cities and argue “new-build gentrification in Switzerland is a process led by capital” (440). Qualitative research in this vein sometimes finds state and private actors work together to push investment into neighborhoods, upscale those areas, and return profits to developers. For example, Schaffer and Smith (1986) documented how private capital and city officials redeveloped and renovated dilapidated and abandoned buildings in Harlem, New York City, preceding a major influx of rich, White outsiders (362). Other research has shown that zoning policies, lending practices, and targeted federal expenditures are often used to reinforce supply-side logic: rezone, invest, and convert (Hackworth, 2002; Hackworth and Smith, 2001; Wyly and Hammel, 1999). Qualitative research has illuminated the profit seeking that sometimes spurred gentrification. The present study aims to more quantitatively test those observations.

Hybrid theories of gentrification resolve the supply versus demand debate by either arguing that both occur simultaneously or setting aside the debate to study other aspects. They do not try to resolve the debate, but rather argue "both production and consumption processes are important in explaining gentrification" (Hyra, 2017: 12). They contend these explanations are "complementary rather than competing" (Hamnett, 1991: 175) and that gentrification "result[s] from both flows of capital and people" (Zuk et al., 2015: 14). Schlichtman and colleagues (2017) think any one-sided claims to resolve this debate belong in graduate student theory seminars because "these phenomena are concomitant" (27). Other hybrid researchers like Ingrid Gould Ellen (2011) are "agnostic about underlying causes" as they examine both elements (3). Similarly, Slater (2012) sets aside the debate altogether, writing it "does not matter whether production or consumption is viewed as more important in driving gentrification, so long as neither is completely ignored" (575).

Many researchers, regardless of their approach, assume gentrifiers are renters. Although this is often a safe assumption, cases in which owner-occupier gentrifiers are more common would represent a variation of the hybrid explanation as the owner-occupier gentrifier changes a neighborhood's demographics while simultaneously investing in it.

Much of the hybridists' empirical research has assumed the simultaneity of consumption and production without modeling the question of sequence explicitly. For instance, Hwang and Sampson (2014) and Timberlake and Johns-Wolfe (2017) constructed datasets that simultaneously measured the supply- and demand-side dynamics of gentrification. These two studies make important contributions to our understanding of how gentrification can occur along racial lines, but they do not to identify whether it is investment or gentrifiers that spark the process. Lance Freeman (2005) developed a method for identifying gentrified neighborhoods that uses both supply- and demand-side forces, though he does not speak to sequence. Using methods from computer science, Torrens and Nara (2007) run simulations that simultaneously model supply and demand to account for human behavior in relocation dynamics. However, these hybridists do not examine which mechanism has stronger or prior predictive power. Our research tests which mechanism leads the other so as to better understand whose decisions (developers or gentrifiers) matter most in sparking gentrification.

Research Design: Data, Methods, and Models

Our research site is New York City, measured annually between 2009 and 2016. The city had an active and tight housing market. It had strong rent regulations, 63% of its residents were renters, and many of its residents lived in public housing (Guamer, 2018; New York City Housing Authority, 2019). The population of New York at this time was diverse and included many immigrants. However, segregation remained high. During the Great Recession of 2007-2008, the federal government targeted the financial sector for relief, stabilizing New York's large financial sector and its overall economy. As a result, the City's housing market recovered quickly. New York City is a useful place to study the sequence of gentrification because it provides a large sample of gentrifiable and gentrifying tracts, its housing market was uncommonly stable during this time, and its status as a global city made it a prime destination for investment capital and gentrifiers alike. Gentrification trends are likely stark there.

We use two samples of New York City census tracts to test gentrification's sequence. So as not to compare gentrifying neighborhoods to those too wealthy to gentrify, the primary sample includes only tracts eligible for gentrification at the start of the period, 2009. Our tract eligibility criteria mirror that of Freeman (2005), a standard measure. Tracts were eligible for gentrification if in 2009 they had: (1) below-city-median household income and (2) a below-city-median percent of its buildings constructed in the last 20 years, indicating disinvestment. The second sample includes tracts ineligible for gentrification based on the same criteria. Both samples exclude tracts with fewer than 1,000 people or no residential units. Employing listwise deletion to omit tracts with two or more years of missing data excluded 66 tract-years from the eligible sample (2.6%) and 180 from the ineligible sample (2.0%). We use the terms "tracts" and "neighborhoods" interchangeably. Since tract boundaries changed in 2010, we harmonized data from 2009 into 2010 boundaries using the Longitudinal Tract Database (Logan et al., 2014).

Dependent and Explanatory Variables

We measure production-side dynamics of gentrification using *residential property value*. It is a measure of a tract's median home value, as reported in the New York City Department of Finance's (DOF) property tax assessment database. We obtained tax assessment data for fiscal years 2009 to 2017 from the DOF website, selecting the "market value: current full value total" variable which represents the total property value before any tax exemptions or deductions have been applied (NYC Department of Finance, 2018). We remove utility and commercial properties from the dataset, leaving residential properties. The DOF's fiscal year stops June 30th. So, to convert the property value data to calendar year data, we attributed half of a property's value to one year and half to the previous.

To aggregate property-level data to the census tract-level, we merged property value data with a 2016 Primary Land Use Tax Lot Output (PLUTO) file (New York City Department of City Planning, 2018). We used the condominium identification number in the PLUTO file to label individual condominiums and counted each as a unit to mirror other properties. We then took the median property value in each tract and inflation adjusted it to 2016 dollars using the all-items-less-shelter Consumer Price Index (CPI) for New York-Newark-Jersey City, NY-NJ-PA. We use the CPI less-shelter measure so as to not control away variation in our variable of interest, housing prices (U.S. Bureau of Labor Statistics, 2019). We then averaged the median property value over five years to mirror the census data, which, as described below, are five-year estimates. This averaging technique has the added benefit of "improv[ing] precision in noisy data" (Ellen et al., 2019: 5fn16). While we cannot say with one-year precision when, for instance, a particular spike in housing prices occurred, we can be sure we are comparing the housing spike to the complementary five-year estimate of gentrifiers. Since the distribution of the variable is strongly right skewed, we take its natural logarithm to induce normality.

Our use of tax assessment data raises a concern that our model is slow to capture changes in the market. While some studies use sale price data to represent price changes more contemporaneously, there are too few home sales in most tracts to generate accurate measures at the neighborhood level. In 2016, the average New York City tract eligible for gentrification saw 13 of its properties sold, or 0.8% of its stock, and 7% of tracts had zero transactions. Sales data also include many “non-arms-length” transactions between family members for below-market-rate prices, further degrading its reliability. Tax assessors can use their expertise to purge such transactions. So, tax assessment data are both more comprehensive and more accurate than sales data at the tract-level. Additionally, in New York City, tax assessments are updated every year, mitigating concerns that our measure lags the market. The New York City DOF assesses all new construction with an in-person appraiser and annually updates all previous properties with hedonic regression modeling incorporating the sale prices of neighboring properties (Robert Rolandi, 2017, personal communication). Our measure therefore incorporates sale price data, although it will take until the next assessment update to appear in the data. By averaging these data across five years we further mitigate against concerns that our data lag the market. We expect state-led gentrification initatives like rezonings and redevelopment projects will be captured by residential property values as the housing market reflects the increased value created by the regulatory changes.

The American Community Survey (ACS) is another possible source of home price data. We believe tax assessment data is more accurate than census home price data because census data miss the 63% of New York’s units that are renter-occupied and rely on the sometimes-faulty memory of survey completers. Cities in which tax assessment data are not updated annually or are not publicly available might adapt this method for use with available data. We use tax assessment data because of its superior accuracy.

The *index of gentrifiers* captures consumption-side dynamics of gentrification. We create the index using a factor analysis of four measures of a tracts' White, middle-class residents: the percent of a tract with a bachelor's degree or higher, the percent non-Hispanic White, the percent in management or professional occupations, and the tract's median household income. The index scale loaded on one common factor (eigenvalue = 2.84). The components have the following factor loading scores: percent with a bachelor's degree 0.95, percent non-Hispanic White 0.69, percent managers or professionals 0.94, and median household income 0.77.

As we noted above, there is no consensus in the literature about whether or when to include race in a measure of gentrifiers. Following recent studies finding gentrifiers are mostly White, we include percent White in our models (Baum-Snow and Hartley, 2017; Ellen et al., 2019; Freeman, 2005; McKinnish et al., 2010). White people often serve as "signals of neighborhood change to potential residents and investors" (Schlichtman et al., 2017: 116). So, for our study of gentrifiers and developers, we expect whiteness to be an important mechanism linking the two elements. Further, as the loading scores indicate, percent White is highly correlated with the three economic variables, suggesting it belongs in the index and that including it as a control variable outside the index could cause problems of multicollinearity. Finally, a definition of gentrifiers that includes White people aligns with the popular conception of gentrification in New York City during our study period, allowing our work greater relevance to New York City policymakers and the public. As a check, we ran a version of the models omitting percent White (Appendix Table model pairs 1 and 2) and found very similar results.

Control Variables

As basic demographic controls, we include tracts' *total population* and their *percent male*. While gentrifiers are not homogenous (Rérat, Söderström and Piguet, 2010), we control for the share of tracts' population *aged 18 to 34,* given the higher mobility of young professionals (McKinnish et al., 2010; Moos, 2016). We include the *vacancy rate* and the *number of residential housing units* to control for neighborhoods with more capacity to accept in-movers because of empty properties or recent construction (Rérat, Söderström, Piguet, et al., 2010). We also control for the *percent of a tract's residents who moved in the previous year*, a measure of residential instability. As public housing is less susceptible to gentrification, we control for *the percent of public housing units*. The *housing unit* and *public housing* controls come from the tax assessment data, while the other controls come from the ACS's 5-year estimates. We take the natural logarithm of all skewed variables—*housing units, vacancy rate, percent public housing*, and *percent moved in the previous year*—to induce normality. The *year* variable controls for macro, sample-wide shifts like the Great Recession of 2008 or city-wide policy changes. Table 1 reports descriptive statistics for each variable included in our models for 2009 and 2016, as well as the percent change between.

[Insert Table 1 about here]

Models and Estimation

Our research design adapts Granger causality theory, which posits that one variable "Granger causes" another if prior values of the explanatory variable have a significant effect on the dependent variable's later values, controlling for past values of the dependent variable (Granger, 1980). We set aside the question of whether this technique indicates causation, instead using it to indicate sequence. One variable *leads* another if its past values are significantly related to future values of the second variable, and not vice versa. We apply this design to gentrification by testing whether lagged values of the *index of gentrifiers* are associated with future *residential property value*. We then flip the two variables and test whether previous *residential property value* relate to future increases in *gentrifiers*. If previous values of one are statistically significant predictors of the other and not vice versa, or, if both are statistically significant but the coefficient of one direction is greater than the coefficient in the inverse estimation, that would suggest one dynamic leads the other. If, however, the coefficients of both are statistically significant and similar in magnitude, that would indicate a more simultaneous sequence, supporting hybrid theory. If most gentrifiers are also owner-occupiers, both variables would change in tandem. This analytic strategy is sometimes called a reciprocal effects design (Allison, 2009) and resembles a cross-lagged model (Finkel, 1995).

This design requires our estimation procedures control for past values of the outcome variable because gentrification's production and consumption dynamics are likely endogenous. Residential property values and influxes of gentrifiers likely positively influence each other in a reciprocal feedback loop. Since we are trying to identify the sequence and directional strength of the elements in this loop, we have to separate the relationship of the lagged explanatory variable to the outcome variable at time *t* from the contemporaneous relationship between the two at time *t*-1. We do this by including a lagged dependent variable as a predictor. We use Arellano and Bond (1991) first-difference, generalized method of moments (GMM) models because they generate efficient and consistent parameter estimates when including lagged dependent variables in datasets with many panels and few periods like ours. But, such dynamic panel models can introduce bias due to second-order autocorrelation (Wooldridge, 2016). So, we use the standard Arellano-Bond test for autocorrelation and find our primary models exhibit no second-order autocorrelation.

Using a first difference estimator allows us to measure change over time. This procedure subtracts each observations' values from their previous year's value and uses the difference to compute the regression. For the index of gentrifiers, this method distinguishes new tract residents from incumbents. Another advantage of the Arellano-Bond GMM estimator is it allows for tract fixed effects. Fixed effects models demean variable values using the within-tract average by removing the tract average from each value. This controls for all time-invariant neighborhood characteristics like land area size, unique history, transportation infrastructure, and proximity to the center city, assuming they did not change during the study period (Allison, 2009).

Our dynamic panel models take the following forms:

$$y_{it} = \mu_t + \beta_2 y_{it-1} + \beta_1 x_{it-1} + z_{it-1} + \alpha_i + \varepsilon_{it}$$

$$x_{it} = \tau_t + \delta_2 x_{it-1} + \delta_1 y_{it-1} + z_{it-1} + \eta_i + \varepsilon_{it}$$

Where y_{it} is the first dependent variable (the logged *median residential property value* in tract i at time t), y_{it-1} is the lagged dependent variable in the first equation and the lagged explanatory variable in the second, x_{it} is the second outcome variable (the logged *index of gentrifiers*), x_{it-1} is the lagged dependent variable in the second equation and the lagged explanatory variable in the first, z_{it-1} represents the vector of lagged control variables, α_i

and η_i are the tract-specific fixed effects, and ε_{it} is the error term. We use a Huber/Whites/sandwich estimator to generate robust standard errors (Winship and Radbill, 1994).

Results

Figure 1 maps changes in median residential property values for eligible tracts. Tracts colored white indicate missing data or areas ineligible to gentrify because of above-city-median incomes, above-city-median recent housing construction, or too few residents. Large sections of Manhattan, Staten Island, eastern Queens, and the areas of Brooklyn closest to Manhattan were ineligible because they were too wealthy or too recently developed. The map shows in black where, between 2009 and 2016, home prices increased. Growth was concentrated in upper and lower Manhattan, large sections of Brooklyn, and the west of Queens, while large sections of the Bronx, east Brooklyn, and east Queens saw declines, indicated in grey.

[Insert Figure 1 about here]

Figure 2 maps the change in the index of gentrifiers for eligible tracts. As before, black indicates increase and grey decrease. Comparing Figures 1 and 2, we see some of the tracts experiencing increases in home prices also saw an influx of high income, credentialed, White professionals: much of northern and central Brooklyn and upper and lower Manhattan. However, the trends are hardly identical. Some parts of south Brooklyn that saw increases in home prices saw a departure of gentrifiers, while large parts of the Bronx and eastern Brooklyn and Queens saw increases in gentrifiers but decreases in home prices.

[Insert Figure 2 about here]

With each map portraying the same time period, no strong conclusions can be drawn about whether demographics precede development or vice versa, but the varying spatial patterns raise doubts about the hybridists' claims that the two are mutually constitutive. Of course, we need to include co-variates and estimate the temporal sequence to know more. For that, we use multi-variable modeling, presented below.

Table 2 presents the coefficients for our Arellano-Bond GMM regression models with tract and year fixed effects. The reciprocal effects design is represented in the table by each model appearing in a pair. The first model in each pair regresses property values on the index of gentrifiers, on the lagged property value measure (the endogeneity control), and on the control variables. The second model in the pair then flips property values to be an explanatory variable and the index of gentrifiers to be the dependent variable and runs the same regression.

Model pair 1 finds the average tract's gentrifier index score had a statistically significant relationship with the tract's median property value in the following year, but property values were not related to subsequent demographic shifts. Model 1A expects a 1% increase in the index of gentrifiers in an eligible-to-gentrify neighborhood to be followed by a 2.7% increase in the neighborhood's median property value. Because property values are log transformed and the gentrifier index is not, we exponentiate the coefficient, subtract one, and multiply by 100 to interpret the coefficient as a percent change ((exp(0.027)-1)*100=2.74%). The average neighborhood in our sample experienced a 6.9% increase in the index of gentrifiers between 2009 and 2016 (see Table 1), a change the model expects to be associated with an 18.7% growth in the neighborhood's property values (6.9*2.7). Model 1B, however, shows no such statistically significant association between property values in one year and the index of gentrifiers in the next. In model pair 1, gentrifiers predict investment, but investment does not predict future gentrifiers.

Model pair 2, which lags the independent variables two years, exhibits the same pattern, though with smaller coefficients. A 1% increase in a tract's gentrifier index is associated with a 0.9% increase its property values two years later ((exp(0.009)-1)*100=0.90%). As with the one-year lag, changes in a neighborhood's property values are not related to its gentrifiers two years hence.

The pattern is somewhat similar in tracts ineligible for gentrification. Model pairs 3 and 4 display results for neighborhoods too wealthy or recently developed to be eligible for gentrification. In such neighborhoods, a 1% increase in the gentrifier index was related to property value growth of 0.9% the next year ((exp(0.009)-1)*100=0.9%) and 0.5% two-years later ((exp(0.005)-1)*100=0.50%). This mimicked eligible tracts. One difference from the eligible tracts was that the one-year lag of property values was related to future increases in gentrifiers, though the magnitude was small. A 1% increase in property value was related to a 0.0006% increase in White, middle-class gentrifiers ((exp(0.062)-1)/100=0.0006). While the demographics-lead-development trend is observable in both eligible and ineligible neighborhoods throughout New York City during this time, the trend is more consistent in tracts eligible to gentrify, suggesting the sequence of supply and demand varies by gentrification context.

As for control variables, in model pair 1, our primary models, a tract's population size was significantly associated with both future property values and future gentrifiers. Since the census tract boundaries remained static, this variable is a proxy for population density. Neighborhoods getting denser saw increases in home prices and the number of gentrifiers. The year variable was significant and positive, as we would expect with both dependent variables increasing city-wide during most study years. No other control variables were statistically significantly in the eligible models related to the outcomes at both time lags, though young people and residential units were negatively related to investment one year out.

[Insert Table 2 about here]

Robustness Checks

As with any modeling procedure, we could have made different choices. To account for this, we ran alternate versions of the models. Some past research has measured gentrifiers' economic class and omitted measures of their race (Landis, 2015; Vigdor, 2002). In the Appendix Table, model pair 1 uses an alternate index of gentrifiers that excludes the measure of racial change (percent non-Hispanic White) and retains only education, occupation, and income measures. The results are substantively identical to our primary models. Another influential decision could have been the criteria we used for determining a tract's gentrification eligibility. Changing sample composition can dramatically affect model results. A common alternative to the below-city-median threshold used above is more conservative criterion of including only tracts whose median income or recent housing construction are below the 40^{th} percentile of the city median. Those results are presented in the Appendix Table as model pairs 3 and 4, and very closely resemble our primary models. Another researcher might choose a different lag structure. So, in addition to our one- and two-year lags presented above, we ran models with three, four, and five-year lags. While neither supply nor demand predicted the other three years out, demand predicted supply—in line with our primary results—four and five years out. Those models are available upon request.

Discussion and Conclusion

To sequence the demand for and supply of housing during gentrification, we adapt Granger causality theory in longitudinal, cross-lagged regression models. While this approach cannot speak to causation, it provides strong support, robust to a battery of alternate specifications, that consumption-side dynamics led production-side ones, at least in New York City between 2009 and 2016. An increase in middle-class White people is a statistically significant predictor of future housing investment, but the reverse is not true. Growth in a neighborhood's residential real-estate market is not associated with subsequent growth in its White, middle-class residents.

These findings have implications for gentrification research. We take these results as evidence the hybridists were too quick to synthesize production and consumption theories. At least during our study period in New York, consumption led production. This is not to say supply-side actors and their development strategies are inconsequential. Production-side dynamics might not be the spark, but rather the sustaining engine of gentrification, entering the picture later. Our results also raise the possibility demand and supply are independent of one another. If this is the case, future research should test if gentrifiers might move into some neighborhoods absent housing price growth or if housing markets in disinvested neighborhoods can tighten absent new in-movers.

Our results have a major take-away for urban theory: we must study time when we study place. We found gentrification's subsidiary elements were not simultaneous. If we theorize all aspects of urban phenomena as occurring simultaneously, we might misunderstand the processes, and when we operationalize the theories, we might inaccurately measure only the beginning or end of the processes. In this way, our study underscores the importance of longitudinal, processional theories and analyses.

Our study suffers from some limitations. First, our tax property data might lag actual changes in market prices. As discussed in the data section above, however, we think this shortcoming is less severe here than with other measures of home price at the tract-level. Additionally, we guard against this lag by averaging the data across five years, adjusting fiscal year data to the previous calendar year, and running our regressions with multiple-year lags. Further, New York City annually updates each property's assessed value using new sales data in a hedonic pricing model, making it more responsive to market changes than other cities that do not use this method. Second, our study is limited to one city between 2009 and 2016. New York City is a global city and therefore our findings might be more applicable to London or Tokyo than to Little Rock or Toledo. Our methodology, however, can be used to test whether supply or demand leads in any city.

Some of our study's limitations suggest future research. Our strategy analyzes middle-class professionals—a conservative marker of gentrification's beginnings—and does not model other possible stages of gentrification. Future research could more explicitly model the different stages of gentrification, perhaps by including artists, young people, childless couples, or LGBTQ people in its measure of gentrifiers. Future research might also use our methodology to test the sequence of production and consumption in commercial, rather than residential, real estate. Also, we do not adjust for both spatial and temporal autocorrelation. Our tract fixed effects will control for any time-invariant spillover effects, but we cannot control for time-variant spatial correlation as we are not aware of a modeling technique that can adjust for both serial and spatial autocorrelation while also supporting our cross-lagged structure. If and when such methods are developed, future research might incorporate them. Finally, our models do not explicitly measure tracts' differing mixtures of regulatory statuses. Some research suggests state-led actions like rezoning or social investment could spark gentrification (e.g. Hackworth and Smith, 2001). We think such state action would appear as increases in our measure of housing prices, as investors react to the regulatory changes. Still, future research might directly account for government influence.

This project provides policymakers and social movements a new and flexible methodology for analyzing the sequence of supply and demand. Cities can reproduce our analysis as an early detection system to determine whether gentrifiers or housing investment are the leading edge of gentrification in their neighborhoods. While New York City's frequently updated property tax data and numerous census tracts allow for analysis more easily there, smaller cities might consider using more years of data or third-party housing price data like that from Zillow to perform their analyses. As scholarly disagreements about whether and when to define gentrifiers as White are ongoing, cities can customize the index of gentrifiers to include ethno-racial groups that might be prevalent in their area or exclude race alltogether. We ran alternate models excluding "percent White" from the measure of a neighborhood's gentrifiers and the results were the same: demand led supply. This similarity in results suggests gentrifiers spur landlord and real estate investment decisions both through the visible presence of new White residents, and also through the less visible consumption decisions of middle-class residents like their willingness to pay higher rent and their preference for upscale retail amenities.

Extant policy responses to gentrification and housing unaffordability have largely encouraged developers to supply new housing (Angotti and Morse, 2016). Our findings suggest policy should focus on demand in addition to supply. It is likely other cities resemble New York's demand-first sequence and intervening to stop gentrification's negative outcomes will be difficult because it is easier to regulate the real estate sector than thousands of people moving semi-independently. But, since our results suggest developers lag in-movers, it will be these individual- and community-level interventions that are more likely to interrupt gentrification early. There are several examples of such demand-side interventions. The federal government could expand subsidies to tenants. City governments could pass "just cause" eviction ordinances to help tenants challenge eviction proceedings, they could implement "right of return" policies to offer displaced residents the first choice of new units built in their neighborhoods, and they could pass "right to purchase" policies to allow tenants the option to buy their building before it is sold to developers (Causa Justa, 2015; Schlichtman et al., 2017). Once cities determine the leading edge of gentrification, they can identify neighborhoods most at risk of further gentrification and concentrate anti-displacement services there.

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[Insert Appendix Table about here]

Table 1. Descriptive statistics of variables used in regression models

Variables	Tracts eligible to gentrify				
	2009		2016		2009-16
	Mean	S.D.	Mean	S.D.	% Change
Population	4,346	2,313	4,395	2,368	1.13%
% moved in previous year	10.26%	5.24%	9.49%	4.84%	-7.54%
% public housing units	5.54%	18.25%	5.32%	17.49%	-4.10%
% male	47.63%	4.78%	47.89%	4.11%	0.55%
% age 18-34	25.60%	5.75%	27.08%	6.20%	5.78%
Housing units	415.25	298.42	414.94	297.69	-0.07%
Vacancy rate	7.15%	4.38%	7.43%	3.81%	3.81%
Index of gentrifiers	2.46	0.50	2.63	0.58	6.95%
% with a bachelor's degree or higher	21.05%	10.06%	25.27%	11.66%	20.05%
% professionals and managers	26.12%	10.91%	29.08%	11.58%	11.34%
% non-Hispanic White	26.17%	28.35%	24.10%	25.76%	-7.89%
Median household income	$40,732	$9,850	$44,099	$13,739	8.27%
Index of gentrifiers (class only)	2.45	0.48	2.64	0.56	7.65%
Median residential property value	$694,784	$614,400	$763,489	$1,193,375	9.89%
Total observations	422		425		

Variables	Tracts ineligible to gentrify				
	2009		2016		2009-16
	Mean	S.D.	Mean	S.D.	% Change
Population	3,808	2,013	3,887	2,000	2.07%
% moved in previous year	10.60%	6.44%	9.60%	5.72%	-9.44%
% public housing units	2.61%	10.49%	2.46%	9.95%	-5.72%
% male	47.96%	4.40%	47.91%	3.86%	-0.08%
% age 18-34	25.38%	7.65%	26.41%	7.83%	4.05%
Housing units	602.39	486.77	613.45	496.03	1.84%
Vacancy rate	8.01%	5.61%	8.45%	5.15%	5.53%
Index of gentrifiers	3.03	0.94	3.16	0.98	4.38%
% with a bachelor's degree or higher	31.30%	19.53%	34.83%	20.14%	11.28%
% professionals and managers	35.98%	16.81%	38.59%	17.47%	7.26%
% non-Hispanic White	37.29%	32.78%	34.25%	30.43%	-8.15%
Median household income	$64,769	$27,834	$64,642	$28,826	-0.20%
Index of gentrifiers (class only)	3.02	0.93	3.17	0.97	4.95%
Median residential property value	$964,050	$1,294,124	$1,100,956	$1,798,709	14.20%
Total observations	1,495		1,496		

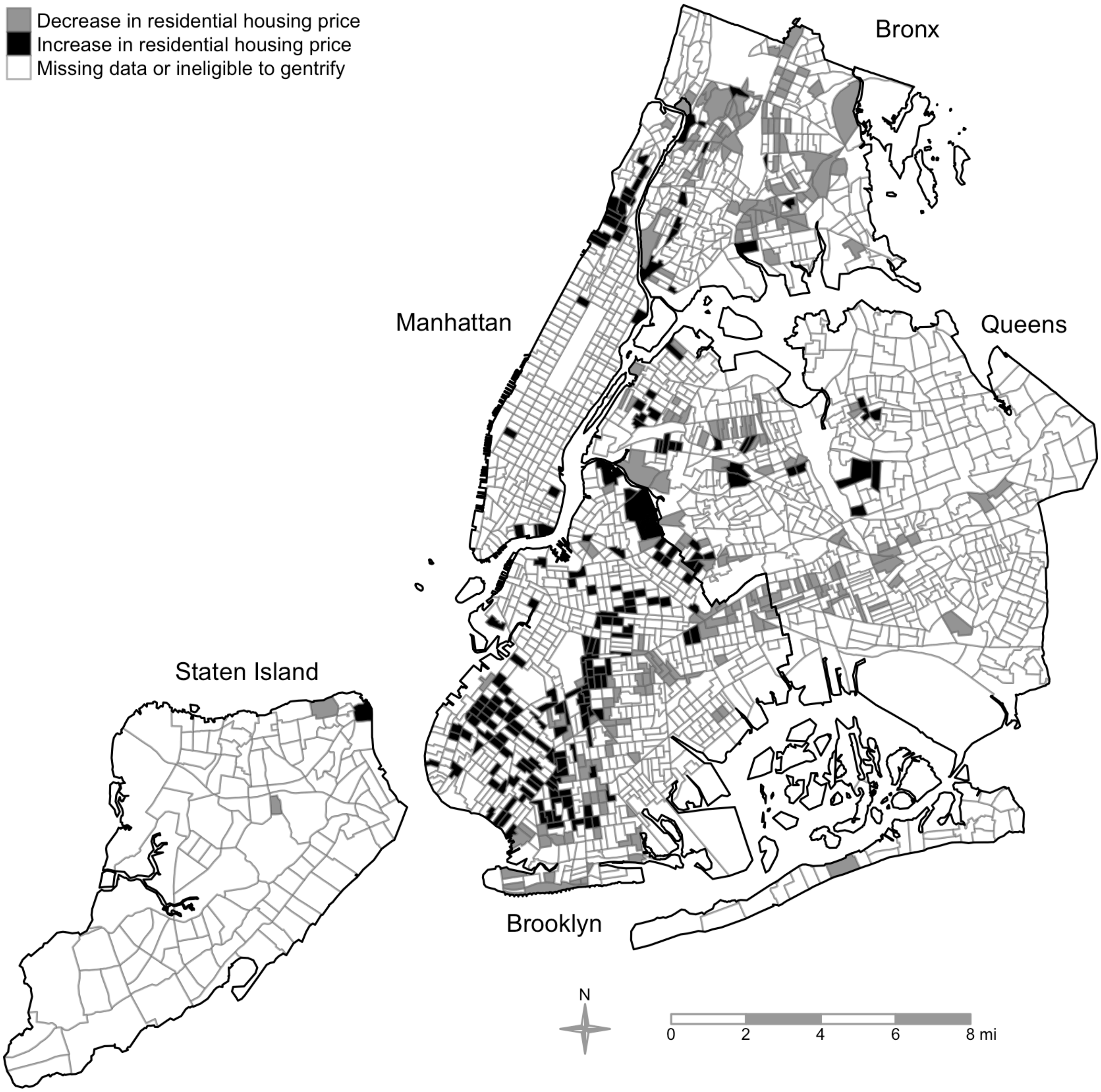

Figure 1. Change in median residential property values for eligible tracts, New York City, 2009-2016

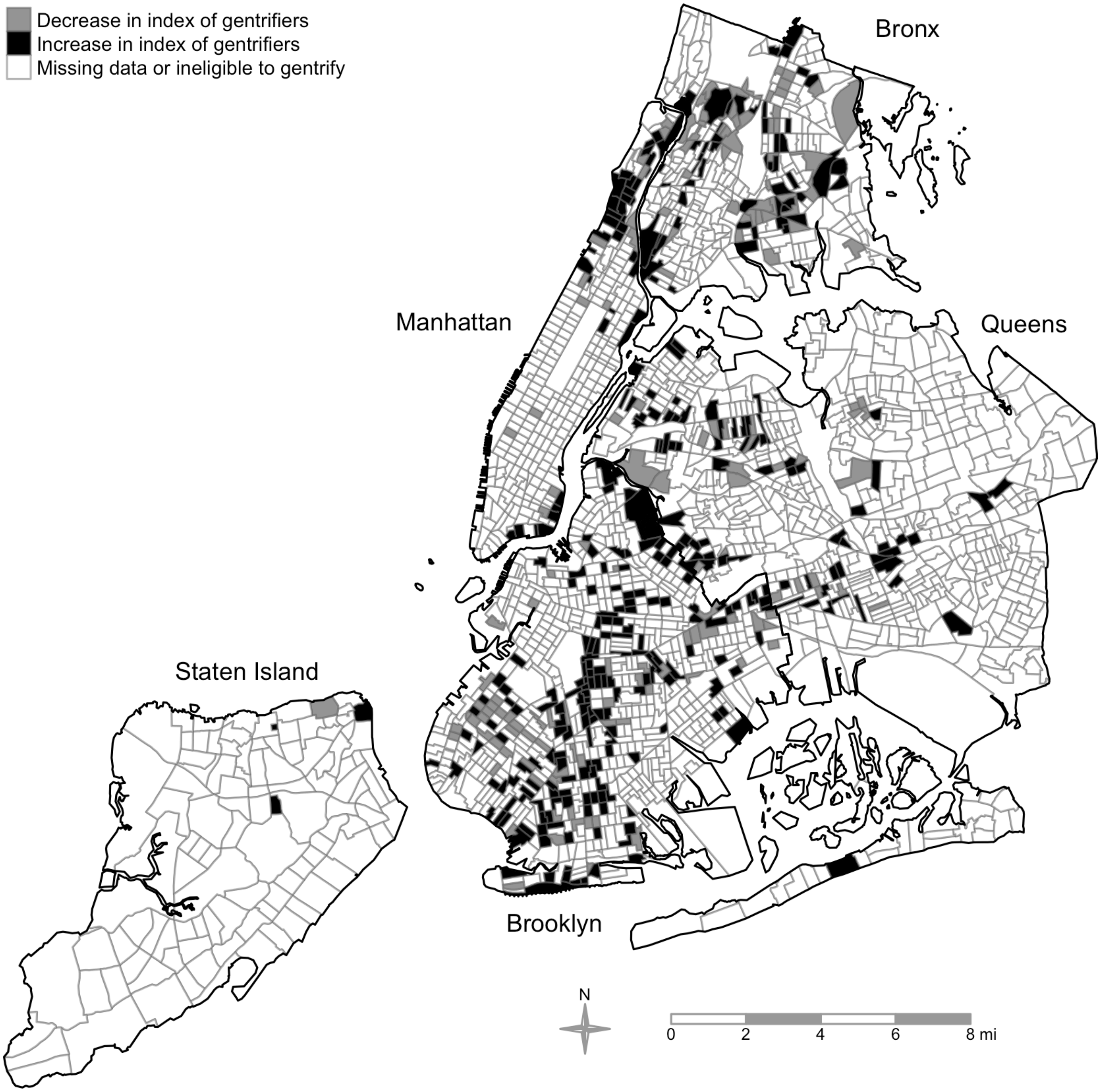

Figure 2. Change in index of gentrifiers, New York City, 2009-2016

Table 2. Unstandardized coefficients, Arellano-Bond GMM regressions with tract and year fixed effects

	Tracts eligible to gentrify				Tracts ineligible to gentrify			
	1-year lag		2-year lag		1-year lag		2-year lag	
	Model Pair 1		Model Pair 2		Model Pair 3		Model Pair 4	
	1A: Residential property value†	**1B:** Index of gentrifiers	**2A:** Residential property value†	**2B:** Index of gentrifiers	**3A:** Residential property value†	**3B:** Index of gentrifiers	**4A:** Residential property value†	**4B:** Index of gentrifiers
Index of gentrifiers	0.027*** (0.00)		0.009*** (0.00)		0.009*** (0.00)		0.005*** (0.00)	
Residential property value		0.095 (0.06)		0.012 (0.86)		0.062* (0.04)		-0.036 (0.30)
Lagged dependent variable	0.795*** (0.00)	0.491*** (0.00)	1.561*** (0.00)	0.416*** (0.00)	0.869*** (0.00)	0.748*** (0.00)	1.565*** (0.00)	0.837*** (0.00)
Twice lagged dependent variable			-0.724*** (0.00)	0.018 (0.46)			-0.678*** (0.00)	0.041** (0.00)
Population	0.000*** (0.00)	0.000* (0.01)	0.000* (0.02)	-0.000 (0.18)	0.000*** (0.00)	0.000*** (0.00)	0.000*** (0.00)	-0.000 (0.22)
% male	-0.001 (0.23)	0.003 (0.06)	0.000 (0.33)	-0.000 (0.87)	0.001*** (0.00)	0.004*** (0.00)	0.000 (0.46)	-0.001 (0.53)
% age 18-34	-0.003*** (0.00)	0.002 (0.24)	-0.000 (0.21)	-0.002 (0.24)	-0.002*** (0.00)	-0.001 (0.15)	-0.000** (0.00)	-0.001 (0.25)
Vacancy rate†	-0.004 (0.07)	0.012 (0.26)	0.002 (0.24)	-0.013 (0.19)	-0.002** (0.01)	0.001 (0.85)	0.000 (0.99)	-0.006 (0.43)
Housing units†	-0.208* (0.04)	-0.105 (0.44)	-0.027 (0.38)	0.089 (0.42)	-0.211** (0.01)	0.100 (0.14)	-0.015 (0.61)	-0.104 (0.19)
% public housing units†	0.016 (0.08)	-0.012 (0.23)	0.001 (0.41)	0.014 (0.33)	0.021* (0.01)	0.002 (0.96)	0.002 (0.75)	0.055 (0.29)
% moved in previous year†	0.004 (0.15)	-0.017 (0.24)	0.000 (0.93)	-0.017 (0.22)	-0.001 (0.59)	0.002 (0.84)	0.000 (0.72)	-0.001 (0.92)
Year	0.007*** (0.00)	0.015*** (0.00)	0.012*** (0.00)	0.018*** (0.00)	0.008*** (0.00)	0.007*** (0.00)	0.012*** (0.00)	0.008*** (0.00)
Constant	3.689*** (0.00)	0.126 (0.90)	2.114*** (0.00)	0.741 (0.48)	2.802*** (0.00)	-1.054* (0.04)	1.420*** (0.00)	1.480* (0.01)
N	2,534		2,110		8,966		7,470	

* p<0.05, ** p<0.01, *** p<0.001; †Variable logged to normalize

Appendix Table. Unstandardized coefficients, Arellano-Bond GMM regressions with tract and year fixed effects, for tracts eligible to gentrify

	1-year lag		2-year lag		1-year lag		2-year lag	
	Model Pair 1		Model Pair 2		Model Pair 3‡		Model Pair 4‡	
	1A: Residential property value†	**1B:** Index of gentrifiers (class only)	**2A:** Residential property value†	**2B:** Index of gentrifiers (class only)	**3A:** Residential property value†	**3B:** Index of gentrifiers	**4A:** Residential property value†	**4B:** Index of gentrifiers
Index of gentrifiers (class only)	0.026*** (0.00)		0.009*** (0.00)					
Index of gentrifiers					0.037*** (0.00)		0.011** (0.01)	
Residential property value		0.092 (0.07)		0.016 (0.81)		0.066 (0.21)		-0.021 (0.72)
Lagged dependent variable	0.795*** (0.00)	0.505*** (0.00)	1.561*** (0.00)	0.439*** (0.00)	0.773*** (0.00)	0.568*** (0.00)	1.544*** (0.00)	0.478*** (0.00)
Twice lagged dependent variable			-0.724*** (0.00)	0.016 (0.49)			-0.731*** (0.00)	0.024 (0.44)
Population	0.000*** (0.00)	0.000* (0.01)	0.000* (0.02)	-0.000 (0.19)	0.000*** (0.00)	0.000 (0.09)	0.000 (0.15)	-0.000 (0.27)
% male	-0.001 (0.23)	0.003* (0.05)	0.000 (0.33)	-0.000 (0.79)	-0.000 (0.43)	0.003 (0.13)	0.001 (0.19)	-0.003 (0.18)
% age 18-34	-0.003*** (0.00)	0.002 (0.29)	-0.000 (0.21)	-0.002 (0.20)	-0.002*** (0.00)	0.002 (0.43)	-0.000 (0.56)	-0.002 (0.28)
Vacancy rate†	-0.004 (0.07)	0.013 (0.22)	0.002 (0.24)	-0.013 (0.21)	-0.005 (0.09)	0.009 (0.52)	0.004 (0.14)	-0.013 (0.27)
Housing units†	-0.208* (0.04)	-0.121 (0.40)	-0.027 (0.38)	0.076 (0.50)	-0.283 (0.12)	0.018 (0.93)	-0.037 (0.56)	-0.049 (0.84)
% public housing units†	0.016 (0.08)	-0.012 (0.18)	0.001 (0.42)	0.015 (0.19)	0.026 (0.12)	-0.008 (0.40)	0.001 (0.23)	0.022* (0.05)
% moved in previous year†	0.004 (0.15)	-0.016 (0.26)	0.000 (0.92)	-0.018 (0.19)	0.000 (0.92)	-0.026 (0.18)	-0.001 (0.60)	-0.015 (0.42)
Year	0.007*** (0.00)	0.016*** (0.00)	0.012*** (0.00)	0.019*** (0.00)	0.006*** (0.00)	0.014*** (0.00)	0.012*** (0.00)	0.019*** (0.00)
Constant	3.689*** (0.00)	0.196 (0.85)	2.113*** (0.00)	0.713 (0.49)	4.295*** (0.00)	-0.371 (0.77)	2.455*** (0.00)	1.821 (0.20)
N	2,534		2,110		1,578		1,315	

* p<0.05 ** p<0.01 *** p<0.001; †Variable logged to normalize; ‡Model pairs 3 & 4 use the 40th percentile eligibility criterion.