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Are Residents Who Are Displaced by Gentrification Better or Worse Off After Relocating?

Alice M. Anigacz
Macalester College, aanigacz@gmail.com

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Are Residents Who Are Displaced by Gentrification Better or Worse Off After Relocating?

Alice M. Anigacz

Advisor: Professor Sarah West

Abstract: This honors thesis examines how individuals displaced by gentrification fare after relocation, with changes in wage and income as the primary measures of well-being. Geo-coded Panel Study of Income Dynamics data is used in conjunction with decennial census tract-level neighborhood data to evaluate nationwide occurrences of gentrification and their effects on the displaced between 1990 and 1995, with a focus on whether changing neighborhood effects can account for the change in well-being. Standard OLS regressions not accounting for neighborhood effects find that compared to a nationwide sample, a sample of movers, and a sample of displaced residents, residents displaced specifically by gentrification do not experience statistically significant wage or income changes. When neighborhood effects are considered, being displaced by gentrification has varying effects on wage and income, and changes in wage and income, which vary based on which neighborhood characteristic is being considered. These effects vary greatly in their consistency with neighborhood effects theory, suggesting that analysis would benefit greatly from improved data.

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I. INTRODUCTION

Gentrification—the buying and renovation of houses and stores in deteriorated urban neighborhoods by upper or middle income families or individuals, which improves property values but often displaces low income families and small businesses—has been an increasingly common urban phenomenon since the 1950s, and yet very few studies have empirically tested what happens to those residents who are displaced by this process in the long run.

According to George and Eunice Grier,

Displacement occurs when any household is forced to move from its residence by conditions which affect the dwelling or its immediate surroundings, and which:

- (1) are beyond the household's reasonable ability to control or prevent;
- (2) occur despite the household's having met all previously-imposed conditions of occupancy; and
- (3) make continued occupancy by that household impossible, hazardous, or unaffordable (HUD, in Le Gates and Hartman, 1981, p. 214).

Past research finds that white professionals and single parents move into gentrifying neighborhoods, as working class residents, the elderly, the unskilled, and the unemployed are displaced (Atkinson 2000). While it is mostly low-income households that are displaced, there are also a significant number of middle-class people that leave the neighborhood (Lyons 1996). Yet many aspects of what happens to this highly diverse but economically disadvantaged group remain unanswered.

This study uses geo-coded Panel Study of Income Dynamics (PSID) data, as have several previous displacement studies. It also explicitly links displacement with gentrification to look at cities around the United States, rather than only at a particular instance or instances of gentrification, and extends from 1990 to 1995. It examines how

individuals' wages and incomes change as they relocate from gentrifying neighborhoods to new ones to measure whether individuals end up better or worse off. The study attempts to answer why the incomes or wages of individuals change as they relocate. Is a significant difference between past and present neighborhood effects—such as a difference in potential role models or a difference in unemployment rates—responsible for the changes in individual wage and income? While this is an issue that has been addressed in previous literature, it has oft been left to the discretion of the residents surveyed to rank their neighborhoods, whereas this study will use decennial census data to evaluate neighborhoods.

Section II will review literature on neighborhood effects and displacement. Section III will provide a theoretical framework and estimation strategy. Section IV will discuss the data and the variable specification. Section V will report regression results and robustness checks. Section VI will discuss conclusions drawn from findings.

II. LITERATURE REVIEW

A. What are Neighborhood Effects?

To understand whether the displaced end up better or worse off, one must understand what changes occur to them when they relocate out of their gentrifying neighborhoods. Most obviously, their neighborhoods change. While different neighborhoods offer a bevy of varying combinations of public transportation, housing, and educational institutions, it must be remembered that gentrification as it is considered in this paper is a purely urban phenomenon. Recent research has shown that a wave of gentrification known as postrecessionary gentrification has been occurring since the period after the recession of the early 1990s and spreading to areas away from the urban

cores of cities (Niedt 2006). However, this study only covers up to 1995, and will not consider suburbs as susceptible to gentrification. Thus, because they are located in the city center, a person encountering gentrification should have enough public transportation options, as most cities do, so that having more educational or other institutions in their immediate neighborhood should not significantly affect them. That is, it is easy for a person living in a city to go to another neighborhood in the city for work, school, etc. In this sense, it may be the difference in neighbors that is the biggest difference for people displaced by gentrification. This concept is known as neighborhood effects, and it speaks to the myriad ways in which neighbors influence each other's behavior (Freeman 2006; Lees 2008; Wilson 1987).

While this paper focuses on neighborhood effects, it cannot be ignored that gentrification can have many other effects on displaced residents. Gentrification carries a large psychic cost, especially for those residents who come from very insular neighborhoods. Losing one's neighbors, close-by relatives, etc. can be traumatic, and this can cause a displaced family to incur costs it had not experienced before, either because of emotional trauma, or because of, for example, the necessity to hire a babysitter when one was readily available at no or lower cost before. Gentrification can also cause displaced residents to feel inept or wronged, and thus cynical towards gentrifying forces. Doubtless, there are many other sources of possible effects of gentrification that will not be discussed in this paper, which will focus solely on neighborhood effects as possible reasons for changes in residents' well being.

Neighborhood effects can be divided into four categories: peer effects, collective efficacy/socialization, social ties, and institutional resources.

Peer effects refers to the idea that like follows like and individuals will be influenced by the behavior of their peers. This is most often used to refer to people witnessing, reacting to, and taking on the behavior of individuals within their own age group. Collective efficacy and collective socialization refer to when the collective actions of the neighborhood are directed at the behavior of local residents or externally, respectively. An example of collective efficacy is the idea of role models for children. The idea is that children need positive role models and adjusting to the change in local behavioral pathologies can affect a resident's life (Wyly 1999). Social ties are those connections that are sources of social satisfaction, and may also facilitate upward mobility by providing sources of information about jobs (Kleit 2001). The mixing of cultures and races is supposedly preferable over a homogenous setting, as it prepares children for the many cultures that they are likely to encounter as adults, and expands the horizons of older residents (Allen 1984). Finally, institutional resources refers to the influence that the upper-classes have with organizations and the ability of the upper-classes to create effective community organizations.

B. Past Research in a Neighborhood Effects Framework

Lyons finds that higher-income movers in Greater London were more likely to move farther away to find neighborhoods that were suitable to their needs, while lower-income residents were more likely to remain near the central city though further away from it than they were in their former neighborhood. Schill and Nathan (1983) have similar findings when they study the displaced in five gentrifying areas in the United States. They find that 22 percent of the displaced had shorter commutes after being displaced, and only 15 percent traveled longer distances. Furthermore, very few of the

displaced relocated away from the city, as only 8 percent of the displaced moved to the city's suburbs or away from the metropolitan area, as compared to 17 percent of voluntary movers (Schill and Nathan 1983). That the displaced remain in the central city or close to their place of work supports the assumption that they have sufficient means of transportation to get to school and work, and should not have to rely upon their new neighborhoods for work or education opportunities within the neighborhood's parameters.

Lower-income residents in London were also more likely to live in enclaves, meaning that many of the lower-income displaced from one neighborhood were likely to relocate to the same neighborhood (Lyons 1996). This suggests that they are likely to maintain the same social ties, which would hinder absorption of the effects of their new neighborhoods or new neighborhood effects in their gentrifying neighborhoods (HUD 1981). One state-sponsored gentrification program in Copenhagen was meant not to displace any residents, but to involve them in the revitalization of the neighborhood, but still ended with some residents moving to purportedly "worse" neighborhoods (Larsen 2008). Dixon (1998) states that long-term residents of the Cabrini-Green houses in Chicago have been forced to move into more substandard homes as they are displaced by gentrification, but fails to cite the source of this information. In these aforementioned cases, the displaced are encountering negative neighborhood effects, as they are either ending up in worse neighborhoods or maintaining connections with other low-income residents from their original neighborhood. However, it cannot be said that gentrification caused those who stayed in their original neighborhoods to experience negative effects.

Two studies focusing on minority migration patterns evaluate mobility between high-income and low-income neighborhoods. They find that white households are typically much less likely to move from high-income to low-income neighborhoods than minority households are, though the rate of this sort of movement for white households has increased dramatically in the 1980s and 1990s (Crowder and South 2005; South, Crowder, and Chavez 2005). Though their studies do not explicitly link mobility with displacement from gentrification, they speculate that this increased trend in downward mobility may be a reflection of gentrification. This would seem to support the displaced ending up worse off in terms of neighborhood effects, as the data find that minority residents are likely to relocate to worse neighborhoods, though it is uncertain whether low-income residents would be moving to even lower-income neighborhoods.

Freeman studies gentrifying neighborhoods in New York City and finds that low-income individuals and individuals without a college degree are less likely to move out of a gentrifying neighborhood than similar individuals in a non-gentrifying neighborhood (Freeman 2005).¹ Similarly, a study of five gentrifying neighborhoods found that over 70 percent of the displaced households, compared to 60 percent of the voluntary movers, relocated within the same zip code or to a neighboring zip code, suggesting that they remain in close proximity to gentrification (Schill and Nathan 1983). This may point to the displaced still being in close enough proximity to garner some positive neighborhood effects from in-movers (Vigdor 2001). But while Freeman's econometric analysis supports the idea that low-income residents do not end up worse off because they are

¹ Generalizations about gentrification in the United States should not be made based on cases of gentrification in New York. New York is a special case in that very few alternative affordable housing options exist, so there may be less of an option to move or benefit to be gained for long-term residents if they choose to relocate out of their gentrifying neighborhood.

more likely to make intra-neighborhood moves or remain in their original housing than be displaced, interviews with long-term residents suggest that there is no or very little social mixing, so that residents cannot benefit from the positive neighborhood effects that upper-class gentrifiers bring (Freeman 2005). As Freeman says, “Income mixing is no promise of upward mobility” (Freeman 2006, p. 206).

A U.S. Department of Housing and Urban Development report (1981) which used PSID and survey data finds that displaced residents from the San Francisco Hayes Valley neighborhood did not experience “severe negative changes in housing characteristics either absolutely or in comparison with other groups.” The Hayes Valley study also states that displaced households were more satisfied with their homes and neighborhoods after moving, which could be a product of positive neighborhood effects within their neighborhood (HUD 1981). Another HUD study that used PSID data found less favorable outcomes for displaced residents, but did not link displacement directly with gentrification (Vigdor 2002). It found that displaced households are likely to experience significant increases in crowding and housing cost burden, but that displacement did not significantly affect housing costs, welfare dependency, or hours worked.

Somewhat contradictory to the aforementioned findings, Schill and Nathan’s (1983) study of five gentrifying areas in the United States found that though rent increased (but only moderately) for many displaced residents, these residents must have been purchasing additional rooms with the additional rent, as crowding did not significantly increase. This study also found that 56 percent of displaced residents rated their new neighborhood as better than the one they were displaced from, whereas 67 percent of voluntary movers found their new neighborhood better than their old one.

Nineteen percent of the displaced reported that their new neighborhood was worse than their previous neighborhood, whereas 13 percent of voluntary movers believed that their new neighborhood was worse (Schill and Nathan 1983). These results suggest that though the majority of displaced residents are ending up better off in terms of neighborhood quality, they are not ending up as better off as non-displaced movers. A study that used American Housing Survey data to focus on gentrification in the Boston area found that of the households facing higher housing costs, the majority also experienced increases in income to offset this increase. Most households within this group also experienced an increase in housing quality, neighborhood quality, or public service quality, or a combination of the three (Vigdor 2002).

The results of both of these studies suggest that positive neighborhood effects are taking place, as incomes and neighborhood quality perceptions increase, though Schill and Nathan's study notes that in comparison to non-displaced movers, the displaced are worse off, even if they are over all better off. This may be because displaced movers display lower income levels than non-displaced movers, and thus it is easier for non-displaced movers to create social ties with residents of the better neighborhoods they move into. This allows voluntary movers to further garner benefits from positive neighborhood effects. On the other hand, the stigma of being low-income and a lack of previous interactions with higher-income individuals may prevent low-income displaced movers from establishing the same social ties within their better relocation neighborhoods.

There are several patterns that reoccur within the cited studies and similar ones. The Copenhagen study as well as Dixon's analysis of gentrification in Chicago both do

not specify what constitutes a better or worse neighborhood. Freeman (2006), Schill and Nathan (1983), and HUD (1981) focus on analysis of interviews or percentage differences rather than conducting econometric analysis. Schill and Nathan's (1983) and HUD's (1981) studies only cover instances of gentrification up until the 1980s. Finally, Vigdor's research (2001), which is most similar of the papers mentioned to the research conducted in this study, only provides original research on the Boston area. By using geocoded PSID and decennial census data, extending the study into the 1990s, performing empirical econometric analysis, and utilizing clear measures of neighborhood characteristics, this study fills a gap in the literature by providing a more comprehensive and nationally representative analysis than past research has, and attempts to quantify many things that were qualitatively analyzed in past research.

III. THEORETICAL FRAMEWORK AND ESTIMATION STRATEGY

In order to determine whether low-income residents are better or worse off after being displaced by gentrification one must create a model that specifies their residential location decision. In this study, the term "household" includes any person living in the home of the reference person. Urban area refers to the larger metropolitan area, and encompasses the neighborhoods of low-income and high-income households. Central city refers to the core of the city, where low-income households are assumed to locate under the theory of spatial mismatch because of their need to utilize public transportation in order to travel to work and school (Wilson 1987). I use a discrete choice framework with general representations of household utility, which is based on Kent's (2008) approach for modeling school district choice, and Vigdor's (2001) discussion of the driving forces of gentrification and relocation decisions in the face of gentrification.

A. Household Location Decision

I assume a household will choose to live in the neighborhood in which net benefits are maximized. The term net benefits refers to the total value generated from living in a neighborhood minus the total cost of living in that neighborhood. Value represents the real dollar value of benefits from living in a specific neighborhood. While the costs of a neighborhood (rent, cost of transportation to work or school, etc.) are obvious, the concept of the value of a neighborhood can be less intuitive. The real dollar value of a neighborhood speaks to the monetary amount one gains from living in one neighborhood rather than another. For example, if living in one neighborhood exposes a resident to peers with better job connections, and thus the resident obtains a better paying job than they would have held in a different neighborhood, then any gains from this job that are over the gains from the job they would have otherwise held are considered to be part of the neighborhood's real dollar value. Things like not having to get a car alarm because the neighborhood is safe enough to not require such precautions are also considered in the value of the neighborhood. In order to maximize value, V , a household chooses a neighborhood so that $V_i > V_j$; for all neighborhoods i, j . A household chooses neighborhood i if:

$$[V(nbhoodcsm_p_i, othercsm_p) - C_i] > [V(nbhoodcsm_p_j, othercsm_p) - C_j] \quad (1)$$

where $nbhoodcsm_p$ represents neighborhood consumption, and $othercsm_p$ represents other consumption. C represents the total cost of living in the neighborhood and the cost of relocating to that neighborhood if it is not the neighborhood in which the household currently resides. The total cost of living in a neighborhood contains the cost of housing, as well as how much the household spends on essentials such as food and other staples,

and transportation costs to school or work. That is, I assume that households will do everyday shopping within their neighborhoods, and therefore the cost they incur from purchasing these goods is dependent on the typical costs of these goods in stores in their neighborhoods. Transportation costs may vary based upon how many public transportation options the neighborhood contains, and whether living in the neighborhood necessitates owning a car, as it would if an individual were living in the outer part of the urban area but working in the central city. The cost of relocating can be substantial, since in addition to the large cost of moving physical possessions, there is a large psychic cost associated with leaving behind the old neighborhood, where one is accustomed to the people, schools, stores, etc. This relocation cost is included in the cost of a neighborhood. Specifically, the cost of relocating to neighborhood j is included in the cost of j if the resident does not already reside in neighborhood j . A household should choose to move only if the value of moving exceeds the cost of moving.

This study is mostly concerned with the effects of people and social networks within a neighborhood on displaced residents who relocate into that neighborhood, so the model will focus on neighborhood and peer effects. All neighborhood-specific characteristics (such as public transportation options, the number of schools, the types of commercial business in the area) other than neighborhood effects are factors of other consumption. Rewriting equation (1), a household's net benefits are now represented as a function of neighborhood effects (which is represented by *nbhoodeffects*) and all other consumption, so that the household chooses to live in neighborhood i if:

$$[V_i(\text{nbhoodeffects}_i, \text{othercsmp}) - C_i] > [V_j(\text{nbhoodeffects}_j, \text{othercsmp}) - C_j],$$

$$\forall i, j \text{ neighborhoods} \quad (2)$$

B. Neighborhood Effects Production Function

Neighborhood effects are a function of peer effects, collective efficacy/socialization, social ties, and institutional resources (Freeman 2006). Research finds conflicting results about the effect of peers and social networks within a neighborhood upon other members of the neighborhood. The following six neighborhood characteristics are identified by Ginther et al. (2000) as measures that are frequently shown to have an effect on children's outcomes in neighborhood effects studies: (1) percent of persons white (*percwhite*), (2) percent of families with a female head (*percfemhead*), (3) percent of persons who are low income (*percpov*), (4) percent of persons who are high income (*perchighinc*), (5) percent of young adults who are dropouts (*percdropout*), and (6) average adult unemployment rate (*unemprate*). Though Ginther (2000) finds that the significance of these variables on children's outcomes decreases as family variables are taken into account, these variables are nonetheless the ones most commonly seen as significant in affecting future outcomes of children. Since this study is concerned with adult outcomes, rather than children's outcomes, family variables should also be less significant, which may in turn suggest that neighborhoods play a larger role as one moves from childhood to adulthood. Taking these factors into account, a household chooses neighborhood *i* if:

$$\begin{aligned}
 & [V_i(f(\text{percwhite}_i, \text{percfemhead}_i, \text{percpov}_i, \\
 & \text{percperchighinc}_i, \text{percdropout}_i, \text{unemprate}_i), \text{othercsmp}) - C_i] \\
 & > \\
 & [V_j(f(\text{percwhite}_j, \text{percfemhead}_j, \text{percpov}_j, \\
 & \text{perchighinc}_j, \text{percdropout}_j, \text{unemprate}_j), \text{othercsmp}) - C_j],
 \end{aligned}$$

$$\forall i,j \text{ neighborhoods} \quad (3)$$

C. Initial Equilibrium

In the pre-gentrification equilibrium, low-income and high-income households reside in different neighborhoods due to the segregating forces of neighborhood effects and other factors, particularly transportation options (Wilson 1987). Low-income households locate within the central city because of their inability to afford cars, and the availability of public transportation in the central city. High-income households locate largely in the outer parts of the urban area, from where they may either commute by automobile to work or choose to work away from the central city. Under this equilibrium, the differences between the values of benefits across households are explained by both the neighborhood and other inputs, as low-income households consume worse neighborhood effects and fewer other goods when compared to higher-income households (i.e. low-income households need car alarms, and high-income households get to find out about better jobs). Assuming a perfectly competitive housing market, each household maximizes its value. In this Pareto optimal condition, no household can increase its net value. Moving to another neighborhood is not an option, because to do so would be to decrease the net value of another household. Therefore, for any household

$$\begin{aligned} & [V(f(\text{percwhite}_i, \text{percfemhead}_i, \text{percpov}_i, \\ & \text{percperchighinc}_i, \text{percdropout}_i, \text{unemprate}_i), \text{othercsmp}) - C_i] \\ & = \\ & [V(f(\text{percwhite}_j, \text{percfemhead}_j, \text{percpov}_j, \\ & \text{perchighinc}_j, \text{percdropout}_j, \text{unemprate}_j), \text{othercsmp}) - C_j], \\ & \forall i,j \text{ neighborhoods} \quad (4) \end{aligned}$$

D. Gentrification

Gentrification can be either income-driven or preference-driven. As an example, income-driven gentrification can be driven by a technological advancement in a specific urban area, which increases the productivity of highly-skilled workers while not affecting the productivity of low-skill workers. I assume highly-skilled workers are high-income, while low-skill workers are low-income. The increase in productivity causes an increase in wages for highly-skilled workers, and this in turn increases highly-skilled workers' willingness to pay to live in the urban area, so they choose to move, and disrupt former neighborhood demographics, in order to maximize their net value. In the case of preference-driven gentrification, high-income households start considering locating closer to the city center more attractive. This can be because neighborhood and housing characteristics in the city center become attractive to the wealthy, or because a decrease in childbearing decreases the demand for space among high-income workers, or because of any number of other reasons that would shift preferences. In any case, their willingness to pay to live in the urban area increases, and they move in order to maximize their net value. In both preference-driven and income-driven gentrification, the distribution of the six neighborhood effects variables changes across neighborhoods as high-income households relocate. Thus, for any low-income household

$$\begin{aligned} & [V_i(f(\text{percwhite}_i, \text{percfemhead}_i, \text{percpov}_i, \\ & \text{percperhighinc}_i, \text{percdropout}_i, \text{unemprate}_i), \text{othercsmp}) - C_i] \\ & \neq \\ & [V_j(f(\text{percwhite}_j, \text{percfemhead}_j, \text{percpov}_j, \\ & \text{perchighinc}_j, \text{percdropout}_j, \text{unemprate}_j), \text{othercsmp}) - C_j], \end{aligned}$$

$$\forall i, j \text{ neighborhoods} \quad (5)$$

The shock of gentrification on the initial equilibrium disrupts a low-income household's maximization of net value, as low-income households are no longer in a Pareto optimal situation because the preferences of low-income households presumably do not shift to perfectly offset the changes in preferences of high-income households. That is, low-income households do not necessarily prefer to trade places with high-income households who now prefer to live in low-income neighborhoods (Vigdor 2001). Denoting their original neighborhood as o (for original), a neighborhood with more positive neighborhood effects as b (for better), and a neighborhood with more negative neighborhood effects as w (for worse), low-income households must choose which of the following optimizes their value in the face of gentrification:

$$V_o(f(\text{percwhite}_o, \text{percfemhead}_o, \text{perc pov}_o, \text{percperchighinc}_o, \text{percdropout}_o, \text{unemprate}_o), \text{othercsmp}) - C_o$$

$$V_b(f(\text{percwhite}_b, \text{percfemhead}_b, \text{perc pov}_b, \text{percperchighinc}_b, \text{percdropout}_b, \text{unemprate}_b), \text{othercsmp}) - C_b$$

$$V_w(f(\text{percwhite}_w, \text{percfemhead}_w, \text{perc pov}_w, \text{percperchighinc}_w, \text{percdropout}_w, \text{unemprate}_w), \text{othercsmp}) - C_w$$

$$(6)$$

E. New Equilibrium

In order to once again maximize their net benefits, low-income households react to gentrification by either moving until they once again maximize the net benefits of their location or remaining in their original neighborhoods. Equilibrium is reached when all households are maximizing their value and garnering the neighborhood effects they desire.

Since gentrification is a purely urban phenomenon, and past studies have shown that the displaced do not locate away from the central city, it is reasonable to assume that in a model of residential location decision in the face of gentrification, all central city households have access to public transportation, and thus all central city households have access to educational institutions and workplaces throughout the city (Lyons 1996; Schill and Nathan 1983). If value generated from transportation is equal for all low-income households who face the potential of displacement across the central city, and transportation options allow access to jobs and schools across the central city, then these characteristics can be removed from the residential location decision model for low-income households, with the exception of specific cases in which low-income households may consider locating out of the central city.

In the case of income-driven gentrification, low-income households may become displaced. If a poor household's cost of moving is zero, and the household can derive the same net value from another area, and household mobility only has effects within the housing market, then the household moves out of the urban area. As mentioned in section (D), this is unlikely to be the case, and the assumptions of a zero moving cost and a lack of effects from housing mobility are unrealistic (Vigdor 2001).

When a low-income household faces moving costs that are so large that they prohibit moving, it affects the net value of its alternative relocation neighborhood, as the cost to move is so great as to exceed the value. Low-income households who rent their housing lose net value in this situation, as the cost of living in their neighborhood increases. Low-income households who own homes may experience increases in costs if property taxes and insurance premia increase, but may also gain the benefit of an increase in housing equity as gentrification occurs, so the overall effect on net value is unclear for these households (Vigdor 2001).

The two aforementioned situations present what happens to low-income households in the extreme cases of no moving costs or completely prohibitive moving costs. In actuality, low-income households are likely to end up somewhere between these two extremes, with some households becoming displaced to better or worse neighborhoods, and others choosing to increase their willingness to pay in order to remain in their original neighborhood (Vigdor 2001).

Preference-driven gentrification can cause the previously mentioned outcomes as well, but also presents a situation in which low-income households can definitely increase their net value. For this to occur, high-income households must have an increase in their willingness to pay for housing close to the central city, as well as a decrease in their willingness to pay for housing away from the central city. This causes there to be more land area where low-income households have a higher willingness to pay than high-income households. This can end in low-income households moving to better areas for a lower cost, since demand for housing in these formerly high-income neighborhoods has decreased. Depending on whether this demand for housing decreases significantly

enough, housing prices throughout the urban area may drop, which would result in increases in net value for renters, and once again ambiguous effects for homeowners (Vigdor 2001).

In both types of gentrification, even if the low-income household desires to stay, other forces may cause it to relocate. Eviction and harassment by landlords increase the cost of staying in the original neighborhood, and may make the cost of relocating appear insignificant in comparison. Conversely, low-income households may decide to remain in the neighborhood if gentrification creates new opportunities in the job market, increases the amount of public services available through increased tax collection from high-income gentrifiers, or directly improves neighborhood quality. Overall, theory cannot predict clearly whether a low-income household will relocate to a better or worse neighborhood, or choose to remain in its original neighborhood.

F. Estimation Strategy

In order to determine whether a person is better or worse off, one must choose a quantifiable measure of the value of benefits of a neighborhood. Ideally, a well-being variable would capture the amount that individuals gain from social service and government assistance programs, the wages and incomes of individuals, and any changes among other factors that are likely to change as neighborhood effects occur.

Wage and income are the two measures of well-being used in this study.² While this is not ideal, income and wage do encompass many other factors that neighborhood effects may affect. For example, if a low-income individual encounters more college-educated individuals in the neighborhood they relocate to, and chooses to pursue higher

² I also attempted to use a ratio of rent to income as a measure of well-being. However, because of high non-response rates in the PSID, there were too few observations remaining after the addition of a rent variable to allow for meaningful analysis.

education, resulting in a diploma they had not previously held, this should then result in an increase in wage and income as well. A displaced individual may also be informed of the benefits of joining a union by better-informed residents in their new neighborhood. On the other hand, moving into a neighborhood with worse neighborhood effects could cause an individual to have to devote more time to protecting their housing and thus detract from time they can spend pursuing measures to increase their income. Relocating to a new neighborhood can also have effects not captured in income changes, such as the psychic effects of changing social ties, and my analysis cannot quantify or account for these factors, unless they affect the individual's income or wage, and even then these factors will not be distinguishable from other factors.

To estimate the effect of relocating on income and wage, one must look at the difference between the income level and wage of the relocated person several years after relocation and the income level they had in their former neighborhood. I choose to look at the individual two years after they have relocated to a new neighborhood, as this seems like an appropriate amount of time to garner new neighborhood effects, and a person is unlikely to relocate again within two years. The dependent variable in the ideal regression equation measures income or wage changes over the two years in natural log form. The natural logs of income and wage are taken because these allow one to see the percent change in income rather than the change in income levels. The percent change is preferable since low-income residents by definition have very low incomes and wages, and thus what may seem like a small change in income or wage for most people may indeed be a large change for a low-income person.

Since the dependent variable is change in income or wages, the independent variables should be changes in income or wage determinants. Traditional Mincerian wage determinants are age, age-squared (for the U-shape relationship with wage), sex, race, union membership, education, industry, and occupation. Age and age-squared are included as levels rather than differences because all residents age the same amount over two years, and thus there is no variation in the variables. Sex and race are included not as changes, but as levels, as well, since they would otherwise be differenced out. While variables like sex or race do not change over time, they may have significant effects on the rate at which an individual's income increases. That is to say, white males may be more easily promoted or otherwise encounter income increases more than typically disadvantaged groups.

A dummy variable equal to one if a household is displaced, and equal to zero otherwise is added. A dummy variable equal to one if a household lived in a gentrifying tract in the base year, and equal to zero otherwise is also added. The two aforementioned variables are interacted to create a variable equal to one if a household was displaced from a gentrifying tract in the base year. Variables accounting for the differences in the six neighborhood effects variables between the gentrifying neighborhood and the relocation neighborhood are included. These six variables are meant to check whether a change in neighborhood effects has a significant effect on changes in income or wage. These six terms are then interacted with the displacement and gentrification dummies in order to see the effects of various neighborhood effects on residents who are displaced by gentrification. The ideal guiding equation appears as follows, using wage as the

dependent variable, though the log difference of income levels would be used as a dependent variable as well:

$$\begin{aligned}
 & \ln(\text{NewWage}) - \ln(\text{OldWage}) = \\
 & \alpha + \beta_1 \text{Age} + \beta_2 \text{Age}^2 + \beta_3 \text{Sex} + \beta_4 \text{Race} + \beta_5 \text{ChangeinUnion} + \beta_6 \text{ChangeinEducation} + \\
 & \quad \beta_7 \text{ChangeinIndustry} + \beta_8 \text{ChangeinOccupation} + \beta_9 \text{Displaced} + \\
 & \beta_{10} \text{FromGentrifyingNeighborhood} + \beta_{11} \text{Displaced} * \text{FromGentrifyingNeighborhood} + \\
 & \quad \beta_{12} \text{ChangeinPercentofWhitePersonsBetweenNeighborhoods} + \\
 & \beta_{13} \text{ChangeinPercentofFamilieswithFemaleHeadBetweenNeighborhoods} + \\
 & \quad \beta_{14} \text{ChangeinPercentofPersonsinPovertyBetweenNeighborhoods} + \\
 & \beta_{15} \text{ChangeinPercentofPersonswithHighIncomeBetweenNeighborhoods} + \\
 & \quad \beta_{16} \text{ChangeinPercentofDropoutsBetweenNeighborhoods} + \\
 & \quad \beta_{17} \text{ChangeinUnemploymentRateBetweenNeighborhoods} + \\
 & \beta_{18} \text{Displa} * \text{Gent} * \text{ChangeinPercentofWhitePersonsBetweeNeighborhoods} + \\
 & \beta_{19} \text{Displa} * \text{Gent} * \text{ChangeinPercentofFamilieswithFemaleHeadBetweenNeighborhoods} + \\
 & \quad \beta_{20} \text{Displa} * \text{Gent} * \text{ChangeinPercentofPersonsinPovertyBetweenNeighborhoods} + \\
 & \beta_{21} \text{Displa} * \text{Gent} * \text{ChangeinPercentofPersonswithHighIncomeBetweenNeighborhoods} + \\
 & \quad \beta_{22} \text{Displa} * \text{Gent} * \text{ChangeinPercentofDropoutsBetweenNeighborhoods} + \\
 & \beta_{23} \text{Displa} * \text{Gent} * \text{ChangeinUnemploymentRateBetweenNeighborhoods} + \varepsilon_i
 \end{aligned}$$

(7)

where Displa is notation for Displaced and Gent is notation for FromGentrifyingNeighborhood, and variables with asterisks are interaction terms. No prediction is being made as to whether displaced residents will be better or worse off, so no predictions of the signs of the coefficients of these variables are made.

IV. SUMMARY STATISTICS

A. Data

This study uses data from the geo-coded Panel Study of Income Dynamics (PSID) in conjunction with decennial census data.³ The geo-codes are tract level and used to link the PSID to census data.⁴ The PSID is a longitudinal, nationally representative study that has been conducted since 1968, and contains social, health, and economic information on nearly 9,000 families and the individuals within those families, residing in the United States. Because the PSID follows the same individuals and families over years, it can be used to observe relocation from one neighborhood to another (i.e. when faced with gentrification). Moreover, when the PSID is linked to geographical data, one can observe how these individuals' and families' statuses change as the characteristics of their neighborhoods change.

This study uses an extraction of data from the 1990 Census of Population and Housing (Tape Files 3A and 3B) collected by Adams (2000) to determine neighborhood characteristics. This dataset includes over 120 census variables and over 100 variables that were derived from those 120. These variables can be linked to many levels of geographic areas, including tracts, and contain information on ethnicity, family structures, income, education, labor force activity, and housing.

The following six variables from Adams' (2000) dataset are used to measure neighborhood characteristics of each tract contained in the PSID data: (1) percentage of

³ The PSID is the most often used data set for national studies of gentrification that require longitudinally linked observations of residents. The American Housing Survey (AHS) is a popular alternative, but since it is longitudinally linked by housing unit, not household, it is not ideal for this paper. Data sets detailing smaller geographic areas are also often used for gentrification research, though these often focus on neighborhoods specifically identified as gentrifying, and by definition offer fewer observations for analysis.

⁴ Census tracts are small, relatively stable geographic areas delineated by the census that typically contain between 2,500 and 8,000 residents. Tracts are meant to follow the same boundaries as recognized neighborhoods.

persons white, (2) percentage of families with female head, (3) percentage of all persons in households with incomes below federal poverty threshold, (4) percentage of families with 1989 incomes greater than \$50,000, (5) percentage of young adults who have not graduated from high school and are not in school, and (6) adult unemployment rate x100. These six variables are meant to mimic those that Ginther et al. (2000) identify as being consistently significant across neighborhoods effects studies.

The PSID data and Adams' (2000) data are used in conjunction with 1990 and 2000 Census of Population and Housing data to determine which tracts/neighborhoods have undergone gentrification in the 1990s. Data from the Neighborhood Change Database (a GeoLytics product) are used to determine how tract definitions have changed between 1990 and 2000. Due to data limitations, this study utilizes only those census tracts whose boundaries did not change and were not renamed between 1990 and 2000. Thus, roughly 49 percent of tracts are represented in the analysis.

The unit of analysis in the study is the individual who describes him or herself as the household head in the PSID, since this is the individual about whom the PSID collects the most data and the only household member for whom the PSID describes geographical movement. Each census tract will be considered a neighborhood.⁵

B. Variable Specification

Table 1 in the appendix contains information on variables used in regressions, their notations, and the data sources from which they come. The PSID contains direct data on income, wage, age, sex, race, union membership, education, industry, occupation,

⁵ This may bias results if a tract identified as gentrifying is larger or smaller than the actual area that is gentrifying. That is, those residents on the fringe of the tract in either direction may not be accurately represented. Since census tracts are meant to represent commonly recognized neighborhoods, and gentrification is usually contained within neighborhoods exhibiting specific characteristics, this is not a large concern, and no corrective measure is taken.

area of residency, and moving. Since the PSID is a panel, and longitudinally linked, differences between these variables from year to year can be calculated for individuals. In many cases, the PSID does not re-ask questions whose answers typically do not change over years, but carries them forward from year to year. Thus, some variation in variables like education may not be captured unless the head chooses to state that he/she pursued further education. While it would be ideal to difference all independent variables for which it is possible, because of this limitation, no person-specific right-hand side variables will be differenced. That is, age, age-squared, sex, race, union status, education level, industry, and occupation will reflect the values for these variables in the period after relocation, rather than reflecting the change in these variables that has occurred since gentrification. This will affect results since differences in these variables would correspond more appropriately with dependent variables that are expressed in differences. Particularly, since neighborhood characteristics variables are expressed in differences, it may be the case that these difference variables will pick up changes that should be attributed to changes in the demographic variables that are expressed in levels. However, since there would be minimal variation in demographic variables if they were differenced because of the re-asking limitation, it is more appropriate to use levels rather than low-variation differences.

Freeman's (2005) framework is used to determine whether a neighborhood was gentrifying in the base period or not. As he states, in order to be considered gentrifying, a neighborhood must meet the following criteria:

1. Be located in the central city at the beginning of the intercensal period.

2. Have a median income less than the median (40th percentile) for that metropolitan area at the beginning of the intercensal period.
3. Have a proportion of housing built within the past 20 years lower than the proportion found at the median (40th percentile) for the respective metropolitan area.
4. Have a percentage increase in educational attainment greater than the median increase in educational attainment for that metropolitan area.
5. Have an increase in real housing prices during the intercensal period (Freeman 2005).

The first qualification for gentrification speaks to the fact that gentrification is a purely urban phenomenon. The second qualification presents a rather high cutoff (40th percentile) for income level in a gentrifying neighborhood, but this is mostly done because the PSID does not contain enough observations of displaced residents living in neighborhoods below this income level to provide meaningful regression results at lower percentiles. The third qualification ensures there has been disinvestment in the neighborhood for the past two decades, thus allowing for housing values to have fallen, and providing gentrifiers with a reinvestment opportunity. The fourth qualification ensures that the neighborhood is indeed moving from a low-income (and thus likely low-skill and low-educational level) to a high-income (and thus likely high-skill and high-income level) neighborhood because of in-movers (who are assumed to have higher levels of educational attainment than people already residing within the neighborhood), and not because of other forces that may be generally increasing educational attainment throughout the central city. The fifth qualification ensures that in-movers are reinvesting

in the neighborhood, specifically in housing. While this may seem like a very strict definition of gentrification that is contingent on many variables, it is helpful in ensuring that instances of gentrification are not overstated.

The response to the “Why moved?” variable in the PSID is used to determine if a person was displaced. The responses of “Response to outside events (involuntary reasons): HU [housing unit] coming down; being evicted; armed services, etc.; health reasons; divorce; retiring because of health” or “Ambiguous or mixed reasons: to save money; all my old neighbors moved away; retiring (NA why)” qualify an individual as displaced. This tends to overstate displacement since moving because of divorce or the armed services, etc. is not necessarily the type of displacement that would be related with gentrification. The data do not offer any way to differentiate these reasons for moving from more clearly displacement-related reasons. A resident has to be displaced from a neighborhood characterized as gentrifying in order to be considered displaced by gentrification.

C. Summary Statistics

Table 2 shows the means of variables used in this sample as compared to national means of those same or similar variables. The summary statistics collected show that the sample used for analysis has more generally disadvantaged individuals than what would have been nationally representative. The PSID sample also shows that typically 20.71% of people moved over two-year time spans, while the census shows that 41.23% of people in the United States moved between 1985 and 1990, a five-year time span. Extrapolating that since 20.71% of PSID observations moved in a two-year period, roughly 51.78% (two-and-half times as many) would move in a five-year period, assuming no repeat

movers, it becomes clear that the PSID may be slightly over-representative of movers. This may mean that instances of being displaced by gentrification are also overstated. However, since it is likely that some movers are repeat movers, the PSID percent of movers is likely closer to the national average than the extrapolation suggests.

Tables 3 through 9 describe additional summary statistics. The income minimum of 1 represents those who are “not working for money.” The 1 is recoded from 0 in order for observations not to be dropped when using the natural log form. The same is done for the wage variable.

Coding for education changed during the sample years, and takes on values of 0-17, with 0 meaning no education, 12 meaning completion of high school, 16 meaning completion of college, and 17 meaning any educational attainment beyond undergraduate education. Thus, education is measured in years up until the value of 16, after which 17 is used to represent any education beyond college.

Sex is coded as 0 for males and 1 for females, so the mean of 0.35 means that only 35% of observations are female. This is because the PSID prefers for the household head to be male and will call a female’s significant other or any male residing in the household the “householder” and the female the “wife” even when the householder has only been a member of the household for a brief time (sometimes only several months). Unfortunately, moving information is not collected on the “wife,” so a householder can report on his moving into the home, but this does not necessarily mean that the “wife” did not already reside in the home prior to him. There is also no way to easily determine whether the “wife” a householder reports for one year is the same as the “wife” reported in other years, which is another reason why “wives” are not used in the analysis. All of

this suggests that single mothers who are displaced by gentrification may not be adequately represented in the sample, and that no conclusions can be drawn about whether displacement by gentrification affect males and females differently.

The sample of households in this paper also seems to be over-representative of the unemployed and those who are not in the labor force, as 31.12% of householders report that they are “Not working for money now.” While the corresponding national percentage is 38.80%, it is notable that the national sample has more women, a higher percentage of non-working age individuals, and a lower level of educational attainment. Thus, it is understandable that the national sample has such a large percentage of individuals who are either not in the labor force or unemployed. The PSID sample consists of household heads, who are mostly working age males, and thus the 31.12% of individuals not working for money is abnormally high. This means that residents displaced from gentrifying neighborhoods are being compared in large part to other disadvantaged residents in this study.

Comparing observations of those displaced by gentrification with all displaced persons, all movers, and all observations, it is clear that those displaced by gentrification have the lowest incomes and wages. Notably, those displaced by gentrification also have the highest percent increase in income two years after relocation. Looking at the changes in neighborhood characteristics variables, while the changes for all movers and all observations are not consistently better or worse, the summary statistics on all displaced residents and residents displaced by gentrification show that almost each neighborhood characteristic shows improvement after relocation. This shows that displaced residents are moving to better neighborhoods. Coupled with the increase in income for residents

displaced by gentrification, this suggests that positive changes in neighborhood characteristics could be significantly affecting income. Changes in wage are much less dramatic for displaced observations, and do not show any consistent patterns across the various groupings of observations.

The mean for moved is 0.21, meaning that 21% of observations in the entire sample moved. Six percent of the entire sample was displaced, and 1% was displaced specifically by gentrification. Looking at only observations that moved in the sample period, 30% were displaced, and 4% were displaced specifically by gentrification. Twelve percent of all displaced observations were displaced by gentrification.

V. ANALYSIS

A. *Estimation Issues*

Initial regressions shows that Variance Inflation Factors (VIF) are high, with many variables above 10 (see Tables 25 and 26), but all variables are theoretically important, and thus no corrective measure is taken. Initial regressions also show that heteroskedasticity is significant, so robust t-statistics are used in all regressions. Dummy variables are created for race, industry, and occupation, for which coefficients and standard errors are reported in separate regression result tables. F tests are also performed on these dummy variables to observe total significance of race, industry, and occupation.

While one would also think that there may be endogeneity between the dependent variables of income and wage, and changes in neighborhood characteristics, this may not be the case in this study because of the way in which variables are specified. That is, one would expect that as a person's income increases, they might relocate to a better

neighborhood. Similarly, a decrease in income might lead to relocation to a worse neighborhood. The fact that income and wage could be affecting neighborhood choice in this way could make it potentially difficult to separate out effects that neighborhood characteristics are having on income or wage. Differencing wage and income, and including neighborhood characteristics should do away with some of the potential for endogeneity. The income and wages that are stated for the base year represent incomes and wages at the time of relocation, and incomes and wages in the relocation neighborhood are incomes and wages two years after relocation. Since it is unlikely that one would move simply because they expect a change in income or wages in the near future (a situation in which a change in wage or income would be driving a change in neighborhood), it is unlikely that income and wage changes are driving neighborhood choices in this model. An example of a situation in which one would relocate because of the expectation of higher income is a recent college graduate moving to a neighborhood where their neighborhood quality will be a function of the starting wage they expect. Being displaced, by definition, also means that a change in one's income or wage is not the primary driving force behind relocating from one neighborhood to another.

Even if a recent change in income or wages is considered in the neighborhood relocation decision, the fact that two years are spent in the relocation neighborhood before the "after" income and wage data is collected means that the difference in income or wages that is observed over this time is something that has occurred while in the new neighborhood, and has not driven the household to yet another relocation. This means that the observed change in income or wage is not causing the change in neighborhood

characteristics. No corrective measure is taken for the potential for endogeneity, since there is a lack of an available instrumental variable to be used as a proxy.

B. Estimation Equation

The following is the basic regression equation used for analysis:

$$\begin{aligned}
 & \ln(\text{NewWage}) - \ln(\text{OldWage}) = \\
 & \alpha + \beta_1 \text{Age} + \beta_2 \text{Age}^2 + \beta_3 \text{Sex} + \beta_4 \text{Race} + \beta_5 \text{Union} + \beta_6 \text{Education} + \beta_7 \text{Industry} + \\
 & \quad \beta_8 \text{Occupation} + \beta_9 \text{Displaced} + \beta_{10} \text{FromGentrifyingTract} + \\
 & \quad \beta_{11} \text{Displaced} * \text{FromGentrifyingTract} + \\
 & \quad \beta_{12} \text{ChangeinPercentofWhitePersonsBetweenTracts} + \\
 & \quad \beta_{13} \text{ChangeinPercentofFamilieswithFemaleHeadBetweenTracts} + \\
 & \quad \beta_{14} \text{ChangeinPercentofPersonsinPovertyBetweenTracts} + \\
 & \quad \beta_{15} \text{ChangeinPercentofPersonswithHighIncomeBetweenTracts} + \\
 & \quad \beta_{16} \text{ChangeinPercentofDropoutsBetweenTracts} + \\
 & \quad \beta_{17} \text{ChangeinUnemploymentRateBetweenTracts} + \\
 & \quad \beta_{18} \text{Displa} * \text{Gent} * \text{ChangeinPercentofWhitePersonsBetweenTracts} + \\
 & \quad \beta_{19} \text{Displa} * \text{Gent} * \text{ChangeinPercentofFamilieswithFemaleHeadBetweenTracts} + \\
 & \quad \beta_{20} \text{Displa} * \text{Gent} * \text{ChangeinPercentofPersonsinPovertyBetweenTracts} + \\
 & \quad \beta_{21} \text{Displa} * \text{Gent} * \text{ChangeinPercentofPersonswithHighIncomeBetweenTracts} + \\
 & \quad \beta_{22} \text{Displa} * \text{Gent} * \text{ChangeinPercentofDropoutsBetweenTracts} + \\
 & \quad \beta_{23} \text{Displa} * \text{Gent} * \text{ChangeinUnemploymentRateBetweenTracts} + \varepsilon_i
 \end{aligned}$$

(8)

The above is the regression equation used in regressions (vii) through (xii). Regressions (i) through (vi) use a similar regression equation, though they do not include any

neighborhood characteristics variables, or interaction terms that include neighborhood characteristics variables. The first three regressions in each of these two sets are run on changes in wage, while the last three are run on changes in income.

Regressions are run first on all observations in the sample, then all moved observations, and finally all displaced observations. While past research typically focuses on comparing those encountering gentrification to all movers, this study uses the aforementioned three sample types in order to see whether those displaced by gentrification fare differently compared to different reference groups. All samples are limited to only residents living in urban areas in the gentrification period so that control observations are as similar as possible to observations of residents displaced by gnetrification.

Regressions (xiii) through (xviii) use the following regression equation:

$$\begin{aligned} \ln(\text{NewWage}) = & \\ & \alpha + \beta_1\text{Age} + \beta_2\text{Age}^2 + \beta_3\text{Sex} + \beta_4\text{Race} + \beta_5\text{Union} + \beta_6\text{Education} + \beta_7\text{Industry} + \\ & \beta_8\text{Occupation} + \beta_9\text{Displaced} + \beta_{10}\text{FromGentrifyingTract} + \\ & \beta_{11}\text{Displaced*FromGentrifyingTract} + \\ & \beta_{12}\text{ChangeinPercentofWhitePersonsBetweenTracts} + \\ & \beta_{13}\text{ChangeinPercentofFamilieswithFemaleHeadBetweenTracts} + \\ & \beta_{14}\text{ChangeinPercentofPersonsinPovertyBetweenTracts} + \\ & \beta_{15}\text{ChangeinPercentofPersonswithHighIncomeBetweenTracts} + \\ & \beta_{16}\text{ChangeinPercentofDropoutsBetweenTracts} + \\ & \beta_{17}\text{ChangeinUnemploymentRateBetweenTracts} + \\ & \beta_{18}\text{Displa*Gent*ChangeinPercentofWhitePersonsBetweenTracts} + \end{aligned}$$

$$\begin{aligned}
& \beta_{19} \text{Displa} * \text{Gent} * \text{ChangeinPercentofFamilieswithFemaleHeadBetweenTracts} + \\
& \quad \beta_{20} \text{Displa} * \text{Gent} * \text{ChangeinPercentofPersonsinPovertyBetweenTracts} + \\
& \beta_{21} \text{Displa} * \text{Gent} * \text{ChangeinPercentofPersonswithHighIncomeBetweenTracts} + \\
& \quad \beta_{22} \text{Displa} * \text{Gent} * \text{ChangeinPercentofDropoutsBetweenTracts} + \\
& \quad \beta_{23} \text{Displa} * \text{Gent} * \text{ChangeinUnemploymentRateBetweenTracts} + \varepsilon_i
\end{aligned}
\tag{9}$$

In this set of regressions, the first three regressions are run on wages in the time period after relocation, while the last three are run on income in the time period after relocation. The purpose of running regressions on post-relocation wages and incomes, rather than differences in wages and incomes, is to ascertain how residents displaced by gentrification fare in comparison to other people in samples, rather than in comparison to how they themselves were doing two years prior, before gentrification and relocation. Thus, the analysis in this study evaluates both how residents displaced by gentrification's well-beings vary across time, and solely in comparison to other groups of residents.

C. Main Results

Gentdispla and its interactions with neighborhood characteristics variables are the variables of interest in these regressions. Thus, the interaction terms of neighborhood characteristics with being displaced by gentrification are analyzed as two-way interaction terms, where *gentdispla* is a dummy equal to 1 if a person was displaced by gentrification in the base period.

Regressions (i) through (vi) do not include neighborhood characteristics, in an attempt to see what the effects of being displaced by gentrification are when neighborhood effects are not considered. Results from these regressions are reported in

tables 10 through 14. In all six regressions presented in these tables, being displaced by gentrification does not have significant effects on changes in income or wage over two years. This suggests that on its own, being displaced by gentrification does not have a significant impact on wage or income change. This may be because of a lack of social mixing in relocation neighborhoods that would prevent neighborhood effects from being absorbed, or because relocation neighborhoods are very similar to the neighborhoods that people relocate from. It could also be that people displaced by gentrification move into either better or worse neighborhoods, and when these two relocation options are not separately analyzed, the results are clouded. It may also be that changes in neighborhood demographics simply do not affect residents. Notably, many of the demographic variables which are often significant in determining wages and income do not show up as significant in these six regressions either. This may be because levels of demographic variables are not ideal for describing changes in the dependent variables of changes in wage and income. However, as discussed in the Summary Statistics section, no better option exists for analysis with these data.

To check whether neighborhood effects are significant in determining outcomes for residents displaced by gentrification, regressions (vii) through (xii) include the six neighborhood characteristic variables and interactions of these terms with dummy variables for displacement and gentrification. Results for these regressions are shown in tables 15 through 19. Unlike in the previous set of regressions, being displaced by gentrification does have significant effects in these regressions, namely when neighborhood effects are considered. This shows that differences between relocation

neighborhoods can account for some of the impact of being displaced by gentrification on changes in wage and income.

In regressions (vii), (viii) and (ix), being displaced by gentrification has a small, positive effect, though it is insignificant. The coefficient on *gentdispladrop* in regression (vii) is -0.028, meaning that when looking at a sample of all residents, for every percentage point increase in dropouts between the gentrifying tract and the tract to which the resident relocates, the wage of a resident displaced by gentrification significantly decreases by 2.8%, thus taking away from some of the original small positive change caused simply by being displaced by gentrification. In regression (viii), the interpretation of *gentdispladrop* is the same, except that the decrease is 2.9% rather than 2.8%, and the sample only includes movers. In regression (ix), which uses a sample of only displaced residents, the decrease is 2.7%. In the regressions in this set that use changes in wage as the dependent variable, *gentdispladrop* is the only variable to show up as significant out of the neighborhood characteristic variables for residents displaced by gentrification. This suggests that of all neighborhood characteristics, the percent of dropouts has the largest effect on the well-being of residents displaced by gentrification. It is likely that school dropouts also have other negative characteristics that may be negatively affecting wages. It should be noted, though, that in economic terms, a 2.8 or 2.9 or 2.7 percent change in wage is not very significant.

Regressions (x) and (xi)—which have changes in income as the dependent variable, and are run on all observations and all moved observations, respectively—have a greater number of significant results for interaction terms of neighborhood effects and being displaced by gentrification. Between these two regressions, all six of the

neighborhood effects variables are shown to have significant effects on the income of residents displaced by gentrification.

In regressions (x) and (xi), all six interaction terms are significant. In regression (xii), *gentdisplahigh* is significant. The coefficient on *gentdisplawhite* is negative in regressions (x) and (xi). The coefficient on *gentdisplapov* is positive in these regressions, as is the coefficient on *gentdisplaunemp*. All of these results are not consistent with theory, as an increase in white people across neighborhoods should lead to income gains, while increases in poverty or unemployment should decrease income. Since the magnitudes of *gentdispla* are so large and negative, and the magnitudes of the neighborhood interaction terms are so large, it is likely that these results are not very meaningful, and that the data could benefit from being disaggregated by whether the person relocated to a better or worse neighborhood. The coefficients on *gentdisplafem* are negative and significant in regressions (x) and (xi), as are the coefficients on *gentdispladrop*. The coefficients on *gentdisplahigh* are positive and significant in regressions (x), (xi), and (xii). The results on these three interaction terms are consistent with theory, as an increase in female-headed households or dropouts should cause income decreases, while an increase in the amount of high-income households should cause income gains. However, the magnitudes on all of these variables are obscenely high, suggesting once again that the data should be disaggregated and otherwise improved upon.

Finally, it is notable that in none of these twelve regressions does being displaced by gentrification without the consideration of neighborhood effects have any negative or positive effects on wage or income or changes in the two. This suggests that any

differences in income or wage that residents encounter are functions of differences in neighborhood characteristics, thus lending support to the theory of neighborhood effects. This also means that people displaced by gentrification are experiencing at least some social mixing, as they are evidently influenced by their neighbors.

In summary, while simply being displaced by gentrification does not have a significant effect on how much one's income or wage changes over the two years after leaving the gentrifying neighborhood, specific neighborhood characteristics can offset or worsen the core effect of being displaced by gentrification. However, because of data limitations, this paper does not accurately address what neighborhood characteristics are important in determining the outcomes of residents displaced by gentrification, as many variables are largely out of line with theory.

D. Robustness

To check the robustness of my results, I use the natural log of post-gentrification relocation wage and the natural log of post-gentrification income as dependent variables, rather than differences. Results for robustness regressions are reported in tables 20 through 24. These results measure how much an individual who was displaced by gentrification's wage or income is different from an individual's who was not. That is, the incomes and wages of residents who were displaced by gentrification are being compared to those of people who were not, in the post period.

In this set of six regressions, the effect of being displaced by gentrification is never significant and always negative, though it varies in magnitude. The only neighborhood effects measures that show up as significant are *gentdispladrop* and *gentdisplapov*.

The coefficient on *gentdisplapov* is significant and positive in regression (xvi), which looks at a sample of all observations and has income as the dependent variable. The coefficient is 0.489, suggesting that for every one percentage point increase in people living in poverty across the two neighborhoods, a resident displaced by gentrification will experience an income that is 48.9% higher than the income of other people living in the neighborhood. This makes sense if residents who are displaced by gentrification move to severely impoverished neighborhoods where their incomes are drastically higher than the incomes of other residents of the neighborhood. This supports the idea that residents displaced by gentrification can move to much worse neighborhoods. This only makes sense if the income of residents displaced by gentrification starts out higher than the average residents of an impoverished neighborhood when they relocate there initially, and manages to remain much higher two years later. It is more difficult to contemplate how moving to a more impoverished neighborhood could cause one's income to increase so significantly. If the former explanation suffices, then this supports the idea that there is very little social mixing between residents displaced by gentrification and their new neighbors, as they are not being affected by the low incomes of their neighbors.

The coefficients on *gentdispladrop* are significant in regressions (xiii), (xiv), (xiv), and (xvii), and consistently negative, though they vary in magnitude. This all suggests that if a resident displaced by gentrification moves to a neighborhood with more dropouts, their income will be significantly lower than that of residents who were not displaced by gentrification. This suggests that social mixing does occur, as residents are negatively influenced by their neighbors' lack of education. That *gentdispladrop* is the variable that most frequently shows up as significant suggests that the percent of dropouts

in a neighborhood has the largest effect on in-movers, or that perhaps dropouts carry many other negative characteristics as well. It should be noted that these neighborhood characteristics are not positive enough to counteract the general negative effect of being displaced by gentrification.

VI. CONCLUSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

Results presented in this paper suggest that residents displaced by gentrification are relatively susceptible to differences in neighborhood characteristics between the gentrifying neighborhoods they leave and the neighborhoods they relocate to. This supports the theory of neighborhood effects, though not always in the direction predicted by theory. This suggests that the data needs to be disaggregated based on whether residents are moving to better or worse neighborhoods, and that more observations of people displaced by gentrification are necessary.

Because this study covers 1990-1995, its findings are most relevant for cities that experienced second-wave gentrification. The large majority of residents displaced by gentrification in the various samples were from California, Illinois, Michigan, Ohio, or Pennsylvania, suggesting that the findings are most reflective of instances of gentrification in these states.

In addition to disaggregating the sample and having more observations of residents displaced by gentrification, future studies should control for the use of housing vouchers and other housing assistance, to attempt to see how much this affects the experience of residents displaced by gentrification. Future research would also benefit from a refined and less ambiguous definition of displacement, the inclusion of a measure

of neighborhood assets (such as number of schools, number of transportation options, etc.), as well as an extended time frame.

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TABLES

Table 1. Variable Specification

Variable Notation	Variable	Data Source
age	Age	PSID
age2	Age squared	PSID
sex	Sex	PSID
race	Race	PSID
union	Whether union member	PSID
edu	Educational attainment	PSID
ind	Current industry	PSID
occ	Current occupation	PSID
wage	Hourly wage rate	PSID
wagediff	Log difference of wages	PSID
inc	Annual labor income	PSID
incdiff	Log difference of income	PSID
moved	Whether moved	PSID
displa	Whether displaced	PSID
gent	Whether resided in gentrifying neighborhood	Census
gentdispla	Whether displaced from a gentrifying neighborhood	PSID and Census
perwhitediff	Difference in percentage of persons white in tract of residence	PSID and Adams/Census
percfemheaddiff	Difference in percentage of families with female head in tract of residence	PSID and Adams/Census
percpovdiff	Difference in percentage of all persons in households with incomes below federal poverty threshold in tract of residence	PSID and Adams/Census
perchighncdiff	Difference in percentage of families with 1989 incomes greater than \$50,000 in tract of residence	PSID and Adams/Census
percdropoutdiff	Difference in percentage of young adults who have not graduated from high school and are not in school in tract of residence	PSID and Adams/Census
unempratediff	Difference in adult unemployment rate x 100 in tract of residence	PSID and Adams/Census
gentdisplawhite	Interaction term: gent*displa*percfemheaddiff	PSID and Adams/Census
gentdisplapov	Interaction term: gent*displa*percpovdiff	PSID and Adams/Census
gentdisplahighinc	Interaction term: gent*displa*perchighncdiff	PSID and Adams/Census
gentdispladrop	Interaction term: gent*displa*percdropoutdiff	PSID and Adams/Census
gentdisplaunemp	Interaction term: gent*displa*unempratediff	PSID and Adams/Census

Table 2. Comparison of PSID observations and 1990 Census		
Variable	PSID	Nation
age	44.87	32.80
male	64.76%	47.97%
female	35.24%	52.03%
union members	15.04%	16.10%
finished high school	66.04%	54.90%
finished college	18.44%	20.34%
inc	24460.80	30056.00
moved*	20.71%	41.23%
not working for money	31.12%	38.80%
Observations**	5,547	248,709,873
*PSID moved states percentage of people moved since 1988, Nation moved states percentage of people moved since 1985		
**There are only 1,181 observations of income, as this variable was only collected for the 1990-1992 wave of studies		

Table 3. Summary Statistics for All Observations								
	Base Year				Two Years Later			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
age	44.87	15.63	17	96	46.87	15.63	19	98
sex	0.35	0.48	0	1	0.35	0.48	0	1
union	0.15	0.36	0	1	0.14	0.35	0	1
edu	12.18	2.99	0	17	12.31	3.04	0	17
wage	4.29	14.09	1	841	4.37	17.23	1	841
inc*	24460.80	30186.32	1	395000	24117.27	30635.09	1	458716
moved	0.21	0.41	0	1				
displa	0.06	0.24	0	1				
gent	0.09	0.29	0	1				
gentdispla	0.01	0.09	0	1				
percwhite	55.91	37.97	0	100	56.31	37.88	0	100
percfemhead	28.77	18.55	0	95	28.56	18.40	0	95
perc pov	19.54	16.55	0	92	19.32	16.45	0	92
perchighinc	26.19	19.94	0	91	26.41	19.93	0	91
percdropout	14.25	11.58	0	100	14.27	11.75	0	100
unemprate	9.97	7.74	0	67	9.85	7.64	0	67
Notes: 5,547 Observations								
*There are only 1181 observations of income, as this variable was only collected for the 1990-1992 wave of studies								

Table 4. Summary Statistics for All Moved Observations

	Base Year				Two Years Later			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
age	36.40	13.45	17	96	38.40	13.45	19	98
sex	0.39	0.49	0	1	0.39	0.49	0	1
union	0.11	0.32	0	1	0.11	0.32	0	1
edu	12.19	2.64	0	17	12.31	2.69	0	17
displa	0.30	0.46	0	1				
gent	0.10	0.31	0	1				
gentdispla	0.04	0.19	0	1				
wage	4.35	14.79	1	471	4.47	22.55	1	752
inc*	20495.76	29068.60	1	240000	21115.87	31057.55	1	321101
percwhite	53.16	37.24	0	100	53.71	37.22	0	100
percfemhead	30.65	18.53	1	95	30.54	18.71	1	95
percpov	20.75	16.34	0	87	20.90	16.75	0	87
perchighinc	23.75	18.86	0	85	23.84	18.94	0	85
percdropout	15.37	11.81	0	100	15.70	12.44	0	100
unemprate	10.20	7.52	0	46	10.19	7.82	0	46

Notes: 1,149 Observations

*There are only 251 observations of income, as this variable was only collected for the 1990-1992 wave of studies

	Base Year				Two Years Later			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
age	37.49	14.42	19	96	39.49	14.42	21	98
sex	0.46	0.50	0	1	0.46	0.50	0	1
union	0.13	0.34	0	1	0.13	0.34	0	1
edu	11.82	2.50	0	17	11.92	2.55	0	17
wage	3.93	4.95	1	39	4.01	5.05	1	34
inc*	14987.67	13556.42	1	52871	15670.73	17985.61	1	89450
gent	0.12	0.33	0	1				
gentdispla	0.12	0.33	0	1				
percwhite	46.68	37.63	0	100	48.05	37.61	0	100
percfemhead	33.91	18.85	5	95	32.99	18.50	5	95
perc pov	23.40	17.15	0	87	22.72	17.16	1	87
perchighinc	20.78	16.94	0	81	21.47	17.76	0	81
percdropout	16.22	11.52	0	64	16.58	12.84	0	100
unemprate	11.17	7.93	1	41	10.86	8.08	0	41

Notes: 342 Observations

*There are only 72 observations of income, as this variable was only collected for the 1990-1992 wave of studies

	Base Year				Two Years Later			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
age	35.12	10.77	19	68	37.12	10.77	21	70
sex	0.49	0.51	0	1	0.49	0.51	0	1
union	0.22	0.42	0	1	0.22	0.42	0	1
edu	11.22	3.00	1	16	11.22	3.00	1	16
wage	4.65	5.95	1	32	4.46	6.18	1	32
inc*	12102.75	17633.14	1	52871	17502.18	23311.34	1	71208
percwhite	27.56	34.04	0	98	29.93	34.52	0	95
percfemhead	45.17	15.26	13	75	43.80	18.56	12	80
perc pov	33.71	15.32	12	75	33.05	20.65	3	87
perchighinc	11.00	6.86	0	28	14.27	14.22	0	76
percdropout	19.44	9.52	0	43	21.44	12.55	0	64
unemprate	16.07	7.93	3	33	15.80	10.05	3	33

Notes: 41 Observations

*There are only 8 observations of income, as this variable was only collected for the 1990-1992 wave of studies

	Frequency	Percent
White	2,943	53.06
Black	2,321	41.84
American Indian, Aleut, Eskimo	23	0.41
Asian, Pacific Islander	19	0.34
Latino	194	3.50
Color other than Black or White	34	0.61
Other	12	0.22
Not reported	1	0.02

Note: 5,547 Observations

	Frequency	Percent
Not Working for Money Now	1,726	31.12
Agriculture, Forestry, and Fisheries	40	0.72
Mining	12	0.22
Construction	286	5.16
Manufacturing	767	13.83
Transportation, Communications, and Other Public Utilities	338	6.09
Wholesale and Retail Trade	579	10.44
Finance, Insurance, and Real Estate	232	4.18
Business and Repair Services	207	3.73
Personal Services	179	3.23
Entertainment and Recreation Services	35	0.63
Professional and Related Services	803	14.48
Public Administration	343	6.18

Note: 5,547 observations

	Frequency	Percent
Not Working for Money Now	1,726	31.12
Professional, Technical, and Kindred Workers	710	12.80
Managers and Administrators, Except Farm	549	9.90
Sales Workers	220	3.97
Clerical and Kindred Workers	464	8.36
Craftsmen and Kindred Workers	538	9.70
Operatives, Except Transport	344	6.20
Transport Equipment Operatives	199	3.59
Laborers, Except Farm	192	3.46
Farmers and Farm Managers	3	0.05
Farm Laborers and Farm Foremen	10	0.18
Service Workers, Except Private Household	544	9.81
Private Household Workers	48	0.87

Note: 5,547 observations

Table 10. Difference Regression Results Without Neighborhood Effects						
	(i) all	(ii) moved	(iii) displa	(iv) all	(v) moved	(vi) displa
	wagediff	wagediff	wagediff	incdiff	incdiff	incdiff
age	-0.016	-0.015	-0.035	-0.094	-0.019	-0.273
	(0.005)***	(0.010)	(0.016)**	(0.036)***	(0.071)	(0.293)
age2	0.000	0.000	0.000	0.001	0.001	0.003
	(0.000)***	(0.000)**	(0.000)**	(0.000)***	(0.001)	(0.003)
sex	0.113	0.202	0.027	0.312	-0.158	-0.835
	(0.028)***	(0.065)***	(0.110)	(0.218)	(0.453)	(1.581)
union	0.003	0.059	0.066	0.093	0.521	0.477
	(0.044)	(0.103)	(0.189)	(0.128)	(0.558)	(1.478)
edu	0.000	-0.011	-0.031	0.046	-0.071	-0.467
	(0.004)	(0.013)	(0.026)	(0.057)	(0.158)	(0.660)
gent	0.047	0.083	-0.049	0.256	0.021	0.734
	(0.045)	(0.119)	(0.162)	(0.259)	(0.612)	(1.687)
displa	0.086	0.120		-0.300	-0.602	
	(0.055)	(0.065)*		(0.453)	(0.495)	
gentdispla	-0.131	-0.158		-0.240	0.350	
	(0.173)	(0.205)		(1.186)	(1.412)	
Constant	-0.272	-0.344	0.657	-0.056	-0.890	6.932
	(0.136)**	(0.293)	(0.527)	(1.153)	(2.560)	(7.549)
Observations	5547	1149	342	1181	251	72
R-squared	0.07	0.10	0.13	0.03	-0.03	-0.22
Absolute values of robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						
Race, Industry, and Occupation dummy variables are included in analysis						

Table 11. Race Dummy Results for Regressions Without Neighborhood Effects						
	(i) all	(ii) moved	(iii) displa	(iv) all	(v) moved	(vi) displa
	wagediff	wagediff	wagediff	incdiff	incdiff	incdiff
Race=White						
Race=Black	0.013	-0.010	-0.057	0.131	0.952	2.395
	(0.028)	(0.069)	(0.145)	(0.194)	(0.422)**	(1.571)
Race=American Indian, Aleut, Eskimo	-0.051	-0.666	-0.174	0.078		
	(0.194)	(0.338)**	(0.284)	(0.495)		
Race=Asian, Pacific Islander	0.419	1.107	-0.323	0.590	1.326	1.685
	(0.200)**	(0.678)	(0.188)*	(0.313)*	(0.894)	(2.358)
Race=Latino	0.047	0.064	0.485	0.517	0.109	1.356
	(0.068)	(0.187)	(0.174)***	(0.394)	(0.667)	(1.975)
Race=Color other than Black or White	0.197	-0.184	-0.236	-1.095		
	(0.089)**	(0.164)	(0.250)	(1.588)		
Race=Other	0.582	-0.025		1.036	0.556	
	(0.239)**	(0.232)		(0.450)**	(0.826)	
Race=Not reported	1.514					
	(0.102)***					
Absolute values of robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 12. Industry Dummy Results for Regressions Without Neighborhood Effects

	(i) all wagediff	(ii) moved wagediff	(iii) displa wagediff	(iv) all incdiff	(v) moved incdiff	(vi) displa incdiff
Industry=Not Working for Money Now						
Industry=Agriculture, Forestry, and Fisheries	-0.643 (0.385)*	-0.301 (0.549)	-1.087 (0.352)***	-0.787 (0.829)	-3.524 (0.883)***	
Industry=Mining	0.000 (0.000)	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)	
Industry=Construction	-0.403 (0.333)	0.014 (0.207)	-1.202 (0.389)***	-0.577 (0.848)	-3.035 (0.706)***	3.331 (2.188)
Industry=Manufacturing	-0.423 (0.328)	0.196 (0.170)	-0.516 (0.395)	-0.635 (0.808)	-3.135 (0.893)***	2.264 (1.667)
Industry=Transportation, Communications, and Other Public Utilities	-0.398 (0.332)	0.097 (0.188)	-0.338 (0.446)	-0.667 (0.808)	-2.877 (0.591)***	
Industry=Wholesale and Retail Trade	-0.327 (0.327)	0.207 (0.132)	-0.619 (0.255)**	-0.799 (0.826)	-2.948 (0.668)***	4.078 (2.189)*
Industry=Finance, Insurance, and Real Estate	-0.515 (0.330)	-0.125 (0.170)	-1.700 (0.356)***	-0.053 (0.879)	-2.289 (0.841)***	3.862 (2.917)
Industry=Business and Repair Services	-0.365 (0.334)	0.012 (0.195)	-1.246 (0.202)***	-0.981 (0.897)	-3.052 (0.688)***	4.408 (2.692)
Industry=Personal Services	-0.675 (0.337)**	-0.354 (0.205)*	-1.381 (0.317)***	-0.649 (0.992)	-2.830 (1.357)**	3.297 (3.578)
Industry=Entertainment and Recreation Services	-0.378 (0.376)	0.767 (0.389)**	0.000 (0.000)	-0.681 (0.834)	-2.604 (0.690)***	
Industry=Professional and Related Services	-0.554 (0.329)*	-0.090 (0.160)	-0.893 (0.229)***	-0.944 (0.834)	-3.457 (0.678)***	3.887 (3.276)
Industry=Public Administration	-0.489 (0.331)	-0.032 (0.197)	-1.155 (0.366)***	-0.795 (0.828)	-3.596 (0.654)***	3.234 (3.064)

Absolute values of robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 13. Occupation Dummy Results for Regressions Without Neighborhood Effects						
	(i) all wagediff	(ii) moved wagediff	(iii) displa wagediff	(iv) all incdiff	(v) moved incdiff	(vi) displa incdiff
Occupation=Not Working for Money Now						
Occupation=Professional, Technical, and Kindred Workers	0.946 (0.330)***	0.569 (0.191)***	1.626 (0.294)***	2.137 (0.878)**	5.498 (1.274)***	1.934 (2.921)
Occupation=Managers and Administrators, Except Farm	0.860 (0.329)***	0.744 (0.161)***	1.606 (0.338)***	1.792 (0.892)**	4.559 (0.955)***	-0.005 (2.375)
Occupation=Sales Workers	0.882 (0.330)***	0.614 (0.149)***	1.578 (0.338)***	1.621 (1.008)	4.641 (1.075)***	0.000 (0.000)
Occupation=Clerical and Kindred Workers	1.149 (0.330)***	0.722 (0.183)***	1.563 (0.308)***	2.110 (0.880)**	4.920 (0.995)***	-0.309 (2.129)
Occupation=Craftsmen and Kindred Workers	1.011 (0.330)***	0.791 (0.199)***	1.748 (0.417)***	1.881 (0.886)**	4.649 (0.947)***	-0.261 (1.901)
Occupation=Operatives, Except Transport	1.120 (0.332)***	0.672 (0.189)***	1.200 (0.384)***	2.022 (0.871)**	4.157 (1.012)***	-0.951 (2.220)
Occupation=Transport Equipment Operatives	1.063 (0.337)***	0.868 (0.257)***	1.165 (0.519)**	2.208 (0.884)**	4.674 (0.981)***	-1.292 (3.074)
Occupation=Laborers, Except Farm	1.014 (0.337)***	0.755 (0.209)***	1.455 (0.348)***	2.383 (0.912)***	4.480 (0.968)***	-0.943 (1.393)
Occupation=Farmers and Farm Managers	1.091 (0.386)***					
Occupation=Farm Laborers and Farm Foremen	1.202 (0.404)***	0.909 (0.580)				
Occupation=Service Workers, Except Private Household	1.173 (0.331)***	0.894 (0.177)***	1.908 (0.127)***	2.462 (0.907)***	5.110 (0.970)***	-1.392 (2.332)
Occupation=Private Household Workers	0.957 (0.358)***	0.731 (0.491)	1.804 (0.329)***	2.271 (1.102)**		
Absolute values of robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 14. F Statistics for Regressions Without Neighborhood Effects						
	(i) all	(ii) moved	(iii) displa	(iv) all	(v) moved	(vi) displa
	wagediff	wagediff	wagediff	incdiff	incdiff	incdiff
Race	2.153	1.524	0.620	0.451	1.171	0.921
	(0.035)**	(0.167)	(0.684)	(0.844)	(0.325)	(0.438)
Industry	2.826	1.646	2.604	0.435	0.269	0.088
	(0.001)***	(0.074)***	(0.003)***	(0.950)	(0.993)	(0.999)
Occupation	3.840	0.746	0.842	0.500	0.237	0.221
	(0.000)***	(0.694)	(0.589)	(0.891)	(0.989)	(0.990)
P values in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 15. Difference Regression Results With Neighborhood Effects						
	(vii) all	(viii) moved	(ix) displa	(x) all	(xi) moved	(xii) displa
	wage diff	wage diff	wage diff	inc diff	inc diff	inc diff
age	-0.016 (0.005)***	-0.016 (0.010)	-0.036 (0.017)**	-0.094 (0.037)**	-0.021 (0.075)	-0.362 (0.354)
age2	0.000 (0.000)***	0.000 (0.000)**	0.000 (0.000)**	0.001 (0.000)***	0.001 (0.001)	0.004 (0.004)
sex	0.113 (0.028)***	0.206 (0.066)***	0.003 (0.114)	0.353 (0.217)	-0.097 (0.452)	-1.092 (1.434)
union	0.001 (0.043)	0.059 (0.101)	0.070 (0.185)	0.052 (0.130)	0.569 (0.612)	0.799 (2.076)
edu	-0.001 (0.004)	-0.016 (0.013)	-0.041 (0.026)	0.053 (0.056)	-0.014 (0.147)	-0.366 (0.649)
gent	0.045 (0.045)	0.075 (0.119)	0.063 (0.153)	0.297 (0.259)	0.083 (0.656)	-3.076 (3.004)
displa	0.086 (0.055)	0.114 (0.066)*		-0.288 (0.458)	-0.605 (0.526)	
gentdispla	0.043 (0.144)	0.023 (0.183)		-3.924 (2.654)	-3.118 (2.989)	
percwhitediff	-0.002 (0.002)	-0.003 (0.002)	0.003 (0.004)	0.004 (0.009)	0.007 (0.014)	0.078 (0.046)
percfemheaddiff	0.004 (0.004)	0.004 (0.006)	0.016 (0.008)*	0.021 (0.026)	0.036 (0.039)	0.232 (0.113)**
percpovdiff	-0.013 (0.004)***	-0.014 (0.006)**	-0.020 (0.010)**	-0.026 (0.034)	-0.004 (0.049)	0.036 (0.129)
perchighincdiff	-0.005 (0.003)**	-0.004 (0.004)	0.000 (0.005)	-0.001 (0.015)	0.003 (0.023)	-0.023 (0.044)
percdropoutdiff	0.001 (0.002)	0.000 (0.003)	0.006 (0.005)	0.017 (0.021)	0.033 (0.025)	0.079 (0.070)
unempratediff	0.000 (0.007)	0.005 (0.009)	0.008 (0.014)	-0.028 (0.056)	-0.110 (0.086)	-0.338 (0.193)*
gentdisplawhite	-0.006 (0.011)	-0.007 (0.012)	-0.012 (0.014)	-3.445 (0.995)***	-4.316 (1.729)**	-10.014 (6.143)
gentdisplafem	0.025 (0.033)	0.029 (0.035)	0.023 (0.038)	-8.897 (2.543)***	-11.264 (4.626)**	-26.686 (16.857)
gentdisplapov	0.005 (0.025)	0.004 (0.027)	0.004 (0.029)	0.922 (0.261)***	1.136 (0.497)**	2.922 (1.962)
gentdisplahigh	-0.017 (0.017)	-0.019 (0.019)	-0.010 (0.022)	0.146 (0.062)**	0.144 (0.086)*	0.587 (0.328)*
gentdispladrop	-0.028 (0.011)***	-0.029 (0.011)**	-0.027 (0.012)**	-0.262 (0.124)**	-0.320 (0.139)**	-0.228 (0.190)
gentdisplaunemp	-0.028 (0.025)	-0.039 (0.028)	-0.035 (0.030)	0.896 (0.271)***	1.388 (0.645)**	3.764 (2.495)
Constant	-0.259 (0.135)*	-0.287 (0.296)	0.735 (0.546)	-0.186 (1.157)	-1.804 (2.547)	6.927 (8.398)
Observations	5547	1149	342	1181	251	72
Adjusted R-square	0.08	0.11	0.14	0.03	-0.02	-0.09
Absolute values of robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						
Race, Industry, and Occupation dummy variables are included in analysis						

Table 16. Race Dummy Results for Regressions With Neighborhood Effects

	(vii) all wagediff	(viii) moved wagediff	(ix) displa wagediff	(x) all incdiff	(xi) moved incdiff	(xii) displa incdiff
Race=White						
Race=Black	0.011 (0.028)	0.002 (0.069)	-0.020 (0.143)	0.124 (0.196)	1.070 (0.439)**	3.820 (1.763)**
Race=American Indian, Aleut, Eskimo	-0.035 (0.192)	-0.624 (0.334)*	-0.042 (0.345)	0.107 (0.513)		
Race=Asian, Pacific Islander	0.425 (0.185)**	1.104 (0.628)*	-0.258 (0.217)	0.598 (0.333)*	1.454 (1.006)	1.852 (2.733)
Race=Latino	0.037 (0.068)	0.009 (0.185)	0.355 (0.198)*	0.433 (0.396)	-0.550 (0.771)	2.331 (1.782)
Race=Color other than Black or White	0.179 (0.092)*	-0.383 (0.264)	-0.663 (0.386)*	-1.090 (1.606)		
Race=Other	0.573 (0.245)**	-0.054 (0.253)		1.081 (0.510)**	0.678 (1.026)	
Race=Not reported	1.715 (0.167)***					

Absolute values of robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 17. Industry Dummy Results for Regressions With Neighborhood Effects									
	(vii) all wagediff	(viii) moved wagediff	(ix) displa wagediff	(x) all incdiff	(xi) moved incdiff	(xii) displa incdiff			
Industry=Not Working for Money Now									
Industry=Agriculture, Forestry, and Fisheries	-0.645 (0.385)*	-0.326 (0.549)	-0.866 (0.452)*	-0.989 (0.892)	-3.787 (1.039)***				
Industry=Mining	0.000 (0.000)	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)				
Industry=Construction	-0.407 (0.334)	-0.039 (0.211)	-1.042 (0.436)**	-0.701 (0.897)	-3.276 (0.824)***	1.665 (3.683)			
Industry=Manufacturing	-0.431 (0.329)	0.122 (0.183)	-0.398 (0.449)	-0.782 (0.865)	-3.645 (0.912)***	-1.031 (3.714)			
Industry=Transportation, Communications, and Other Public Utilities	-0.404 (0.332)	0.048 (0.197)	-0.197 (0.505)	-0.789 (0.866)	-3.073 (0.718)***				
Industry=Wholesale and Retail Trade	-0.330 (0.328)	0.154 (0.148)	-0.429 (0.309)	-0.874 (0.878)	-3.066 (0.809)***	3.642 (3.604)			
Industry=Finance, Insurance, and Real Estate	-0.500 (0.331)	-0.065 (0.175)	-1.253 (0.331)***	-0.203 (0.936)	-2.744 (1.006)***	3.248 (3.338)			
Industry=Business and Repair Services	-0.363 (0.335)	-0.025 (0.206)	-0.963 (0.276)**	-1.126 (0.952)	-3.128 (1.006)***	9.223 (4.753)*			
Industry=Personal Services	-0.675 (0.338)**	-0.401 (0.213)*	-1.114 (0.316)**	-0.816 (1.040)	-2.852 (1.565)*	6.039 (4.574)			
Industry=Entertainment and Recreation Services	-0.392 (0.376)	0.674 (0.395)*	0.000 (0.000)	-0.810 (0.897)	-2.915 (0.816)***				
Industry=Professional and Related Services	-0.559 (0.330)*	-0.151 (0.172)	-0.705 (0.285)**	-1.090 (0.906)	-3.760 (0.881)***	4.441 (3.842)			
Industry=Public Administration	-0.487 (0.332)	-0.082 (0.208)	-0.960 (0.427)**	-0.884 (0.899)	-3.955 (0.822)***	0.978 (2.096)			
Absolute values of robust standard errors in parentheses									
* significant at 10%; ** significant at 5%; *** significant at 1%									

Table 18. Occupation Dummy Results for Regressions With Neighborhood Effects

	(vii) all wagediff	(viii) moved wagediff	(ix) displa wagediff	(x) all incdiff	(xi) moved incdiff	(xii) displa incdiff
Occupation=Not Working for Money Now						
Occupation=Professional, Technical, and Kindred Workers	0.954 (0.331)***	0.647 (0.205)***	1.527 (0.311)***	2.315 (0.941)**	5.877 (1.384)***	2.449 (3.399)
Occupation=Managers and Administrators, Except Farm	0.867 (0.330)***	0.819 (0.174)***	1.534 (0.381)***	1.936 (0.951)**	4.855 (1.067)***	1.855 (3.766)
Occupation=Sales Workers	0.882 (0.331)***	0.654 (0.164)***	1.414 (0.369)***	1.781 (1.061)*	4.927 (1.169)***	1.458 (3.737)
Occupation=Clerical and Kindred Workers	1.153 (0.331)***	0.782 (0.196)***	1.382 (0.335)***	2.233 (0.925)**	5.181 (1.065)***	0.225 (3.492)
Occupation=Craftsmen and Kindred Workers	1.028 (0.330)***	0.904 (0.203)***	1.744 (0.446)***	2.080 (0.945)**	5.193 (1.028)***	1.337 (3.649)
Occupation=Operatives, Except Transport	1.121 (0.333)***	0.720 (0.200)***	1.052 (0.442)**	2.167 (0.926)**	4.254 (1.069)***	-1.687 (3.400)
Occupation=Transport Equipment Operatives	1.079 (0.338)***	0.978 (0.265)***	1.072 (0.562)*	2.393 (0.939)**	5.066 (1.054)***	0.000 (0.000)
Occupation=Laborers, Except Farm	1.025 (0.337)***	0.830 (0.218)***	1.309 (0.418)***	2.675 (0.978)***	5.312 (1.185)***	1.393 (4.292)
Occupation=Farmers and Farm Managers	1.096 (0.386)***					
Occupation=Farm Laborers and Farm Foremen	1.203 (0.405)***	0.996 (0.584)*				
Occupation=Service Workers, Except Private Household	1.178 (0.332)***	0.962 (0.193)***	1.713 (0.219)***	2.619 (0.984)***	5.466 (1.229)***	-2.813 (3.589)
Occupation=Private Household Workers	0.960 (0.358)***	0.800 (0.498)	1.495 (0.318)***	2.505 (1.157)**		

Absolute values of robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 19. F Statistics for Regressions With Neighborhood Effects						
	(vii) all	(viii) moved	(ix) displa	(x) all	(xi) moved	(xii) displa
	wagediff	wagediff	wagediff	incdiff	incdiff	incdiff
Race	2.189	1.483	0.368	0.381	1.538	1.804
	(0.032)**	(0.181)	(0.871)	(0.892)	(0.193)	(0.165)
Industry	2.775	1.445	1.737	0.409	0.317	0.814
	(0.001)***	(0.139)	(0.065)*	(0.961)	(0.986)	(0.595)
Occupation	3.802	0.858	0.919	0.552	0.313	0.650
	(0.000)***	(0.582)	(0.516)	(0.854)	(0.970)	(0.747)
P values in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 20. Level Regression Results With Neighborhood Effects						
	(xiii) all	(xiv) moved	(xv) displa	(xvi) all	(xvii) moved	(xviii) displa
	wage	wage	wage	inc	inc	inc
age	-0.003	-0.003	-0.012	0.081	0.126	-0.073
	(0.004)	(0.008)	(0.014)	(0.033)**	(0.090)	(0.323)
age2	0.000	0.000	0.000	-0.001	-0.002	0.000
	(0.000)	(0.000)	(0.000)	(0.000)***	(0.001)**	(0.003)
sex	0.049	0.216	0.172	-0.650	-1.297	-3.263
	(0.025)*	(0.059)***	(0.093)*	(0.187)***	(0.443)***	(1.354)**
union	0.658	0.616	0.487	0.440	0.854	0.783
	(0.045)***	(0.093)***	(0.170)***	(0.125)***	(0.307)***	(1.424)
edu	-0.011	-0.008	-0.011	0.112	0.155	0.287
	(0.004)***	(0.011)	(0.020)	(0.047)**	(0.115)	(0.466)
gent	0.058	0.063	-0.044	0.316	-0.651	-3.505
	(0.041)	(0.088)	(0.139)	(0.241)	(0.601)	(2.149)
displa	0.067	0.094		0.208	-0.077	
	(0.047)	(0.055)*		(0.370)	(0.419)	
gentdispla	-0.221	-0.178		-1.887	-1.461	
	(0.139)	(0.160)		(1.323)	(1.948)	
percwhitediff	-0.001	-0.003	-0.003	0.015	0.025	0.071
	(0.001)	(0.002)	(0.004)	(0.010)	(0.014)*	(0.042)
percfemheaddiff	-0.001	-0.003	0.003	0.041	0.061	0.261
	(0.004)	(0.005)	(0.008)	(0.026)	(0.036)*	(0.092)***
percpovdiff	-0.002	-0.002	-0.007	-0.042	-0.034	-0.090
	(0.003)	(0.005)	(0.007)	(0.032)	(0.043)	(0.087)
perchighincdiff	-0.004	-0.004	-0.002	0.008	0.002	0.016
	(0.003)*	(0.003)	(0.005)	(0.011)	(0.018)	(0.040)
percdropoutdiff	0.000	-0.002	0.004	0.030	0.032	0.081
	(0.002)	(0.003)	(0.004)	(0.018)*	(0.021)	(0.053)
unempratediff	-0.007	-0.009	-0.007	-0.010	-0.006	-0.124
	(0.005)	(0.007)	(0.012)	(0.046)	(0.068)	(0.158)
gentdisplawhite	-0.009	-0.006	-0.003	-0.855	-0.087	-5.087
	(0.010)	(0.010)	(0.012)	(0.642)	(1.510)	(5.655)
gentdisplafem	0.020	0.027	0.025	-2.479	-0.242	-13.743
	(0.027)	(0.028)	(0.028)	(1.702)	(4.106)	(15.607)
gentdislapov	0.017	0.015	0.017	0.489	0.242	1.907
	(0.020)	(0.020)	(0.021)	(0.186)***	(0.470)	(1.819)
gentdisplahigh	0.046	0.038	0.037	0.005	0.001	0.379
	(0.028)	(0.027)	(0.028)	(0.037)	(0.075)	(0.279)
gentdispladrop	-0.019	-0.019	-0.020	-0.096	-0.180	-0.141
	(0.009)**	(0.009)**	(0.011)*	(0.064)	(0.092)*	(0.154)
gentdisplaunemp	-0.022	-0.030	-0.027	0.094	-0.266	1.625
	(0.019)	(0.019)	(0.021)	(0.223)	(0.572)	(2.285)
Constant	0.044	-0.154	0.218	0.549	0.601	2.883
	(0.126)	(0.255)	(0.458)	(0.967)	(2.341)	(7.398)
Observations	5547	1149	342	1181	251	72
Adjusted R-squared	0.48	0.45	0.52	0.73	0.58	0.47
Absolute values of robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						
Race, Industry, and Occupation dummy variables are included in analysis						

Table 21. Race Dummy Results for Level Regressions With Neighborhood Effects							
	(xiii) all wagediff	(xiv) moved wagediff	(xv) displa wagediff	(xvi) all incdiff	(xvii) moved incdiff	(xviii) displa incdiff	
Race=White							
Race=Black	0.084 (0.026)***	0.037 (0.061)	-0.073 (0.108)	0.055 (0.160)	0.438 (0.413)	2.931 (1.888)	
Race=American Indian, Aleut, Eskimo	-0.145 (0.189)	-0.551 (0.388)	0.012 (0.127)	-0.155 (0.746)			
Race=Asian, Pacific Islander	0.045 (0.171)	0.350 (0.614)	-0.550 (0.262)**	1.246 (1.327)	1.157 (0.757)	1.984 (2.266)	
Race=Latino	0.202 (0.069)***	0.328 (0.163)**	0.321 (0.348)	-0.074 (0.414)	-1.239 (0.714)*	1.625 (1.893)	
Race=Color other than Black or White	-0.119 (0.115)	0.042 (0.732)	1.267 (0.299)***	-2.444 (1.482)*			
Race=Other	0.026 (0.266)	-0.901 (0.404)**		3.920 (2.799)	-1.056 (1.011)		
Race=Not reported	0.241 (0.156)						
Absolute values of robust standard errors in parentheses							
* significant at 10%; ** significant at 5%; *** significant at 1%							

Table 22. Industry Dummy Results for Level Regressions With Neighborhood Effects

	(xiii) all wagediff	(xiv) moved wagediff	(xv) displa wagediff	(xvi) all incdiff	(xvii) moved incdiff	(xviii) displa incdiff
Industry=Not Working for Money Now						
Industry=Agriculture, Forestry, and Fisheries	-1.065 (0.363)***	-0.069 (0.334)	-0.676 (0.558)	-0.473 (0.358)	-1.024 (0.928)	
Industry=Mining	0.000 (0.000)	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)	
Industry=Construction	-0.177 (0.332)	0.706 (0.220)***	0.335 (0.342)	-0.666 (0.354)*	-0.520 (0.722)	2.615 (3.465)
Industry=Manufacturing	-0.279 (0.327)	0.726 (0.198)***	0.694 (0.333)**	-0.210 (0.288)	-1.201 (0.744)	0.373 (3.116)
Industry=Transportation, Communications, and Other Public Utilities	-0.320 (0.330)	0.555 (0.206)***	0.979 (0.355)***	-0.094 (0.290)	-0.035 (0.621)	
Industry=Wholesale and Retail Trade	-0.343 (0.328)	0.659 (0.177)***	0.665 (0.245)***	-0.869 (0.333)***	-0.527 (0.756)	2.895 (3.385)
Industry=Finance, Insurance, and Real Estate	-0.750 (0.331)**	0.367 (0.185)**	-0.076 (0.325)	-0.106 (0.400)	-0.452 (0.577)	4.332 (2.654)
Industry=Business and Repair Services	-0.405 (0.334)	0.658 (0.233)***	0.871 (0.488)*	-0.806 (0.418)*	-0.098 (0.866)	9.293 (3.895)**
Industry=Personal Services	-0.890 (0.336)***	0.077 (0.252)	-0.469 (0.330)	-1.625 (0.613)***	-1.433 (1.226)	4.893 (4.085)
Industry=Entertainment and Recreation Services	-0.662 (0.358)*	0.095 (0.409)	0.000 (0.000)	0.030 (0.301)	-0.481 (0.684)	
Industry=Professional and Related Services	-0.536 (0.330)	0.299 (0.191)	-0.032 (0.242)	-0.447 (0.357)	-0.538 (0.727)	4.444 (3.419)
Industry=Public Administration	-0.820 (0.332)**	0.160 (0.218)	0.280 (0.355)	-0.183 (0.313)	-0.708 (0.631)	3.073 (2.181)

Absolute values of robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 23. Occupation Dummy Results for Level Regressions With Neighborhood Effects									
	(xiii) all wagediff	(xiv) moved wagediff	(xv) displa wagediff	(xvi) all incdiff	(xvii) moved incdiff	(xviii) displa incdiff			
Occupation=Not Working for Money Now									
Occupation=Professional, Technical, and Kindred Workers	1.059 (0.330)***	0.278 (0.209)	0.672 (0.313)**	7.506 (0.417)***	6.289 (1.202)***	2.750 (2.869)			
Occupation=Managers and Administrators, Except Farm	0.818 (0.328)**	0.085 (0.173)	0.249 (0.308)	7.395 (0.443)***	5.534 (0.894)***	4.725 (2.783)*			
Occupation=Sales Workers	0.963 (0.332)**	0.048 (0.172)	0.415 (0.374)	7.236 (0.599)***	6.116 (1.047)***	2.997 (2.974)			
Occupation=Clerical and Kindred Workers	1.807 (0.331)***	0.831 (0.194)**	0.907 (0.268)**	7.267 (0.434)***	6.242 (0.953)***	3.412 (2.937)			
Occupation=Craftsmen and Kindred Workers	1.845 (0.330)***	1.051 (0.208)**	1.162 (0.350)**	7.124 (0.440)**	5.940 (0.926)**	1.755 (2.725)			
Occupation=Operatives, Except Transport	2.198 (0.326)**	1.190 (0.202)**	1.303 (0.311)**	6.926 (0.442)**	5.155 (1.185)**	-0.206 (2.828)			
Occupation=Transport Equipment Operatives	1.822 (0.331)***	1.218 (0.261)**	0.977 (0.461)**	7.300 (0.439)***	5.871 (0.919)***	0.000 (0.000)			
Occupation=Laborers, Except Farm	1.998 (0.332)***	1.151 (0.217)**	1.418 (0.270)**	7.047 (0.453)***	5.694 (1.020)***	4.793 (3.329)			
Occupation=Farmers and Farm Managers	1.181 (0.364)**								
Occupation=Farm Laborers and Farm Foremen	2.590 (0.399)***	1.137 (0.545)**							
Occupation=Service Workers, Except Private Household	1.836 (0.330)***	0.924 (0.189)**	1.342 (0.144)**	7.007 (0.449)***	5.578 (1.017)***	0.377 (3.064)			
Occupation=Private Household Workers	1.285 (0.359)***	0.185 (0.394)	0.530 (0.353)	8.569 (0.715)***					

Absolute values of robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 24. F Statistics for Level Regressions With Neighborhood Effects						
	(xiii) all	(xiv) moved	(xv) displa	(xvi) all	(xvii) moved	(xviii) displa
	wagediff	wagediff	wagediff	incdiff	incdiff	incdiff
Race	2.889	2.231	1.031	1.919	0.879	1.508
	(0.005)***	(0.038)**	(0.399)	(0.075)**	(0.477)	(0.230)
Industry	16.377	3.919	4.126	1.539	0.235	0.590
	(0.000)***	(0.000)***	(0.000)***	(0.104)	(0.996)	(0.779)
Occupation	74.109	12.359	3.612	0.612	0.315	0.654
	(0.000)***	(0.000)***	(0.000)***	(0.805)	(0.969)	(0.744)
P values in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 25. VIF on Wage Regression		
	VIF	1/VIF
Industry=Professional and Related Services	80.08	0.01
Occupation=Professional, Technical, and Kindred Workers	73.18	0.01
Industry=Manufacturing	67.68	0.01
Industry=Wholesale and Retail Trade	59.05	0.02
Occupation=Managers and Administrators, Except Farm	57.74	0.02
Occupation=Service Workers, Except Private Household	55.06	0.02
Occupation=Craftsmen and Kindred Workers	54.03	0.02
Occupation=Clerical and Kindred Workers	49.68	0.02
age2	47.99	0.02
age	46.46	0.02
Industry=Public Administration	38.19	0.03
Industry=Transportation, Communications, and Other Public Utilities	36.44	0.03
Occupation=Operatives, Except Transport	32.35	0.03
Industry=Construction	30.08	0.03
Industry=Business and Repair Services	25.09	0.04
Industry=Finance, Insurance, and Real Estate	24.24	0.04
Occupation=Sales Workers	23.88	0.04
Occupation=Transport Equipment Operatives	22.67	0.04
Occupation=Laborers, Except Farm	21.21	0.05
Industry=Personal Services	19.15	0.05
Industry=Agriculture, Forestry, and Fisheries	5.95	0.17
Occupation=Private Household Workers	5.34	0.19
Industry=Entertainment and Recreation Services	4.92	0.20
percfemheaddiff	4.37	0.23
percpovdiff	4.22	0.24
unempratediff	2.67	0.37
Occupation=Farm Laborers and Farm Foremen	2.55	0.39
percwhitediff	2.15	0.47
perchighincediff	1.69	0.59
edu	1.59	0.63
gentdispla	1.49	0.67
sex	1.38	0.73
Race=Black	1.32	0.76
union	1.31	0.77
percdropoutdiff	1.22	0.82
displa	1.17	0.85
Occupation=Farmers and Farm Managers	1.15	0.87
gent	1.11	0.90
Race=Latino	1.08	0.93
Race=Color other than Black or White	1.04	0.96
Race=Not reported	1.03	0.97
Race=American Indian, Aleut, Eskimo	1.02	0.98
Race=Asian, Pacific Islander	1.01	0.99
Race=Other	1.01	0.99
Mean VIF	18.95	

Table 26. VIF on Income Regression

	VIF	1/VIF
Occupation=Professional, Technical, and Kindred Workers	57.33	0.02
Industry=Professional and Related Services	56.68	0.02
Industry=Manufacturing	52.63	0.02
age2	49.17	0.02
age	47.86	0.02
Occupation=Managers and Administrators, Except Farm	44.39	0.02
Industry=Wholesale and Retail Trade	43.15	0.02
Occupation=Service Workers, Except Private Household	39.10	0.03
Occupation=Craftsmen and Kindred Workers	37.49	0.03
Occupation=Clerical and Kindred Workers	35.72	0.03
Industry=Public Administration	29.25	0.03
Occupation=Operatives, Except Transport	22.72	0.04
Industry=Construction	22.03	0.05
Industry=Transportation, Communications, and Other Public Utilities	21.48	0.05
Industry=Finance, Insurance, and Real Estate	17.89	0.06
Occupation=Sales Workers	16.60	0.06
Industry=Business and Repair Services	16.47	0.06
Occupation=Laborers, Except Farm	13.38	0.07
Occupation=Transport Equipment Operatives	13.06	0.08
Industry=Personal Services	11.98	0.08
percovdiff	5.32	0.19
percfemheadiff	4.91	0.20
gentdispla	4.29	0.23
unempratediff	3.55	0.28
Industry=Entertainment and Recreation Services	3.04	0.33
Occupation=Private Household Workers	2.94	0.34
percwhitediff	2.34	0.43
edu	1.78	0.56
Industry=Agriculture, Forestry, and Fisheries	1.70	0.59
perchighincediff	1.67	0.60
Race=Black	1.42	0.71
sex	1.41	0.71
percdropoutdiff	1.37	0.73
union	1.36	0.74
displa	1.20	0.83
gent	1.12	0.89
Race=Latino	1.10	0.91
Race=Color other than Black or White	1.03	0.97
Race=Other	1.03	0.97
Race=American Indian, Aleut, Eskimo	1.02	0.98
Race=Asian, Pacific Islander	1.02	0.98
Mean VIF	1139.43	