Migration Flows in a Millennial City Washington, D.C. 2005-2014[†]

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Abstract

One difficulty in the quantitative study of migration stems from disentangling between economic, non-economic and housing market factors. By focusing on residential migration within a single city, one can minimize this caveat and isolate the impact of income and housing market factors on neighborhood choice. However, due to general equilibrium effects of the migration process on the relative attractiveness of each neighborhood, this solution requires the use of exhaustive data sources.

Using a gravity framework, we estimate patterns of residential migration flows between the 179 census tracts of a very polarized city that has become iconic of gentrification: Washington, DC. To that end, we analyze restricted-access individual income and real property tax rolls from 2005 to 2014, combined with data from the American Community Survey, National Bureau of Economic Research, and the National Neighborhood Indicators Partnership. We propose a measure of residential migration based on income flows across neighborhoods and show that it helps depict urban dynamics in a more complete pattern than classical individual-based flow measures.

Overall, we find that within city migrants, mostly low-to-moderate income households, move to more racially diverse neighborhoods, with cheaper housing, lesser amenities to the exception of EITC recipients, who are less sensitive to differences in neighborhood quality. These results are mostly stable over time, which means that the Great Recession did not alter households' preferences regarding local amenities in Washington DC.

I. Introduction

The population of the District of Columbia has become increasingly diverse since 2000. Prior to the millennium, the District's population was in constant decline, and predominantly black. In 1980, 70 percent of the District's population was black; in 2000, the share of black population fell to 61 percent and then to 51 percent by 2010 (Tatian, and Lei, 2014). The influx of white population has driven the population growth in D.C (Sturtevant, 2013).

The recent population growth in DC increased demand for housing and caused a dramatic increase in home sale prices (Tatian, and Lei, 2014). The increase in home and rental prices has made D.C. one of the most expensive places to live in the country. Based on the Standard & Poor's Case-Shiller Home Price Index, an average home bought in the District of Columbia in 2000 was worth 111 percent more in 2014 (Quealy, 2013)[3]. Furthermore, rental prices have skyrocketed. More than 50 percent of D.C metropolitan area residents are primarily renters (Department of Numbers, 2016). In 2011, the renter fraction of the population increased by 2 percentage point to 59 percent and 35 percent for the metropolitan area and the U.S. average, respectively (Ibid). At the same time the number of rental units available in the District for under $800 decreased by 47 percent to roughly 34,000 and the number of rental units existing in the District for $1,000 or more drastically increased by 92 percent from about 51,000 units in 2005 to approximately 98,000 in 2012 (Tatian, and Lei, 2014).

[3] The District's housing price index is 39 percentage points above the US 20 city index (Quealy, 2013)

The changing demographic and economic compositions of the city represent some policy shift purposely executed by the District government after the millennium (Sturtevant, 2013). Specifically, in 2003, one of then Mayor Anthony Williams' focus was to attract 100,000 new residents to the District of Columbia over 10 years by prioritizing investments in amenities to attract middle- and upper-income singles and couples over families (Sturtevant, 2013). Policies tailored to encourage investments in restaurants, retail, and entertainment development in emerging neighborhoods, as well as the construction of high-end condominiums and apartments in neighborhoods that had lacked investment were enacted. The District government also recognized the need to reform the District of Columbia public school system by appointing new school chancellor among other things, to create an environment that was attractive to young, childless, and relatively wealthy households (Sturtevant, 2013). Policies enacted by the District government and executed to increase the District population therefore have far reaching consequences. The changing demographic composition of the District caused gentrification (Brown-Robertson and Muhammad, 2014; Hamnet, 2003; Kennedy and Leonard, 2001). The rise in population especially among millennials into the District is a key hallmark of neighborhood change (McKinnish, Walsh, and White, 2010). Frey (2013), found that the District ranks as the most desired metropolitan area to live for 25-to-34-year olds.

Through urban renewal programs and various economic development initiative, DC government attracted younger, and more affluent residents to the city. At the same time DC government created a relatively generous cash program for lower income population. The Earned Income Tax Credit (EITC), a refundable tax credit that supports low-income working families. The EITC benefits in DC were gradually increased. Since 2009 DC has provided supplemental credit up to 40 percent of the federal credit. The benefits to the families with dependents can change between 7 to 45 cents per dollar earned based on the number of dependents and the annual maximum set by the policy (Brown-Robertson et al., (2016). Since, compared to Maryland and Virginia, DC has a more generous ETC program, those who might be hurt by gentrification also have incentive to stay in DC. This paper attempts to investigate the extent at which government policies like EITC have affected he location decision of low-income earners in DC.

This paper builds on Sturtevant's (2013) and Toney and Ellis (2012) research on what population growth and demographic change would mean for the District. This paper improves on the previous studies by focusing on neighborhood migration flows both within and in and out of DC. This research is unique in the sense that it will be the first paper to study migration flows by census tract within the District of Columbia using individual income tax and real property tax data. By focusing on the migration patterns of EITC beneficiaries, we can evaluate the effectiveness the EITC policy as a counter force to mitigate or reduce the displacement effects of gentrification.

To account for the effects of gentrification and EITC policy on migration patterns within DC, we employ gravity model. Gravity model has been widely used to study trade flows between countries. And more recently it has been extended to include the study of migration flows. In the gravity model migration flows between two places are determined by the pull and push factors related to the relative attractiveness of the destination and origin places. Following Silva and Tenreyro (2006) we use the Poisson Pseudo-Maximum-Likelihood (PPML) model to analyze within DC migration flows. PPML produces more robust estimates compared to gravity models estimated by OLS. In gravity model migration flows between places is used as dependent variable. When there is no migration between places dependent variable will have zero values and OLS will drop these observations. Consequently, OLS estimates will be biased (Silva and Tenreyro, 2006). The presence of higher proportion of zeros in dependent variable also causes heteroscedasticity in OLS estimation. The PPML model does not drop zero values of dependent variable and therefore produces consistent estimates in the presence of heteroscedasticity (Silva and Tenreyno, 2006).

This paper is organized as follows. Section 2 establishes previous literature on migration flow sand neighborhood change. Section 3 discusses the theoretical framework of the model. Section 4 describes the data and methodology. Section 5 gives the descriptive analysis. Section 6 offers the findings from the empirical analysis, and Section 7 concludes the paper with any implications from the findings.

2. Literature Review

Migration flows play an important role in the demographic composition of local communities. Neighborhood population changes can lead to neighborhood change, population (residential) displacement or revitalization, and gentrification. Gentrification refers to neighborhood changes that are characterized by the influx of new residents of a higher socioeconomic status relative to incumbent residents and rising housing values due to a bid up on the rent for land (Alonso, 1964; Ding, Hwang, and Divringi, 2015). In gentrifying neighborhoods, the bidding for land causes neighborhoods to transform from low income communities into higher income communities thereby pricing out lower income out of their neighborhoods. Therefore, , residential displacement is viewed as the biggest consequence resulting from neighborhood revitalization and gentrification. Grier and Grier (1978, p. 8) note that “displacement occurs when any household is forced to move from its residence by conditions which affect the dwelling or 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" where "forced" is loosely used to be dependent on economic factors like increase in rental and housing prices (Zuk, Bierbaum, Chapple, Gorska, Loukaitou-Sideris, Ong, and Thomas, 2015).

Schachter (2001) analyzed why people moved in the United States using the 2000 current population survey. The highest percentage of people relocates for housing related reasons. This is true for inter-county and intra-county movers in the United States, where inter-county movers are households that moves across county boundaries and intra-county movers locate within a county. Schachter (2001) found housing affordability to be the third highest housing related reasons to move in the United States behind new/ better home or apartment and home ownership, respectively. Quigley and Raphael (2004) later expand on the issue of housing affordability. Quigley and Raphael (2004) note that housing affordability comes from two factors: the cost of housing the largest single expenditure for most households; and rental and housing cost has escalated in most U.S metropolitan areas. Quigley and Raphael (2004) found that the poor and near poor have experienced a decrease in housing affordability since the 1960s. Specifically, the median rent-to-income ratio of poor and near poor households and the proportion of households spending more than 30 percent of income on rent has increased. Since near poor and poor households are increasingly unable to afford their housing cost, it is expected that households moving within the District will choose to relocate to neighborhoods with cheaper housing cost than their previous neighborhood.

McKinnish, Walsh and White (2009) used the characteristics of the households moving into, moving out of and staying in these neighborhoods to analyze the demographic processes underlying the gentrification of low-income urban neighborhoods during the 1990's. The research primarily focused on whether the demographic processes of neighborhood gentrification are consistent with the story of displacement and harm to low-income and minority families discussed by previous researchers. McKinnish et al. (2009) used 1990 and 2000 census long form data to create a map of time-consistent census tracts between 1990 and 2000, to identify a set of gentrifying tracts, and the gentrifying tracts to non-gentrifying tracts in the same metropolitan area that were similarly poor in 1990. Their research show that neighborhood gentrification in gentrifying tracts is due to a disproportionate in-migration of white college graduates with no children under 40 years old. The analysis also found that residential out-migration showed no evidence of disproportionate exit of low-education or minority householders.

Ellen and O'Regan (2010, p. 1) noted that while the patterns of neighborhood change and gentrification have been widely documented, there has been limited research on how these neighborhoods changed, through what channels, and with what consequences. As such, the assumption is that neighborhoods change because higher income, usually white, households move into low-income, minority neighborhoods, involuntarily displacing the vulnerable residents, encouraging racial transition in the process. Ellen and O'Regan's (2010) research consequently, focused on comparing migration patterns (of entry, exit, and non-movers), incumbent upgrading and other neighborhood changes in economically rising low-income neighborhoods to those in other economically stagnant low-income neighborhoods. Using longitudinal housing unit/household level data from the American Housing Survey (AHS) from 1985 through 2005 and census tract data from the decennial census data from 1990 and 2000, Ellen and O'Regan (2010) found that although there was little evidence of displacement, the rate of residents leaving rising low-income neighborhoods was high. Upon further investigation, they concluded that owners exiting gaining neighborhoods had incomes that were considerably lower than owners exiting non-gaining tracts, contributing to the rise in neighborhood income, while exiting homeowners in stagnant low-income neighborhoods had higher incomes on average than the original homeowners, hence lowering the neighborhood's average income. Therefore, this selective exit of homeowners contributed to neighborhood change. Additionally, in these gaining neighborhoods, Ellen and O'Regan (2010) found evidence of larger income increase among non-movers than non-movers in non-gaining neighborhoods. Interestingly, for patterns of racial transition, on average, Ellen and O'Regan (2010) found no evidence that the populations in gaining neighborhoods became whiter as the neighborhoods changed economically. Specifically, they found that "the share of housing units in gaining neighborhoods that began the decade occupied by minority households and ended occupied by white households was smaller than the share of units experiencing the reverse racial transition -- going from an original household that is white to one that is minority" (Ellen and O'Regan, 2010, p. 23). This study also investigates whether households moving within the District locate to lower income neighborhoods than their origin neighborhood. Brown-Robertson et al., (2016) studied whether DC EITC program reduced the out migration of the EITC beneficiaries from gentrifying neighborhoods. They found that the program had a small effect on the likelihood of staying in gentrifying neighborhoods in case of married filers.

Sturtevant (2013) analyzed the demographic and socioeconomic characteristics of the District of Columbia's in-migrants, out-migrants, and non-movers to explore evidence of gentrification between 2006 and 2010. The focus of the study is to understand the effect migration into and out of the District of Columbia had on the greater Washington, DC metropolitan area, and the effect of population change in urban areas. Sturtevant (2013) contend that migration is primarily why gentrification occurs so that a socioeconomic analysis of in-migrants relative to existing residents and out-migrants is critical to understanding if and how new residents are changing the city. Sturtevant (2013) used data from the 2006–2010 ACS 5-year PUMS file to analyze the average characteristics of movers who changed residences over the same period. Sturtevant (2013) found that there is evidence of displacement both within the city and to other places in the Washington, DC metropolitan area. Primarily, she found that less educated and lower income households are more likely to move than college-educated and higher income households. Furthermore, among black households, higher incomes households are relatively more likely to move out of the District of Columbia and into the suburbs compared to not moving. However, among white households, this positive relationship between income and out-migration from the city to the suburbs is not observed. These studies rely on census data and they only focus on the displacement effects recent population growth in DC. Our study's contribution is that it uses a more comprehensive administrative data to study migration flows within DC. This paper uses the District of Columbia individual income tax data to provide a micro-level analysis of residents in the District of Columbia from 2005 to 2014. We also try to account important pull and push factors that affect residents' migration decisions. We hypothesize that DC's generous EITC program can work as a pull factor against the displacement effects of gentrification.

3. Theoretical Framework

The use of gravity model in economics is rooted in international trade. The model has been extended to include the analysis of migration since it measures the movement of individuals between origin and destination places. Specifically, the gravity model states that demographic force or the interaction between two centers i and j is directly related to the origin and destination population sizes and inversely related to the distance between them (Greenwood, 2005, and Constantin, 2004) so that:

$$T_{jk} = G\,\frac{P_i P_j}{d_{ij}},$$

where $T_{ij} = total\ population\ flows\ (in\ both\ directions) between\ i\ and\ j,$
$G = constant,$
$P_i = population\ of\ origin\ i,$
$P_j = population\ of\ destination\ j, and$
$d_{ij} = distance\ between\ i\ and\ j$

The following relation is used to determine the interaction between a given zone, i, and all other zones of the spatial system:

$$T_{i1} + T_{i2} + \cdots + T_{ij} + \cdots + T_{in} = G_1 \frac{P_i P_1}{{d_{i1}}^{b1}} + G_2 \frac{P_i P_2}{{d_{i2}}^{b2}} + \cdots + G_j \frac{P_i P_j}{{d_{ij}}^{bj}} + \cdots + G_n \frac{P_i P_n}{{d_{in}}^{bn}}$$

Since the relative attraction of neighborhoods is being considered, the attraction between *neighborhood*$_i$ and *neighborhood*$_j$ is calculated as:

$$T_{ij} = \frac{\mathrm{G} \frac{\mathrm{P_i P_j}}{{d_{\mathrm{ij}}}^{\mathrm{b}}}}{\mathrm{G_1} \frac{\mathrm{P_1}}{{d_{\mathrm{i1}}}^{\mathrm{b1}}} + \mathrm{G_2} \frac{\mathrm{P_2}}{{d_{\mathrm{i2}}}^{\mathrm{b2}}} + \ldots + \mathrm{G_j} \frac{\mathrm{P_k}}{{d_{\mathrm{ik}}}^{\mathrm{bk}}} + \cdots + \mathrm{G_n} \frac{\mathrm{P_n}}{{d_{\mathrm{in}}}^{\mathrm{bn}}}} = \frac{\mathrm{G.P_i.P_j}\,.\,{d_{\mathrm{ij}}}^{-\mathrm{b}}}{\sum_{\substack{\mathrm{k}=1 \\ \mathrm{k} \neq \mathrm{i,j}}}^{\mathrm{n}} \mathrm{G_k.P_k}\,.\,{d_{\mathrm{ik}}}^{-\mathrm{bk}}}$$

Assuming that the denominator is **A$_i$,** then

$$T_{ij} = G.P_i.A_i.P_j\,.\,{d_{ij}}^{-b}$$

Alternatively written as:

$$T_{ij} = O_i.A_i.D_j\,.\,{d_{ij}}^{-b}$$

where $O_i = Number\ of\ people\ originating\ in\ Neighborhood\ i$
$D_j = the\ attraction\ of\ neighborhood\ j$

The gravity model is usually specified in the log form to linearize the model. In this study we use the ratio-type model that compares the attractiveness of destination neighborhood to the origin neighborhood in Washington, D.C. The model can therefore be rewritten as:

$$lnT_{jk} = ln\beta_0 + \beta_1 ln(pop_k/pop_j) + \beta_2 ln(X_{kj}) + \varepsilon_{kj},$$

Where
$lnT_{jk} = \log$ *of the total population flows (in both directions) between j and k,*
$lnpop_k/pop_j$ = *log of the ratio of neighborhood destination to neighborhood origin population,*
lnX_{kj} = *log of the ratio of neighborhood destination to origin matrix variables*

We use the Poisson Pseudo Maximum Likelihood (PPML) model to estimate the gravity model because PPML can estimate the gravity model in the presence of heteroscedasticity. One of the advantages of PPML is that it allows the gravity model to be estimated in its original form. The PPML estimates the gravity model assuming the exponential functional form of the Poisson regression. This is because a^b can be written as $e^{b*\log(a)}$.The right-hand side of the gravity equation can therefore be written as an exponential function of the logs of the regressors and therefore can be estimated using Poisson regression (Silva, 2017[4]). Thus, the empirical model for this study can be rewritten as:

$$T_{jk} = e^{\left(ln\beta_0 + \beta_1 ln\left(\frac{pop_k}{pop_j}\right) + \beta_2 ln(X_{kj}) + \Pi_{jk} + \varepsilon_{kj}\right)},$$

Where
T_{jk} = *total population flows (from origin to destination neighborhoods) between j and k*

[4] The exponential information and explanation of PPML is from email correspondence with Santos Silva, J.M.C.

pop_k/pop_j = *log of the ratio of neighborhood destination to neighborhood origin population,*
$X_{kj} = log\ of\ the\ ratio\ of\ neighborhood\ destination\ to\ origin\ matrix\ variables$
Π_{jk}= *neighborhood fixed effects*

The traditional labor market model of immigration posits that population and incomes are attractive forces in migration as well as language and culture (Lewer and Van den Berg, 2008). For movers within the District of Columbia where culture, language and labor market opportunities are similar, other attractive or unattractive forces drive migration within the District. These attractive forces include amenity differentials between the origin and destination, such as median income, access to grocery stores, proximity to public transportation and elementary schools. The push factors or unattractive forces include crime, number of fast food restaurants, and number of foreclosure notices in a neighborhood.

4. Data

The data used in this analysis were drawn from four sources—the District of Columbia individual income and real property tax rolls, the NeighborhoodInfo DC, the National Bureau of Economic Research's (NBER) census tract distance database, and the American Community Survey (ACS). This study first analyzes migration flow between census tracts within D.C. between 2006 and 2014, then we examine movers within the District that received EITC to investigate the impact of government policies on location decisions.

The analysis is limited to the 2005-2014 period which coincides with the time the District has experienced a vast increase in population, and increased economic growth, especially in the private sector.

The migration flow data is obtained from the individual income tax return forms filed by residents of the District of Columbia. The individual income tax form is a requirement for a resident whose permanent legal residence is within the District during the taxable year or maintained a place of residence in D.C. for a total of 183 days or were a member of the United States armed forces and D.C was their legal residence for tax purposes[5]. The individual tax return is unique because it is an address-level-data on households. Households are matched from year to year using a person's social security number. Information in the individual income tax data include home addresses, wages, business income, capital gains, real estate income. federal and DC adjusted gross income, number of dependents, filing status (single, married filing jointly, married filing separately, head of household, widow, dependent, domestic partners), Earned Income Tax Credits (EITC), to name a few. The individual income tax data is useful in studying household's decision to move since the location information is available and geocoded by census tract, neighborhood, and ward.

The individual income tax data does have some weaknesses. First, the tax data only contains households that file tax returns and therefore likely understates the total population flows in the District of Columbia. The understated household population flow might be located among families that are not required to file income taxes. About 85 percent of individuals living in the District are represented in the data (Moored and Metcalf, 2015). Secondly, some households that are required to file taxes may decide not to file taxes each year leading to gaps in the data. The tax forms do not include some key demographic information of individuals like race, sex, and level of education. It should be noted that the individual income tax data is an extract from the District of Columbia Office of Tax and Revenue.

[5] The general instructions for the DC income tax return lists individuals who must file a return and those who do not need to file the individual income tax return each year.

Since the data is an extract, some addresses in the dataset were missing. Only about 5 percent of the data are dropped for analysis. These data limitations should be considered when interpreting results from this analysis.

The real property dataset contains property values, billing information and other information of all real properties in DC. The real property data is used to get annual assessment values of properties from 2005 to 2014. Like the individual income data, the real property dataset is also geocoded using addresses to determine the neighborhood locations.

Data on property and violent crime rates was retrieved from NeighborhoodInfo DC. Data retrieved from the American community Survey include proportion of respondents by educational attainment, race, and housing tenure. Finally, distance between census tracts was retrieved from the National Bureau of Economic Research's (NBER) census tract distance database. The NBER database "are great-circle distances calculated using the Haversine formula based on internal points in the geographic area" (NBER, 2015). The great-circle distance is usually the shortest distance between two points on the surface of a sphere.

Households are assumed to make the decision to move at time t and physically move at time t+1. Additionally, perfect information is assumed, and households based their location decision on information available at time t. The data is therefore divided into 9 sub- groups to analyze year by year movements within the District of Columbia. The sub-groups by years are 2005-2006, 2006-2007, 2007-2008, 2008-2009, 2009-2010, 2010-2011, 2011-2012, 2012-2013, and 2013-2014. Using addresses included in the individual tax data, a matrix of resident's movement in the District is constructed. The matrix data consists of 179 x 178 census tracts to provide total of 31,862 observations per sub-group. Additionally, a new transition population variable was also created at the census tract level. The transition population is the number of filers that moved from one census tract at time t into another at time t+1. A stipulation that an individual must have a geocoded D.C. address at time t is made when creating the transition population matrix dataset to capture families that move into a different census tract at time t+1.

5. Descriptive Analysis of Migration Patterns in DC

Before analyzing the hypothesis postulated in this paper, here is a brief analysis on the demographic make-up of in-migrants and out-migrants. The District of Columbia has experienced population growth since 2005. The descriptive analysis provides a better understanding of the population changes in the District of Columbia. This study will use the tax filers, households and residents; and census tracts and neighborhood interchangeably moving forward.

Washington, D.C is dense a city and is first in the density rank in the United States since 1910 (Census Bureau, 2010). The District has an average of 3857 households per square mile. Households include singles, married families, domestic partners, and households with dependents. Figure 1 shows how the Districts population has been increasing per square mile since 2005.

Figure 1: Population per Sq. mile

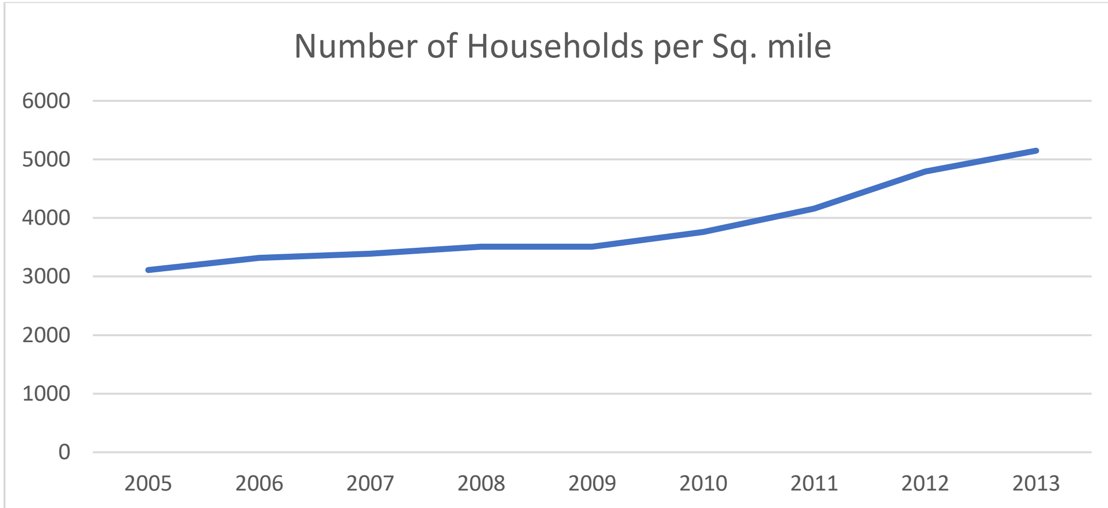


Table 1: Summary of new tax filers by filing status (Percentage)

ALL NEW FILERS				EITC NEW FILERS			
YEAR	Single	Married	Head of Households	**Year**	Single	Married	Head of Households
2005	84.9%	10.3%	4.8%	**2005**	56.7%	4.4%	38.9%
2006	85.4%	9.9%	4.8%	**2006**	52.9%	5.1%	41.9%
2007	85.0%	10.0%	4.9%	**2007**	59.9%	2.4%	37.7%
2008	86.7%	8.7%	4.6%	**2008**	60.7%	3.4%	35.9%
2009	86.4%	9.3%	4.3%	**2009**	61.2%	4.3%	34.5%
2010	86.4%	9.9%	3.7%	**2010**	65.6%	5.4%	29.1%
2011	86.9%	9.2%	3.9%	**2011**	60.6%	5.7%	33.7%
2012	86.5%	9.6%	3.9%	**2012**	59.7%	5.5%	34.8%
2013	84.5%	11.3%	4.1%	**2013**	61.1%	4.9%	34.0%

†Note: This is the percentage of D.C. residents that spent less than 12 calendar months in the individual income tax data at time t in a 2-year period. They are defined as new residents the purposes of this study.

On average, the District welcomed 12,310 new tax filers per year from 2005 to 2013. Table 1 shows the percentage of new residents by their filing status as defined by the District government for tax purposes. An average of 10 percent of new residents into the District are married. Married households are families that are married or domestic partners, and for tax purposes, file their income taxes either jointly or separately. The percentage of married tax filers coming into the District is constant over the 2005–2013 period. Most of the new residents moving into the District each year are single, and the percentage of single tax filers moving into D.C. has steadily increased since 2005. A single tax filer is an individual who is unmarried, divorced or legally separated or were widowed and have not remarried. More than half of new residents receiving EITC benefits are also single. Research has shown that in-migrants tend to be younger. The District attracts young adults for many reasons: it is the capital of the United States with a lot of government job opportunities for recent graduates, there are many good universities located in the Washington, D.C., and it is in a metropolitan area. Sturtevant (2013) noted that "in-migrant households were significantly more likely to be headed by people between the ages of 18 and 24, with the biggest share in the 22–24-year-old age range" (p. 285). It is also more likely that individuals within the age group of 18 and 38 are single. Head of householders also are single individuals that are unmarried or legally separated and pay over half of the costs of maintaining a home for a qualifying person, such as a child or parent. Table 1 also shows that the percentage of head of householders moving into the city has steadily declined from about 5 percent in 2005 to 4 percent in 2013. The share of households with dependents new to the District receiving EITC has also declined as shown in table 1. The reason for the decline in the share of head of households moving to D.C. maybe because of the higher cost of living in the city. Most head of householders tend to be single mothers as about 84 percent of single parent families are single mothers in the United States (Dawn, 2016).

Table 2: Summary of tax filers leaving the city by filing status (Percentage)

ALL FILERS MOVING OUT OF D.C				EITC FILERS MOVING OUT OF D.C			
YEAR	Single	Married	Head of Households	**Year**	Single	Married	Head of Households
2006	83.6%	6.4%	10.0%	**2006**	46.8%	3.3%	49.8%
2007	77.0%	14.0%	9.0%	**2007**	37.4%	5.4%	57.2%
2008	84.9%	7.4%	7.8%	**2008**	52.7%	2.9%	44.4%
2009	87.3%	5.7%	7.0%	**2009**	59.1%	2.1%	38.8%
2010	88.1%	4.5%	7.3%	**2010**	59.6%	2.1%	38.3%
2011	90.8%	4.8%	4.4%	**2011**	59.2%	3.5%	37.3%
2012	87.9%	5.2%	6.9%	**2012**	56.5%	1.9%	41.6%
2013	82.1%	8.0%	9.9%	**2013**	48.0%	5.9%	46.2%
2014	80.6%	9.7%	9.7%	**2014**	47.6%	5.7%	46.7%

†Note: This is the percentage of D.C. residents that spent less than 12 calendar months in the individual income tax data at time t+1 in a 2-year period. They are defined as residents leaving the city for the purpose of this study.

The City is however losing an average of 4404 residents per year, but it gains about three times more residents in this period. Table 2 shows that single individuals also make up most households leaving the city. The share of single households leaving the city however has steadily declined since 2012, which is a couple of years after the end of the great recession. However, the share of married residents, and head of households moving out of the city has increased since 2011 corresponding to the start of the economic recovery from the great recession. This trend is the same for households receiving EITC benefits. One of the reasons for such trend may also be that the district is becoming increasingly unaffordable. Having a lower income may deter head of households from moving into the city while also encouraging married families and head of households to leave the city.

Table 3: Median Income of In-Migrants and Out Migrants

YEARS	IN-MOVERS MEDIAN INCOME	EITC IN-MOVERS MEDIAN INCOME	YEARS	OUT-MOVERS MEDIAN INCOME	EITC OUT-MOVERS MEDIAN INCOME
2005	$41,103	$14,617	**2006**	$27,783	$10,744
2006	$37,627	$15,272	**2007**	$39,906	$13,638
2007	$43,858	$16,678	**2008**	$32,724	$10,541
2008	$42,842	$12,803	**2009**	$31,383	$8,808
2009	$42,325	$12,282	**2010**	$32,937	$10,457
2010	$42,916	$11,378	**2011**	$33,938	$10,194
2011	$44,174	$12,112	**2012**	$35,311	$11,470
2012	$45,217	$11,885	**2013**	$33,888	$11,215
2013	$45,647	$11,662	**2014**	$38,229	$12,991

Generally, the median income of new residents is higher than that of households leaving the District. Residents moving into the city are moderate income households while out-migrants are usually low-to-moderate income households. Table 3 shows the yearly median federally adjusted gross income of households that move out of the District. The only exception occurred in 2007 when a greater number of households with higher median income moved out of the city than in-movers. This corroborates previous research findings that one of the signs of neighborhood displacement and gentrification is the out-migration of lower income households (Ellen and O'Regan, 2010; Sturtevant, 2014; Brown-Robertson, Mohammed, Ward and Bell, 2013). Next is an analysis of the demographical makeup of within city movers.

Migration within Washington, D.C.

People generally move to seek a better quality of life therefore their destination choice has some implications on both the origin and destination communities. The data shows that 126,087 households moved between census tracts within the District between 2006 and 2014. Table 4 below shows the breakdown of the migration flow within the District by year. The value of using the individual income tax data is that we can observe household location decision within DC through their physical addresses so long as they file their annual income tax. The number of households that moved between census tracts in time t+1 represents the migration flows within the District per year. Migration flow represents within city movers, also known as the transition population variable, and is defined as households whose address in the individual income tax data is in a census tract in Washington, D.C. at time t and whose address is in a different census tract at time t+1. On average, about 5 percent of the population moved within the District between 2006 and 2014. However, 2014 represents the year with the highest percentage of movers within D.C. at 11% while there were approximately no movers within the District in 2010 which also corresponds to the end of the great recession. This is not surprising as most household were still dealing with the aftermath of the great recession in 2010. In other years, however, less than 10 percent of the population moved to a different census tract within the District.

Table 4: characteristics of movers within D.C

YEAR	TOTAL FILERS IN DC	TOTAL FILERS THAT MOVED TO ANOTHER CENSUS TRACT	MOVERS AS A % OF TOTAL POPULATION	EITC MOVERS AS A % OF TOTAL MOVERS	EITC MOVERS AS A % OF EITC POPULATION
2005-2006	212614	4003	1.88	44.2	4.68
2006-2007	226898	18333	4.04	18.7	8.89
2007-2008	231777	8805	3.80	33.0	7.09
2008-2009	239963	11979	4.99	24.6	6.96
2009-2010	239768	39	0.02	5.1	0.00
2010-2011	257181	9659	3.76	22.2	4.64
2011-2012	284461	20017	7.04	24.2	9.42
2012-2013	327720	14001	4.27	12.0	3.03
2013-2014	351895	39251	11.15	21.5	14.00

†Note: The percentage of filers with D.C. addresses in one neighborhood at time t, and different D.C. addresses in another neighborhood in the individual income tax data at time t+1 for all tax filers and by demographic group

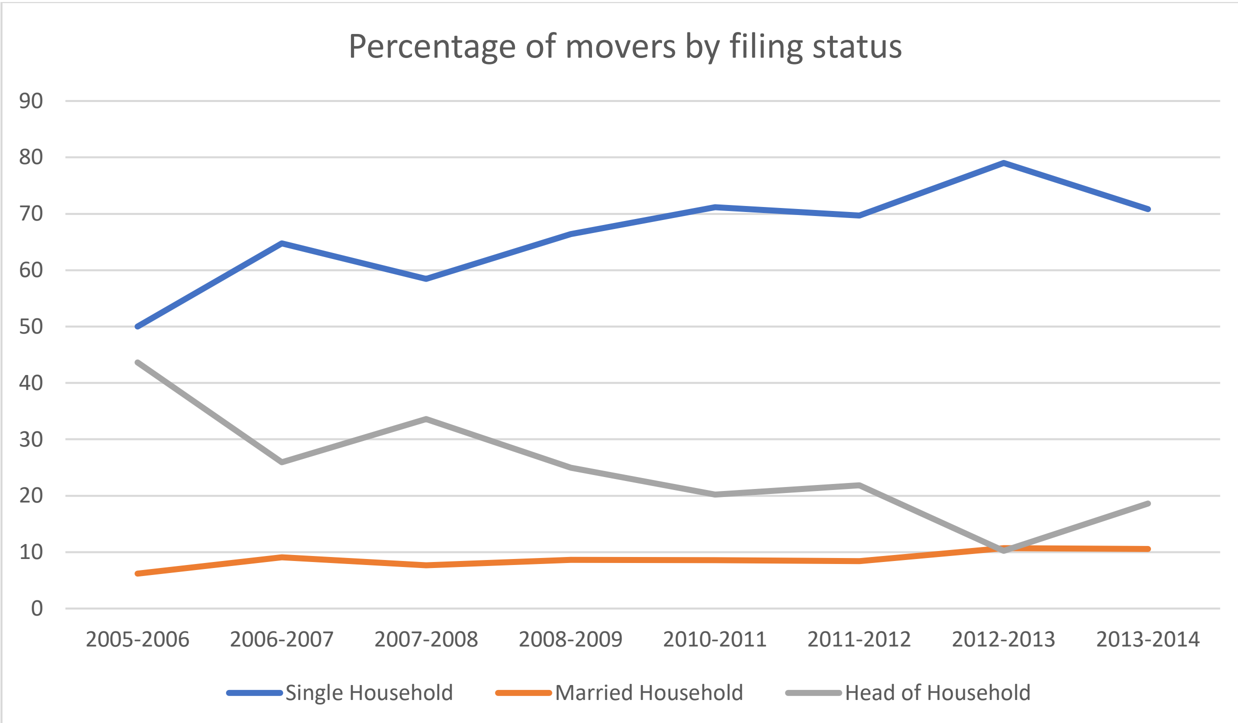
Among EITC recipients, about 28,151 households moved within D.C. between 2006 and 2014, which makes up about 22.3 percent of households that moved within the District in the same time period. This shows that the EITC population is moving a lot within the District although this group, on average, make up only about 18 percent of the total population as shown in table 5 below. The EITC population represent a special population in the United States and D.C. because they are low-to-moderate working income families that receive some government tax cash transfer benefits through the income tax system. Studying the location decisions of EITC households could shed a light on the migration behavior of the poor and near-poor on government subsidies.

Table 5: Characteristics of Movers within Washington D.C-EITC population

Year	Total EITC population	EITC population as % of total population
2005	37800	17.78
2006	38626	17.02
2007	40982	17.68
2008	42286	17.62
2009	43590	18.18
2010	46194	17.96
2011	51391	18.07
2012	55702	17.00
2013	60195	17.11

Single households are the most movers within the District. As figure 2 shows, about 69 percent of movers are single. About 22 percent of movers are head of householders while married households make up about 8 percent of all movers within the District. Interestingly, the number of single households moving within the District has been steadily increasing while the reverse is the case for households with dependents.

Figure: 2: Movers by Filing Status- All households



Among EITC recipients, households with dependents represent the highest percentage of within city movers. As shown in figure 3 below, an average of 18 percent of EITC within city movers are head of householders. This is reasonable as households with dependents is about 64 percent of the EITC population. However, the share of EITC head of household recipients moving within the District as a percentage all within D.C movers has been declining since 2006 while the share of single households has been slightly increasing in the same time period. Single EITC recipients make up about 6.5 percent of all within city movers while married household on EITC moving within the city represent 1 percent of all movers.

Figure 3: Movers by Filing Status- EITC households

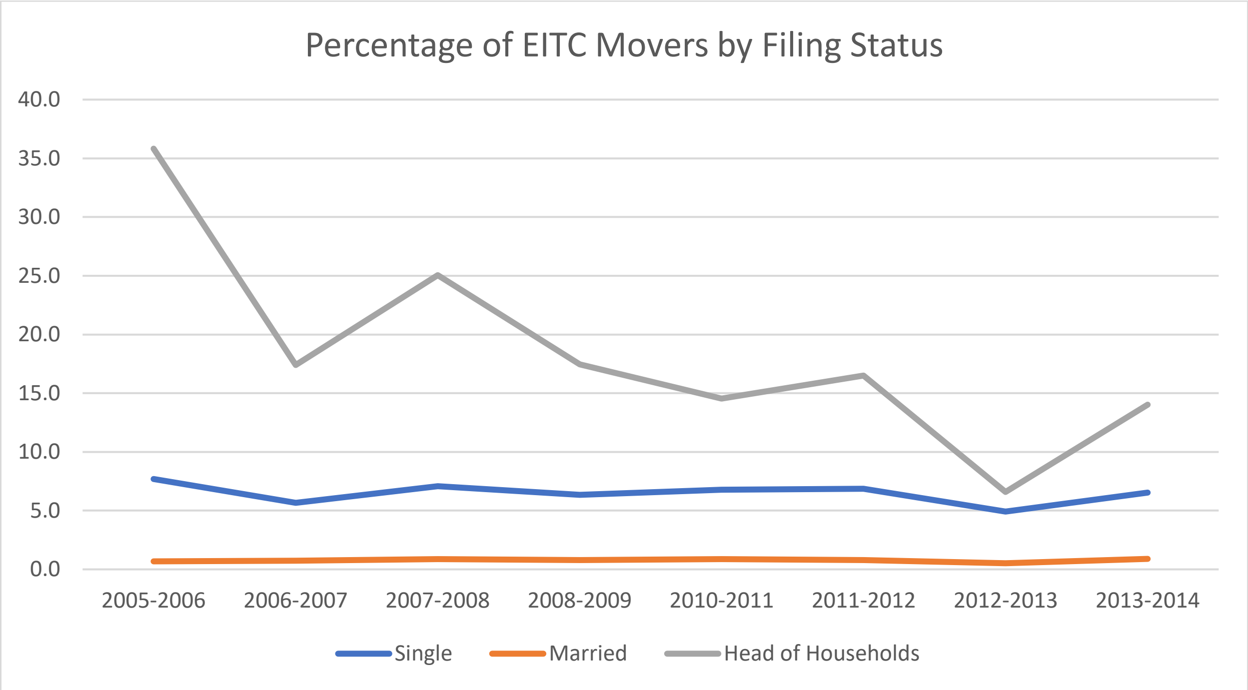


Table 6 below shows that movers within the District generally have a lower income than non-movers. On average, the median federally adjusted gross income (FAGI) for within D.C. movers is about $34,297 while the average income of non-movers is approximately $44,569. For EITC household, the average median income is lower at $14,748. Majority of movers within the District are low-to-moderate income families, especially EITC recipients. This finding is important in the broader discussion of neighborhood change and population displacement in the District, and specifically for the analysis of migration flow within D.C. With the rising cost of living in the District of Columbia, figure 4 below provides support for the gentrification hypothesis. The median rent as a percentage of monthly median income for households that do not move (non-movers) have been increasing from about 27 percent in 2005 to an estimate of 32 percent in 2013. Overall, movers spend more of their monthly income on rent than non-movers. Movers spend about 39 percent of their monthly income on rent while non-movers spend on average 29 percent of their income on rent.

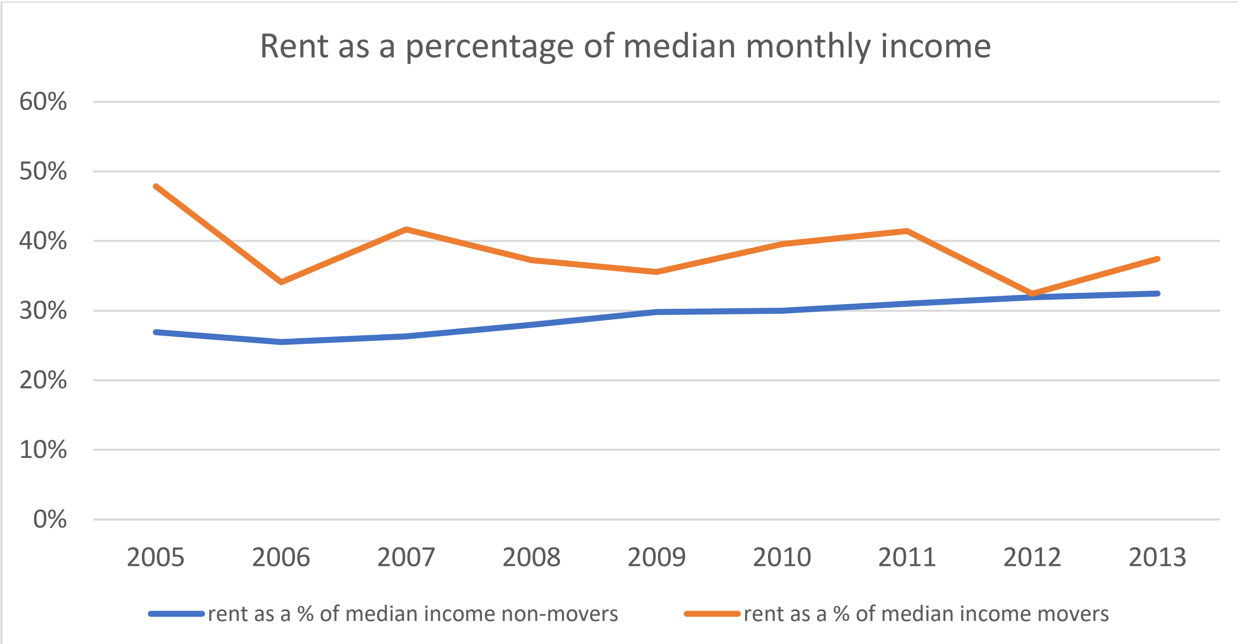
Table 6 Median Income of Residents who moved within DC vs. Non-movers

Year	Movers	Movers (EITC)	Non-Movers
2005-2006	$22,391	$15,268	$39,863
2006-2007	$31,438	$14,672	$42,051
2007-2008	$27,834	$15,311	$44,065
2008-2009	$33,712	$16,353	$44,906
2009-2010	$36,859	**	$43,956
2010-2011	$34,718	$14,668	$45,810
2011-2012	$34,254	$14,225	$45,808
2012-2013	$45,296	$12,707	$46,031
2013-2014	$42,171	$14,785	$48,629

†Note: The real income of filers who moved to another neighborhood in t+1within Washington, D.C. vs. households that stayed in the same neighborhood within D.C. at time t+1

** confidential data. Number of observations too few.

Figure 4: Housing Affordability by median income and rent



†Note: Median gross rent data retrieved from ACS; Median income data retrieved from Individual income tax roll

One of the reasons why housing affordability is pervasive in the District, on the one hand, may be the increase in the demand for housing especially with an increasing population. A shortage in the supply of affordable housing to low-to-moderate income households via new construction, on the other hand, can exacerbate the housing affordability issue (Goodman, 2001).

The above analysis reveals that movers within the District are for the most part, single, low-to-moderate income households. Next, we analyze the location decisions of within city movers. Are people moving to higher income or lower income neighborhoods? We compare the median incomes of the destination census tracts and the origin census tracts.

Table 7: Comparison of median incomes of origin and destination census tracts (within city migrants)

YEAR	% MOVE TO LOWER INCOME CENSUS TRACT	% MOVE TO HIGHER INCOME CENSUS TRACT	EITC-% MOVE TO LOWER INCOME CENSUS TRACT	EITC-% MOVE TO HIGHER INCOME CENSUS TRACT
2005-2006	52.2%	47.8%	50.1%	49.9%
2006-2007	52.8%	47.2%	51.4%	48.6%
2007-2008	52.3%	47.7%	50.1%	49.8%
2008-2009	53.2%	46.8%	51.5%	48.5%
2010-2011	46.4%	53.6%	47.5%	52.6%
2011-2012	54.0%	46.0%	52.9%	47.1%
2012-2013	54.4%	45.6%	54.7%	45.5%
2013-2014	54.0%	46.0%	51.4%	48.7%

The displacement effects of migration are measured by the median income of the destination census tract compared to the income of their origin. However, the gap between the number of residents moving to less attractive census tract compared to the origin is very small. Tables 8 and 9 below however tells a different story on migration flow when neighborhood quality (median income) is compared to household income. The focus of the tables is the middle columns. The tables depict the location decision of non-EITC and EITC households. The tables compare the household income of within city migrants to the median census tract income of the origin and destination at time t.

Table 8: Migration flow to Destination Neighborhood compared to Household Income: Non-EITC Households

YEAR	NON-EITC: INITIALLY IN CENSUS TRACT WITH MORE AMENITIES	NON-EITC: INITIALLY IN CENSUS TRACT WITH LESS AMENITIES	NON-EITC: % MOVE TO CENSUS TRACT WITH LESS AMENITIES	NON EITC: % MOVE TO CENSUS TRACT WITH MORE AMEITIES
2005-2006	47.6%	52.4%	54.7%	45.3%
2006-2007	40.4%	59.6%	53.1%	46.9%
2007-2008	48.5%	51.5%	52.3%	47.7%
2008-2009	55.5%	44.5%	52.8%	47.2%
2010-2011	57.1%	42.9%	40.9%	59.1%
2011-2012	58.5%	41.5%	43.3%	56.7%
2012-2013	55.0%	45.0%	46.5%	53.5%
2013-2014	50.0%	50.0%	52.3%	47.7%

For example, 52.4 percent of non-EITC households that moved in 2006 lived in census tract with median income less than their household's income in 2005. However, in 2006 after the move, 54.7 percent of households live in census tract with median income lower than their household's income in 2005. So that 52.4 percent of households initially lived in neighborhoods with less amenities (measured by median income of the census tract) and in 2006, about 6 percent more non-EITC residents moved to census tracts with less amenities. Less amenities would mean that the quality of the neighborhood would be lower than the quality of neighborhoods with more amenities.

Table 9: Migration flow to Destination Neighborhood compared to Household Income- EITC Households

YEAR	EITC-INITIALLY IN CENSUS TRACT WITH MORE AMENITIES	EITC-INITIALLY IN CENSUS TRACT WITH LESS AMENITIES	EITC-% MOVE TO CENSUS TRACT WITH LESS AMENITIES	EITC-% MOVE TO CENSUS TRACT WITH MORE AMENITIES
2005-2006	81.4%	18.6%	18.5%	81.5%
2006-2007	84.8%	15.1%	14.2%	85.8%
2007-2008	84.5%	15.5%	16.1%	83.9%
2008-2009	83.2%	16.8%	17.2%	82.8%
2010-2011	85.6%	14.3%	13.8%	86.2%
2011-2012	85.2%	14.7%	15.9%	84.1%
2012-2013	86.6%	13.3%	14.3%	85.7%
2013-2014	82.7%	17.3%	16.9%	83.1%

Table 8 shows a steady increase in the number of non-EITC households moving to census tracts with less amenities from 2006-2014 in column 3 except for 2007 and 2011. However, for EITC households, the move to neighborhoods with less amenities are sporadic. That is, there is no trend among EITC movers in table 9. While EITC households are moving a lot within the District, there is a difference in their location decisions compared to households not receiving the government benefit. Note that EITC beneficiaries have lower incomes than the median income of their neighborhoods. When they move from one census tract to another most of them have lower incomes compared to the median incomes of the destination and origin census tracts.

Migration Patterns within DC

To study migration flows within the District from 2005 to 2014, we use structural gravity model, which attempts to explain migration flows between two neighborhoods by their relative attractiveness. Our main explanatory variables are median income and median assessment value of single-family homes in D.C. We also control for other relevant pull and push factors such as racial composition, crime, and proxies for commuting costs. The data is divided into 9 sub- groups to analyze year by year movements within the District. However, the year 2009-2010 is dropped because there was approximately no migration flow in 2010. The matrix data consists of 179 x 178 census tracts that provide a total of 31,862 observations per sub-group.

Table 10 gives a summary of the variables that is considered to have an impact on within-city movers. The table includes the mean and standard deviation for all observations in the data, and the last two columns are summary statistics for observations with a positive migration flow. The migration flow between two census tracts within the District is about 2 per year for observations with positive flows but less than 1 per year for the entire sample. However, the variance of the migration flow between the census tracts at 1.8 for the full sample, and 4.7 for the observations with positive migration flow mean that both samples reveal immense migration flows. Table 10 gives a summary of the variables for EITC within-city movers. The migration flow between two census tracts within the District is about 1 per year for observations with positive flows for EITC within city movers.

The variables of interest in our analysis are income and the assessment value of single-family homes in the destination census tract. Income for our analysis is a measure of neighborhood amenities and quality so that the level of attractiveness is positively related to median income. The assessed home values measure housing affordability in the District. Assessment value is used instead of rent because there is a strong correlation between rent and income at 0.722. The assessment value and income of the observations with positive migration flow in column 3 below is lower than that of the full sample. The average median income in the District is $49,000 while the income of the destination neighborhoods for within city migrants is lower at $45,226. This result is not surprising because the renters are more mobile than the owners and the neighborhoods with higher share of renters have relatively lower median income than those with the higher share of owners.

Table 10: Summary of Economic Characteristics per Destination Neighborhoods

	All Observations		Observation with Positive Flows	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Transition population	0.467	1.342	2.053	2.160
Distance between census tracts	4.002	2.146	2.776	1.803
Assessment value ($)	445845.600	335747.300	441338.900	312965.100
Income ($)	46900.120	31033.760	45225.960	22783.420
Violent crime (per1000)	16.622	41.821	14.117	10.296
Property crime (per1000)	71.946	331.231	49.894	53.161
Age	41.595	6.403	40.361	5.994
Homeownership rate	0.431	0.225	0.415	0.205
Renter rate	0.558	0.228	0.584	0.205
Distance to metro	0.638	0.392	0.612	0.372
White ratio	0.311	0.302	0.302	0.288
Black ratio	0.546	0.356	0.548	0.343
Hispanic ratio	0.084	0.087	0.093	0.094
Total population	1365.029	639.124	1543.478	670.368
Single ratio	0.596	0.135	0.607	0.129
Married ratio	0.181	0.112	0.168	0.091
Head of household ratio	0.224	0.168	0.225	0.164
High school or less ratio	0.302	0.219	0.310	0.210
Some college education ratio	0.189	0.103	0.188	0.100
Bachelor's degree or more ratio	0.497	0.297	0.501	0.288
Observations	286758		65220	

Note: Reported summaries are unweighted.

The same goes for the value of homes in D.C. The average home value in the District is about $445,845 while for census tracts with positive migration flows, the average home is valued at $441,339. For observations with positive EITC migrant flow, the average median income is lower at $33,136, and the median home assessment value is $296,048 shown in table 11 below.

Table 11: Summary of Economic Characteristics per Destination Neighborhoods- EITC

	All Observations		**Observation with Positive Flows**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Transition population	0.106	0.448	1.394	0.915
Distance between census tracts	4.002	2.146	2.899	1.952
Assessment value ($)	445845.600	335747.300	296048.400	200935.300
Income ($)	46900.120	31033.760	33136.330	14095.190
Violent crime (per1000)	16.622	41.821	16.948	8.104
Property crime (per1000)	71.946	331.231	45.566	26.276
Age	41.595	6.403	40.719	5.011
Homeownership rate	0.431	0.225	0.357	0.202
Renter rate	0.558	0.228	0.642	0.203
Distance to metro	0.638	0.392	0.684	0.384
White ratio	0.311	0.302	0.136	0.199
Black ratio	0.546	0.356	0.751	0.273
Hispanic ratio	0.084	0.087	0.078	0.100
Total population	1365.029	639.124	1401.380	589.579
Single	0.596	0.135	0.539	0.115
Married	0.181	0.112	0.129	0.063
Head of household	0.224	0.168	0.331	0.153
High school or less	0.302	0.219	0.440	0.181
Some college education	0.189	0.103	0.240	0.090
Bachelor’s degree or more	0.497	0.297	0.320	0.237
Observations	286758		21833	

We regress migration flows against differential attractiveness of destination and origin census tracts. Our control variables in this study include demographic characteristics of the destination and origin census tracts, destination and origin population, and geographic determinants of migration. Demographic characteristics include age, race, level of education, filing status (single, married or head of household), crime rate, and housing tenure. The geographical determinants of migration include the distance between origin and destination census tracts which measures commuting cost between census tracts, and the distance between census tract and the closet metro train station.

6. Empirical Analysis and Results

Estimation results for the year-by-year migration flow within the District are shown in tables 12 to 15. The dependent variable is the number of within city migrants, and all specifications are estimated using the Poisson Pseudo-Maximum Likelihood (PPML), and OLS estimators. OLS regression is used as a benchmark in this analysis. Recall that the PPML estimator is proven to be a better model when the OLS assumption of constant variance of the error term is violated. Silva and Tenreyro (2006) contends that in the presence of heteroscedasticity in the gravity model, Ordinary Least Square (OLS) estimates are severely biased, distorting the interpretation of the model. Silva and Tenreyro (2006) analysis find the Poisson Pseudo-Maximum-Likelihood model (PPML) to be a more robust estimator since it provides more adequate analysis in cases where there is no migration flow between two census tracts; and the biases of the PPML are always insignificant compared to other estimators in the presence of heteroscedasticity.

First, the model is estimated without fixed effects which controls for the impact of time invariant characteristics of the origin and destination census tracts. These time-invariant characteristics are things we do not observe that can be either pull or push factors for within city migrants. Next, we estimate the model with fixed effects to control for the time invariant characteristics to see the differences in our results.

6.1 Estimation without fixed effects

Tables 12 and 13 show the results of the PPML estimations without fixed effects. The specification for the model is written as:

$$m_{jk,t+1} = \beta_0 + \beta_1 \ln\left(1 + Income_{kj,t}\right) + \beta_2 \ln\left(1 + Assessment\ value_{kj,t}\right) + \beta_3 \ln\left(1 + \ Distance_{kj,t}\right) \\ + \beta_4 \ln\left(1 + \ Population_{kj,t}\right) + \beta_5 \ln\left(1 + \ Demographic\ characteristics_{kj,t}\right) + \beta_6 \ln\left(\ 1 + \ Closet\ metro_{kj,t}\right) \\ + \ \varepsilon_{kj,t}$$

$m_{jk,t+1}$: is the number of migration flow from the origin census tract$_j$ to the destination census tract$_k$ at time t+1. The number of within city movers in each year from 2006 to 2014

$\ln Fagi_{jk,t}$: the log of the ratio of the median federally adjusted gross income in destination census tract$_k$ to the median federally adjusted gross income in origin census tract$_j$ at time t

$\ln Assessment\ value_{jk,t}$: the log of the ratio of the median assessment value of single-family homes in destination census tract$_k$ to the median assessment value of single-family homes in origin census tract$_j$ at time t

$\ln Distance_{jk,t}$: the log of the (distance in miles) from the origin census tract to the destination census tract

$\ln Population_{jk,t}$: the log of the ratio of the population in destination census tract$_k$ to the population in origin neighborhood j at time t

$\ln Demographic\ characteristics_{jk,t}$: is the log of the ratio of each demographic variables in the destination census tract to the demographic variables in the origin census tract at time t. these variables include age, race, level of education, filing status, and crime rate.

$\ln Closest\ metro_{jk,t}$: the log of the ratio of the distance (in miles) between the census tract and closest metro of the destination census tract to that of the origin census tract at time t.

Tables 12 and 13 shows the year to year results for all households and EITC recipients using the PPML estimator. The results of our OLS regressions are in the Appendix on pages 53 and 54. The PPML without fixed effects show that on average, within city migrants are moving to neighborhoods with lower percentage of white population and sometimes move to neighborhoods with a higher percentage of African American population. The increase in within city migration into black neighborhoods could mean that neighborhoods with more African American population may be cheaper than neighborhoods with a higher percentage of white population. The PPML results is similar the findings in our OLS regression on page 53. Also, the OLS and PPML estimator similarly find that within city movers are less likely to locate to neighborhoods with more distance to the metro system than their origin neighborhood. The Census Bureau (2014) find that about 38 percent of workers in the District use public transportation, making it the most common mode of transportation. Increased distance to the metro system may limit access to the District's public transportation system which may disrupt the daily routine of households moving within the city, especially those reliant on the transit system.

The OLS and PPML estimators find that within city migrants, including EITC recipients, in the District move to lower income neighborhoods compared to their origin neighborhood. Logically, it can be assumed that housing costs should be lower in neighborhood with less Area Median Income (AMI), so that, renters looking to decrease their housing burden as a percent of income would search for optimal housing in lower income neighborhoods. Therefore, destination neighborhoods with higher income compared to the origin neighborhood would be a push factor for migration flow. Unsurprisingly, high end apartments would locate in neighborhoods with higher gross income as the District become increasingly more expensive. In terms of housing affordability, the we see some discrepancies between both estimators for all movers within D.C. and for EITC households. For all within city movers, the OLS regression find that people are often moving into houses with higher rents compared to their origin neighborhood making housing affordability a non-issue. The PPML model, on the other hand, find that within city migrants move into neighborhoods with lower housing prices than their origin neighborhood showing an affordability issue. That is, based on the OLS regression, we can interpret the results as thus: within city migrants generally move to neighborhoods with lower amenities and higher housing prices compared to their origin neighborhood; while with the PPML model, we find that destination neighborhoods with lower income are housing costs are a pull factor for migration flow.

For within city movers receiving EITC benefits, both models find that migrants move to neighborhoods with lower rent compared to the origin neighborhood. Housing affordability is consistently an issue with EITC recipients moving within the District. Destination neighborhoods with lower housing costs is therefore more attractive for EITC recipients. Additionally, tables 12 and 13 show that the coefficient for the PPML estimator is generally larger than that of OLS. So PPML estimator captures a larger effect that OLS regression model. Next, we present the estimated results with fixed effects.

Table 12: PPML results for all households- No fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(7) 2013	(8) 2014
Age	-1.139***	-0.781***	-0.910***	-0.881***	-0.852***	-0.0264	0.156	0.222
	(0.256)	(0.160)	(0.177)	(0.170)	(0.194)	(0.154)	(0.183)	(0.137)
Income	**-1.185*** **	**-0.623*** **	**-1.141*** **	**-0.964*** **	**-1.217*** **	**-0.353*** **	**-0.419*** **	**-0.485*** **
	(0.121)	**(0.0909)**	**(0.125)**	**(0.109)**	**(0.112)**	**(0.0951)**	**(0.108)**	**(0.0768)**
Assessment value	**-0.234*** **	**-0.0957***	**-0.162** **	**0.135** **	**0.355*** **	**-0.143*** **	**0.0420**	**-0.186*** **
	(0.0710)	**(0.0502)**	**(0.0641)**	**(0.0668)**	**(0.0603)**	**(0.0480)**	**(0.0535)**	**(0.0385)**
Violent crime	-0.288***	-0.0223	-0.209***	-0.121***	-0.0710*	0.0303	-0.00434	-0.0342
	(0.0603)	(0.0341)	(0.0396)	(0.0351)	(0.0400)	(0.0277)	(0.0358)	(0.0234)
Property crime	0.419***	0.0947**	0.183***	0.0741*	0.0744	0.0147	0.185***	0.114***
	(0.0680)	(0.0417)	(0.0478)	(0.0425)	(0.0484)	(0.0365)	(0.0431)	(0.0302)
Homeowners	0.0152	-0.0371	0.438***	0.658***	0.243***	0.291***	-0.106**	-0.142***
	(0.0693)	(0.0343)	(0.0451)	(0.0470)	(0.0577)	(0.0417)	(0.0520)	(0.0317)
Renters	-0.177**	-0.203***	-0.0213	0.112**	0.0148	0.0877*	-0.440***	-0.301***
	(0.0720)	(0.0360)	(0.0447)	(0.0445)	(0.0465)	(0.0453)	(0.0657)	(0.0471)
Metro distance	-0.144***	-0.0721**	-0.0463	-0.0953***	-0.152***	-0.0364	-0.0575	-0.0748***
	(0.0555)	(0.0328)	(0.0414)	(0.0344)	(0.0388)	(0.0303)	(0.0367)	(0.0252)
White	-0.285***	-0.317***	-0.293***	-0.377***	-0.215***	-0.274***	-0.435***	-0.327***
	(0.0380)	(0.0193)	(0.0267)	(0.0241)	(0.0203)	(0.0196)	(0.0229)	(0.0191)
Black	-0.186***	0.0566*	-0.165***	-0.0741**	-0.131***	0.122***	-0.0814	0.116***
	(0.0498)	(0.0297)	(0.0410)	(0.0330)	(0.0503)	(0.0413)	(0.0535)	(0.0378)
Hispanic	-0.0179	0.0129	-0.0577**	-0.0157	-0.0429**	0.0555***	0.00502	-0.00825
	(0.0331)	(0.0177)	(0.0262)	(0.0193)	(0.0192)	(0.0184)	(0.0205)	(0.0148)
Population	-0.0528	-0.0350	-0.0389	-0.179***	0.152***	0.144***	0.0339	0.156***
	(0.0602)	(0.0386)	(0.0475)	(0.0409)	(0.0447)	(0.0397)	(0.0468)	(0.0349)
Single	-1.332***	-0.640***	-0.439**	-0.784***	-0.0727	-0.899***	1.411***	-0.245
	(0.272)	(0.153)	(0.221)	(0.193)	(0.193)	(0.165)	(0.196)	(0.158)
Married	0.312***	0.586***	0.312***	0.350***	0.342***	0.00158	0.486***	0.486***
	(0.106)	(0.0662)	(0.0963)	(0.0804)	(0.0987)	(0.0748)	(0.0952)	(0.0652)
Hhld	-0.567***	-0.434***	-0.431***	-0.374***	-0.583***	-0.491***	0.0357	-0.327***
	(0.0841)	(0.0484)	(0.0676)	(0.0560)	(0.0794)	(0.0561)	(0.0632)	(0.0503)
Distance	-1.546***	-1.852***	-1.744***	-1.833***	-1.970***	-1.995***	-2.195***	-1.910***
	(0.0471)	(0.0285)	(0.0357)	(0.0314)	(0.0332)	(0.0274)	(0.0324)	(0.0230)
Constant	3.593***	3.786***	3.254***	3.403***	3.092***	3.285***	1.576***	3.551***
	(0.306)	(0.164)	(0.229)	(0.197)	(0.217)	(0.172)	(0.199)	(0.166)
Observations	25,098	25,632	25,632	27,234	27,768	28,124	28,302	28,124
R-squared	0.109	0.299	0.202	0.261	0.274	0.328	0.312	0.395
Neighborhood FE	No	No	No	No	No	No	No	No

Table 13: PPML results for EITC recipients- No fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(8) 2013	(9) 2014
Age	-0.0536**	-0.0504	-0.110***	-0.109***	-0.0567**	0.0449	0.0270	0.150**
	(0.0257)	(0.0434)	(0.0308)	(0.0321)	(0.0266)	(0.0468)	(0.0236)	(0.0676)
Income	**-0.0325*** **	**-0.140*** **	**-0.142*** **	**-0.149*** **	**-0.116*** **	**-0.142*** **	**-0.0321** **	**-0.196*** **
	(0.00893)	**(0.0218)**	**(0.0174)**	**(0.0177)**	**(0.0140)**	**(0.0258)**	**(0.0133)**	**(0.0361)**
Assessment value	**-0.0219*** **	**0.00930**	**0.00460**	**0.0254*** **	**0.00403**	**-0.0628*** **	**-0.00999**	**-0.111*** **
	(0.00653)	**(0.0115)**	**(0.00930)**	**(0.00925)**	**(0.00784)**	**(0.0136)**	**(0.00657)**	**(0.0181)**
Violent crime	-0.0115***	-0.00918	-0.0217***	-0.0162***	-0.00696*	-0.00993	0.00222	-0.0149
	(0.00415)	(0.00727)	(0.00488)	(0.00500)	(0.00401)	(0.00707)	(0.00417)	(0.0106)
Property crime	0.00476	-0.0183*	0.0168**	-0.00260	0.00727	0.00278	-0.00663	-0.0293**
	(0.00590)	(0.00964)	(0.00695)	(0.00679)	(0.00597)	(0.0103)	(0.00552)	(0.0140)
Homeowners	0.00388	0.0417***	0.0819***	0.0847***	0.0425***	0.0751***	0.0243***	0.0725***
	(0.00544)	(0.00906)	(0.00751)	(0.00890)	(0.00747)	(0.0115)	(0.00576)	(0.0156)
Renters	0.00450	0.00986	0.00508	0.00656	-0.00730	0.0268**	0.00616	0.0338
	(0.00550)	(0.00904)	(0.00706)	(0.00806)	(0.00667)	(0.0129)	(0.00750)	(0.0212)
Metro distance	-0.0123***	-0.0350***	-0.00150	-0.0160***	-0.00198	-0.00485	-0.00124	-0.00980
	(0.00440)	(0.00766)	(0.00578)	(0.00589)	(0.00476)	(0.00844)	(0.00444)	(0.0123)
White	-0.00346	-0.0131***	-0.00549*	-0.0117***	0.00544**	0.0118***	0.00160	0.0387***
	(0.00239)	(0.00415)	(0.00321)	(0.00338)	(0.00233)	(0.00445)	(0.00233)	(0.00696)
Black	-0.00991***	-0.0146**	-0.0138***	-0.0228***	-0.0113**	-0.0283***	-0.00686	-0.0331**
	(0.00343)	(0.00588)	(0.00434)	(0.00482)	(0.00440)	(0.00879)	(0.00519)	(0.0154)
Hispanic	-0.00523**	-0.0194***	-0.0180***	-0.00188	-0.000359	0.00831*	0.00603**	0.0269***
	(0.00250)	(0.00451)	(0.00336)	(0.00317)	(0.00257)	(0.00500)	(0.00247)	(0.00652)
Population	-0.00418	-0.0220**	-0.0141*	-0.0239***	0.00904	0.0243**	-0.00230	0.0504***
	(0.00582)	(0.0105)	(0.00804)	(0.00803)	(0.00671)	(0.0119)	(0.00601)	(0.0169)
Single	-0.0940***	-0.188***	-0.135***	-0.192***	-0.128***	-0.410***	-0.120***	-0.773***
	(0.0192)	(0.0340)	(0.0281)	(0.0287)	(0.0218)	(0.0430)	(0.0230)	(0.0693)
Married	-0.00222	-0.00600	-0.0300**	-0.0331**	-0.0211*	-0.0954***	-0.0452***	-0.200***
	(0.00855)	(0.0160)	(0.0137)	(0.0136)	(0.0110)	(0.0188)	(0.0104)	(0.0292)
Hhld	-0.0285***	-0.0753***	-0.0554***	-0.0534***	-0.0400***	-0.0974***	-0.0333***	-0.178**
	(0.00571)	(0.00944)	(0.00742)	(0.00826)	(0.00686)	(0.0122)	(0.00658)	(0.0195)
Distance	-0.0633***	-0.180***	-0.114***	-0.117***	-0.0943***	-0.215***	-0.0886***	-0.363***
	(0.00379)	(0.00651)	(0.00499)	(0.00509)	(0.00412)	(0.00726)	(0.00383)	(0.0107)
Constant	0.347***	0.805***	0.585***	0.658***	0.446***	0.965***	0.332***	1.673***
	(0.0237)	(0.0409)	(0.0325)	(0.0338)	(0.0275)	(0.0495)	(0.0255)	(0.0768)
Observations	25,098	25,632	25,632	27,234	27,768	28,124	28,302	28,124
R-squared	0.027	0.056	0.047	0.046	0.036	0.060	0.033	0.078
Neighborhood FE	No	No	No	No	No	No	No	No

6.2 Estimation with Fixed Effects

Tables 14 and 15 below reveal the results of the PPML estimations with fixed effects for all observations and for migrants receiving EITC benefits. The results of our OLS regressions is in the Appendix on pages III and IV. PPML with fixed effects is the preferred estimator for this analysis. The specification for the model is written as:

$$m_{jk,t+1} = \beta_0 + \beta_1 \ln\left(Income_{kj,t}\right) + \beta_2 \ln\left(Assessment\ value_{kj,t}\right) + \beta_3 \ln\left(Distance_{kj,t}\right) + \beta_4 \ln\left(Population_{kj,t}\right) + \beta_5 \ln\left(Demographic\ characteristics_{kj,t}\right) + \beta_6 \ln\left(Closet\ metro_{kj,t}\right) + \Pi_{jk} + \varepsilon_{kj,t}$$

$m_{jk,t+1}$: is the number of migration flow from the origin census tract$_j$ to the destination census tract$_k$ at time t+1. The number of within city movers in each year from 2006 to 2014

$\ln Fagi_{jk,t}$: the log of the ratio of the median federally adjusted gross income in destination census tract$_k$ to the median federally adjusted gross income in origin census tract$_j$ at time t

$\ln Assessment\ value_{jk,t}$: the log of the ratio of the median assessment value of single-family homes in destination census tract$_k$ to the median assessment value of single-family homes in origin census tract$_j$ at time t

$\ln Distance_{jk,t}$: the log of the (distance in miles) from the origin census tract to the destination census tract

$\ln Population_{jk,t}$: the log of the ratio of the population in destination census tract$_k$ to the population in origin neighborhood j at time t

$\ln Demographic\ characteristics_{jk,t}$: is the log of the ratio of each demographic variables in the destination census tract to the demographic variables in the origin census tract at time t. these variables include age, race, level of education, filing status, and crime rate.

$\ln Closest\ metro_{jk,t}$: the log of the ratio of the distance (in miles) between the census tract and closest metro of the destination census tract to that of the origin census tract at time t.

Π_{jk}: is the origin and destination census tract fixed effects

PPML Results

All within city migrants:

In addition to amenities, the underlying racial composition of neighborhoods should be noted. Generally, within migrants move into less populated neighborhoods, with lower percentage of white, Hispanic, and black population. This shows how much the city has become of a racial "melting pot". While the District black population has been in constant decline since 1980 (Tatian and Lei, 2014), studies have shown that most migrants into the District are white (Sturtevant, 2014, Tatian and Lei, 2014). This is causing a shift in the racial composition of neighborhoods as the city continues to become more racially diverse with additional number of households move into, and within the District in search for communities with affordable standard of living. Also, households, often, move to neighborhoods with more access to public transportation. Since metro system is the most common mode of transportation in the District, an increase in ratio of distance to the closest train station between the destination and origin neighborhood reduces the likelihood of migration by about 40 percent per year. Furthermore, within city movers are 78 percent less likely to move to neighborhoods that increases their commuting cost per year. This is measured by the distance variable between census tracts. Distances between origin and destination census tract captures commuting costs and related costs including cost of moving away from friends, family, and distance to childcare centers, etc.

Table 14 also show that households moving within the District overall locate to neighborhoods with lower income neighborhoods and lower housing costs compared to their origin neighborhood. A 1-point increase in the neighborhood median income ratio between the destination and origin census tracts decreases the likelihood of migration flow by about 99 percent per year.

Table 14: PPML results with fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(7) 2013	(8) 2014
Age	-24.89***	-14.41***	-21.75***	-5.834**	-7.343**	-4.904**	-9.121***	-8.261***
	(5.959)	(2.881)	(4.104)	(2.959)	(2.931)	(2.043)	(2.398)	(1.658)
Income	**-5.190*** **	**-5.194*** **	**-5.789*** **	**-5.052*** **	**-5.919*** **	**-5.883*** **	**-5.371*** **	**-5.767*** **
	(1.096)	**(0.450)**	**(0.681)**	**(0.559)**	**(0.562)**	**(0.443)**	**(0.501)**	**(0.377)**
Assessment value	**-1.265*** **	**-1.285*** **	**-1.540*** **	**-1.508*** **	**-0.764*** **	**-1.373*** **	**-1.295*** **	**-1.201*** **
	(0.382)	**(0.171)**	**(0.261)**	**(0.225)**	**(0.283)**	**(0.219)**	**(0.235)**	**(0.162)**
Violent crime	-0.273*	0.0201	-0.318***	-0.284***	-0.151*	-0.0213	-0.157**	-0.158***
	(0.157)	(0.0696)	(0.106)	(0.0778)	(0.0819)	(0.0639)	(0.0727)	(0.0455)
Property crime	0.310	-0.106	0.436	0.689***	0.322	-0.0895	0.317**	0.0980
	(0.382)	(0.166)	(0.266)	(0.197)	(0.211)	(0.161)	(0.142)	(0.106)
Homeowners	-0.357	-0.413***	0.101	0.572**	0.0311	0.116	-0.310	0.197
	(0.276)	(0.131)	(0.221)	(0.228)	(0.280)	(0.161)	(0.215)	(0.123)
Renters	0.540	0.240	-0.120	-0.0384	0.250	-0.0778	1.205***	0.116
	(0.404)	(0.184)	(0.297)	(0.326)	(0.400)	(0.335)	(0.419)	(0.264)
Metro distance	-0.581**	-0.649***	-0.529***	-0.927***	-0.830***	-0.922***	-0.757***	-0.609***
	(0.267)	(0.123)	(0.187)	(0.146)	(0.163)	(0.127)	(0.135)	(0.0997)
White	-0.199***	-0.322***	-0.289***	-0.366***	-0.281***	-0.227***	-0.383***	-0.194***
	(0.0648)	(0.0351)	(0.0476)	(0.0418)	(0.0428)	(0.0347)	(0.0460)	(0.0270)
Black	-0.355***	-0.140**	-0.527***	-0.395***	-0.492***	-0.473***	-0.0435	-0.157**
	(0.131)	(0.0582)	(0.0857)	(0.0806)	(0.0963)	(0.0769)	(0.102)	(0.0726)
Hispanic	-0.187***	-0.0950**	-0.0507	-0.109***	-0.0601	-0.0736*	-0.0276	-0.0994***
	(0.0665)	(0.0381)	(0.0472)	(0.0403)	(0.0495)	(0.0399)	(0.0601)	(0.0350)
Population	-0.107	-0.321	-1.148***	-0.604*	0.0202	-0.292	-0.283	-0.464**
	(0.524)	(0.261)	(0.378)	(0.314)	(0.319)	(0.235)	(0.262)	(0.182)
Single	-3.680	-7.186***	-7.166***	-2.071	-6.260***	-5.270***	-2.415	-6.232***
	(2.868)	(1.469)	(2.174)	(1.774)	(1.991)	(1.726)	(2.159)	(1.487)
Married	1.311**	1.767***	2.089***	0.528	1.395***	0.365	0.819**	0.216
	(0.637)	(0.296)	(0.441)	(0.355)	(0.392)	(0.291)	(0.356)	(0.236)
Hhld	-1.271***	-0.872***	-0.492***	-0.744***	-0.548***	-0.605***	-0.710***	-0.691***
	(0.278)	(0.113)	(0.164)	(0.158)	(0.162)	(0.116)	(0.131)	(0.0984)
Distance	-1.386***	-1.511***	-1.439***	-1.519***	-1.586***	-1.511***	-1.667***	-1.490***
	(0.0482)	(0.0268)	(0.0367)	(0.0307)	(0.0335)	(0.0259)	(0.0320)	(0.0207)
Constant	26.46***	16.09***	17.75***	14.15***	5.766***	19.92***	4.686**	15.60***
	(5.085)	(2.441)	(2.971)	(2.695)	(2.081)	(2.187)	(2.026)	(1.447)
Observations	24,534	25,488	25,344	26,775	27,612	27,650	28,302	27,966
R-squared	0.265	0.577	0.404	0.498	0.508	0.620	0.633	0.702

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

An increase in housing prices in the destination neighborhood relative to the origin neighborhood decreases the likelihood of migration by an average of about percent 71 percent per year. The decrease in migration flow to higher income neighborhood and housing prices is a consistent pattern for all within city movers and is important finding in this study. Most within city movers are low-to-moderate income households. This finding speaks to the housing affordability issue for low-to-moderate income families probably due to the limited supply of affordable housing for low-to-moderate income households in D.C. Per the Joint Center for Housing Studies (2013), the 2007 housing crisis increased the demand for rental housing in the United States. D.C. usually has a higher rate of renters than homeowners and the housing crises most like widen that gap. As housing cost rises, more low-to-moderate income households looking to stay in the District will move to neighborhoods with less amenities or lower quality neighborhoods in search for cheaper housing. However, as more households look for affordable housing in lower income neighborhood, increase in the demand for affordable housing also leads to a price increase. The increase in price would result in the out-migration of lower income households, concurring with Sturtevant (2013) findings that lower income households are more likely to move out of the District. Cheaper housing is a big pull factor for all households moving within the District. The destination amenities however are a push factor for within city migrants.

The difference between the PPML estimator with and without fixed effects is that when time-invariant characteristics within the census tract are controlled for, within city migrants are more consistent in moving to neighborhoods with lower housing costs than without the fixed effects. Next, we investigate the migration flow of EITC households to see whether there is a difference in their migration behavior since they represent a special class of lower income households that receive some form of government benefit through the income tax system.

Table 15: PPML EITC results with fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(7) 2013	(8) 2014
Age	-19.13	-16.37**	-19.10**	12.31	14.15*	2.820	5.272	-0.161
	(13.32)	(7.966)	(9.014)	(7.883)	(7.510)	(4.750)	(7.252)	(3.750)
Income	**1.589**	**-0.248**	**0.333**	**-1.032**	**0.688**	**2.373****	**-1.116**	**0.425**
	(2.932)	**(1.452)**	**(1.957)**	**(1.622)**	**(1.482)**	**(1.085)**	**(1.430)**	**(0.851)**
Assessment value	**-0.0570**	**-1.224*****	**-3.329*****	**-1.139*****	**-2.346*****	**-1.644*****	**-1.929****	**-0.769***
	(0.740)	**(0.397)**	**(0.630)**	**(0.439)**	**(0.828)**	**(0.560)**	**(0.858)**	**(0.402)**
Violent crime	-1.625***	-0.445*	-1.179***	-0.724**	-0.398	-0.702***	-0.573**	-0.765***
	(0.587)	(0.254)	(0.346)	(0.302)	(0.252)	(0.202)	(0.257)	(0.133)
Property crime	0.373	0.321	0.583	1.875***	1.712***	0.633	-0.344	0.187
	(1.035)	(0.475)	(0.582)	(0.581)	(0.610)	(0.415)	(0.476)	(0.287)
Homeowners	-1.036***	-0.0584	0.544*	0.508	0.834*	0.138	-0.122	0.558***
	(0.394)	(0.200)	(0.309)	(0.322)	(0.474)	(0.201)	(0.343)	(0.164)
Renters	0.417	-0.136	-1.227**	-1.054	-1.837**	-1.441**	-0.717	-1.032**
	(0.682)	(0.326)	(0.508)	(0.688)	(0.893)	(0.593)	(0.943)	(0.475)
Metro distance	0.494	0.372	0.390	-0.665**	-0.387	-0.0294	-0.879**	-0.251
	(0.452)	(0.267)	(0.360)	(0.316)	(0.345)	(0.257)	(0.409)	(0.203)
White	0.00538	-0.0315	0.125	-0.00278	0.0323	0.0276	-0.0765	0.0498
	(0.0989)	(0.0620)	(0.0796)	(0.0689)	(0.0691)	(0.0493)	(0.0853)	(0.0399)
Black	-1.255***	-0.324	-0.776**	-1.183***	-0.619	-1.163***	-0.298	-0.441*
	(0.375)	(0.239)	(0.352)	(0.394)	(0.384)	(0.298)	(0.424)	(0.250)
Hispanic	-0.264***	-0.266***	-0.132*	-0.201***	-0.143*	-0.263***	-0.0591	-0.199***
	(0.0888)	(0.0603)	(0.0698)	(0.0571)	(0.0731)	(0.0526)	(0.0958)	(0.0469)
Population	-2.074**	-1.290**	-2.294***	-2.502***	-1.381*	-1.548***	-1.105	-1.167***
	(0.991)	(0.571)	(0.720)	(0.665)	(0.725)	(0.491)	(0.775)	(0.406)
Single	-0.667	-0.656	-2.126	1.128	-2.719	2.448	-3.352	3.227
	(5.426)	(3.360)	(5.003)	(4.001)	(4.629)	(3.274)	(5.507)	(2.913)
Married	0.562	0.692	1.537	-0.764	-0.541	-1.064*	-0.399	-0.758*
	(1.133)	(0.688)	(0.935)	(0.805)	(0.862)	(0.565)	(0.904)	(0.425)
Hhld	-1.174	-1.741***	-1.561**	-1.301**	-1.064*	-1.621***	-1.275**	-1.972***
	(0.987)	(0.463)	(0.677)	(0.608)	(0.594)	(0.385)	(0.532)	(0.335)
Distance	-1.259***	-1.330***	-1.253***	-1.231***	-1.261***	-1.141***	-1.279***	-1.176***
	(0.0694)	(0.0463)	(0.0563)	(0.0526)	(0.0631)	(0.0441)	(0.0755)	(0.0342)
Constant	17.78*	14.96**	24.05***	-7.623	-7.396	-0.363	5.190	-2.105
	(10.38)	(7.295)	(6.767)	(6.713)	(6.003)	(4.133)	(5.338)	(3.974)
Observations	17,097	23,525	20,187	24,131	24,552	26,524	26,707	27,492
R-squared	0.209	0.354	0.275	0.286	0.234	0.379	0.168	0.476

EITC within city migrants:

In general, households on EITC consistently move to neighborhoods with lower population and a lower percentage of African American, and Hispanic households. This can be due to the increased diversity the city is experiences as D. C's population growth continues. Interestingly, table 15 shows that often, distance to the metro train station is not a significant factor in the location decisions of EITC recipients. Research has shown that lower income households would want to locate closer to the city center to have better access to public transportation (Glaeser et al., 2008). However, EITC may be dissuaded to live in close proximity to the train station because neighborhoods closer to the metro transportation system are usually more expensive because the higher prices of the residential market are felt more on the blocks with the best public transportation access (Freed, 2014). That is, rental prices of apartments sitting on top a metro station in the District range from 33 percent to 100 percent[6] more than apartment units away from the metro lines in the District. EITC households are also 70 less likely to move into neighborhoods that increases their commuting cost when compared to their origin neighborhood. Many EITC households are single families with dependents and an increase in commuting cost like to daycare centers, babysitters can carry a high enough burden to discourage migration flow making distance a push factor for within city migrants.

Within city migrants receiving EITC generally move to neighborhoods with lower house prices compared to their origin neighborhood. This move is consistent across years and a 1-point increase in the assessment value ratio between the destination and origin census tract decreases within city migration by an estimated average of 78 percent per year. This finding point to the prevalence of housing affordability in the District. The results however show that EITC within city migrants are not generally moving into lower

[6] Calculations based on prices in Freed's article.

income neighborhoods or neighborhoods with less amenities. Instead, EITC households generally do not consider amenities to be a significant factor in their location decision. Destination amenities therefore is neither a push nor pull factor for EITC households moving within D.C. EITC households usually consists of lower income households that are most likely receiving other welfare benefits like housing vouchers. The housing subsidy programs may play a role in choosing the type of neighborhoods EITC households decide to locate to. EITC and other government programs can be a pull factor for low income households receiving the benefits. EITC program equals to 40 percent of the federal EITC and is the most generous EITC programs in the United States (Hardy, Muhammed, and Samudra, 2015). EITC and other D.C. government programs may also act as a restraint to the number of lower income households moving out as families get priced out of their homes due to increasing housing cost.

Controlling for time-invariant characteristics greatly changes the results for within city movers receiving EITC benefits. Households on EITC consistently moved to neighborhoods with lower amenities than their origin neighborhood, and generally moved to neighborhoods with lower housing cost without controlling for the fixed effects as shown in table 13 on page 37 above. Meaning that without fixed effects, higher housing cost and better amenities in destination neighborhoods are push factors for EITC households moving within the District. however, with the preferred estimator, we find that only housing costs of the destination neighborhood act as a push factor for EITC households.

7. Conclusion

The District has experienced an increase in population since the millennium. The city has welcomed an average of 12,310 new residents per year. About 86 percent of new comers into the District are single; 10 percent are married families; and about 4 percent are single households with dependents. Among new residents receiving earned income tax credits (EITC) about 55 percent are single, 36 percent are head of households; and 4.6 percent are married families. The District is also losing an average of 4404 residents per year. Most households leaving the District are also single individuals and generally have a lower income than new residents moving into the city.

About 126,087 households moved within the District between 2006 and 2014. 23.3 percent of within city movers are on EITC. Households moving within the city usually have a lower income than non-movers and spend a higher share of their median monthly income on rent. On average, within city movers spend about 39 percent of their monthly income on rent while non-movers spend on about 29 percent of their income on rent. This means that housing affordability maybe part of the reason within city migrants choose to move with D.C. looking for cheaper housing cost. This paper explored migration patterns within DC by using administrative data from DC government. BY combining income tax data with property assessment data in DC we are able to observe migration patterns within and in-and-out of DC. Previous studies of gentrification and neighborhood change data used census tract or neighborhood level data. We observe address level data that covers all residents that filed income tax with the District. Individual and property tax roll from 2005 to 2014 is used for the analysis. The data is further sub divided demographically and by year to investigate yearly patterns of within city migration flow. Within city migration is investigated using the gravity model. The gravity model has its origin in the field of economics in the study of trade flows between counties. It has been extended to include the study of migration flow. Migration patterns to and from the District vary by income and household characteristics. The share of married residents, and head of households moving out of the city has increased since 2011 corresponding to the start of the economic recovery from the great recession. This trend is the same for households receiving EITC benefits. One of the reasons for such trend may also be that the district is becoming increasingly unaffordable. Having a lower income may deter head of households from moving into the city while also encouraging married families and head of households to leave the city. Throughout the period we observed that median incomes of in movers are higher than median income of out movers in case of non-EITC beneficiaries and EITC beneficiaries.

Within city migrants, mostly low-to-moderate income households, generally move to neighborhoods with relatively lower housing prices, and amenities. The results show that neighborhood amenities that attract households moving within the district stay the same before and after an economic shock. Among all households, neighborhoods with closer distance to the metro system is a strong pull for movers, while an increase in commuting cost reduces the likelihood of migration. Neighborhoods with more affordable housing attract movers within the District. As rental price increase, households wanting to remain in Washington, DC move to lower price neighborhoods. However lower income families can eventually be priced out of the District due to rising housing cost which is a precursor for neighborhood change and gentrification.

Within city movers who receive EITC benefits generally move to neighborhoods with lower housing costs. However, neighborhood amenities are not an important factor in their location decision within D.C. This is because EITC recipients may want to stay in DC to not lose more generous EITC benefits provided by DC government. They are also more likely to receive other government subsidies that enable EITC recipients the affordability of living in more expensive neighborhoods. Additionally, EITC program may have also decreased the number of households moving out of the District due to gentrification.

This research shows the importance of housing affordability on within city migration. It further begs the question as to what proportion of households that relocated within the District eventually move out due to housing affordability. This question relates to the gradual change in neighborhood composition as households move from one community to another. Future studies will focus on the income flows of migration within the District of Columbia, and whether within city migration differ across neighborhoods.

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Appendix

Table I: OLS results for all households- No fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(8) 2013	(9) 2014
Age	-0.0536**	-0.0504	-0.110***	-0.109***	-0.0567**	0.0449	0.0270	0.150**
	(0.0257)	(0.0434)	(0.0308)	(0.0321)	(0.0266)	(0.0468)	(0.0236)	(0.0676)
Income	**-0.0325*** **	**-0.140*** **	**-0.142*** **	**-0.149*** **	**-0.116*** **	**-0.142*** **	**-0.0321** **	**-0.196*** **
	(0.00893)	**(0.0218)**	**(0.0174)**	**(0.0177)**	**(0.0140)**	**(0.0258)**	**(0.0133)**	**(0.0361)**
Assessment value	**-0.0219*** **	**0.00930**	**0.00460**	**0.0254*** **	**0.00403**	**-0.0628*** **	**-0.00999**	**-0.111*** **
	(0.00653)	**(0.0115)**	**(0.00930)**	**(0.00925)**	**(0.00784)**	**(0.0136)**	**(0.00657)**	**(0.0181)**
Violent crime	-0.0115***	-0.00918	-0.0217***	-0.0162***	-0.00696*	-0.00993	0.00222	-0.0149
	(0.00415)	(0.00727)	(0.00488)	(0.00500)	(0.00401)	(0.00707)	(0.00417)	(0.0106)
Property crime	0.00476	-0.0183*	0.0168**	-0.00260	0.00727	0.00278	-0.00663	-0.0293**
	(0.00590)	(0.00964)	(0.00695)	(0.00679)	(0.00597)	(0.0103)	(0.00552)	(0.0140)
Homeowners	0.00388	0.0417***	0.0819***	0.0847***	0.0425***	0.0751***	0.0243***	0.0725***
	(0.00544)	(0.00906)	(0.00751)	(0.00890)	(0.00747)	(0.0115)	(0.00576)	(0.0156)
Renters	0.00450	0.00986	0.00508	0.00656	-0.00730	0.0268**	0.00616	0.0338
	(0.00550)	(0.00904)	(0.00706)	(0.00806)	(0.00667)	(0.0129)	(0.00750)	(0.0212)
Metro distance	-0.0123***	-0.0350***	-0.00150	-0.0160***	-0.00198	-0.00485	-0.00124	-0.00980
	(0.00440)	(0.00766)	(0.00578)	(0.00589)	(0.00476)	(0.00844)	(0.00444)	(0.0123)
White	-0.00346	-0.0131***	-0.00549*	-0.0117***	0.00544**	0.0118***	0.00160	0.0387***
	(0.00239)	(0.00415)	(0.00321)	(0.00338)	(0.00233)	(0.00445)	(0.00233)	(0.00696)
Black	-0.00991***	-0.0146**	-0.0138***	-0.0228***	-0.0113**	-0.0283***	-0.00686	-0.0331**
	(0.00343)	(0.00588)	(0.00434)	(0.00482)	(0.00440)	(0.00879)	(0.00519)	(0.0154)
Hispanic	-0.00523**	-0.0194***	-0.0180***	-0.00188	-0.000359	0.00831*	0.00603**	0.0269***
	(0.00250)	(0.00451)	(0.00336)	(0.00317)	(0.00257)	(0.00500)	(0.00247)	(0.00652)
Population	-0.00418	-0.0220**	-0.0141*	-0.0239***	0.00904	0.0243**	-0.00230	0.0504***
	(0.00582)	(0.0105)	(0.00804)	(0.00803)	(0.00671)	(0.0119)	(0.00601)	(0.0169)
Single	-0.0940***	-0.188***	-0.135***	-0.192***	-0.128***	-0.410***	-0.120***	-0.773***
	(0.0192)	(0.0340)	(0.0281)	(0.0287)	(0.0218)	(0.0430)	(0.0230)	(0.0693)
Married	-0.00222	-0.00600	-0.0300**	-0.0331**	-0.0211*	-0.0954***	-0.0452***	-0.200***
	(0.00855)	(0.0160)	(0.0137)	(0.0136)	(0.0110)	(0.0188)	(0.0104)	(0.0292)
Hhld	-0.0285***	-0.0753***	-0.0554***	-0.0534***	-0.0400***	-0.0974***	-0.0333***	-0.178***
	(0.00571)	(0.00944)	(0.00742)	(0.00826)	(0.00686)	(0.0122)	(0.00658)	(0.0195)
Distance	-0.0633***	-0.180***	-0.114***	-0.117***	-0.0943***	-0.215***	-0.0886***	-0.363***
	(0.00379)	(0.00651)	(0.00499)	(0.00509)	(0.00412)	(0.00726)	(0.00383)	(0.0107)
Constant	0.347***	0.805***	0.585***	0.658***	0.446***	0.965***	0.332***	1.673***
	(0.0237)	(0.0409)	(0.0325)	(0.0338)	(0.0275)	(0.0495)	(0.0255)	(0.0768)
Observations	25,098	25,632	25,632	27,234	27,768	28,124	28,302	28,124
R-squared	0.027	0.056	0.047	0.046	0.036	0.060	0.033	0.078

Table II: OLS results for EITC households- No fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(7) 2013	(8) 2014
Age	-0.118***	-0.464***	-0.228***	-0.171**	-0.299***	-0.0654	-0.0793	0.359*
	(0.0420)	(0.122)	(0.0643)	(0.0845)	(0.0751)	(0.129)	(0.105)	(0.206)
Income	**-0.104*** **	**-0.388*** **	**-0.263*** **	**-0.346*** **	**-0.262*** **	**-0.225*** **	**-0.165*** **	**-0.542*** **
	(0.0146)	**(0.0614)**	**(0.0364)**	**(0.0465)**	**(0.0396)**	**(0.0713)**	**(0.0589)**	**(0.110)**
Assessment value	**-0.0192***	**-0.0109**	**-0.000840**	**0.102*** **	**0.116*** **	**-0.0169**	**0.0806*** **	**-0.0868**
	(0.0107)	**(0.0324)**	**(0.0194)**	**(0.0244)**	**(0.0221)**	**(0.0376)**	**(0.0292)**	**(0.0551)**
Violent crime	-0.0107	0.0337*	-0.0150	0.0137	0.0138	0.100***	0.0890***	0.157***
	(0.00678)	(0.0204)	(0.0102)	(0.0132)	(0.0113)	(0.0195)	(0.0185)	(0.0323)
Property crime	0.0288***	-0.0160	0.00828	-0.0234	-0.00479	-0.0696**	-0.0214	-0.0958**
	(0.00962)	(0.0271)	(0.0145)	(0.0179)	(0.0169)	(0.0284)	(0.0245)	(0.0427)
Homeowners	-0.00607	-0.0130	0.127***	0.241***	0.0366*	0.175***	0.0324	-0.169***
	(0.00888)	(0.0255)	(0.0157)	(0.0234)	(0.0211)	(0.0319)	(0.0256)	(0.0477)
Renters	-0.0180**	-0.0769***	0.00332	0.0289	0.00735	0.0541	-0.0877***	-0.218***
	(0.00898)	(0.0254)	(0.0147)	(0.0212)	(0.0189)	(0.0357)	(0.0333)	(0.0646)
Metro distance	-0.0164**	-0.0581***	-0.0105	-0.0297*	-0.0318**	0.00827	-0.00821	-0.0362
	(0.00718)	(0.0215)	(0.0121)	(0.0155)	(0.0135)	(0.0233)	(0.0197)	(0.0374)
White	-0.0156***	-0.0869***	-0.0391***	-0.0635***	-0.0311***	-0.0333***	-0.0513***	-0.0613***
	(0.00390)	(0.0117)	(0.00669)	(0.00891)	(0.00657)	(0.0123)	(0.0104)	(0.0212)
Black	-0.0132**	0.0328**	-0.0175*	-0.0284**	-0.0146	0.0916***	0.00408	0.164***
	(0.00559)	(0.0165)	(0.00907)	(0.0127)	(0.0124)	(0.0243)	(0.0230)	(0.0469)
Hispanic	-0.00272	-0.00847	-0.0184***	0.00257	-0.0151**	0.0703***	0.0397***	0.0574***
	(0.00408)	(0.0127)	(0.00701)	(0.00834)	(0.00725)	(0.0138)	(0.0110)	(0.0199)
Population	-0.0166*	-0.0714**	-0.0395**	-0.0954***	0.0394**	0.0618*	0.000541	0.162***
	(0.00949)	(0.0295)	(0.0168)	(0.0211)	(0.0190)	(0.0328)	(0.0267)	(0.0515)
Single	-0.146***	-0.323***	-0.185***	-0.387***	-0.141**	-0.916***	-0.124	-1.092***
	(0.0313)	(0.0955)	(0.0588)	(0.0756)	(0.0616)	(0.119)	(0.102)	(0.211)
Married	0.0476***	0.389***	0.0578**	0.0843**	0.0947***	-0.0500	0.105**	0.429***
	(0.0139)	(0.0449)	(0.0285)	(0.0358)	(0.0311)	(0.0520)	(0.0463)	(0.0890)
Hhld	-0.0521***	-0.191***	-0.103***	-0.103***	-0.110***	-0.289***	-0.0387	-0.387***
	(0.00932)	(0.0265)	(0.0155)	(0.0217)	(0.0194)	(0.0337)	(0.0292)	(0.0595)
Distance	-0.228***	-1.295***	-0.566***	-0.875***	-0.761***	-1.584***	-1.257***	-2.931***
	(0.00619)	(0.0183)	(0.0104)	(0.0134)	(0.0116)	(0.0200)	(0.0170)	(0.0327)
Constant	0.823***	3.523***	1.689***	2.335***	1.954***	3.873***	2.559***	6.745***
	(0.0386)	(0.115)	(0.0679)	(0.0891)	(0.0777)	(0.137)	(0.113)	(0.234)
Observations	25,098	25,632	25,632	27,234	27,768	28,124	28,302	28,124
R-squared	0.078	0.201	0.141	0.178	0.176	0.222	0.198	0.276

Table III: OLS results for All households- with fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(7) 2013	(8) 2014
Age	-1.538**	-18.19***	-7.611***	-9.272***	-10.25***	-12.62***	-14.91***	-25.58***
	(0.655)	(1.832)	(0.987)	(1.248)	(0.956)	(1.367)	(1.122)	(2.295)
Income	**-0.596*** **	**-2.460*** **	**-1.466*** **	**-2.305*** **	**-1.605*** **	**-3.070*** **	**-1.326*** **	**-5.919*** **
	(0.0756)	**(0.248)**	**(0.151)**	**(0.195)**	**(0.170)**	**(0.291)**	**(0.228)**	**(0.444)**
Assessment value	**0.0176**	**-0.106**	**0.0690**	**0.0829**	**0.0528**	**0.0877**	**0.0238**	**-0.341** **
	(0.0304)	**(0.0867)**	**(0.0521)**	**(0.0716)**	**(0.0752)**	**(0.124)**	**(0.0983)**	**(0.163)**
Violent crime	0.0201	0.112**	-0.0530*	-0.145***	-0.0283	0.0753	0.0434	0.112
	(0.0184)	(0.0507)	(0.0277)	(0.0364)	(0.0313)	(0.0506)	(0.0441)	(0.0707)
Property crime	0.0618	-0.167	0.190***	0.378***	0.0764	-0.297**	-0.139	-0.558***
	(0.0413)	(0.106)	(0.0651)	(0.0844)	(0.0779)	(0.128)	(0.0890)	(0.163)
Homeowners	-0.0147	0.00338	0.122**	0.247***	0.127*	0.184*	0.291***	0.587***
	(0.0316)	(0.0861)	(0.0506)	(0.0750)	(0.0688)	(0.100)	(0.0936)	(0.172)
Renters	-0.00423	-0.100	-0.114*	-0.131	-0.0761	-0.512***	-0.229	-0.439
	(0.0358)	(0.0966)	(0.0593)	(0.0850)	(0.0752)	(0.140)	(0.149)	(0.290)
Metro distance	-0.139***	-0.628***	-0.223***	-0.519***	-0.423***	-0.912***	-0.634***	-1.363***
	(0.0324)	(0.0893)	(0.0534)	(0.0683)	(0.0589)	(0.1000)	(0.0812)	(0.158)
White	-0.0344***	-0.00570	-0.0421***	-0.0315*	0.0338***	0.101***	0.175***	0.289***
	(0.00754)	(0.0216)	(0.0128)	(0.0163)	(0.0128)	(0.0224)	(0.0201)	(0.0409)
Black	0.0341**	0.0468	-0.00128	-0.181***	-0.226***	-0.720***	-0.553***	-0.602***
	(0.0148)	(0.0402)	(0.0240)	(0.0354)	(0.0365)	(0.0666)	(0.0609)	(0.120)
Hispanic	-0.0451***	-0.109***	-0.107***	-0.0712***	-0.0781***	-0.116***	0.182***	0.257***
	(0.0101)	(0.0289)	(0.0174)	(0.0207)	(0.0185)	(0.0363)	(0.0308)	(0.0606)
Population	-0.0585	-1.253***	-0.672***	-1.234***	-1.282***	-2.681***	-2.620***	-5.738***
	(0.0452)	(0.135)	(0.0850)	(0.109)	(0.0967)	(0.153)	(0.127)	(0.256)
Single	-1.265***	-7.432***	-4.800***	-6.100***	-6.012***	-13.50***	-11.09***	-26.64***
	(0.246)	(0.730)	(0.466)	(0.559)	(0.501)	(0.918)	(0.785)	(1.756)
Married	0.0623	1.153***	0.450***	0.712***	0.695***	0.958***	1.042***	0.964***
	(0.0519)	(0.154)	(0.0998)	(0.117)	(0.105)	(0.181)	(0.159)	(0.298)
Hhld	-0.105***	-0.700***	-0.127***	0.0257	0.0278	0.222**	-0.214***	0.0156
	(0.0260)	(0.0706)	(0.0433)	(0.0561)	(0.0562)	(0.0873)	(0.0712)	(0.149)
Distance	-0.305***	-1.404***	-0.646***	-0.928***	-0.719***	-1.412***	-1.046***	-2.675***
	(0.00801)	(0.0229)	(0.0136)	(0.0175)	(0.0149)	(0.0251)	(0.0211)	(0.0386)
Constant	3.846***	15.92***	8.418***	11.29***	15.52***	25.62***	21.74***	54.82***
	(0.551)	(1.051)	(0.543)	(0.710)	(0.803)	(1.233)	(1.055)	(2.236)
Observations	25,098	25,632	25,632	27,234	27,768	28,124	28,302	28,124
R-squared	0.174	0.359	0.260	0.306	0.295	0.378	0.366	0.449

Table IV: OLS results for EITC households- with fixed effects

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2011	(6) 2012	(7) 2013	(8) 2014
Age	1.557***	2.640***	0.974**	2.236***	1.761***	4.333***	0.939***	7.021***
	(0.398)	(0.659)	(0.471)	(0.472)	(0.345)	(0.490)	(0.273)	(0.732)
Income	**-0.345*** **	**-0.966*** **	**-0.577*** **	**-0.518*** **	**-0.454*** **	**-0.561*** **	**-0.250*** **	**-1.283*** **
	(0.0459)	**(0.0892)**	**(0.0720)**	**(0.0740)**	**(0.0614)**	**(0.104)**	**(0.0556)**	**(0.142)**
Assessment value	**0.0720*** **	**0.231*** **	**0.0698*** **	**0.112*** **	**0.109*** **	**0.191*** **	**0.0557** **	**0.255*** **
	(0.0185)	**(0.0311)**	**(0.0249)**	**(0.0271)**	**(0.0271)**	**(0.0443)**	**(0.0240)**	**(0.0519)**
Violent crime	0.0165	0.0394**	-0.00589	0.0341**	-0.00513	0.0187	-0.00521	0.0268
	(0.0111)	(0.0182)	(0.0132)	(0.0138)	(0.0113)	(0.0181)	(0.0107)	(0.0226)
Property crime	0.0471*	0.113***	0.106***	0.0874***	0.0668**	0.0756*	0.0168	0.105**
	(0.0250)	(0.0379)	(0.0311)	(0.0320)	(0.0281)	(0.0458)	(0.0217)	(0.0521)
Homeowners	-0.0479**	0.0333	0.0276	-0.0304	-0.0279	-0.215***	-0.0709***	0.0233
	(0.0192)	(0.0309)	(0.0242)	(0.0284)	(0.0248)	(0.0360)	(0.0228)	(0.0549)
Renters	-0.0162	-0.0875**	-0.0894***	-0.136***	-0.0631**	-0.139***	0.0156	-0.212**
	(0.0217)	(0.0347)	(0.0283)	(0.0322)	(0.0271)	(0.0501)	(0.0363)	(0.0925)
Metro distance	-0.00951	-0.0154	0.0121	-0.0700***	-0.0402*	-0.0522	-0.0626***	-0.119**
	(0.0197)	(0.0321)	(0.0255)	(0.0258)	(0.0212)	(0.0358)	(0.0198)	(0.0504)
White	-0.0381***	-0.0622***	-0.0514***	-0.0553***	-0.0146***	-0.0386***	-0.0123**	-0.0826***
	(0.00458)	(0.00777)	(0.00611)	(0.00619)	(0.00462)	(0.00802)	(0.00489)	(0.0130)
Black	0.0441***	0.101***	0.0989***	0.0977***	0.0779***	0.165***	0.0486***	0.322***
	(0.00896)	(0.0144)	(0.0115)	(0.0134)	(0.0132)	(0.0239)	(0.0148)	(0.0384)
Hispanic	-0.0378***	-0.0842***	-0.0750***	-0.0941***	-0.0830***	-0.225***	-0.0466***	-0.146***
	(0.00615)	(0.0104)	(0.00832)	(0.00785)	(0.00666)	(0.0130)	(0.00751)	(0.0193)
Population	0.0252	0.0789	-0.0706*	-0.0214	-0.0108	0.160***	-0.0108	0.168**
	(0.0274)	(0.0484)	(0.0406)	(0.0411)	(0.0348)	(0.0550)	(0.0310)	(0.0818)
Single	-0.658***	-1.536***	-0.864***	-0.718***	-0.735***	-2.693***	-0.579***	-5.197***
	(0.150)	(0.262)	(0.223)	(0.212)	(0.181)	(0.329)	(0.191)	(0.560)
Married	-0.0760**	-0.112**	-0.0399	-0.0976**	-0.0226	-0.476***	-0.0660*	-0.889***
	(0.0315)	(0.0554)	(0.0477)	(0.0444)	(0.0378)	(0.0648)	(0.0387)	(0.0951)
Hhld	-0.0122	-0.0218	-0.0363*	-0.0951***	-0.0557***	-0.183***	-0.0346**	-0.239***
	(0.0158)	(0.0254)	(0.0207)	(0.0212)	(0.0203)	(0.0313)	(0.0173)	(0.0475)
Distance	-0.128***	-0.336***	-0.199***	-0.194***	-0.139***	-0.293***	-0.119***	-0.560***
	(0.00486)	(0.00823)	(0.00648)	(0.00663)	(0.00536)	(0.00900)	(0.00514)	(0.0123)
Constant	0.185	-0.209	1.384***	1.058***	-0.258	1.405***	0.719***	3.870***
	(0.334)	(0.378)	(0.260)	(0.269)	(0.290)	(0.442)	(0.257)	(0.713)
Observations	25,098	25,632	25,632	27,234	27,768	28,124	28,302	28,124
R-squared	0.145	0.228	0.183	0.199	0.145	0.263	0.103	0.336

Table V: Parsimonious regressions without fixed effects (PPML)

VARIABLES	(1) All years	(2) All years	(3) All years	(4) All years	(5) All years
Income	0.00436	0.00225	-0.226***	-0.247***	-0.177***
	(0.0210)	(0.0208)	(0.0173)	(0.0173)	(0.0150)
Assessment value	-0.0452**	-0.0445**	-0.195***	-0.207***	-0.267***
	(0.0178)	(0.0178)	(0.0144)	(0.0145)	(0.0114)
Metro distance	-0.0114				
	(0.0122)				
Distance	-1.970***	-1.971***	-2.036***	-2.035***	
	(0.0124)	(0.0124)	(0.0110)	(0.0110)	
White	-0.294***	-0.293***			
	(0.00707)	(0.00698)			
Black	-0.175***	-0.176***			
	(0.00861)	(0.00855)			
Hispanic	0.0275***	0.0282***			
	(0.00684)	(0.00679)			
Population	-0.167***	-0.168***	-0.127***		
	(0.0120)	(0.0118)	(0.0110)		
Constant	2.334***	2.327***	2.238***	2.168***	-0.428***
	(0.0241)	(0.0235)	(0.0179)	(0.0166)	(0.00851)
Observations	246,886	246,886	275,366	275,366	275,366
R-squared	0.198	0.198	0.195	0.194	0.002
Neighborhood FE	no	no	no	no	no

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

Table VI: Parsimonious regressions without fixed effects (PPML)-EITC

VARIABLES	(1) all years	(2) all years	(3) all years	(4) all years	(5) all years
fagi	-0.815***	-0.806***	-0.228***	-0.243***	-0.182***
	(0.0374)	(0.0370)	(0.0258)	(0.0260)	(0.0229)
assessSingfam	-0.295***	-0.300***	-0.106***	-0.117***	-0.196***
	(0.0263)	(0.0262)	(0.0217)	(0.0217)	(0.0178)
metrodistance	0.0397**				
	(0.0193)				
white	-0.191***	-0.194***			
	(0.0149)	(0.0147)			
black	-0.756***	-0.754***			
	(0.0114)	(0.0114)			
hispanic	-0.0431***	-0.0450***			
	(0.0152)	(0.0152)			
population	-0.114***	-0.109***	-0.0908***		
	(0.0167)	(0.0166)	(0.0148)		
distance1	-1.286***	-1.283***	-1.500***	-1.499***	
	(0.0201)	(0.0200)	(0.0173)	(0.0173)	
Constant	1.104***	1.128***	0.0911***	0.0413*	-1.948***
	(0.0405)	(0.0388)	(0.0270)	(0.0251)	(0.0117)
Observations	246,886	246,886	275,366	275,366	275,366
R-squared	0.043	0.044	0.045	0.045	0.000
Neighborhood FE	no	no	no	no	no

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

Table VII: Parsimonious regressions with fixed effects (PPML)

VARIABLES	(1) all years	(2) all years	(3) all years	(4) all years	(5) all years
fagi	-2.865***	-2.858***	-3.976***	-3.670***	-4.623***
	(0.0877)	(0.0876)	(0.0791)	(0.0777)	(0.0755)
assessSingfam	-0.704***	-0.694***	-1.323***	-1.298***	-3.317***
	(0.0475)	(0.0472)	(0.0495)	(0.0498)	(0.0651)
metrodistance	-0.889***				
	(0.0605)				
white	-0.373***	-0.382***			
	(0.0109)	(0.0109)			
black	-0.701***	-0.699***			
	(0.0193)	(0.0193)			
hispanic	-0.0537***	-0.0510***			
	(0.0111)	(0.0111)			
population	0.0324	0.0519	0.717***		
	(0.0751)	(0.0748)	(0.0749)		
distance1	-1.634***	-1.668***	-1.844***	-1.844***	
	(0.0123)	(0.0124)	(0.0109)	(0.0109)	
Constant	10.83***	8.344***	8.778***	-0.586	-2.241***
	(0.216)	(0.187)	(0.157)	(0.714)	(0.521)
Observations	246,886	246,886	275,366	275,366	275,366
R-squared	0.341	0.340	0.325	0.325	0.144
Neighborhood FE	no	yes	yes	yes	yes

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

Table VIII: Parsimonious regressions with fixed effects (PPML)-EITC

VARIABLES	(1) all years	(2) all years	(3) all years	(4) all years	(5) all years
fagi	-1.377***	-1.376***	-1.430***	-1.597***	-2.472***
	(0.175)	(0.175)	(0.166)	(0.151)	(0.138)
assessSingfam	-0.549***	-0.549***	-0.787***	-0.789***	-2.112***
	(0.0741)	(0.0741)	(0.0701)	(0.0704)	(0.122)
metrodistance	-0.168				
	(0.111)				
white	-0.0669***	-0.0675***			
	(0.0148)	(0.0148)			
black	-1.221***	-1.222***			
	(0.0497)	(0.0497)			
hispanic	-0.0692***	-0.0688***			
	(0.0148)	(0.0148)			
population	-0.727***	-0.724***	-0.328**		
	(0.141)	(0.141)	(0.134)		
distance1	-1.337***	-1.341***	-1.407***	-1.409***	
	(0.0178)	(0.0178)	(0.0147)	(0.0147)	
Constant	3.471***	3.257***	0.763	-0.275	-4.309***
	(0.512)	(0.492)	(0.583)	(0.322)	(0.358)
Observations	242,725	242,725	270,725	270,725	270,725
R-squared	0.233	0.233	0.230	0.230	0.145
Neighborhood FE	yes	yes	yes	yes	yes

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