The Impact of Housing Vouchers on Crime in U.S. Cities and Suburbs

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Abstract

This paper tests the common belief that subsidized housing contributes to higher crime rates. To do this, I use panel data on over 200 U.S. cities and estimate fixed effects models to control for unobserved differences between cities that may affect both voucher use and crime. Additionally, I estimate models that focus on the suburbs, to see if the steady increase in vouchers there has had any effect on crime.

In cities, I find that vouchers have a weak, negative relationship with violent crime rates, although these estimates are not particularly robust. In suburban areas, there is no observed relationship between vouchers and crime, suggesting that controversies in those communities blaming voucher households for elevated crime rates are misguided.
Keywords: Crime, Public housing, Vouchers, Low-income housing

Introduction

Over the past two decades, there has been a shift by federal and local housing policymakers away from large, centralized public housing developments via a number of programs, including the Housing Choice Voucher (voucher), Low-Income Housing Tax Credit (LIHTC), and HOPE VI programs. Two goals of the voucher program in particular are to increase access to less distressed neighborhoods and to break-up clusters of poverty and the co-occurring social problems that accompany concentrated poverty, including crime.

However, attempts to disperse voucher households to neighborhoods and localities with higher opportunity are often met with resistance, explicitly on the grounds that incoming voucher households will bring with them increased crime. In exurban Los Angeles, the cities of Lancaster and Palmdale have been sued by civil rights groups for engaging in harassment and surveillance of Latino and black voucher recipients (Medina 2011). The mayor of Lancaster defends these efforts as vital for crime control due to the growing voucher population in his city. In Memphis, journalist Hanna Rosin presented correlational evidence that diffusing subsidized housing via HOPE VI and vouchers in Memphis not only changed the spatial location of crime, but led to crime increases *citywide* – perhaps due to the police's reduced inability to target crime hotspots, the difficulty of providing social services to a dispersed impoverished population, and disrupted social networks. She suggests that this is a growing concern among police chiefs and criminologists nationwide.

This paper attempts to identify whether crime rates in cities and suburbs are related to subsidized housing policies, focusing primarily on the Housing Choice Voucher Program. Using city and county-level crime data from the FBI's Uniform Crime Reports and voucher, HOPE VI, and public housing data from the U.S. Department of Housing and Urban Development (HUD), I estimate the extent to which the prevalence of voucher households affects crime in U.S. cities. My data set contains covers 215 cities from 1997 to 2008, allowing me to estimate fixed effects models that control for unobservable differences between cities. Additionally, I use lagged specifications to further identify causal linkages between vouchers and crime, and estimate models on a sample of suburban areas to identify whether the growth in voucher populations in the suburbs has affected crime rates in those jurisdictions.

My findings suggest that there is virtually no relationship between voucher household prevalence and crime rates at the city level. Although cities and suburban areas with more vouchers per capita also have higher crime rates, this relationship disappears when controls are added. These findings suggest that controversies surrounding vouchers in city and suburban jurisdictions are being fueled by misinformation. Although communities with a higher prevalence of voucher households appear to be higher in crime, there is no evidence that this is due to voucher households increasing crime.

Recent Trends in Crime and Rental Housing Subsidies

U.S. cities have seen a wealth of change in the past 25 years in crime and rental housing subsidies. In the mid-1990s, as crime rates were leveling off and dropping across the country, U.S. cities also underwent a substantial shift in how they invest in subsidized housing. These shifts were led by HUD and feature a number of programs to encourage the spatial diffusion of households receiving housing subsidies, including HOPE VI, the LIHTC, and vouchers. On the supply side, HOPE VI has been responsible for demolishing and revitalizing tens of thousands of public housing units, and the LIHTC is now the primary funding vehicle through which affordable rental housing is constructed in the United States. On the demand side, the voucher program is the largest rental housing subsidy in the country, supporting over two million households nationwide. Whereas public housing was virtually the only housing subsidy through the early 1970s, by 2004 the LIHTC and voucher programs had a role in nearly 60 percent of the nearly 7 million subsidized units for low-income households (Schwartz 2006). Fig. 1 displays the substantial growth in the voucher and LIHTC programs and the slow but steady decline in the number of public housing units nationwide during the data period (1997 to 2008), alongside the trend in crime, which has continued to decline since 1997.

[Insert fig. 1 about here]

These concurrent trends in crime and housing subsidy policies suggest that we should be skeptical when people blame voucher households for elevated crime rates in their communities. On the contrary, as vouchers have eclipsed public housing units as the primary way to provide housing subsidies, crime has decreased. Researchers and policymakers have examined several reasons for the crime decline, focusing most commonly on economic and demographic factors, in addition to policing and incarceration (Barker 2010). It is likely that many of these factors heavily outweigh the role of vouchers and other housing policies in the crime decline. However, these strong trends contradict the conventional wisdom represented by Rosin (2008), who suggests if not for the deconcentration of subsidized housing through the voucher program, crime would have decreased even more. Furthermore, given the increased presence of voucher households in suburban communities, it is time we examine how such mobility patterns are affecting crime in those areas.

Theory and Empirical Evidence

There are a number of reasons why subsidized housing may affect crime in cities. First, the poor are disproportionately victims and perpetrators of crime, and occupy subsidized housing by definition. Subsidized households are also disproportionately members of minority groups, as are victims and perpetrators of crime. However, those receiving housing subsidies are also more likely to be females and their children, and the elderly are also overrepresented. These are populations that are less likely to be involved in crime, rendering population-based assumptions less conclusive. Crime may also be linked to subsidized housing if the presence of this housing leads to urban decline. Additionally, the physical design and environment of high-rise public housing has been shown to contribute to crime (National Commission on Severely Distressed Housing 1992; Popkin et al 2000, Schneider and Kitchen 2002).

On the other hand, it is important to note that housing subsidies are a form of public investment. Vouchers provide additional purchasing power for households, not just on housing but potentially on all other goods. Ellen and Horn (2012) estimate that the median voucher household with children earns $13,000 annually, pays $1,000 per month in rent, and the post-tax benefit of the voucher is equivalent to $8,000 per year – a 60 percent increase in income. At the household level, these subsidies may make it less necessary to engage in criminal activity for financial benefit. For cities and neighborhoods, housing vouchers are a substantial investment that can have important positive impacts on a number of social outcomes, potentially including reduced crime.

It is important to discuss what drives the growth in the number of voucher households because this is the intervention and change that I am testing in this paper. First, voucher numbers may increase due to HOPE VI and other public housing demolitions, given many jurisdictions replace some of these demolished units with vouchers to displaced households. However, according to HUD's data, a city's voucher population has a strong, positive relationship with the number of public housing households in a city (controlling for population), so it does not appear to be the case that vouchers are merely replacing public housing units. On the other hand, voucher growth does appear to be strongly related to HOPE VI spending – those cities that have been receiving larger funds from HUD to demolish public housing also have higher voucher numbers (again, controlling for population).

Second, since the late 1990s, all vouchers are portable, meaning voucher holders are largely free to move across jurisdictions and use their vouchers in cities and suburbs other than those that issued the voucher. Thus, the voucher population (in either cities or suburbs) can grow because people used their vouchers to move across jurisdictional borders. Examining data on vouchers in suburban and city jurisdictions, I find that the voucher population has grown considerably faster in the suburbs. In the empirical analysis, I test whether suburban voucher population growth affects crime in those areas.

It is also possible that voucher numbers grow through increases in the utilization rate. There are a number of ways in which utilization can increase – perhaps due to better targeting of the subsidies to populations that are more likely to use them, the implementation of Source of Income (SOI) laws that prohibit discrimination by landlords against using vouchers to pay for housing, a better job by local housing authorities of connecting voucher holders to housing, or more accessible rental markets. Voucher use can also increase and be captured in the data if local housing authorities project greater need (due to higher poverty rates or population growth) and are successful in obtaining additional funds from HUD. Empirically, SOI laws are strongly correlated with voucher growth (Freeman 2012), and the strongest growth occurred in larger cities on the coast, suggesting that more liberal and active housing authorities have been more proactive in recent years in bringing in additional voucher funding and/or connecting voucher households to housing opportunities. It is unlikely, however, that housing authorities are able to issue substantial vouchers in a timely fashion as economic conditions decline in a city. Thus, a limitation of this study is that changes in the voucher population may occur at different time lags relative to important dynamics (e.g. poverty, unemployment, rents) that may affect crime.

Empirical Evidence

Much of what we know empirically about the relationship between crime and subsidized housing focuses on traditional public housing. There is mixed evidence on the effect that public housing has on neighborhood crime rates (Farley 1982; McNulty and Holloway 2000; Roncek et al 1981). More conclusive are the handful of case studies of public housing developments that paint a picture of particularly dangerous places to live (Kotlowitz 1991; Popkin et al 2000). Looking at scattered-site public housing, Goetz et al (1996) found in Minneapolis that police calls from areas surrounding scattered-site developments decrease after these developments were built. However, there was evidence that as the developments age, crime increases over time. Galster et al (2003) found no impacts from dispersed public housing or supportive housing on crime rates in Denver.

Looking at vouchers, Suresh and Vito (2009) examine the spatial concentration of homicides before and after efforts in Louisville, KY to deconcentrate public housing, primarily through HOPE VI and vouchers. They find that homicides moved to the parts of the city where public housing and voucher tenants moved, although their analyses are purely cross-sectional and descriptive.

Van Zandt and Mhatre (2009) look at the relationship between clusters of housing voucher households and crime in Dallas, TX. They consider a cluster to be 10 or more voucher households during any month between October 2003 and

July 2006, and examine crime data within a quarter mile radius of the apartment complexes containing these voucher clusters. Unfortunately, the police only collected crime data in those areas if the number of voucher households was 10 or more, due to a consent decree resulting from a desegregation case. This not only led to gaps in coverage and limited the number and type of neighborhoods examined, but the police may have deliberately focused crime control efforts on these areas, reducing the reliability of the data. Given those limitations, the authors find that clusters of voucher households are associated with higher rates of crime. However, they find no relationship between changes in crime and changes in the number of voucher households, suggesting that while voucher households tend to live in high-crime areas, they are not necessarily the cause of higher crime rates. Thus, efforts to estimate the effect of vouchers on crime must account for the fact that voucher households disproportionately live in high crime neighborhoods and cities.

Ellen et al (2012) and Popkin et al (2012) also examine the relationship between vouchers and crime in neighborhoods. Ellen et al use longitudinal crime and voucher data from 10 U.S. cities between 1997 and 2008. The authors find that crime is higher in neighborhoods with housing vouchers, but their models suggest that reverse causality is the reason – voucher households move to higher crime neighborhoods and do not necessarily cause the higher crime rates in those neighborhoods.

Popkin et al are specifically examining public housing transformation and what happens to crime in the neighborhoods where former public housing residents move in Atlanta and Chicago. They find that crime declined substantially in the areas where public housing was demolished. However, in neighborhoods in both cities where a relatively high concentration of residents relocated (often using vouchers), they observed significant increases in crime. In Chicago, the authors conclude, the increased property crime in destination neighborhoods outweighed the decreased crime in origin neighborhoods. The authors suggest that relocation should be targeted to avoid significant clustering of the relocated population.

All of the studies mentioned thus far look at these relationships at the neighborhood level. Freedman and Owens (2011) is the only study that zooms out at larger level of geography – the authors examine the effect that the LIHTC has on crime in counties. Using an instrumental variables strategy that exploits a discontinuity resulting from the designation of qualified census tracts (QCTs) where developers have added tax credit incentives for locating in such tracts, the authors find that LIHTC development in the poorest neighborhoods results in lower violent crime at the county level.

Although there is a growing body of evidence on the relationship between subsidized housing and crime, there is still a limited understanding of how the voucher program may affect crime and almost no knowledge on the aggregate impacts across cities. Although neighborhood-level models may be identified with more precision, there are a number of reasons why a city-level analysis of these effects is essential. First, police budgets are commonly determined at the city level, as are major housing and land use decisions. Second, crime statistics are widely available at the city level, whereas tract-level crime rates are only available in select cities and years. Third neighborhood-level analyses are not able to capture crime spillovers to adjacent neighborhoods. Criminals do not always commit crimes in their residential neighborhoods, meaning city-level analyses are more likely to capture crime effects in the aggregate. Relatedly, there may be nonlinear relationships between subsidized housing and crime at the neighborhood level that make aggregate crime effects unclear. Rosin (2008) suggested a number of reasons why the dispersion of subsidized households may affect crime: the increased challenge of policing multiple crime fronts, the difficulties in linking dispersed low-income populations to social services, and the loss in social networks that had thrived in concentrated housing projects. Galster (2005) suggests another – that decreases in the amount of high poverty tracts (which the voucher program may contribute to through subsidized housing dispersion) is likely concurrent with increases in the proportion of the population living in mid-poverty census tracts. Those increases can have negative aggregate, citywide effects along a number of social indicators, including crime.

Data and Methods

To estimate the extent that housing vouchers affect crime in U.S. cities, I use data from 1997 to 2008 on vouchers, LIHTCs, public housing, and HOPE VI from HUD, Uniform Crime Report data from the FBI, and socioeconomic characteristics from the U.S. Census on the 215 U.S. cities with population greater than 100,000 as of the 2000 Census.[i] These data include annual counts of housing subsidies (LIHTC, public housing, vouchers, and HOPE VI), violent and property crimes from the FBI Uniform Crime Report system, and race, poverty, and income data that are linearly interpolated between census years using data from the 1990 and 2000 U.S. Censuses and the 2005-09 American Community Survey. I also include MSA-level unemployment rates from the U.S. Bureau of Labor Statistics, and state-level incarceration rates from the U.S. Department of Justice, Bureau of Justice Statistics.

Descriptive statistics for the sample are provided in Table 1. The average city in the sample has just over 330,000 people, although the median city is much smaller, closer to 175,000. There are nearly 60 total (property plus violent) crimes per 1000 people over the entire data period – 52 of those are property crimes. However, that masks considerable decreases over time. In 1997, that number was 68.7, and by 2008 the average crime rate had declined to 51.5 crimes per 1,000 persons. The voucher program is the most prevalent of the three major housing subsidy programs – there were an average of 2,732 vouchers issued per city per year, compared to 2,141 LIHTC units and 1,706 public housing units. Housing subsidies also changed substantially over time – the number of vouchers per year more than doubled from 1997 to 2008, the number of LIHTC units nearly tripled, and the number of public housing units has barely changed.

[Insert table 1 about here]

Using these data, I estimate a set of fixed effects regression models to control for unobserved characteristics of cities that do not vary over time that may affect crime rates and voucher prevalence. Additionally, I use lagged and lead specifications – voucher variables lagged one year and one year into the future –to better isolate the causal relationship between vouchers and crime. This strategy controls for the fact that voucher households may move to cities with higher crime rates, due in part to the fact that rents are likely to be lower. This results in a two-way relationship between voucher household prevalence and crime. Similarly, they may be less likely to move to the suburbs if suburban crime rates are lower relative to the central city (and rents are relatively higher). As noted, Ellen et al (2012) find that voucher households are frequently found in neighborhoods where crime rates are rising. If that is the case in cities – voucher holders are less likely to migrate to lower crime suburbs and/or are more likely to move into higher crime central cities (or high-crime suburbs) – the observed relationship between voucher holders and crime would be biased upward by this association. Thus, the lag and lead specifications are designed to isolate the causal direction.

The baseline specification begins with the city-level crime rate on the left-hand side of the equation, and vouchers per capita on the right-hand side, along with per capita rates of LIHTCs, public housing units, HOPE VI revitalization grant dollars awarded, MSA unemployment rates, state-level incarceration rates, and a set of control variables reported by the U.S. Census in 1990, 2000, and the 2005-09 American Community Survey, interpolated linearly (percent in poverty, median family income, percent Hispanic, and percent non-Hispanic Black). All of the crime and housing variables are expressed as per capita rates in order to control for changes in population. The equation can be expressed as:

$$(1)\,\mathrm{CrimeRate}_{irt} = \alpha + \beta_1 \mathrm{Voucher}_{irt} + \beta_2 \mathrm{LIHTC}_{irt} + \ + \beta_3 \mathrm{PH}_{irt} + \beta_4 \mathrm{HOPE}_{irt} + \beta_5 X'_{irt} + \mathrm{City}_i + R_r * T_t + \ e_{irt}$$

where $\mathrm{CrimeRate}_{irt}$ is the crime rate in city i region r, and year t, $\mathrm{Voucher}_{irt}$, LIHTC_{irt}, PH_{irt}, and HOPE_{irt} denote the per capita voucher, LIHTC, public housing, and HOPE VI totals in city i, region r, and year t, respectively. X'_{irt} is the set of covariates described above. Again, in some models the voucher variables are lagged to limit endogeneity. City_i and $T_t * R_r$ are city and year*region fixed effects, respectively. In all models, LIHTC units and HOPE VI dollars are measured as accumulating up through that year – the number of LIHTC units in

2000 (or HOPE VI dollars awarded) includes units that were built (or dollars awarded) from 1997-2000. The region-year interaction term uses the nine regions determined by the U.S. Census as an interaction term with the time trend. This modified time effect allows for the slope of the time trend to be conditional on the region of the country where a given city is located, because the nationwide crime trend is much less relevant than the crime trend of cities in the sample that are in the nearby census region. Given I am looking at variation across cities (over time) I cluster the standard errors at the city level.

Additionally, households (with or without vouchers) may be aware of crime trends in their city (or potential destination cities), and use that information to help determine whether they should move in the near future. It may even be the case that they use these trends to predict future crime rates and use that information in moving decisions. To control for this, I estimate models with a linear city-specific time trend on the right-hand side of the equation, as a robustness check.

A key mechanism through which voucher numbers can change in a city is through mobility across place boundaries within an MSA. As voucher mobility has become a higher priority for HUD and local housing authorities, suburban voucher populations have grown faster than city ones. Covington, Freeman, and Stoll (2011) report that in 2008 nearly half of all housing voucher recipients lived in the suburbs, with steady growth in the proportion of vouchers in the suburbs occurring from 2000 to 2008. Using the data for this paper, I calculate that the suburban per capita voucher populations grew about 75 percent faster than the city per capita voucher population from 2000-2006. Further, the controversies in suburban Los Angeles suggest that the most vocal opposition to voucher mobility exists in these areas.

To assess whether the growth of the suburban voucher population has affected crime in those areas, I estimate a set of models that focuses on the suburban portions of the MSAs that contain cities in the baseline sample. For these models, the estimation is the same, but the sample is restricted to suburban areas instead of cities greater than 100,000. I created this sample by gathering data for the 114 MSAs that contain cities in the original sample, and then subtracted central city housing subsidy, crime, population, and demographic numbers from the MSA totals, leaving the suburban portions of the MSAs. In some cases, large cities from the original sample are more suburban (such as Overland Park, KS and Plano, TX). In those cases, they are counted as suburbs for the suburban analysis. With the exception of the MSA unemployment and state-level incarceration rates, all of the variables in the model (including the population denominator), are identified at the suburb level.

Results

Table 2 displays the OLS results. The first two models present violent crimes per person as the dependent variable, and the next two models use property crimes per person. The first and third results columns present models that control for the time trend using year fixed effects, and the second and fourth models control for the time trend using the more stringent region*year fixed effects. It is clear from these four models that there is not a strong relationship between crime and vouchers, or any of the subsidized housing variables. There is a small, negative association between vouchers and violent crime (10% significance level). The magnitude of this relationship is also quite small – the coefficient of 0.058 suggests that a one standard deviation rise in the voucher rate is associated with 0.0003 fewer crimes per capita, which is quite small relative to the mean of 0.0075 crimes per capita (in other words, a 75 percent increase in the voucher rate would lead to a 4 percent decrease in the violent crime rate). There is no relationship at all, judging from these models, between vouchers per capita and property crime rates. There is a small positive association between public housing and property crime. LIHTC units and HOPE VI spending do not appear to have any relationship with crime. The demographic variables move in the hypothesized directions – the cities with higher percent of non-Hispanic Blacks and households below the poverty line have higher crime rates. Unemployment and incarceration rates do not have strong effects on the crime rate, perhaps due to these variables being measured at the MSA and state levels, respectively.

[Insert table 2 about here]

In Table 2, where vouchers and crimes were measured in the same year, it is possible that greater crime levels could be causing fewer vouchers to be used in the cities in the sample, rather than the other way around. To address reverse causality, I estimate models with lagged and future vouchers on the right-hand side. If lagged vouchers are highly correlated with crimes, then we can assume that vouchers are causing decreased crime and not vice versa, given crime in the future cannot cause voucher numbers observed in the past. If future vouchers are related to crime in the past then we can assume that vouchers are moving to higher crime cities rather than causing the crime.

Table 3 displays the results from four models – in the first, the independent variable is lagged vouchers (t-1), the second includes lagged and future vouchers (t+1) in the same model. All models displayed include region*year fixed effects. We see here that the violent crime models (first two columns) suggest a slightly stronger relationship between lagged vouchers per capita and violent crime rates. The coefficient on lagged vouchers is nearly identical to the coefficient on vouchers in the current year, but the standard error is slightly smaller, making it significant at the 5 percent level in the first model. Once I control for the future voucher rate, the coefficient is again only significant at the 10 percent level. In the property crime models, the voucher-crime relationship remains nonexistent. In all of the models, future vouchers do not relate to crime rates. Non-significant coefficients on the future voucher variables suggest that it is relatively unlikely that voucher households are disproportionately moving to high crime cities. The weakly significant and negative coefficients on lagged vouchers suggest that while it is unlikely that increased voucher presence leads to lower crime rates, there is absolutely no evidence that vouchers *increase* crime. Additionally, I estimated models using lagged versions of the public housing, HOPE VI, and LIHTC variables, and none of those coefficients were significant in any models.

[Insert table 3 about here]

As noted, the lagged specifications may not be perfectly isolating the causal relationship between vouchers and crime. Households may identify trends in crime rates and use this information to predict future crime and use these predictions in their residential location decisions. Although the region*year fixed effects control for these trends to some extent, those controls are at a larger level of geography. As a robustness check, I add a linear city-specific time trend in a set of models displayed in Table 4. At the top of the table, voucher and crime rates are measured in the same year, and in the bottom section, the lag/lead specifications are displayed as in Table 3. In these models, the region-year interaction term and city fixed effects are replaced with city-year interactions on the right-hand side of the equation. The results are relatively consistent with the other baseline results. The biggest change is that the coefficient on the voucher rate in time t is significant at the 10 percent level. However, that coefficient is no longer significant if the voucher rate is lagged. In fact, the coefficient on voucher rates in the following year (voucher rate, t+1) is very similar to the coefficient in time t, and the standard error is larger than the coefficient on the lagged term. This suggests that any positive relationship between vouchers and crime more likely reflects the fact that voucher households move to higher crime cities than voucher households cause higher crime rates in cities.

[Insert table 4 about here]

In the next analysis, I test whether the nature of this relationship differs in suburban areas. In the results discussed thus far, the sample has included about 90 cities that would be considered suburbs (such as Plano, TX, several non-central cities in southern California, Stamford, CT), but many of these suburbs are quite urban. As discussed above, the voucher population has also suburbanized considerably over the years. There is reason to believe that these trends could potentially affect crime in those areas. Less urban, more affluent areas may be ill-equipped to serve and police an influx of lower-income households, and crime rates may spike as a result.

To test this theory, I take the 114 MSAs that contain the cities in the previously analyzed sample of cities, and run these models using variables constructed only from the non-central city portions of these MSAs. Table 5 presents the results of models using the same specification outlined in Equation 1 on the suburban sample. The results here are very consistent with those in the city sample. The weakly significant coefficients found in the violent crime models in the city sample are not significant in the suburban sample, but this is perhaps due to the smaller sample size. The magnitude of the (insignificant) voucher coefficients is very similar across the two samples

Looking at the other housing subsidy variables, HOPE VI spending has a weakly negative relationship with violent crime. LIHTC units per capita have a strong, positive relationship with property crime. I also estimated models with lagged versions of these variables in models not shown here. Lagged HOPE VI spending had a stronger, negative relationship with both types of crime, suggesting a lag between HOPE VI spending and demolition effects. Public housing continued to have no relationship, and the LIHTC's relationship with property crime disappeared (although there was a weakly significant and positive coefficient in the violent crime models.

[Insert table 5 about here]

The conclusion from these models is that there does not appear to be a relationship between vouchers and crime in U.S. cities and suburbs. There are some weakly significant findings that suggest a negative relationship, but these results are not very robust. However, it is important to note that regression models using rates have disadvantages. Some argue that using population as the denominator for both the dependent variable and key independent can amplify bias resulting from inaccurate population measurement, particularly in fixed effects models (Ellen and O'Regan 2010; Griliches and Hausman 1986; Levitt 1998). In the data in this paper, annual population estimates are provided by the FBI for the Uniform Crime Report system, and are not likely to be as accurate as decennial Census counts. Thus, I ran a set of models using counts of the key variables – crimes, vouchers, LIHTC and public housing units, HOPE VI dollars – rather than per capita rates, presented in Table 6. The counts are logarithmically transformed to reduce the impact of outliers. These models also include the natural log of population on the right-hand side to control for population differences between cities and years.

The top of the table shows the city-level results, which are largely consistent with the findings using rates. We see here that even the weak relationships between vouchers and violent crime observed in the previous models no longer hold. Once more, I ran these models using the natural log of vouchers on the suburban sample, shown in the bottom half of the table. Current year, lagged, and future vouchers all have an insignificant and negative relationship with crime in the suburbs, controlling for population, and there is no relationship with property crime. These results provide further evidence that the relationship expressed using rates is consistently weak.

Discussion

There is a growing body of work that examines the relationships between subsidized housing and crime, largely focusing on these relationships at the neighborhood level. This paper attempts to identify whether there are aggregate effects across cities. The results suggest that recent controversies over increased voucher presence in suburban communities are fueled by misinformation – there is no observable relationship between city or suburban crime rates and the proportions in those communities. If there is a relationship at all, these data suggest that there is a weak, negative relationship between vouchers and crime in large cities, and there is no relationship at all between vouchers and crime in suburban areas.

A sensible explanation for this lack of a relationship is simply that voucher households do not alter the crime landscape in metropolitan areas, and if they do, they do not do so to the extent that is detectable at such a large level of geography. However, these findings are consistent with much of the growing body of work at the neighborhood level, summarized above.

Recent events and trends suggest that we pay particular attention to how these relationships play out in suburban communities. The mayor of suburban Lancaster, CA is being sued for harassing voucher households, acts he justifies by asserting that these households are responsible for elevated crime rates in his city. Further, Lancaster is part of a greater trend of robust growth in suburban voucher populations. Allard and Roth (2010) document that suburban social service agencies are less numerous, handle larger service areas, and are less equipped to handle increased demand in the face of the suburbanization of poverty. Given this context, it is likely that the suburbs that house a growing number of voucher households are often relatively distressed and lacking in the kind of social service safety net that is more common in central cities. This could have impacts on a number of social problems, including crime. According to the evidence compiled in this paper, that has not been the case in recent years.

The goal of the voucher program to increase access to higher opportunity neighborhoods is a laudable one. And the evidence here suggests that these efforts are unlikely to increase crime in suburban communities, where many such neighborhoods exist. It may not be sensible, however, to rapidly accelerate and incentivize mobility to suburban jurisdictions, particularly without attending to the weaker social safety net that Allard and Roth (2010) describe. Rather, it is more logical to engage in what Popkin et al (2012) term “responsible relocation.” Popkin and colleagues suggest several aspects of housing policy that could constitute responsible relocation, including relocation counseling and follow-up, supportive services, while expanding incentives to voucher households for locating in better neighborhoods.

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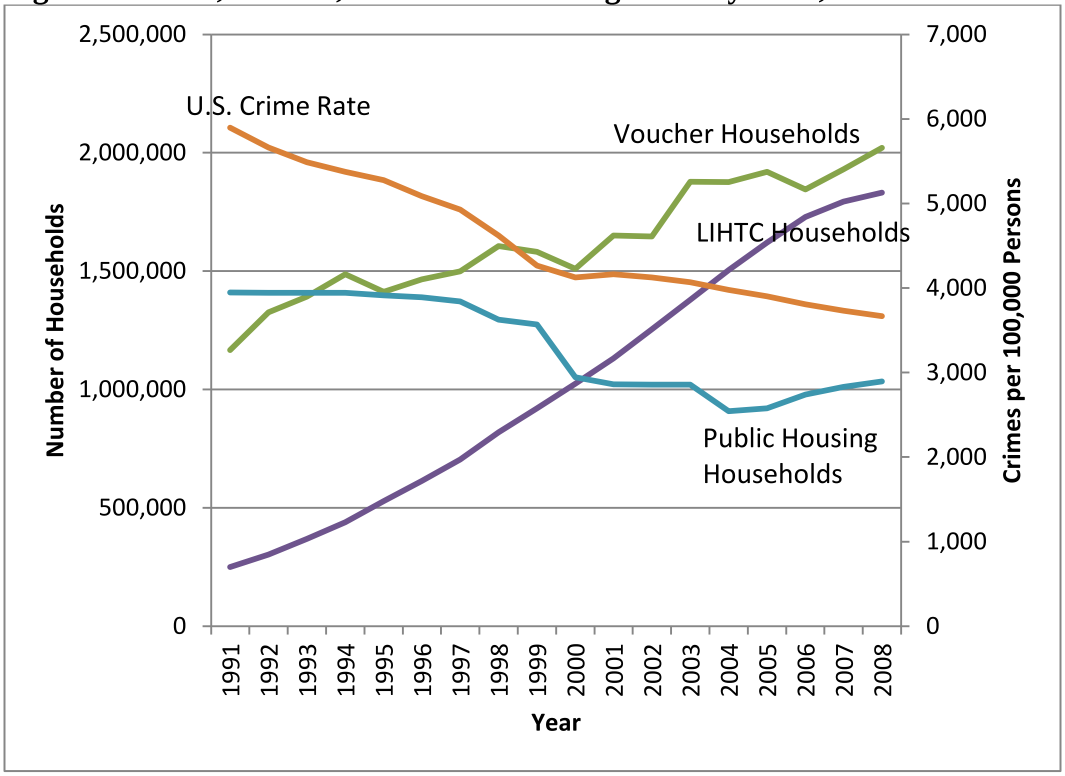
Fig. 1: Voucher, LIHTC, and Public Housing Units by Year, 1990-2008



Sources: Author's calculations of HUD data; Schwartz 2006; FBI Uniform Crime Reports

Table 1: Descriptive Statistics – Unweighted Sample Means (N = 2,399)

Variable	Mean	Std. Dev.	Min	Max
Population	330,396	643,430	70,842	8,220,196
Log(Population)	12.3	0.7	11.2	15.9
Crimes per 1000 persons	59.7	24.1	9.6	154.4
Property Crimes per 1000 persons	52.1	20.8	9.0	130.4
Violent Crimes per 1000 persons	7.6	4.8	0.0	33.5
Voucher Households	2731.8	6328.8	0.0	115310.0
Public Housing Units	1705.7	8132.2	0.0	146449.0
LIHTC Units	2140.6	4493.3	0.0	71232.0
HOPE VI ($)	15,600,000	35,700,000	0	258,000,000
Voucher Rate	0.008	0.006	0.000	0.052
Public Housing Rate	0.004	0.005	0.000	0.026
LIHTC Units per Person	0.006	0.005	0.000	0.032
HOPE VI ($ per Person)	38.4	78.7	0.0	521.1
% Non-Hispanic White	0.530	0.205	0.036	0.950
% Non-Hispanic Black	0.169	0.174	0.001	0.834
% Hispanic	0.209	0.190	0.009	0.942
% Poverty	0.142	0.063	0.016	0.373
Median Family Income ($)	31,866	17,824	642	101,590
MSA Unemployment Rate	0.050	0.015	0.017	0.182
State Incarceration Rate	0.005	0.002	0.001	0.008

Table 2: Baseline Model Results, City Sample

	Dep. Var.: Violent Crimes Per Person		Dep. Var.: Property Crimes Per Person	
Voucher Rate, t	-0.0595*	-0.0581*	0.0435	0.0141
	(0.0314)	(0.0318)	(0.108)	(0.114)
HopeVI $ / Person, t	-0.00106	-0.00303	-0.00489	-0.000153
	(0.00256)	(0.00247)	(0.00999)	(0.00911)
Public Housing Rate, t	0.0498	0.0433	0.129	0.233*
	(0.0479)	(0.0419)	(0.171)	(0.133)
LIHTC Rate, t	0.0255	0.0430	-0.168	-0.168
	(0.0596)	(0.0613)	(0.178)	(0.178)
% Hispanic, t	-0.0110**	-0.00700	0.000961	0.00255
	(0.00539)	(0.00519)	(0.0190)	(0.0190)
% Non-Hispanic Black, t	0.0682***	0.0605***	0.136***	0.116***
	(0.0146)	(0.0159)	(0.0413)	(0.0343)
% Poverty, t	0.0146**	0.0151**	-0.0146	0.00310
	(0.00593)	(0.00671)	(0.0205)	(0.0206)
Median Fam Income ($1000), t	-0.000139	-0.000854	-0.00997*	-0.00729
	(0.00136)	(0.00150)	(0.00598)	(0.00628)
MSA Unemployment Rate, t	0.00850	0.000403	-0.00778	-0.0110
	(0.00621)	(0.00707)	(0.0272)	(0.0300)
State Incarceration Rate, t	0.0735	-0.0324	-0.226	-1.129
	(0.209)	(0.298)	(0.728)	(0.944)
Observations	2,404	2,404	2,426	2,426
Adjusted R-squared	0.130	0.209	0.291	0.359

Note: Standard errors clustered at the city level in parentheses. All models include constant term and city fixed effects. Columns 1 and 3 include year fixed effects and columns 2 and 4 include region*year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Identifying Causality using Lags and Leads, City Sample

	Dep. Var.: Violent Crimes Per Person		Dep. Var.: Property Crimes Per Person	
Voucher Rate, t-1	-0.0608**	-0.0563*	-0.0611	-0.0115
	(0.0302)	(0.0317)	(0.0991)	(0.100)
Voucher Rate, t+1		0.0140		0.0863
		(0.0258)		(0.106)
HopeVI $ / Person, t	0.000964	0.000667	0.00685	0.00354
	(0.00188)	(0.00323)	(0.00809)	(0.0127)
Public Housing Rate, t	0.0498	0.0458	0.305**	0.257*
	(0.0359)	(0.0343)	(0.150)	(0.152)
LIHTC Rate, t	0.0395	0.0536	-0.138	-0.102
	(0.0489)	(0.0545)	(0.192)	(0.195)
% Hispanic, t	-0.00627	-0.00656	0.00961	0.00865
	(0.00471)	(0.00455)	(0.0198)	(0.0202)
% Non-Hispanic Black, t	0.0545***	0.0554***	0.0975***	0.0960**
	(0.0142)	(0.0147)	(0.0344)	(0.0390)
% Poverty, t	0.0127**	0.0131**	0.0111	-0.00191
	(0.00593)	(0.00645)	(0.0211)	(0.0229)
Median Fam Income ($1000), t	-0.000114	-0.000226	-0.00591	-0.00722
	(0.00139)	(0.00144)	(0.00587)	(0.00572)
MSA Unemployment Rate, t	0.00194	0.000575	-0.0103	-0.00790
	(0.00624)	(0.00677)	(0.0297)	(0.0310)
State Incarceration Rate, t	-0.182	-0.144	-1.658*	-1.718*
	(0.267)	(0.289)	(0.902)	(0.946)
Observations	2,177	2,047	2,192	2,054
Adjusted R-squared	0.203	0.197	0.335	0.305

Note: Standard errors clustered at the city level in parentheses. All models include constant term and city and region*year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Robustness Checks – Controlling for Linear Crime Trend, Voucher Coefficients

	Dep. Var.: Violent Crimes Per Person	Dep. Var.: Property Crimes Per Person
Voucher Rate, t	0.0377	0.192*
	(0.0250)	(0.103)
Observations	2,404	2,426
Adjusted R-squared	0.420	0.535
Voucher Rate, t-1	-0.0272	0.0280
	(0.0184)	(0.0864)
Voucher Rate, t+1	0.0614***	0.173
	(0.0221)	(0.107)
Observations	2,047	2,054
Adjusted R-squared	0.491	0.505

Note: Standard errors clustered at the city level in parentheses. All models include constant term and control for log(population), log(HOPE VI spending), log(public housing), log(LIHTC units), percent Hispanic, percent non-Hispanic Black, percent poverty, median family income, MSA unemployment rate, state incarceration rate, and city fixed effects and a city-specific linear time trend (city*year interactions).

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

Table 5: Model Results, Suburb Sample

	Dep. Var.: Violent Crimes Per Person		Dep. Var.: Property Crimes Per Person	
Voucher Rate, t	0.0538		0.259	
	(0.0924)		(0.343)	
Voucher Rate, t-1		0.0137		0.249
		(0.0837)		(0.340)
Voucher Rate, t+1		0.0455		0.368
		(0.0514)		(0.275)
HopeVI $ / Person, t	-0.0183*	-0.0159*	-0.0923	-0.114
	(0.0104)	(0.00926)	(0.0819)	(0.0718)
Public Housing Rate, t	-0.145	0.0178	-0.00423	0.00254
	(0.147)	(0.128)	(0.596)	(0.530)
LIHTC Rate, t	-0.0439	-0.0499	1.224***	1.047***
	(0.0528)	(0.0651)	(0.213)	(0.276)
Suburb % Hispanic, t	0.00830	0.00810	0.0969***	0.122***
	(0.00613)	(0.00617)	(0.0313)	(0.0348)
Suburb % Non-Hispanic Black, t	0.00164	-0.000616	-0.0156	-0.0135
	(0.00389)	(0.00251)	(0.0203)	(0.0173)
Suburb % Poverty, t	-0.00402*	-0.00388	0.0190	0.0355***
	(0.00229)	(0.00240)	(0.0116)	(0.00561)
MSA Unemployment Rate, t	0.0181*	0.0126*	0.00386	0.00380
	(0.0103)	(0.00735)	(0.0347)	(0.0328)
State Incarceration Rate, t	0.764*	0.693**	0.592	1.403
	(0.415)	(0.309)	(1.278)	(1.386)
Observations	1,179	951	1,188	955
Adjusted R-squared	0.119	0.115	0.377	0.406

Note: Standard errors clustered at the MSA level in parentheses. All models include constant term, and city and region*year fixed effects.

Table 6: Logarithmic Count Variables – Voucher Coefficients

	DV: Log(Violent Crimes)		DV: Log(Property Crimes)	
City Sample				
Log(Vouchers), t	0.00501		-0.00311	
	(0.0427)		(0.00605)	
Log(Vouchers), t-1		-0.0152		-0.00393
		(0.0211)		(0.00539)
Log(Vouchers), t+1		-0.00607		-0.00153
		(0.0114)		(0.00703)
Observations	2,404	2,086	2,426	2,107
Number of Cities	215	215	215	215
Adjusted R-squared	0.262	0.194	0.319	0.289
Suburb Sample				
Log(Vouchers), t	-0.199		-0.0463	
	(0.123)		(0.0441)	
Log(Vouchers), t-1		-0.0934		-0.0221
		(0.0570)		(0.0301)
Log(Vouchers), t+1		-0.472**		-0.0383
		(0.209)		(0.0731)
Observations	1,097	897	1,143	936
Number of Cities	109	109	110	110
Adjusted R-squared	0.106	0.156	0.069	0.073

Note: Standard errors clustered at the city level in parentheses. All models include constant term and control for log(population), log(HOPE VI spending), log(public housing), log(LIHTC units), percent Hispanic, percent non-Hispanic Black, percent poverty, median family income, MSA unemployment rate, state incarceration rate, and city and region*year fixed effects.

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

Appendix 1a: Logarithmic Count Variables, City Sample

	DV: Log(Violent Crimes)		DV: Log(Property Crimes)	
Log(Vouchers), t	0.00501		-0.00311	
	(0.0427)		(0.00605)	
Log(Vouchers), t-1		-0.0152		-0.00393
		(0.0211)		(0.00539)
Log(Vouchers), t+1		-0.00607		-0.00153
		(0.0114)		(0.00703)
Log(Population), t	0.598**	0.459**	0.553***	0.553***
	(0.260)	(0.193)	(0.0941)	(0.108)
Log(HopeVI $), t	-0.0134**	-0.00304	-0.000967	-0.00106
	(0.00605)	(0.00637)	(0.00152)	(0.00199)
Log(Public Housing), t	0.0146	0.0263	0.00321	0.00517*
	(0.0220)	(0.0227)	(0.00292)	(0.00268)
Log(LIHTC), t	0.0357	0.0166	-0.00132	-0.00218
	(0.0378)	(0.0315)	(0.00570)	(0.00584)
% Hispanic, t	1.520	0.287	0.628	0.675
	(1.140)	(0.899)	(0.420)	(0.500)
% Non-Hispanic Black, t	8.111***	4.727***	1.370***	1.206*
	(2.010)	(1.435)	(0.523)	(0.614)
% Poverty, t	3.271**	2.164**	0.0233	-0.0782
	(1.411)	(1.075)	(0.384)	(0.448)
Median Fam Income ($1000), t	-0.000949	-0.000174	-0.000261	-0.000332
	(0.00278)	(0.00239)	(0.00123)	(0.00129)
MSA Unemployment Rate, t	-0.331	0.943	0.220	0.0979
	(1.980)	(1.415)	(0.533)	(0.570)
State Incarceration Rate, t	0.000166	-4.75e-05	-0.000175	-0.000244
Observations	2,404	2,086	2,426	2,107
Number of Cities	215	215	215	215
Adjusted R-squared	0.262	0.194	0.319	0.289

Note: Standard errors clustered at the city level in parentheses. All models include constant term and city and region*year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1b: Logarithmic Count Variables, Suburb Sample

	DV: Log(Violent Crimes)		DV: Log(Property Crimes)	
Log(Vouchers), t	-0.199		-0.0463	
	(0.123)		(0.0441)	
Log(Vouchers), t-1		-0.0934		-0.0221
		(0.0570)		(0.0301)
Log(Vouchers), t+1		-0.472**		-0.0383
		(0.209)		(0.0731)
Log(Population), t	-0.281	-0.141	0.0694	0.142
	(0.365)	(0.327)	(0.151)	(0.166)
Log(HopeVI $), t	-0.00346	-0.00239	0.00124	-0.000461
	(0.00749)	(0.0082)	(0.00497)	(0.00537)
Log(Public Housing), t	-0.0232	-0.0192	0.0145	0.0177
	(0.0257)	(0.0356)	(0.0122)	(0.0147)
Log(LIHTC), t	-0.0724	0.0278	0.0293	0.0274
	(0.202)	(0.218)	(0.0655)	(0.0846)
% Hispanic, t	0.397	-0.471	-0.694	-0.145
	(1.764)	(2.298)	(1.237)	(1.287)
% Non-Hisp Black, t	2.451	2.294	1.539	1.888
	(2.092)	(2.035)	(1.364)	(1.298)
% Poverty, t	-1.476	0.873	-0.314	-0.00127
	(1.386)	(2.866)	(0.541)	(0.425)
MSA Unemployment Rate, t	1.934	1.570	-0.386	0.211
	(2.197)	(2.441)	(1.180)	(1.400)
State Incarceration Rate, t	78.97	29.28	32.32	20.33
	(94.33)	(100.5)	(41.84)	(41.93)
Observations	1,097	897	1,143	936
Adjusted R-squared	0.106	0.156	0.069	0.073

Note: Standard errors clustered at the MSA level in parentheses. All models include constant term and city and region*year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Endnotes

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[i] There are actually 238 such cities, 23 of them did not have usable crime data for most of the relevant years. I also removed Honolulu from the sample, because the city and MSA are one in the same, a fact that skewed the results in some models.