

Impact of Housing Choice Voucher on Crime: A Spatial Econometric Analysis

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Abstract

This paper estimates both the direct and spillover effects of housing choice voucher (HCV) on neighborhood crime in St. Louis County using the spatial Durbin model with fixed effects (SDM-FE), which accounts for spatial dependence in both the response and explanatory variables. The analyses reveal that the HCV rate has significant direct and indirect effects on the crime rate. A one-unit increase in the HCV rate in a census tract (defined as one additional voucher per 1,000 housing units) is associated with a 1.7–1.8% increase in the local crime rate. Accounting for spatial spillovers, an additional voucher unit in neighboring tracts contributes a further 0.6–0.7% increase to local crime. The total impact of an additional voucher unit is approximately a 2.5% increase in the crime rate. Evaluated at the sample mean of 24 crimes per 1,000 residents, the result corresponds to approximately 0.6 additional property crimes per 1,000 people, or 2.6 additional annual crime incidents in an average census tract of 4,300 residents. These findings are robust to alternative HCV rate measures and spatial model specifications.

JEL Codes: C21, K42, I38

1.0 Introduction

In its 2024 report on the state of the nation's housing market, the Joint Center for Housing Studies at Harvard University (JCHS) highlighted the need for all stakeholders to address the rising challenge of housing affordability and the soaring number of homeless individuals in the United States. With only a brief period of continuous drop between August 2022 and January 2023, the S&P CoreLogic Case-Shiller national home price index has been on an upward trajectory, reaching a new record high of 320.14 in May 2024 (see Fig. 1). As a result, the number of burdened households that spend at least 30% of their income on housing has accelerated to more than 42 million in 2022, with poor households accounting for over half of the burden (JCHS, 2024). Housing subsidies represent one of the policies that the federal government uses to make housing more affordable for the poor.

The U.S. Department of Housing and Urban Development (HUD)'s Housing Choice Voucher (HCV) program represents the most extensive housing subsidy program in the United States. In 2023, the HUD earmarked about \$30.3 billion for the program to meet the needs of approximately 2.3 million low-income households. While the program is intended to increase the well-being of low-income families by enhancing their access to quality and affordable housing units, there have been concerns about its potential to create a negative externality, namely, increasing the crime rate in neighborhoods receiving voucher holders. One of the most controversial issues among researchers within the last decade includes the claim that the rise in HCV holders increases the crime rate in their new destinations (Hendey et al., 2016). Presentations about HCV holders in the media only serve to exacerbate this idea. While many studies have empirically investigated this claim using data from different counties and states with mixed results, the existing studies have mostly ignored the inherent spatial dependence between housing location and crime. This is a major shortcoming because the usual assumption of independent observations in non-spatial models is easily violated with spatial data where the observations interact and create spillovers (Elhorst, 2024). This study seeks to fill the above gap.

Examining the impact of the government-funded housing subsidy programs on crime is crucial for informing decisions about the programs' continuation in view of their relative social costs and benefits. This paper contributes to the literature by employing a spatial econometric technique that accounts for spatial dependence among census tracts in St. Louis County, allowing for the estimation of the spillover effects. Other things being equal, any crime-inducing factor in one tract may influence crime in nearby tracts due to spatial feedback effects. Besides, it is very reasonable to assume that crime in one tract is dependent on and contributes to crime in contiguous census tracts, and ignoring this spillover effect may lead to biased estimates (Elhorst, 2024; Galster et al., 2002; LeSage & Pace, 2009).

While a few of the previous studies partially addressed spatial dependence by including a spatial lag of the dependent variable (e.g., Hendey et al., 2016; Van Zandt & Mhatre, 2013), their methods do not fully capture spatial dependence.

According to LeSage & Pace (2009), when the nature of spatial dependence is uncertain, as in many real-life applications, it becomes necessary to include the spatial lags of both the dependent and independent variables. More importantly, existing studies do not explicitly quantify the spatial spillover effects of housing vouchers, which are relevant for evaluating the broader consequences of the program. Recent advances in spatial econometric analysis provide tools for quantifying such effects (Anselin, 2003; LeSage & Pace, 2009). From a policy perspective, if housing vouchers affect not only the neighborhoods where they are concentrated but also surrounding areas, policymakers need to consider these broader consequences when evaluating the program's effectiveness.

This study builds on existing research by providing the first estimates of the spillover effects of housing vouchers on crime using the Spatial Durbin Model with fixed effects (SDM-FE), which accounts for unobserved heterogeneity and spatial dependence. The study also contributes to the existing literature by shifting focus from large urban cities, typically characterized by centralized governance and policing structures, to a suburban context with highly fragmented municipal institutions. With over 90 autonomous municipalities and more than 50 police departments and a sharp socio-economic and racial boundary (the Delmar Divide), St. Louis County provides a unique suburban context to investigate the spillover effects of HCV on crime where high-income and low-income census tracts are adjacent. Moreover, the study formally tests whether neighborhood income amplifies or moderates the impact of HCV on crime.

The analyses reveal that the HCV rate has significant direct and indirect effects on the crime rate. A one-unit increase in the HCV rate in a census tract (defined as one additional voucher per 1,000 housing units) is associated with a 1.7–1.8% increase in the local crime rate. When accounting for spatial spillovers, an additional voucher unit in neighboring tracts contributes a further 0.6–0.7% increase to local crime. The total impact of an additional voucher unit is approximately a 2.5% increase in the crime rate. Evaluated at the sample mean of 24 crimes per 1000 residents, this corresponds to approximately 0.6 additional property crimes per 1000 people, or 2.6 additional annual crime incidents in an average census tract of 4,300 residents. These findings are robust to alternative HCV rate measures and spatial model specifications.

1.1 Overview of the Housing Choice Voucher Program

The U.S. government offers different housing subsidy programs to assist low-income households, the elderly, and individuals with disabilities. The three most prevalent options at present are public housing, tenant-based housing choice vouchers (HCV), and privately owned, project-based housing. Today, tenant-based assistance is the most common form of housing subsidy. The program started with the Section 8 certificate and voucher programs created in 1974 and 1983, respectively. These programs were later replaced by the HCV program under legislation enacted in 1998 (Office of Policy Development and Research (PD&R), 2025). The program allows low-income households to find and lease private market housing units, but unlike the Section 8 certificates, the vouchers are without a maximum rent limit, allowing the voucher holders to supplement the value of the voucher, which depends on the fair market rent. The fair market rent is defined as the 40th percentile of the gross rents of recent movers for normal housing units that meet the set standards (PD&R, 2025).

The public housing agency (PHA) in each state administers the housing voucher program in partnership with the U.S. Department of Housing and Urban Development (HUD). Families receiving housing vouchers must find suitable rental units of their choice among those whose owners have agreed to participate in the program. Minimum health and safety standards are set by the PHA. Once a family selects an apartment, they notify their PHA, which ensures the rental units meet the required standards. Upon approval, the tenant signs a lease contract with the landlord. The PHA then pays the voucher amount directly to the landlord, while the family covers any balance above the voucher.

Eligibility for the housing vouchers is determined by the PHAs based on the size of the family and the annual gross income. This eligibility is restricted to U.S. citizens and non-citizens with eligible immigration status. In general, a family's income must not exceed 50% of the median income of the chosen location, and the law mandates every PHA to allocate three-quarters of its vouchers to applicants whose incomes are at most 30% of the area median income. The PHA determines

the maximum allowable housing assistance, typically as either the payment standard minus 30% of the family's monthly adjusted income or the house's gross rent minus 30% of the adjusted monthly income (HUD, 2025).

2.0 Literature Review

Although a large body of literature has examined the relationship between housing subsidies and crime, the evidence remains mixed. Several studies investigate the crime effect of subsidized housing programs more broadly, while others focus on the Housing Choice Voucher (HCV) program. Galster et al. (2002), combining weighted least squares with focus-group methods, found that supportive housing developments in Denver had no significant effect on crime, except in larger complexes (53 or more residents), where violent crime rose. Using ordinary least squares, Albright et al. (2013) reached a similar conclusion for low-income housing developments in New Jersey. In contrast, Freedman and Owens (2011), using an instrumental-variable approach, found that low-income housing development in poor U.S. neighborhoods significantly reduced violent crime, with no effect on property crime at the county level.

A more relevant strand of research examines the HCV program specifically. Ellen et al. (2012) controlled for unobserved neighborhood fixed effects and time effects and found no significant effect of voucher holders on crime. Exploiting the exogenous variation from a randomized wait-list lottery, Carr and Coppola (2020) similarly found no effect of voucher receipt on the likelihood of arrest among heads of household in Houston, even among groups with a higher propensity for crime. Hendey et al. (2016) estimated dynamic panel models with the Arellano-Bond estimator and found no positive association between growth in HCV holders and violent crime in Chicago. However, the authors found a positive association between HCV and property crime in higher poverty neighborhoods or once voucher concentration exceeded a threshold. Mast and Wilson (2013), using quantile regression on annual data from Charlotte-Mecklenburg County (2000–2009), found a positive association between vouchers and crime that was more pronounced in neighborhoods with higher voucher concentrations. Using correlation analysis and OLS with a spatial lag of the dependent variable, Van Zandt and Mhatre (2013) found only a mild cross-sectional association between HCV concentration and crime in Dallas apartment complexes, with no relationship between changes in voucher counts and changes in crime—suggesting that voucher holders are drawn to already high-crime areas by limited housing options elsewhere, rather than driving crime upward themselves.

Although Hendey et al. (2016) and Van Zandt and Mhatre (2013) are close in spirit to this study, as both incorporate a spatial autoregressive term to account for spatial dependence, this paper extends their analysis by incorporating spatial lags of both the dependent and independent variables, quantifying the spillover effects, and comparing the performance of alternative spatial panel models.

3.0 Methodology

3.1 Conceptual framework

Becker's (1968) theory, which depicts a criminal as a utility-maximizing economic agent, predicts that impoverished individuals who anticipate earning more from criminal activity than from legal pursuits will be more inclined to commit crimes (Ellen et al., 2012). Given that voucher holders typically represent a lower-income demographic with a higher level of poverty, it is plausible that neighborhoods with a high concentration of voucher holders may experience a higher incidence of crime compared to those with fewer voucher holders, assuming all other factors remain equal.

There are broadly two possible channels through which HCV can affect neighborhood crime. First, there is the income effect of receiving a housing voucher. HCV is a form of income transfer that improves poor households' financial conditions and reduces their financial pressures. This income effect may lead to a lower neighborhood crime rate. The second channel is through the neighborhood effect. Since the HCV is designed to allow voucher holders to afford housing in better locations, voucher holders with criminal tendencies could have greater opportunities for committing crime in wealthier neighborhoods. As a result, crime may increase with more affluent targets. The positive social influence of more

organized neighborhoods may also lead to a reduction in crime. Figure 2 depicts the conceptual framework discussed above.

3.2 Empirical Strategy

To establish a baseline, I begin the empirical investigation with the standard fixed effects and dynamic panel models. These baseline models are introduced to allow for the comparison of my results with previous studies that adopted similar methods, such as Ellen et al. (2012) and Hendey et al. (2016). The models are estimated using fixed effects and Arellano-Bond estimators, respectively. By regressing the crime rate on the HCV rate and a vector of control variables, the following fixed effects model is specified:

$$\ln(Crime_{it}) = \beta HCV_{it} + X_{it}\phi + \mu_i + \varepsilon_{it}$$

1

where $Crime_{it}$ is the crime rate in each tract i for year t , HCV_{it} is the HCV rate in tract i for year t , and X_{it} is a vector of economic, social, and demographic control variables that influence the crime rate in tract i at year t . The tract fixed effect is captured by μ_i , while ε_{it} is the idiosyncratic error term and is assumed to be independently and identically distributed. The natural logarithm of the crime rate is used due to the skewness of the crime data, and the HCV and crime count were normalized through their conversion to rates per 1,000 housing units and 1,000 people, respectively. The control variables include the median household income, minority (non-white) share, percentage of population that is male, percentage of people below 18 years, the poverty rate, and the home ownership rate. Similar measures have been used in previous studies (see Ellen et al., 2012; Mast & Wilson, 2013; Van Zandt et al., 2013). Eq. (1) is estimated using the fixed effects (within) estimator.

Since the current crime rate may depend on the previous crime rate, a dynamic panel model may be necessary to capture this inertia effect. Eq. (1) is modified with the inclusion of a one-year lag of the crime rate. The resulting Eq. (2) can no longer be estimated consistently using the within estimator because, after the within transformation, the lagged dependent variable will be correlated with the transformed error term, and the bias created does not vanish even as N goes to infinity (Nickell, 1981). I estimate Eq. 2 using the Arellano-Bond (1991) generalized method of moments (GMM) estimator. The estimator addresses Nickell bias and the endogeneity associated with including lagged dependent variables in dynamic panel models with short time dimensions.

$$\ln(Crime_{it}) = \ln(Crime_{i,t-1}) + \beta HCV_{it} + X_{it}\phi + \mu_i + \varepsilon_{it}$$

2

To account for spatial dependence in both the dependent and independent variables, the following spatial Durbin model with fixed effects (SDM-FE) is specified, following LeSage and Pace (2009):

$$\ln(Crime_{it}) = \rho(W \times \ln(Crime_{it})) + \beta_1 HCV_{it} + \beta_2(W \times HCV)_{it} + X_{it}\phi + WX_{it}\vartheta + \mu_i + \varepsilon_{it}$$

3

Equation 3 is the main estimating equation for this study. The additional terms in Eq. 3 are described below. ρ represents the spatial autoregressive coefficient. W is the spatial weight matrix for the neighbors, which was calculated using the k -nearest neighbors (KNN) method with $k = 4$. In this method, each spatial unit is considered a neighbor to its (k) nearest units, ensuring that each unit has exactly (k) neighbors. β_1 and ϕ measure the direct effects of the HCV rate and the controls on the crime rate. However, as LeSage and Pace (2009) warned, the coefficients β_2 and ϑ associated with the terms with spatial interactions cannot be interpreted as indirect effects. Rather, the correct indirect effects must be derived

by taking the partial derivatives of the reduced form Eq. (4) below with respect to the explanatory variables with spatial interactions. The error term ε_{it} is assumed to be approximately normally distributed.

$$\ln(Crime_{it}) = (I - \rho W)^{-1}[\beta_1 HCV_{it} + \beta_2(W \times HCV)_{it} + X_{it}\phi + WX_{it}\vartheta + \mu_i + \varepsilon_{it}]$$

4

3.3 Data

The study uses annual data for the period 2015–2022 with crime data obtained from the National Incident-Based Reporting System (NIBRS) and the Federal Bureau of Investigation's (FBI) Uniform Crime Report. Both sources provide location data on personal and property crimes reported to multiple police departments across St. Louis County. This study focuses on property crime because Becker's (1968) theory is particularly applicable to such crimes. Using the latitude and longitude of reported crime locations, I geocode and aggregate this data to the census tract level. The original data contained data covering 144 tracts in 2015 and 221 tracts in 2022. The tracts' designation for 2015–2019 was based on the 2010 decennial census, while the designation for the remaining years was based on the 2020 census.

I obtain data on occupied HCV units from the U.S. Housing and Urban Development (HUD) database. The original data contains 212 tracts in 2018 and 240 tracts in 2022. Data on other variables used in the study, such as median household income, minority share of the population, male percentage of the population, under-18 percentage of the population, and home ownership rate, were derived from the American Community Survey (ACS) 5-Year Estimates. I removed census tracts with more than 3 years of missing data for any variable from the final dataset. For census tracts with at most three missing values of crime or HCV in a year, I use linear interpolation to calculate the missing values.

To link the tracts in the 2010 and 2020 censuses, I use the IPUMS National Historical GIS (NHGIS) crosswalk files, which provide interpolation weights for allocating census counts from a specified set of source zones to a specified set of target zones (IPUMS NHGIS, 2024). The crosswalks are comparable to the relationship files of the U.S. Census Bureau; however, the NHGIS crosswalks include interpolation weights derived from sophisticated models where each interpolation weight indicates the proportion of a source zone's characteristics to allocate to a specific target zone (IPUMS NHGIS, 2024). For this reason, I apply the weight for housing unit interpolation to both the HCV and the homeownership rate. The population interpolation weight was used for all other variables. I also consider 2010 as the source and 2020 as the target zone. In other words, my final dataset is based on 2020 census tract designation. Finally, I use balanced panel data with a total of 984 observations for 123 census tracts over a period of eight (8) years. Table 1 describes the variables used in this study, while Table 2 provides the descriptive statistics.

As shown in Table 2, the yearly property crime rate for the census tracts ranges from 0.15 to 240.76, with an average of about 24 crimes per 1000 people. This is higher than the national average, which was about 20 crimes per 1000 people in 2022 (Pew Research Center, 2024). There are approximately 29 or 35 occupied HCV units per 1000 total or occupied housing units on average. The HCV rate ranges between 0.35 and 208, or 253 units per 1000 total/occupied housing

Table 1
Variable Definitions

Variable Name	Definition
Crime	The rate of property crime per 1,000 people
HCV (1)	The rate of occupied HCV units per 1,000 occupied housing units
HVC (2)	The rate of occupied HCV units per 1,000 total housing units
Inc	Median household income
Poverty	Percentage of the population below the poverty line
Minority	Percentage of the population that is non-white
Male	Percentage of the population that is male
Under18	Percentage of population who are less than 18 years of age
Ownership	Percentage of owner-occupied housing units

Table 2
Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Crime	984	23.59	26.17	0.15	240.76
HCV (1)	984	34.60	48.55	0.35	252.63
HCV (2)	984	28.72	39.02	0.35	207.95
Poverty	984	13.03	10.02	0.15	56.08
Male	984	46.92	3.84	27.15	62.16
Under18	984	22.53	5.59	5.84	46.14
Minority	984	42.90	34.34	0.59	100
Ownership	984	64.33	18.85	16.11	99.47
Inc	984	61412.61	26333.37	16208	183828

units. The lowest and highest poverty rates for the period were 0.2% and 56%, respectively. Furthermore, the minority share spans from 0.6% to 100%, with an average of 43%, while the median household income varies between \$16,208 and \$183,828, with an average of about \$61,413. The percentage of the population that is male for the sample varies between 27% and 62%, with a mean of approximately 47%. On average, about 23% of the population are less than 18 years of age, while approximately 64% of all housing units are owner-occupied.

4.0 Results and Discussion

As a precursor to the regression analysis, Figure 3 visually shows the within-tract association between crime and HCV. The figure indicates a weak positive co-movement between the variables. The correlation result in Table 3 confirms the existence of a positive but weak association between crime and HCV. Similarly, the poverty rate and minority share have weak positive correlations with crime rate, whereas income and ownership rate have weak negative correlations with it. Both male and under-18 proportions have negligible negative correlations with the crime rate. The correlation matrix further reveals that both poverty rate and minority share have very strong correlations with the HCV rate. Since most of the previous studies included both the poverty rate and minority share as controls, this study follows the tradition by specifying two full models that include all the control variables. In addition, a third model excluding poverty rate (also highly correlated

with income) and minority share is specified to avoid the multicollinearity problem, improve the precision of the estimates, and isolate the partial effect of the HCV rate.

Table 3. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ln_Crime	1.000								
(2) HCV (1)	0.168	1.000							
(3) HCV (2)	0.161	0.994	1.000						
(4) ln_Inc	-0.174	-0.686	-0.689	1.000					
(5) Poverty	0.135	0.758	0.758	-0.830	1.000				
(6) Male	-0.004	-0.373	-0.372	0.370	-0.390	1.000			
(7) Under18	-0.008	0.501	0.499	-0.239	0.411	-0.131	1.000		
(8) Minority	0.151	0.782	0.789	-0.653	0.722	-0.449	0.468	1.000	
(9) Ownership	-0.248	-0.572	-0.572	0.771	-0.686	0.252	-0.136	-0.492	1.000

4.1 Preliminary (Non-Spatial) Analysis

Table 4 presents the estimates for the baseline models with three alternative specifications for each of the fixed effects (FE) and the Arellano-Bond GMM estimates. The first specification includes all the control variables, while the third excludes poverty and minority (both of which are highly correlated with the HCV) to address a potential multicollinearity issue that may affect the precision of the estimates. The second specification includes an interaction term between HCV and income. This is the preferred specification in this study. The inclusion of the interaction term helps in testing two competing hypotheses: whether higher neighborhood income amplifies the impact of HCV on crime (the '*high-target opportunity*' hypothesis) or moderates it due to better neighborhood resources and social control (the '*buffer effect*' hypothesis).

The FE results indicate that the HCV rate has a positive effect on the crime rate, but the effect is statistically insignificant when the interaction term is included. Without the interaction term, a 1-unit increase in the HCV rate is associated with a 1.8-1.9% increase in the crime rate, holding other factors constant. In other words, an additional unit of HCV per 1,000 housing units in a census tract corresponds to a 1.8-1.9% increase in crime per 1000 people. Once the interaction term is included, we find no evidence of a direct relationship between HCV and crime. However, the negative coefficient of the interaction term does not support the hypothesis that high-income tracts experience higher crime due to better crime opportunities. Instead, the result indicates that income mitigates the negative impact of HCVs on crime, supporting the buffer effect hypothesis.

Income and minority share have consistent positive impacts on crime. While the positive effect of minority share is expected, the observed positive association between neighborhood income and crime may be explained by the fact that high-income tracts are more likely to report criminal activities than lower-income tracts. The results also suggest that the under-18 population has a negative impact on crime. This may be attributed to the fact that tracts with a higher proportion of children are more family-oriented and have a stronger commitment to neighborhood stability.

Table 4. Fixed Effects and Arellano-Bond GMM Estimates

Dependent Variable (Y): ln (Crime)						
	Fixed Effects Estimates			Arellano-Bond GMM Estimates		
	I	II	III	I	II	III
HCV	0.018** (0.008)	0.013 (0.010)	0.019** (0.008)	0.028 (0.039)	0.025 (0.020)	-0.003 (0.019)
ln (Inc)	3.051*** (0.409)	3.476*** (0.456)	3.131*** (0.421)	1.595*** (0.372)	1.693*** (0.489)	2.633*** (0.456)
Inc*HCV[1]		-0.017* (0.009)			-0.006 (0.014)	
Poverty	0.022* (0.012)	0.017 (0.012)		0.026 (0.042)	0.008 (0.008)	
Male	0.007 (0.018)	0.008 (0.018)	0.002 (0.019)	0.003 (0.012)	0.002 (0.010)	0.002 (0.010)
Under18	-0.027* (0.016)	-0.030** (0.015)	-0.017 (0.016)	-0.008 (0.015)	-0.005 (0.010)	-0.0003 (0.009)
Minority	0.032*** (0.009)	0.029*** (0.009)		-0.004 (0.012)	-0.002 (0.009)	
Ownership	-0.007 (0.008)	-0.007 (0.008)	-0.012 (0.008)	-0.013 (0.008)	-0.013* (0.007)	-0.022*** (0.006)
lag(Y)				0.668*** (0.081)	0.620*** (0.107)	0.448*** (0.078)
Within R ²	0.24	0.25	0.21			
F statistic	12.33***	12.79***	12.47***			

Sargan test				19.12	18.77	2.70
Instrument count				20	21	12
AR(2)				-0.55	-0.58	-0.14
Wald test				506***	230***	284***
Obs.	984	861	984	738	738	615

To address the potential endogeneity of HCV and account for persistence in crime, the Arellano-Bond GMM estimator was employed to estimate the dynamic versions of the previous three models. The results indicate that income retains its significant positive impact on crime after controlling for the effect of past crime. There is also clear evidence of the inertial effect of crime: a 1% increase in crime in the previous year is associated with a 0.45-0.68% increase in crime in the current year, keeping other factors constant. Homeownership rate now appears negatively associated with crime, and the diagnostic tests indicate that the models are correctly specified. Specifically, the Sargan test statistics are all insignificant at the 5% level, implying the null hypothesis that the instruments are valid cannot be rejected. Moreover, the Wald test suggests the joint significance of the explanatory variables, and the models are free from second-order serial correlation based on the insignificant autocorrelation test results.

The FE and the GMM estimates above have notable shortcomings. First, the FE model cannot address the problem of endogeneity, which may occur due to reverse causality between the crime rate and the HCV rate. As demonstrated by Ellen et al. (2012), the HCV rate may increase with a rise in the crime rate. Besides, the model completely ignores the spatial dependence between the tracts in St. Louis County, leading to biased estimates. Although the Arellano-Bond estimator is suitable for addressing the endogeneity problem, it does not give unbiased estimates because it also fails to account for the spatial dependence between the census tracts. More importantly, none of those estimators are designed to estimate the spillover effects, which are the focus of this study. It is therefore imperative to consider a spatial panel model that overcomes the limitations highlighted above and provides estimates of both direct and indirect effects of HCV on crime.

4.2 Spatial Econometric Analysis

The Spatial Durbin Model with tract fixed effects (SDM-FE) is chosen for the main analysis and inference because it outperforms the alternative spatial models (for the preferred specification), including the Spatial Autoregressive Model (SAR), based on the Likelihood Ratio (LR) test and the Akaike Information Criterion (AIC). The choice of SDM also aligns with its theoretical superiority over the alternative spatial models in providing unbiased estimates even in the face of model misspecification regarding the true data-generating process (LeSage & Pace, 2009). Nonetheless, the SAR specifications are included as part of the robustness tests. The SDM-FE estimates for the three alternative model specifications earlier considered under the non-spatial analysis are presented in Table 5.

The results indicate that the HCV has significant direct and indirect (spillover) effects on crime across the specifications. A one-unit increase in the HCV rate in a census tract is associated with an increase of 1.7-1.8% in local crime, while an additional HCV unit in neighboring tracts increases the crime rate by 0.6-0.7%, other things being equal. The aggregate effect of an additional HCV is approximately a 2.5% increase in the crime rate. Evaluated at the sample mean of 24 crimes per 1,000 people, this corresponds to approximately 0.6 additional property crimes per 1,000 residents, or 2.6 additional crimes in an average census tract of 4,300 people. Notably, the total impact of HCV on crime from the SDM result is larger

than the estimate from the standard FE model, roughly by the magnitude of the spillover effect. In essence, the standard FE model underestimates the full impact of HCV on crime by ignoring the spillover effect.

The results further show that income, poverty rate, and minority share have significant positive impacts on crime, while the under-18 population only has a significant negative direct effect. The male percentage

Table 5. SDM-FE

Dependent Variable: ln (Crime)						
	Model I		Model II		Model III	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
HCV	0.017*** (0.005)	0.006* (0.003)	0.018*** (0.005)	0.007* (0.004)	0.017*** (0.005)	0.006** (0.003)
ln (Inc)	2.416*** (0.225)	0.742*** (0.185)	2.066*** (0.239)	1.944*** (0.336)	2.411*** (0.204)	0.901*** (0.194)
Inc*HCV			-0.043 (0.030)	-0.005 (0.009)		
Poverty	0.019** (0.008)	-0.007 (0.010)	0.017** (0.007)	0.025** (0.011)		
Male	0.001 (0.010)	0.006 (0.017)	0.001 (0.010)	0.011 (0.007)	-0.002 (0.010)	-0.001 (0.018)
Under18	-0.023*** (0.009)	-0.007 (0.013)	-0.022*** (0.008)	-0.014 (0.012)	-0.016* (0.008)	-0.008 (0.013)
Minority	0.025*** (0.007)	0.010** (0.004)	0.018*** (0.007)	0.008** (0.004)		
Ownership	-0.0001 (0.005)	-0.004 (0.005)	0.003 (0.005)	-0.012*** (0.004)	-0.004 (0.005)	-0.006 (0.005)
Rho	0.242*** (0.040)		0.179*** (0.043)		0.276*** (0.039)	
Obs.	984		984		984	
AIC	346.02		319.09		358.69	
BIC	419.40		402.25		412.50	
LR test (χ^2)	2.39		29.88***		0.875	

Note: The Likelihood Ratio (LR) test evaluates the nested restriction that the spatial lag of the independent variables ($W X$) equals zero. A significant LR test result ($p < 0.01$) indicates that the Spatial Durbin Model (SDM) provides a superior fit to the data compared to the more parsimonious Spatial Autoregressive (SAR) model. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

and homeownership rate have insignificant direct effects on crime, but the latter exerts a significant indirect impact. We find no evidence for the ‘*high-target opportunity*’ or ‘*buffer-effect*’ hypothesis because the interaction term is statistically insignificant. However, both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) clearly show that the full model with the interaction term has a better fit than the two alternative specifications. Therefore, the specification is consistently preferred throughout the analysis conducted in this study. The significant LR test result (for the preferred specification) underscores the necessity to fully account for spatial dependence with the spatial lags of the response and explanatory variables for reliable estimates. In particular, the rho (ρ) provides strong evidence of significant crime spillover between the census tracts. These results are consistent across the three specifications.

Robustness Check

As robustness checks, the study considers a battery of sensitivity analyses. I estimated the preferred SDM-FE specification using a different measure of HCV (HCV rate per 1,000 *occupied* housing units), an alternative functional form (log-log model), and a one-year lag of the HCV measure employed for the main analysis (HCV rate per 1,000 *total* housing units). Finally, I re-estimated the three models in the main analysis using the SAR approach. As Table 6 clearly shows, the alternative HCV measure has lower direct and total impacts and an insignificant indirect impact on crime compared to the first measure. In sum, an additional HCV unit will increase the crime rate by approximately 1.7%, corresponding to roughly 1.8 additional crime incidents annually in a census tract with 4,300 residents. Moreover, HCV has a larger lagged effect on crime than contemporaneous effect. An additional HCV unit in the previous year is associated with about a 3.1% increase in the current year’s crime rate, or 3.2 additional crime incidents for the average

Table 6. SDM-FE (Alternative HCV & Functional Form, and Lagged HCV)

Dependent Variable: ln (Crime)						
	Alt. HCV		Log-Log Model		Lagged HCV	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
HCV	0.012*** (0.003)	0.005 (0.003)	-0.084 (0.085)	-0.001 (0.072)	0.021*** (0.006)	0.009** (0.004)
ln (Inc)	2.072*** (0.241)	1.980*** (0.326)	2.074*** (0.244)	2.053*** (0.366)	1.859*** (0.247)	1.976*** (0.333)
Inc*HCV	-0.026 (0.022)	-0.003 (0.007)	0.631 (0.535)	0.190 (0.154)	-0.070 (0.050)	-0.013 (0.015)
Poverty	0.017** (0.007)	0.026** (0.011)	0.019*** (0.007)	0.029*** (0.011)	0.016** (0.007)	0.028** (0.012)
Male	0.002 (0.010)	0.012* (0.007)	0.002 (0.009)	0.012* (0.007)	-0.001 (0.010)	0.011 (0.007)
Under18	-0.021** (0.008)	-0.012 (0.012)	-0.021** (0.008)	-0.013 (0.012)	-0.019** (0.009)	-0.018 (0.012)
Minority	0.018** (0.007)	0.009** (0.004)	0.016** (0.007)	0.009** (0.004)	0.015** (0.007)	0.008 (0.004)
Ownership	0.003 (0.005)	-0.013 (0.004)	0.000 (0.005)	-0.015*** (0.004)	0.001 (0.005)	-0.013 (0.004)
Rho	0.184*** (0.043)		0.184*** (0.043)		0.212*** (0.045)	
Obs.	984		984		861	
AIC	319.48		330.54		145.00	
BIC	402.64		413.70		225.89	

Note: Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

census tract population. The interaction term remains insignificant, suggesting no evidence in favor of either the *'high-target opportunity'* or *'buffer-effect'* hypothesis. The result of the log-log

model shows no evidence of a significant effect of HCV on crime. However, the model has a poorer fit compared to any of the alternatives.

The SAR results in Table 7 are very similar to the main SDM results presented earlier. The results provide supporting evidence for the significant direct and indirect impacts of HCV on crime with almost the same magnitude as in the SDM across the three specifications. Specifically, the results imply that a one-unit increase in the HCV rate is associated with a 1.7-1.9% increase in the local crime rate. An additional voucher unit in neighboring tracts contributes a further 0.6-0.7% increase to local crime. The total impact of an additional voucher unit is approximately a 2.5% increase in the crime rate, equivalent to almost 0.6 additional crimes per 1,000 people, or 2.6 additional annual crime incidents in an average census tract of 4,300 residents. This perfectly aligns with the result of the preferred SDM specification. The primary distinction between the SAR and SDM results is the statistical significance of the interaction term, which provides empirical support for the *'buffer effect'* hypothesis, suggesting that neighborhood income moderates the potential adverse effect of HCV on crime. The implication is that the 2.6 average increase in crime is likely a product of spatial heterogeneity: the effect is unevenly distributed and most likely driven by much higher spikes in *'unbuffered'* low-income tracts, which may lack the necessary informal social controls and institutional resources to neutralize the program's negative externalities.

While the SAR model picks up the interaction effect, the SDM fails to capture that perhaps because the inclusion of neighbor-specific controls (WX) makes it harder to isolate that effect. The AIC for the interaction model is lower than the alternative specifications, just as in the SDM

Table 7. SAR-FE

Dependent Variable: ln (Crime)						
	Model I		Model II		Model III	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
HCV	0.017*** (0.005)	0.005*** (0.002)	0.019*** (0.005)	0.006*** (0.002)	0.017*** (0.005)	0.006** (0.002)
ln (Inc)	2.447*** (0.221)	0.764*** (0.167)	2.459*** (0.220)	0.759*** (0.166)	2.429*** (0.201)	0.882*** (0.175)
Inc*HCV			-0.057* (0.031)	-0.017* (0.010)		
Poverty	0.018** (0.008)	0.006** (0.003)	0.018** (0.008)	0.006** (0.003)		
Male	0.003 (0.010)	0.001 (0.003)	0.003 (0.010)	0.001 (0.003)	-0.002 (0.010)	-0.001 (0.004)
Under18	-0.024*** (0.008)	-0.007** (0.003)	-0.025*** (0.008)	-0.008** (0.003)	-0.016* (0.008)	-0.006* (0.003)
Minority	0.025*** (0.007)	0.008*** (0.003)	0.024*** (0.007)	0.008*** (0.003)		
Ownership	-0.001 (0.005)	-0.0003 (0.002)	-0.001 (0.005)	-0.0001 (0.002)	-0.004 (0.005)	-0.002 (0.002)
Rho	0.242*** (0.040)		0.245*** (0.043)		0.278*** (0.039)	
Obs.	984		984		984	
AIC	334.41		332.97		349.56	
BIC	373.55		377.00		378.91	
LR test (χ^2)	2.39		29.88***		0.87	

Note: The Likelihood Ratio (LR) test evaluates the nested restriction that the spatial lag of the independent variables ($W X$) equals zero. A significant LR test result ($p < 0.01$) indicates that the Spatial Durbin Model (SDM) provides a superior fit to the data compared to the more parsimonious Spatial Autoregressive (SAR) model. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

results. Therefore, both SAR and SDM estimates support the choice of the preferred interaction model. Comparing the preferred specification's AIC for SAR and SDM, the AIC for SDM is lower than that of SAR, suggesting that the SDM provides a better fit for this study data. The significant LR test also corroborates this submission.

[1] For a meaningful interpretation of the main effect of HCV, $\ln(\text{income})$ is mean-centered, since $\ln(\text{income}) = 0$ corresponds to a median income of \$1 which is not realistic. The estimated coefficient of HCV now represents the effect at the sample mean of income.

Conclusion

This paper examines the impact of HCV on property crime in St. Louis County using the spatial Durbin model with tract fixed effect (SDM-FE). The model accounts for spatial dependence in crime and the explanatory variables and provides estimates of the spillover effects. The analysis employs panel data covering 123 census tracts in St. Louis County for the period 2015–2022. The results indicate that the HCV rate has positive and significant direct and indirect impacts on the crime rate. This holds for both the contemporaneous and lagged effects. A one-unit increase in the HCV rate is estimated to increase the local crime rate by 1.7–1.8%, while a one-unit increase in the HCV rate in neighboring tracts is associated with a 0.6–0.7% increase in the crime rate.

Using the sample average of 24 crimes per 1000 people and the mean population of 4300, the total effect of HCV concentration on crime corresponds to an average of 2.6 additional property crimes in each census tract annually. When a one-year lag of the HCV rate is considered, the crime rate increases by about 2.1% in response to a one-unit increase in the local HCV rate and by approximately 0.9% in response to a one-unit increase in neighboring tracts' HCV rates. The combined effect translates to approximately 3.1 additional annual property crimes. These results are robust to alternative HCV rate measures and spatial model specifications.

The finding regarding the positive effect of HCV on property crime is supported by Hendey et al. (2016), Mast & Wilston (2013), and Van Zandt and Mhatre (2013), who documented evidence of a positive association between HCV and crime in Chicago, Mecklenburg County, and Dallas, respectively. The study strengthens the previous findings using a more robust spatial econometric technique and further provides evidence of a significant spillover effect of the HCV concentration in St. Louis County.

The findings of this paper suggest that to mitigate the crime effect associated with subsidized HCV housing units in St. Louis County, policymakers should focus on deconcentrating the occupied units. By limiting voucher concentration in distressed tracts and encouraging mobility to higher-income areas where the '*buffer effect*' appears significant, stakeholders can minimize the negative impact of the HCV program. The Housing Authority of St. Louis County should prioritize mobility programs that redirect assisted households away from high-concentration tracts toward neighborhoods with lower voucher saturation. The significant buffer effect observed in higher-income areas indicates that such redistribution can interrupt the concentration-crime feedback mechanism identified in this analysis. A practical mechanism for achieving this is the adoption of Small Area Fair Market Rents (SAFMRs), which sets voucher payment standards to submarket rather than metropolitan-wide average rents, broadening the range of neighborhoods financially accessible to voucher holders. Importantly, deconcentration must be pursued alongside place-based investments in distressed tracts, addressing the underlying socioeconomic conditions that drive both voucher clustering and elevated crime.

While this study advances the HCV-crime literature by documenting direct and spillover effects of voucher concentration on property crime in St. Louis County, several limitations warrant acknowledgment. First, the findings reflect the specific socio-spatial and institutional context of St. Louis County, which may not be generalizable to other jurisdictions. Replication using broader, nationally representative samples would strengthen the external validity of the results. Second, the spatial econometric framework adopted does not resolve potential endogeneity arising from reverse causation between HCV and crime. These limitations weaken causal claims. Future research should employ quasi-experimental designs that exploit policy-induced variation in voucher allocation while accounting fully for spatial dependence to more credibly identify the causal relationship between HCV concentration and crime.

Declarations

Author Contribution

O.M. singlehandedly wrote and reviewed the manuscript.

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Data Availability

The data and analysis code for this study were deposited into Zenodo repository and are accessible at the following URL: <https://doi.org/10.5281/zenodo.22781969>.

Footnotes

1. See the Atlantic's article by Hanna Rosin (2008) on American Murder Mystery.
2. Carr & Koppa (2020) opine that voucher receipt could also guarantee the funds or leisure time to partake in criminal activities, thereby increasing neighborhood crime.
3. Moreover, my sample lacks sufficient data on personal crime.
4. I use the number of occupied HCV units instead of the number of people or the number of people per unit because these two have too many missing values due to low reporting (the HUD treats tracts with less than 11 reporting households or tracts with less than 50% reporting as missing; coded - 4 and - 5, respectively).
5. The FE and Dynamic Panel results for the unbalanced panel data without interpolation are similar to the ones for the balanced panel dataset. However, the codes for the spatial panel models did not work for the unbalanced panel data due to the limitation of the `pspatreg` R package.
6. The property crime counts averaged 94 crimes over the period, with a low of 1 and a high of 553. There were between 1 and 443 occupied units of HCV, with an average of 54 units.
7. For a meaningful interpretation of the main effect of HCV, $\ln(\text{income})$ is mean-centered, since $\ln(\text{income}) = 0$ corresponds to a median income of \$1 which is not realistic. The estimated coefficient of HCV now represents the effect at the sample mean of income.

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Figures

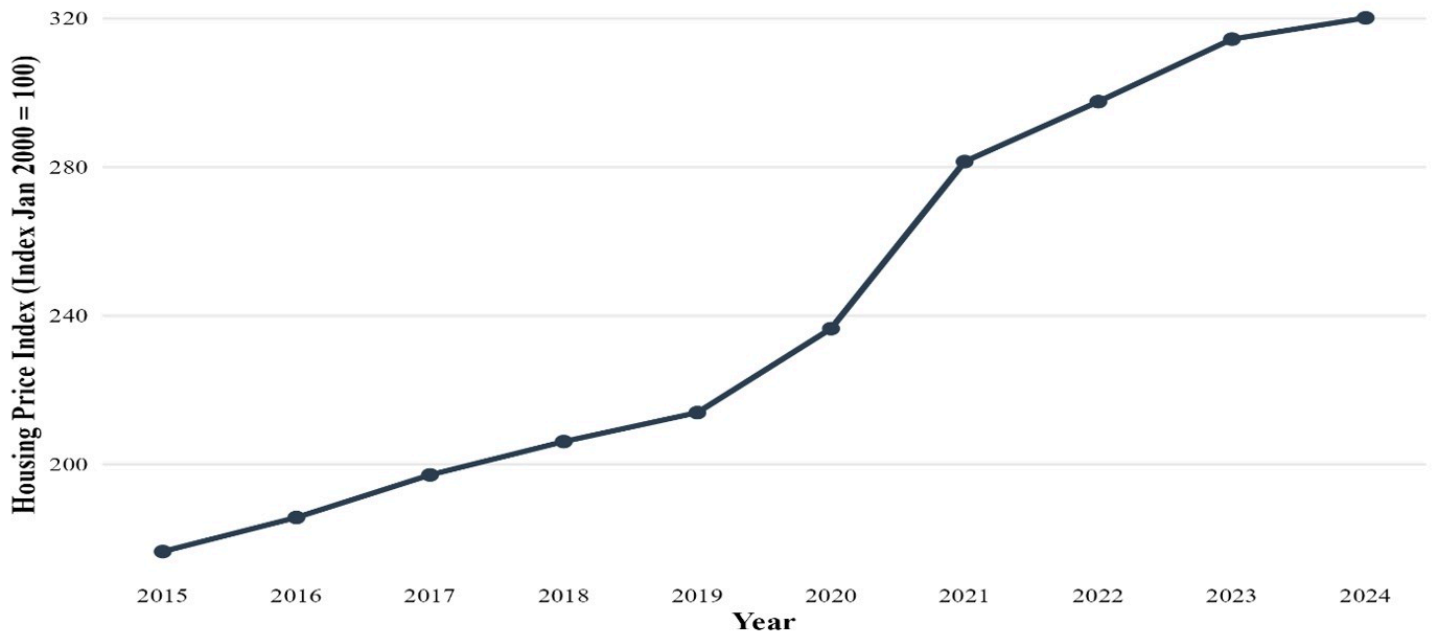


Figure 1. Housing Price Index

Figure 1

See image above for figure legend.

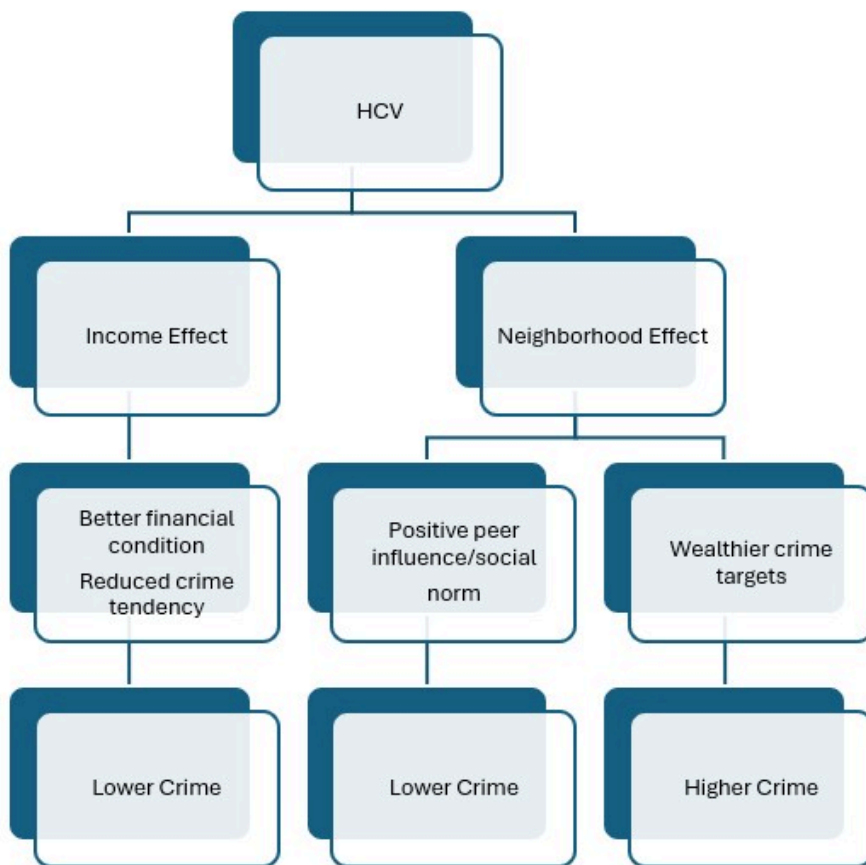


Figure 2

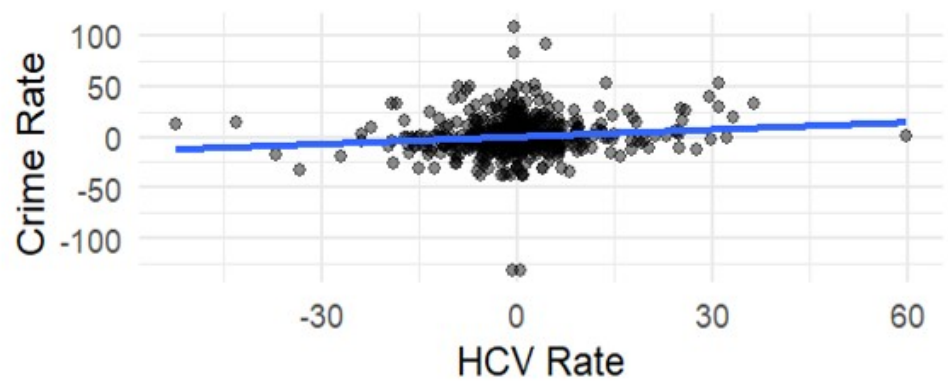


Figure 3

Association Between HCV Rate and Crime Rate

Note: Both variables are demeaned within tract.