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Crime Rate, Housing Price, and Value of A Statistical Case of Homicide

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Abstract

We use the fixed effects property hedonic approach with MSA level data to study the impact of the plunge in crime rates in 1990s on local housing price. For a general measure of crime rate, we compose FBI's seven categories of crime into a crime index by using the Sellin-Wolfgang (1964)'s weight of seriousness for different crime categories. To control for potential omitted variable bias, we use an instrumental variable approach based on the legalization of abortion in the 1970s as proposed by Donohue and Levitt (2001). We find a significantly negative relation between crime rate and housing price and further use the estimate to interpret people's marginal willingness to pay for reductions in crime. We obtain a value of a statistical case of homicide of 1.9 million in 1999 dollars.

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1. Introduction

Crime could be a life-threatening issue and it is hard for individuals to fight crime. As a result, societies usually rely on the government to provide public safety as a local public good. However, the amount of money a local government should spend on reducing crime is difficult to measure. The most challenging task in the cost and benefit analysis is to estimate people's willingness to pay for a safer neighborhood. The revealed preference method and the property hedonic model are commonly used to estimate the marginal willingness to pay (MWTP) for a change in the level of local public goods, such as environmental quality (e.g., Kiel and McClain, 1995; Leggett and Bockstael, 2000; Chay and Greenstone, 2005). These methods can similarly be used in the study of crime. In this paper, we use the hedonic approach to explore the relation between changes in crime rate during the 1990s and changes in housing price during that period. We then translate the estimates into people's willingness to pay for a reduction in crime.

During the 1990s, crime rate dropped sharply and unexpectedly among all categories of crime and across all parts of the United States (Levitt, 2004; Pope and Pope, 2012). According to data by the Federal Bureau of Investigation (FBI), violent crime rate and property crime rate plunged by 33% and 30% respectively during that decade. These declines were largely unexpected, as experts actually predicted an explosion in crime rate for the 1990s (Levitt, 2004). Although it must interest researchers a lot to look for the causes of the decline, we believe it is also worthwhile to look at the effect side of it.

Exploiting the plunge in crime rate of 1990s, we investigate the relation between crime rate and housing price. Applying fixed-effects hedonic model with housing price and crime data at the level of metropolitan statistical area (MSA), we find that a decline in crime rate is associated with a significant increase in local housing price. To further address potential omitted variable bias, we implement an instrumental variable strategy, where the instrument is constructed based on MSA-level abortion rates in 1970s and 1980s. The logic of the instrument follows the argument in Donohue and Levitt (2001), who show that the unexpected crime rate drop in 1990s was largely driven by the legalization of abortion in 1970s. The estimates from the instrumental variable regressions reinforce the negative relation between crime rate and housing price. As the ultimate goal of our paper is to provide a quantitative estimate on people's willingness to pay for crime reduction, we consider the impact of all types of crimes on housing price. Using only one crime category (e.g., homicide) while ignoring others (e.g., property crime) will apparently lead to an overestimated coefficient (on homicide) in hedonic model. Therefore, we construct a crime index using data on all seven types of crimes reported by the FBI together with the Sellin-Wolfgang weights on crime seriousness. Based on that crime index and our preferred model specification with instrumental variable, we estimate that people's MWTP for avoiding homicide, i.e., the value of a statistical case of homicide, is approximately 1.9 million in 1999 dollars.

Our paper contributes to the literature studying the relation between crime rate and housing price. Earlier studies (Thaler, 1978; Lynch and Rasmussen, 2001; Gibbons, 2004) mainly exploit cross-sectional variance in crime rate to investigate its impact on housing price, leaving omitted variable bias a large concern for the interpretation of the results. More recently, researchers explore temporal changes in crime rate to deliver more convincing casual relations. For example, Linden and Rockoff (2008) and Pope (2008) study how moveins of a sex offender affect the housing prices in Montgomery County, Ohio and Hillsborough County, Florida, respectively. Both papers find a negative relation between crime risk and property values, but the results pertain to specific counties and only one particular type of crime. The paper most closely related to our work is Pope and Pope (2012), who also investigate the crime rate drop in 1990s. Yet, our paper covers a more extensive cross-section of the U.S. market (297 MSAs) and a more detailed (annual) time series. We also propose a new instrumental variable strategy to address potential omitted variable bias. And most importantly, we construct a comprehensive measure to include all crime categories, which enables us to estimate people's willingness to pay for a reduction in crime, both at general and specific levels.

2. Data

2.1. Data sources

Our sample covers 297 MSAs in the United States from 1992 to 2000. We combine data from four different sources. We collect the annual MSA-level crime rate in all categories from Uniform Crime Report (UCR) published by the FBI. We obtain the annual MSA-level housing data from the Housing Price Index (HPI) published by the Federal Housing Financing Agency (FHFA). Other annual MSA-level demographic characteristics such as population and income are gathered and derived from the Current Population Survey (CPS) conducted by the U.S. Census Bureau and the Bureau of Labor Statistics. Finally, we obtain the state-level abortion rate in the 1970s and 1980s from the Guttmacher Institute and post-1990 county-level abortion rate from the Johnston's Archive.

Our main independent variable is the crime rate reported by the FBI. We start our sample from 1992 because the crime rate was still increasing in the year 1990 following the trend in the 1980s and also because it might take some time for people to realize the decline and update their beliefs in crime rate. The FBI gather and release the crime data based on reports from local law enforcement agencies through UCR annually. The data is an unbalanced panel because there is a deadline for the local agencies to report their annual crime data and some agencies miss the deadline from year to year. The FBI divides crime into seven categories: murder and nonnegligent manslaughter, forcible rape, robbery, aggravated assault, burglary, larceny-theft and motor vehicle theft. The first four types of crimes are categorized into violent crimes while the last three are considered as property crimes. The FBI reports the crime rate (per 100,000 people) on all seven categories.

Since the data on the seven types of crimes are highly correlated, we can neither include only one type of crime in regressions, nor all of them. Including only one crime type will lead to omitted variable bias and inflate the effect of that crime type. Including all crime categories separately will give rise to multicollinearity. Therefore, we create a crime index variable which is composed of all seven crime categories. It is certain that not all types of crimes should be given the same weight (e.g., murder is apparently more serious than theft), so we adopt the methodology suggested by Sellin and Wolfgang (1964) and calculate a weighted crime index based on the severity of the offenses.

Sellin and Wolfgang published *The Measurement of Delinquency* in 1964, in which they develop a method to measure the seriousness of different types of crime. The method allowed researchers to better understand the "qualitative elements in criminal behavior", according to Wellford and Wiatrowski (1975) in a work following Sellin and Wolfgang. In their original work, Sellin and Wolfgang made a list of 141 cases of crime and asked participants who were mainly university students to rate the seriousness of all the cases. From the rating of the participants, Sellin and Wolfgang created the scale of offense seriousness that is adopted in this paper. The seven categories of crime are given the following weights: murder and nonnegligent manslaughter (26.4), forcible rape (14.7), robbery (4.6), aggravated assault (5), burglary (2.4), larceny-theft (2.1), and motor vehicle theft (3.1). According to this weighting method, an additional case of homicide per 100,000 people increases the crime index by 26.4 units, which is approximately 11 times larger than the contribution of an additional burglary. The Sellin and Wolfgang scale is replicated by various studies in different parts of the world (e.g., Normandeau, 1966; Akman, Normandeau, and Turner, 1967; Velez-Diaz and Megargee, 1970; Hsu, 1973; Rossi, Waite, Bose, and Berk, 1974), and the replication studies mostly prove the Sellin and Wolfgang scale to be reliable (Wellford and Wiatrowski, 1975).

As a robustness check on our crime index, we consider two alternative weights based on victim cost estimates reported in Miller, Cohen, and Wiersema (1995) and Chalfin and McCrary (2018). Unlike the ex-ante perspective taken in surveys in Sellin and Wolfgang (1964), the victim cost method takes an ex-post perspective and estimates cost of crime on victims based on medical expenses and lost wages for tangible cost, and jury awards for intangible cost. To the degree that we want to estimate people's MWTP for crime reduction, an ex-ante perspective better reflects people's willingness and is, therefore, more appropriate. Another issue with victim cost weights is that for all crime categories other than murder, cost of crime is estimated based on the above-mentioned method, but the cost of murder is calculated based on an averaged value of a statistical life estimated in other studies in the literature, usually non-crime related (for example, people's MWTP to avoid health risks or job risks). This creates an inconsistency in the methodology of the weight estimates, resulting in a weight for murder that is about 30 to 50 times higher than the second highest weight (rape). Given these considerations, we use Sellin-Wolfgang weights as our main specification to estimate people's MWTP and take victim cost weights as a robustness check.

We then collect MSA-level housing data, Housing Price Index (HPI), from the FHFA between 1994 and 2002. The time scopes of the data on housing price and crime are slightly different because we assume there is a time lag between the decline in crime rate and its effect on housing price. The HPI is a broad measure of the price movement of single-family detached properties. Based on the data of conforming mortgage transactions obtained from Freddie Mac and Fannie Mae, FHFA estimates and publishes quarterly average price changes in repeat sales or refinancings on the same properties. The estimation is based on a modified version of the weighted-repeat sales methodology proposed by Case and Shiller (1989). The first quarter of 1995 is set as the benchmark with an assigned index of 100, and the quarterly index is adjusted for inflation. We convert the quarterly data into annual data by taking an unweighted average (the results are almost identical if we take a weighted average based on the standard deviation of the estimates). To convert the price index into dollar values, we use the MSA-level median housing prices from 2000 census provided by National Historical Geographic Information System.

We also collect data on demographic characteristics, which include household income, age structure, education level, race composition, housing ownership, poverty and unemployment rate. Since the census only provides demographic data on 2000 and our estimation is based on annual MSA-level data, we derive those information from the CPS. We collect individual demographic characteristics from March CPS and then convert them into aggregated MSA-level demographic information by using the weight suggested by the CPS.

Finally, we collect state-level abortion rates in the 1970s and 1980s from the Guttmacher Institute and post-1990 county-level abortion rates from the Johnston's Archive. Abortion was legalized in the United States after 1973, so we are unable to find information on abortion rate before that year. To construct an instrument for a given MSA in a given year, we calculate an annual MSA-level effective abortion rate based on the formula suggested in Donohue and Levitt (2001). We further illustrate the construction of our instrumental variable in the next section.

2.2. Descriptive statistics

Figure 1 presents the maps of MSA-level crime rate in 1992 and the percentage change in crime rate between 1992 and 2000. The top graph categorizes all MSAs into six equal-sized bins (same number of MSAs) and paints each MSA based on its crime index level. The graph shows that in early 1990s, California, Florida, Louisiana, and Texas are the states with the highest number of MSAs with high crime rate. The bottom graph depicts the change in the crime rate during the 1990s. The dramatic decline in crime rate is evident: 93% of MSAs had a crime index in 2000 lower than its level in 1992, and 32% of MSAs experienced a 30% or more decline in the crime index. A similar trend is also observed if we instead use the unweighted index or any single crime category. These observations suggest that our data provide enough variations both across time and across MSAs in the key explanatory variable to identify the effect of crime on property value.

Table 1 presents summary statistics on variables that we use in the subsequent regressions. The first two columns show sample means for 1992 and 2000, and the last two columns test whether the means are significantly different between 1992 and 2000. The monetary figures are denoted in 1999 dollars. Consistent with our hypothesis, we find that from 1992 to 2000, the mean housing price index (adjusted for inflation) increased roughly by 12% while the crime index decreased by 25%. Regarding demographics, income per household rose by approximately 5%, unemployment rate decreased by 2.9 percentage points, and poverty rate decreased by 1.3 percentage points. The increase in education attainment is also evident: 2.7 and 3.0 percentage-point increases in high school and college attainment, respectively. The race and age compositions were roughly the same at the beginning and the end of the period.

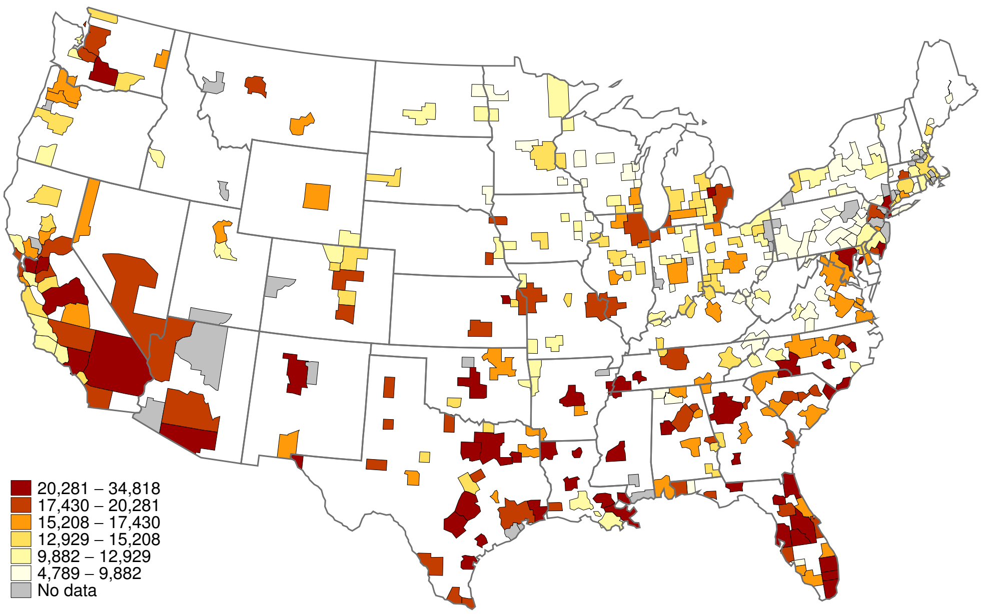
3. Empirical methodology

3.1. Hedonic model

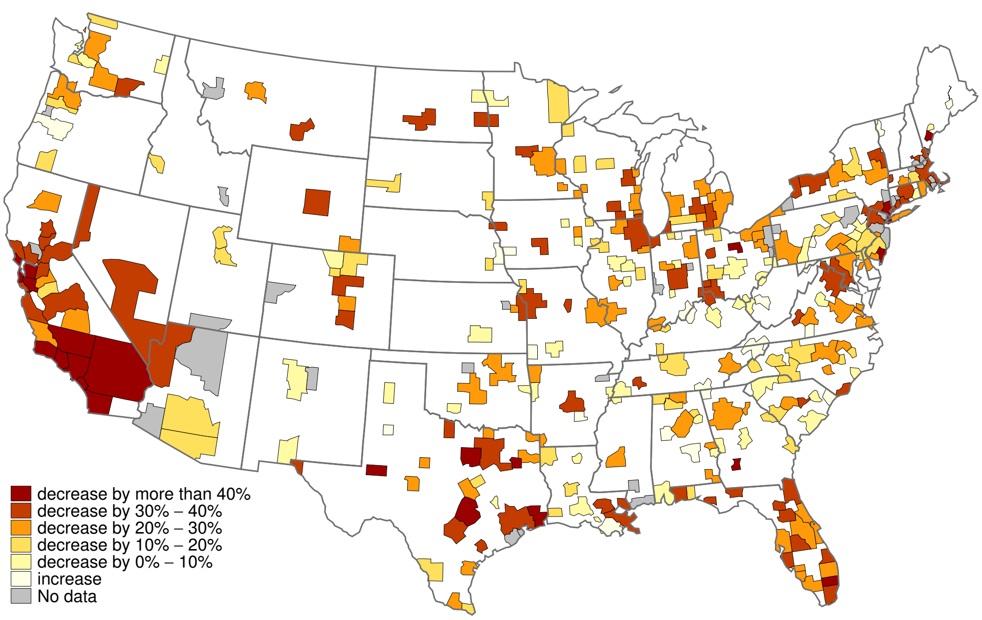
We use hedonic regression with MSA-level panel data to estimate the effect of crime on housing price. Specifically, we estimate the following hedonic model:

$$p_{i,t} = \beta Crime_{i,t-1} + \gamma X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \ ,$$

Figure 1: Crime Index from 1992 to 2000



(a) Crime index in 1992



(b) Crime index change from 1992 to 2000

where $p_{i,t}$ is the logarithm of MSA i's HPI at time t, $Crime_{i,t-1}$ is the logarithm of crime index, $X_{i,t}$ is the set of demographic control variables, α_i is the MSA fixed effect, λ_t is the time dummy, and $\varepsilon_{i,t}$ is the idiosyncratic error term. To reduce measurement errors, we combine the data of two adjacent years to generate one time period. We assume that there is a one period lag between the realized crime rate and its effect on the housing price.

The use of MSA-level data implicitly assumes the existence of a national housing market.

Table 1: Summary Statistics

Notes: Columns (1) and (2) report the average MSA characteristics in 1992 and 2000, respectively. Column (3) reports the sample mean difference between 1992 and 2000, and column (4) reports the p-value of the two-sample mean difference test.

	Sample mean		Sample difference test	
	1992	2000	Diff	p-value
	(1)	(2)	(3)	(4)
Housing price index	108.19	120.73	12.54	0.00
Crime index	15580.51	11680.97	-3899.54	0.00
Income per household	43983.37	46294.22	2310.86	0.01
Population	642873	720947	78074	0.36
Unemployment rate %	7.71	4.83	-2.88	0.00
Poverty %	13.17	11.88	-1.30	0.02
Old people %	12.54	12.36	-0.18	0.66
High school graduate %	81.00	83.71	2.72	0.00
College graduate %	21.41	24.43	3.02	0.00
White population %	86.03	84.48	-1.55	0.12
Owned house %	67.57	69.42	1.85	0.04

Although it is hard to prove whether the housing market is nationally integrated or segmented at MSA level, migration data show that in general U.S. population is highly mobile. Based on Census microdata and American Community Survey data, Molloy, Smith, and Wozniak (2011) find that in 1990s, approximately 3% of the U.S. population moves across MSAs annually and 12% of the population moves across MSAs in a five-year period. This high mobility suggests that people's MWTP for lower crime might not be only reflected in housing price variations within MSAs, but also partly in variations across MSAs. Indeed, some other papers also use low-resolution (e.g., county level), nationwide data to study the impact of local amenity on housing price (e.g., air quality in Chay and Greenstone, 2005).

As argued in Chay and Greenstone (2005), our identification based on cross-MSA variations brings both benefit and cost. The benefit side is that our results reflect the entire U.S. population's average MWTP for crime reduction, while studies using data of a single community (e.g., Linden and Rockoff, 2008; Pope, 2008) only reflect MWTP of the specific local population. Yet, this benefit comes at the cost of losing the ability to explore within-MSA variations. To the degree that within-MSA sorting might be greater than cross-MSA sorting, our results could underestimate people's MWTP.

3.2. Instrumental variable

In the above estimation equation, although we include MSA fixed effects to absorb time-invariant unobservables, there might still exist some time-varying unobserved factors that influence both crime rate and housing price. For example, there could exist local policies during that time period such as housing subsidies for households with low income. Such a policy might reduce the crime rate because low income families could potentially invest more time and money in their children and keep them away from violence and crime. At the same time, housing subsidies could also have an impact on the local housing market through increased demand. Based on such concern, we propose an instrumental variable strategy to better address the issue of omitted variables.

The instrument we implement is the MSA-level abortion rate in the 1970s and 1980s, based on Donohue and Levitt (2001). The U.S. Supreme Court's Roe v. Wade decision in 1973 announced the legalization of abortion. After 1973, there was a significant increase in abortion rates in almost all states across the country. Such trend continued until the beginning of 1980s and was then followed by a steady decrease throughout the 1980s and 1990s.

We argue for the validity of the instrument based on the time lag between the abortion data and the housing data. The abortion data we use are from the 1970s and 1980s and the housing price data are from the 1990s, so there is at least a 10 year gap between the two. Therefore, abortion rates in 1970s and 1980s are not likely to be correlated with MSA unobserved characteristics in 1990s, such as the local housing policy mentioned above. The abortion rates might be correlated with some demographic characteristics (e.g., population) in later periods which may then affect housing price. However, the demographics are less of a concern as they can be measured and are controlled for in the regressions.

The argument for the relevance of the instrument comes from Donohue and Levitt (2001), who propose that unwanted children have a higher risk for crime, while the legalization of abortion reduces the number of unwanted birth. They find that the increase in abortion rate in the 1970s and early 1980s leads to a significant reduce of crime rates in the 1990s. In a commentary paper, Foote and Goetz (2008) point out a coding error in Donohue and Levitt (2001) and find weaker results after correcting the error. Our instrumental variable strategy, however, should not be affected by these issues for two reasons. First, Donohue and Levitt (2001) use five different approaches, all of which point to the same relation between abortion and crime. The coding error is only in the last approach, while our instrument is mainly based on the fourth approach. Second, we identify the relation between abortion and crime at MSA level, which is presumably more accurate than the relation at the state level as in Donohue and Levitt (2001). Moreover, the F-statistic in the first stage regression also indicates that our instrument is highly relevant.

Ideally, we would like to have direct data on MSA-level abortion rate to use as the instrument, but abortion data in the 1970s and 1980s are only available at the state level (Guttmacher Institute). Yet, more disaggregated county-level data are available starting in the 1990s (Johnston's Archive). So we construct our estimated MSA-level abortion rate as follows. First, for each sample MSA, we find its corresponding counties based on the code scheme from the Census Bureau. Then for each county i, we use post-1990 abortion data to estimate the relation between county abortion rate and its belonging state's abortion rate with the following equation: $county\_abortion_{i,t} = \alpha_i + \beta_i state\_abortion_{i,t} + \varepsilon_{i,t}$. Next, we use the estimated $\hat{\alpha_i}$ and $\hat{\beta_i}$ together with state-level abortion rates to estimate county-level abortion rates for each year in the 1970s and 1980s.[1] Finally, we calculate MSA-level abortion rates as the weighted average abortion rate of the MSA's counties, where the weights are county populations from the Census Bureau.

To capture the idea that the legalization of abortion reduced crime only gradually because

[1]Out of 765 counties in our sample, we are able to find at least 10 observations for regression for 692 counties. For the remaining counties, we use state abortion rate as proxy.

young children usually do not commit crime, we adopt the concept of the "effective abortion rate" in Donohue and Levitt (2001). Specifically, it is calculated as the average abortion rate in MSA$_i$ across all cohorts of arrestees weighted by cohort a's share in the population of arrestees, i.e., $Eff\_abortion_{i,t} = \sum_a Abortion_{t-a}(Arrests_a/Arrests_{total})$. The youngest cohort we consider is the cohort of age 10, and the oldest is of age 27 (which is the oldest cohort to be affected by 1973 Roe v. Wade in 2000). For example, to calculate the effective abortion rate in 1992, we use the MSA-level abortion rate from 1973 to 1982, which corresponds to the cohorts of age 10 to 19 in 1992. The cohort's share in the population of arrestees is measured by the three year national average arrest data between 1981 and 1983. The effective abortion rate is calculated for all seven crime (arrest) categories. An abortion index is then created using the Sellin-Wolfgang weights, similar to the calculation of the crime index. We use the effective abortion rate index as the instrument for the crime index and estimate the following equation:

$$p_{i,t} = \beta Crime_{i,t-1}(Eff\_abortion_{i,t-1}) + \gamma X_{i,t-1} + \alpha_i + \lambda_t + \varepsilon_{i,t} .$$

The result from this hedonic model with instrumental variable is our preferred estimate.

4. Results

4.1. Estimation results

Regression results are presented in Table 2. Panel A reports our main specification with the crime index calculated based on Sellin-Wolfgang weights. Columns (1) and (2) present the OLS estimates of the hedonic model with MSA and time fixed effects. Consistent with our hypothesis, the coefficient of *Log(crime index)* in column (1) is significantly negative at the 1% level. A one percent decrease in crime index increases local housing price by approximately two percents. The coefficient of crime slightly decreases in column (2) where demographic controls are added, but is still significant at the 1% level.

Table 2: The impact of crime rate on housing price

Notes: The table presents the effect of crime rate on housing price using MSA-level data from 1992 to 2000. The dependent variable is the logarithm of Housing Price Index. Panel A reports regression results with crime index calculated with the Sellin-Wolfgang seriousness weights. The instrumental variable used in columns (3) to (6) is the MSA-level effective abortion rate defined as in Donohue and Levitt (2001). Panel B reports the value of a statistical case of homicide based on the coefficients estimated in each model specification in Panel A. Panels C and D report regression results with crime index calculated with victim cost estimates in Miller, Cohen, and Wiersema (1995) and Chalfin and McCrary (2018), respectively. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

	OLS		Instrumental variable			
			First stage		Second stage	
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Regression: crime seriousness (Sellin and Wolfgang, 1964)					
Log(crime index)	-2.0510***	-1.7310***			-5.0896***	-4.6416***
	(0.3862)	(0.3807)			(0.7334)	(0.8509)
Effective abortion rate			-0.0052***	-0.0047***		
			(0.0004)	(0.0005)		
Household income		0.2068***		-0.0015		0.2001***
		(0.0558)		(0.0076)		(0.0590)
Population		0.0138***		-0.0020***		0.0039
		(0.0047)		(0.0005)		(0.0048)
Unemployment rate		-0.0505		0.0145		0.0279
		(0.1087)		(0.0132)		(0.1056)
Poverty %		-0.0276		-0.0012		-0.0123
		(0.0692)		(0.0091)		(0.0707)
Old people %		-0.0283		-0.0013		-0.0177
		(0.0661)		(0.0099)		(0.0770)
High school graduate %		-0.1861***		0.0146*		-0.1416**
		(0.0661)		(0.0085)		(0.0692)
College graduate %		0.0567		0.0064		0.0762
		(0.0490)		(0.0074)		(0.0581)
White population %		-0.0313		0.0011		-0.0113
		(0.0520)		(0.0065)		(0.0507)
Owned house %		-0.0226		-0.0056		-0.0312
		(0.0438)		(0.0056)		(0.0440)
MSA and time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,023	1,023	1,023	1,023	1,023	1,023
Adjusted R^2	0.8512	0.8591	0.7012	0.7132	0.3217	0.3438
	B. Value of a statistical case of homicide ($M 1999)					
Discount rate 5%	0.84	0.71			2.08	1.89
Discount rate 3%	0.51	0.43			1.27	1.16
	C. Regression: crime cost (Miller et al., 1995)					
Log(crime index)	-0.7649***	-0.5396**			-3.6575***	-3.6726***
	(0.2558)	(0.2385)			(0.8063)	(1.1001)
	D. Regression: crime cost (Chalfin and McCrary, 2018)					
Log(crime index)	-0.4214**	-0.2648			-3.7119***	-3.8333***
	(0.1969)	(0.1819)			(0.9623)	(1.3771)

In columns (3) to (6), we move to our preferred specification where effective abortion rate is used as an instrumental variable. We first present the first stage results in columns (3) and (4). Consistent with the findings in Donohue and Levitt (2001), the increase in abortion rate is significantly related to the subsequent decrease in crime rate. The first stage F-stat is also well above 10, suggesting that our instrument does not suffer from the weak instrument problem (Bound, Jaeger, and Baker, 1995). Columns (5) and (6) present the second stage estimates. In line with the OLS results, the coefficient of *Log(crime index)* is still significantly negative at the 1% level. The magnitude of the coefficient under the instrumental variable strategy is larger than that of the OLS estimates.

In Panels C and D, we conduct robustness checks with crime index calculated based on victim cost weights. Consistent with our main results in Panel A, we continue to find a significantly negative relation between crime rate and housing price.

4.2. Statistical value of homicide

In this section, we use the estimates in Table 2 to interpret the economic magnitude of our findings, i.e., people's MWTP for changes in crime risk.

We calculate people's MWTP for the reduction in a certain type of crime by estimating the effect of that crime type on housing price, holding other crime types constant. For example, to calculate MWTP for a one-unit decrease in homicide risk, we first translate a one-unit decrease in homicide into a 26.4-unit decrease in the crime index, then use the regression estimates to calculate the effect on housing price, and finally use the sample average housing price to calculate the dollar value of avoiding a statistical case of homicide.

It might be useful to notice that a necessary condition for the above-mentioned method to correctly capture people's MWTP is that the relative weights of different crime categories in Sellin-Wolfgang's crime index need to be equal to people's actual perception of dollar value of avoiding different crimes as reflected in housing prices. The following simplified example illustrates the case. Suppose there are only two types of crimes, homicide and robbery, and housing price is affected by these two crimes based on the $Price = \beta_1 Homicide + \beta_2 Robbery + \varepsilon$. The crime index is formed as $Crime = \alpha_1 Homicide + \alpha_2 Robbery$. Homicide and robbery are related as $Homicide = \gamma Robbery + \xi$. In this case, the true MWTP for homicide risk is reflected by β_1. As argued earlier in the paper, since homicide and robbery are highly correlated, in practice, it is rarely possible to include both homicide and robbery in the hedonic model and identify them separately. One way to address this issue is to regress housing price on the crime index, which yields the coefficient $\frac{\beta_1+\beta_2\gamma}{\alpha_1+\alpha_2\gamma}$. Then, a one-unit change in homicide results in an α_1-unit change in the crime index, and an $\alpha_1\frac{\beta_1+\beta_2\gamma}{\alpha_1+\alpha_2\gamma}$-unit change in housing price. If the weights of homicide and robbery in the crime index are equal to their effects on housing price, i.e., $\alpha_1/\alpha_2 = \beta_1/\beta_2$, then $\alpha_1\frac{\beta_1+\beta_2\gamma}{\alpha_1+\alpha_2\gamma} = \beta_1$, which is the true MWTP. However, if the relative weight of homicide in the crime index is larger (smaller) than the relative effect of homicide on housing price, then the MWTP calculated based on our method will overestimate (underestimate) the true MWTP of avoiding homicide.

To calculate the value of a statistical case of homicide, we adopt a few common assumptions in the literature (e.g., Davis, 2004). We assume that housing price capitalizes the present discount value of all future homicide risk associated with living there. We further assume that people live infinitely, discount future risk at a 5% annual rate, and their perceived level of homicide risk in all future years equals to the current level of homicide risk. For a 3% annual discount rate, the value of a statistical case of homicide is smaller by a factor of 0.61.

Based on these assumptions, a one-unit decrease in annual homicide risk is equivalent to a 21-unit (1+1/0.05) decrease in lifetime homicide risk. Therefore, a decrease of lifetime homicide risk by one per 100,000 people is equivalent to a 0.0087% (26.4/21/14,414, where 14,414 is the sample average crime index) decrease in average annual crime index, and is associated with a 0.0404% (4.64 $\times$ 0.0087%, based on our preferred estimate) increase in housing price. As the mean housing price is $121,681 (in 1999 dollars), this means a $49.16 ($0.0404\% \times 121,681$) increase in housing price. Since the homicide risk is measured over per 100,000 people and the average number of members per household is about 2.6, the value of a statistical case of homicide is about 1.89 million dollars ($49.16/2.6 \times 100,000$). We report the value of a statistical case of homicide based on different hedonic model specifications and discount rates in Panel B of Table 2.

It might be noted that the value of a statistical life we estimated from homicide is lower than the value of a statistical life estimated from cancer, mortality in labor, etc, which typical ranges from $4 million to $9 million (Gayer, Hamilton, and Viscusi, 2000; Viscusi and Aldy, 2003; Davis, 2004). One potential reason is that the weight of homicide relative to other crimes in Sellin-Wolfgang's index (e.g., 11 times larger than burglary) might be smaller than the actual effect of homicide relative to other crimes on housing price, so our method might underestimate people's MWTP to avoid homicide. This is possible, because Sellin and Wolfgang use in their initial study university students as subjects, which also spurred criticism at that time (Wellford and Wiatrowski, 1975). Moreover, the Sellin and Wolfgang weights are basic and additive, while a murder in reality could have several assaults committed along with the homicide, making people's perception of murder a lot more serious than an independent case of homicide. Hence, the value of a statistical case of homicide we obtain could be lower than the actual MWTP to avoid being murdered. Nevertheless, to our knowledge, we are the first paper that attempts to use comprehensive national crime data to estimate people's MWTP for a safer neighborhood and translate that MWTP into a value of a statistical case of homicide.

5. Conclusion

This paper exploited the unexpected crime plunge during the 1990s to offer an estimate on people's willingness to pay for a safer living environment. We collect crime data and housing price on annual MSA-level and calculate the Sellin and Wolfgang's weighted crime index in order to derive a comprehensive crime variable. To control for the potential bias in the fixed-effects hedonic model, we use the effective abortion rate derived from abortion data in 1970s and 1980s (Donohue and Levitt, 2001) as an instrumental variable. Based on our preferred model specification, we estimate that people's willingness to pay to avoid homicide is around 1.49 million in 1999 dollars.

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