

Estimating the Willingness to Pay to Avoid Violent Crime: A Dynamic Approach

By KELLY C. BISHOP AND ALVIN D. MURPHY*

The hedonic model, which has been used extensively in the environmental, urban, and real estate literatures, allows for the estimation of the implicit prices of housing and neighborhood attributes (such as square footage, local crime rates, and school quality), as well as households' demand for these nonmarketed amenities. A recognized drawback of the existing hedonic literature is that the models assume a myopic decision maker, i.e., households do not look to the future when choosing where to live today. In this paper, we apply a dynamic hedonic model of demand to estimate the willingness to pay to avoid violent crime.

The existing literature, based on Sherwin Rosen's seminal 1974 paper, estimates households' willingness to pay for a given amenity by taking advantage of the first-order conditions for utility maximization, i.e., by requiring that the marginal change in price associated with an increase in amenity consumption will be equal to the marginal utility associated with the increase. Given that these first-order conditions are derived from a myopic utility maximization problem (and not the maximization of a lifetime utility function), the traditional model will yield unbiased estimates only under the assumption that households are not forward-looking when they purchase a house. Considering the substantial transaction costs that are present in the real estate market (both monetary and psychological), this assumption is unlikely to hold in most real-world applications.

Bishop and Murphy (2011) expand the existing hedonic framework by allowing households to be forward-looking with respect to the amenities of interest. In that paper, the familiar

optimality condition is redefined to require that the marginal change in current price is equal to the marginal benefit of an increase in amenity consumption this period *plus* the associated change in future utility flow.

Here, we apply a simplified version of that dynamic estimator to an unusually rich set of data comprised of merged panels of housing transactions and crime rates in the Bay Area of California, allowing us to estimate households' willingness to pay to avoid violent crime. We find that the average household is willing to pay \$472 per year to avoid a 10 percent increase in violent crime. Comparing these estimates with those obtained under the traditional, myopic version of the model, we find the myopic model underestimates this willingness to pay by 21 percent.

I. Model

A. Framework

Households (denoted $i \in \{1, \dots, N\}$) have demographic attributes, \mathbf{z} , and care about their consumption of some continuous, time-varying amenity, x , and other amenities, \mathbf{h} . At the beginning of each period, the household has an endowment level of these amenities, defined by the household's current residence.

In each period t , the household chooses whether to reoptimize their consumption of amenities. We denote this decision $d_{i,t} = j$, where $j \in \{0, 1\}$. If the household chooses not to reoptimize ($d_{i,t} = 0$), it does not move, incurs no moving cost, and consumes the endowment level. If the household chooses to reoptimize ($d_{i,t} = 1$), it moves, incurs a moving cost, and decides how much of each amenity to consume.

Given this setup, the implicit price of consuming x may be represented by the direct period rental cost of x and the moving costs that are incurred if the household chooses to reoptimize. Rental costs are a function of the level of amenities consumed and are known up to the

*Bishop: Olin Business School, Washington University in St. Louis, One Brookings Drive, St. Louis, MO 63130 (e-mail: kbishop@wustl.edu); Murphy: Olin Business School, Washington University in St. Louis, One Brookings Drive, St. Louis, MO 63130 (e-mail: murphy@wustl.edu). The authors would like to thank Bart Hamilton, Aviv Nevo, Tom Thibodeau, and Chris Timmins for helpful comments.

parameter vector γ . Moving costs are comprised of a common term, MC , and an additively separable idiosyncratic shock, $\epsilon_{i,t}$.

$$p_{i,t}^j = r(x_{i,t}, \mathbf{h}_i; \gamma) + (MC + \epsilon_{i,t}) \cdot I_{[j=1]}.$$

In each period, the household has choice-specific utility defined by rental costs and by the direct consumption of amenities, which is a function of demographic attributes and is known up to the parameter vector α ; $\eta_{i,t}$ is an idiosyncratic shock to preferences:

$$(1) \quad u_{i,t}^j = u(x_{i,t}, \mathbf{h}_i, \mathbf{z}_i, \eta_{i,t}; \alpha) - p_{i,t}^j.$$

We define the household's problem as choosing $d_{i,t}$ to maximize the discounted sum of expected per-period utilities. As the household knows that it will behave optimally at all future decisions, we can recursively define the values associated with $d_{i,t} = 0$ and $d_{i,t} = 1$. The state space at time t , $\mathbf{s}_{i,t}$, includes all variables that affect the household's decision at time t . The discount factor is represented by β .

$$(2) \quad v_{i,t}^j = u_{i,t}^j + \beta E[\max\{v_{i,t+1}^0, v_{i,t+1}^1\} | \mathbf{s}_{i,t}, d_{i,t} = j].$$

If the household decides not to reoptimize (i.e., if $v_{i,t}^0 > v_{i,t}^1$), it makes no further decision and consumes the endowment in the current period. If the household chooses to reoptimize, x (and \mathbf{h}) are chosen to maximize the associated lifetime utility, $v_{i,t}^1$.¹

For comparison, in the traditional, myopic model it is assumed that x is optimally chosen to maximize $u_{i,t}$ (versus $v_{i,t}$), ignoring the effect of this period's choice on future levels of utility. Thus, when estimating the model (even if the researcher is using data on movers alone), this assumption will clearly lead to biased estimates of preference parameters and the per-period willingness to pay.

¹ This is a slight abuse of notation. Technically, households reoptimize if $v^1(s, x^*(s)) > v^0(s)$ and choose x to maximize $v^1(s, x)$.

B. Estimation

The estimation of dynamic models is usually extremely computationally demanding, if not impossible. However, Bishop and Murphy (2011) show that by applying recent advances in the estimation of these models,² one is able to easily estimate a single future-value term (in a separate first stage) and incorporate it into the familiar Rosen estimating equation.

Assuming that $\epsilon_{i,t}$ is distributed logistically (with scale parameter σ), the value of reoptimizing, $v_{i,t}^1$, can be written as

$$u_{i,t}^1 + \beta \sigma_\epsilon E[\ln(e^{\frac{v_{i,t+1}^0}{\sigma_\epsilon}} + e^{\frac{\bar{v}_{i,t+1}^1}{\sigma_\epsilon}}) | s_{i,t}, d_{i,t} = 1],$$

where \bar{v}^1 denotes $E_c[v^1]$. The probability of reoptimizing can then be written as

$$(3) \quad P_{i,t}^1 = \frac{e^{\frac{\bar{v}_{i,t}^1}{\sigma_\epsilon}}}{e^{\frac{v_{i,t}^0}{\sigma_\epsilon}} + e^{\frac{\bar{v}_{i,t}^1}{\sigma_\epsilon}}}.$$

Rearranging the log probability of reoptimizing in period $t + 1$,

$$\ln\left(e^{\frac{v_{i,t+1}^0}{\sigma_\epsilon}} + e^{\frac{\bar{v}_{i,t+1}^1}{\sigma_\epsilon}}\right) = \frac{\bar{v}_{i,t+1}^1}{\sigma_\epsilon} - \ln(P_{i,t+1}^1),$$

reveals a mapping between value functions and conditional choice probabilities. This allows us to rewrite $v_{i,t}^1$ as a function of the probability of reoptimizing in period $t + 1$:

$$u_{i,t}^1 + \beta \sigma_\epsilon E\left[\frac{\bar{v}_{i,t+1}^1}{\sigma_\epsilon} - \ln(P_{i,t+1}^1) | s_{i,t}, d_{i,t} = 1\right].$$

Recall that if $d_{i,t} = 1$, the household then makes the continuous choice of how much x to consume. In this paper, we assume that the household's current choice of x affects only next period's reoptimization decision by determining next period's endowment.³ In other words, the household's choice of x does not affect the value of reoptimizing in period $t + 1$. (The current

² See Peter Arcidiacono and Robert A. Miller (2010), which builds off the framework laid out in V. Joseph Hotz and Miller (1993).

³ This assumption rules out certain types of wealth effects.

choice of x does, however, affect the value of *not* reoptimizing in period $t + 1$.) Thus:

$$(4) \quad \frac{\partial E[\bar{v}_{i,t+1}^1 | \mathbf{s}_{i,t}, d_{i,t} = 1]}{\partial x_{i,t}} = 0$$

and x^* is then given by the argument that maximizes:

$$u_{i,t}^1 - \beta \sigma_\epsilon E[\ln(P_{i,t+1}^1) | \mathbf{s}_{i,t}, d_{i,t} = 1].$$

For notational convenience, we define a future value component as

$$FV(x_{i,t}) = E[\ln(P_{i,t+1}^1) | \mathbf{s}_{i,t}, d_{i,t} = 1].$$

Using the first-order condition for $x_{i,t}^*$, we form the following simple estimating equation where primes denote the derivative with respect to x :

$$(5) \quad u'(x_{i,t}, \mathbf{h}_i, \mathbf{z}_i, \eta_{i,t}; \boldsymbol{\alpha}) - r'(x_{i,t}, \mathbf{h}_i; \boldsymbol{\gamma}) - \beta \sigma_\epsilon FV'(x_{i,t}) = 0.$$

Setting $\beta = 0$, this equation becomes the familiar estimating equation from the traditional approach, where the marginal increase in price is equated with the marginal benefit associated with increased x . The dynamic approach requires that the marginal increase in current price is equated with the marginal benefit of increased x in the current period *plus* the associated change in discounted future utility.

From a computational standpoint, the dynamic approach requires only the additional first-stage estimation of $FV'(x_{i,t})$ (i.e., the estimation of the change in the future probability of reoptimizing).⁴

A small complication exists as $FV'(x_{i,t})$ is correlated with the error, $\eta_{i,t}$, as discussed in Dennis Epple (1987) and Timothy J. Bartik (1987). However, one can easily solve this either by using market dummies as instruments for $FV'(x_{i,t})$ (as suggested by Bartik) or by employing the

econometric inversion estimator developed in Bishop and Christopher Timmins (2010).⁵

C. Empirical Specification

In our estimation, we derive households' willingness to pay to avoid violent crime in the Bay Area of California.⁶ We treat each county in the Bay Area as a separate market, denoted k , and allow the parameters of the rent function to vary by market.⁷ For household attributes, \mathbf{z} , we include race, income, and year. For housing attributes, \mathbf{h} , we include age, square footage, lot size, number of rooms, census-tract fixed effects, and year.

We assume that the preference shock, $\eta_{i,t}$, is distributed i.i.d. $N(0, \sigma_\eta)$ over both households and time. In addition, we make the simplifying assumption that $\eta_{i,t}$ is observed after the household decides whether to reoptimize, but before the household decides how much crime to consume. Bishop and Murphy (2011) discuss how to estimate the model under more general assumptions about $\eta_{i,t}$.

Assuming a log specification for the rental function (with error e_i) and setting $\beta = 0.95$, we parameterize flow utility (equation (1)) as

$$u_{i,k,t}^j = \alpha_0 + (\mathbf{z}_i^T \boldsymbol{\alpha}_1 + \eta_{i,t})x_{i,t} + \mathbf{h}_i^T \boldsymbol{\alpha}_2 - \exp(\gamma_{0,k} + \gamma_{1,k}x_{i,t} + 0.5\gamma_{2,k}x_{i,t}^2 + \mathbf{h}_i^T \boldsymbol{\gamma}_3 + e_i).$$

Letting hats denote known parameters from the first-stage estimation, the household's first-order optimality condition for x (equation (5)) is given by

$$(\hat{\gamma}_{1,k} + \hat{\gamma}_{2,k} x_{i,t})r_{i,t} = \mathbf{z}_i^T \boldsymbol{\alpha}_1 - \beta \sigma_\epsilon \widehat{FV}'(x_{i,t}) + \eta_{i,t}$$

⁵ See Ivar Ekeland, James J. Heckman, and Lars Nesheim (2004) and Nicolai V. Kuminoff and Jaren C. Pope (2010) (and the papers cited therein) for a discussion of the identification of the hedonic model.

⁶ Violent crimes are defined by RAND as "crimes against people, including homicide, forcible rape, robbery, and aggravated assault."

⁷ We use data from the following five counties: Alameda, Contra Costa, Marin, San Mateo, and Santa Clara.

⁴ For simplicity, households take expectations only with regard to future crime. See Bishop and Murphy (2011) for details on estimating the model when households are also forward-looking with respect to price parameters.

where $r_{i,t}$ is the household's observed housing rent in the data.⁸

This is our main estimating equation. We estimate this in the second stage using the observed choices of $x_{i,t}^*$ by the movers in the data, as nonmovers are not assumed to be satisfying the first-order condition for x . In addition to estimating the parameters of the rent function in the first stage, we recover the change in the future probability of reoptimizing. We accomplish this by estimating the probability of reoptimizing with a flexible Logit and the transition of violent crime with an AR(1) regression.

II. Data

The main dataset we employ is a unique two-sided panel of housing attributes and buyer characteristics. The housing data include detailed characteristics of all houses that sold over the period 1990 to 2008, including geographic coordinates. We are able to merge the buyer characteristic data on race and income (for all buyers taking out a mortgage) provided by the Home Mortgage Disclosure Act.⁹ Finally, we are able to create a unique, distance-weighted measure of the number of violent crimes for each house using data reported for 79 cities in the RAND California Database.

III. Results

The estimation results from both the dynamic model and the myopic model are presented in Table 1.¹⁰ Given the large number of observations ($N = 369,015$), all estimates are, not surprisingly, significant at the 1 percent level based on bootstrapped standard errors. For ease of exposition, we do not report the year-specific willingness-to-pay intercepts.

We find that the average household dislikes violent crime ($\text{mean}(\mathbf{z}_i^T \boldsymbol{\alpha}_1) < 0$) and is willing to pay \$13.45 per year to avoid one additional crime per 100,000 residents. This translates to a

⁸ In practice, we follow the literature and define the yearly rental equivalent for owners as 0.075^* (property value).

⁹ For a detailed description of this merge, see Patrick Bayer et al. (2010).

¹⁰ We estimate the price functions separately for each county. In all cases, price is decreasing in crime ($\gamma_{1,k} < 0$) but at a decreasing rate ($\gamma_{2,k} > 0$). The same price function is used for the estimation of both the dynamic and myopic models.

TABLE 1—ESTIMATION RESULTS

	Dynamic	Myopic
$\text{mean}(\mathbf{z}_i^T \boldsymbol{\alpha}_1)$	-13.45	-10.66
α_{Income}	-0.06 (0.002)	-0.05 (0.001)
α_{Black}	1.40 (0.298)	0.73 (0.092)
α_{Hispanic}	1.70 (0.203)	1.00 (0.052)
α_{White}	-2.63 (0.125)	-1.62 (0.125)
σ_ϵ	5,923.76 (1,041.70)	- -
Observations	369,015	369,015

willingness to pay of \$471.86 per year to reduce total violent crime by 10 percent at the average level of violent crime (350.92 per 100,000 residents).

We find that, on average, white households have the strongest distaste for violent crime, while Hispanic households have the weakest; white households are willing to pay \$4.32 more than Hispanic households to avoid one additional crime per 100,000 residents.¹¹ We find that an additional \$1,000 in income increases willingness to pay by \$0.06, all else equal. This translates to an income elasticity of 0.56 calculated at the mean income of \$118,941 (in 2000 dollars).

The coefficient on the future value term, σ_ϵ , implies a reasonable standard deviation of moving costs of \$10,745.

In the myopic model, we find the average household is willing to pay only \$10.66 per year to avoid an additional violent crime per 100,000 residents. This figure represents a 20.74 percent downward bias when compared with the estimate from the dynamic model.¹²

With crime falling over our sample period, it may be optimal for a household to choose a house with relatively high crime at present. While the dynamic model captures this optimal forward-looking behavior, the myopic model

¹¹ The omitted race is Asian.

¹² The test for whether the myopic willingness to pay is statistically different from the dynamic willingness to pay is simply the test for whether the coefficient on the future value term (σ_ϵ) is significantly different from zero.

interprets a higher-crime choice as a weaker distaste for violent crime.

IV. Conclusion

We estimate a dynamic model of household choice and use it to calculate a willingness to pay to avoid violent crime. By introducing moving costs into the hedonic framework, the problem is broken into a two-part, discrete-continuous decision, allowing for the application of recent advances in the estimation of this class of model.

We apply both our dynamic model and the traditional, myopic model to a rich, two-sided panel dataset describing the Bay Area of California between 1990 and 2008. Estimates derived using the dynamic model imply a mean willingness to pay of \$472 per year to avoid a 10 percent increase in violent crime and suggest substantial preference heterogeneity in the observed characteristics of income and race.

Estimates derived using the unrealistic myopic model are found to suffer from a 21 percent downward bias. Considering benefit-cost analyses and the provision of local public goods (such as police), the myopic model would understate a community of 100,000 local residents' joint willingness to pay to avoid a single additional violent crime by approximately \$278,870 per year.

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