Hedonic Prices and Implicit Markets: Estimating the Marginal Willingness to Pay For Large Reductions in Crime Without Instrumental Variables*

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Abstract

Since the publication of Rosen's "Hedonic Prices and Implicit Markets", property value hedonics has become the workhorse model for valuing local public goods and amenities, despite a number of well-known and well-documented econometric problems. For example, Bartik (1987) and Epple (1987) each describe a source of endogeneity in the second stage of Rosen's two-step procedure that has proven difficult to overcome using standard econometric arguments. This problem has led researchers to avoid estimating marginal willingness-to-pay functions altogether, relying instead on the first-stage hedonic price function, which can only be used to value *marginal* changes. We propose a new econometric procedure to recover the marginal willingness-to-pay function that avoids these endogeneity problems while remaining computationally light and easy to implement. We apply this estimator to data on large changes in violent crime rates in the Los Angeles and San Francisco metropolitan areas. Results indicate that marginal willingness to pay increases by between twenty to thirty cents with each additional case of violent crime per 100,000 residents, suggesting that simply using the first-stage hedonic price function to value non-marginal reductions in crime (like those that occurred during the 1990s) may lead to severely biased estimates of welfare.

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1 Introduction

Dating back to the work of Court (1939), Grilliches (1961) and Lancaster (1966), hedonic techniques have been used to estimate the implicit prices associated with the attributes of differentiated products. Rosen's (1974) seminal work proposed a theoretical structure for the hedonic regression and a two-stage procedure for the recovery of marginal willingness to pay (MWTP) functions for heterogeneous individuals. Importantly, his two-stage approach allowed for two sources of preference heterogeneity: individuals' MWTPs could differ with (i) their individual attributes and (ii) the quantity of the product attribute that they consume. The latter is particularly important when considering non-marginal policy changes (i.e., any change that is large enough to alter the individual's willingness to pay at the margin). The two-stage procedure suggested by Rosen (and further developed by subsequent authors) uses variation in implicit prices (obtained either by combining data from multiple markets or by allowing for non-linearity in the hedonic price function) to identify a MWTP function.

With Rosen (1974) as a backdrop, property value hedonics has become the workhorse model for valuing local public goods and environmental amenities, despite a number of well-known and well-documented econometric problems.[1] Our concern in this paper is with an important problem that arises in the second stage of Rosen's two-step procedure. In separate papers, Bartik (1987) and Epple (1987) describe a source of endogeneity that is difficult to overcome using standard exclusion restriction arguments. Specifically, they note that unless the hedonic price function is linear, the hedonic price of a product attribute varies systematically with the quantity consumed. The researcher therefore faces a difficult endogeneity problem in the application of Rosen's second stage. Moreover, because of the equilibrium features of the hedonic model, there are very few natural exclusion restrictions that one can use to solve this endogeneity problem. In particular, within-market supply-side shifters – the typical instrument choice when estimating a demand equation – are not valid in this context. This has generally left researchers to choose from a variety of weak instrument strategies or instruments based on cross-market preference homogeneity assumptions that may be difficult to justify.[2] With a few exceptions, the hedonics literature has subsequently ignored Rosen's second stage, focusing instead on recovering estimates of the hedonic price function and valuing only marginal changes in amenities [see, for example, Black (1999), Gayer, Hamilton, and Viscusi (2000), Bui and Mayer (2003), Davis (2004), Figlio and Lucas (2004), Chay and Greenstone (2005), Linden and Rockoff (2008), Pope (2008), Greenstone and Gallagher

[1]See Taylor (2003) and Palmquist (2005) for a comprehensive discussion with a particular focus on environmental applications. Some of these problems arise in the first stage of Rosen's two-step procedure; for example, omitted variables that may be correlated with the local attribute of interest. There is a large and growing literature that describes both quasi-experimental and structural solutions to this problem (see Parmeter and Pope (2009) for a discussion).

[2]Bound, Jaeger, and Baker (1995) discusses the biases that result from using weak instruments (i.e., instruments that do a poor job of predicting the endogenous variable).

(2008), Bajari, Cooley, Kim, and Timmins (2010), and Gamper-Rabindran, Mastromonaco, and Timmins (2011)].[3]

In this paper, we propose an estimation procedure for the recovery of the structural parameters underlying the MWTP function that avoids the Bartik-Epple endogeneity problem altogether. We do this by exploiting the relationship between the quantity of the amenity being consumed and the attributes of the individuals doing the consumption. That such a relationship should exist in hedonic equilibrium goes back to the idea of "stratification" found in Ellickson (1971), which became the basis for the estimable Tiebout sorting models of Epple and a variety of co-authors.[4] Our proposed method is identified even in a single-market setting, given a flexible representation of the hedonic price function. Importantly, our procedure is computationally simple and easy to implement. Moreover, it does not require any more in terms of data or assumptions than does the standard hedonic model.

To demonstrate the usefulness of this approach, we implement our estimation procedure using data on large changes in crime rates in the San Francisco Bay and Los Angeles Metropolitan Areas during the 1990's. We find that recovering the full MWTP function is economically important. In particular, an individual's marginal willingness to pay to avoid an incident of violent crime (measured by cases per 100,000 residents) increases by 20 to 30 cents with each additional incident. Non-marginal reductions in crime of the sort seen in California and the rest of the nation during the 1990's therefore have the potential to significantly affect MWTP. We find that naive estimators that ignore this effect yield estimates of total willingness to pay for crime reductions in Los Angeles and San Francisco that are significantly upwardly biased. Similar problems are likely to arise in other settings where policy changes are not marginal – e.g., air quality, school reform, hazardous waste remediation.

Finally, note that our analysis operates within the well-established confines of the theory found in the hedonics literature. Of particular importance, the hedonic model assumes that individuals are not able to re-optimize in response to large changes in amenities and local public goods. There is a growing literature on equilibrium sorting models that are designed to deal specifically with this issue. See Kuminoff, Smith, and Timmins (2010) for an overview.

This paper proceeds as follows. Section 2 describes the endogeneity problem discussed

[3]Deacon et al. (1998) noted that "To date no hedonic model with site specific environmental amenities has successfully estimated the second stage marginal willingness to pay function." Since that time, a number of papers have examined the problem of recovering preferences from hedonic estimates. Bajari and Benkard (2005) avoid the Bartik-Epple endogeneity problem by relying on strong parametric assumptions on utility that turn Rosen's second-stage from an estimation problem into a preference-inversion procedure. We report results based on their suggested procedure in our application. Ekeland, Heckman, and Nesheim (2004) provide an alternative approach to recovering MWTP that imposes very little in terms of parametric restrictions but requires an additive separability assumption in the MWTP specification.

[4]See, for example, Epple, Filimon and Romer (1984), Epple and Romano (1998), Epple and Platt (1998), and Epple and Sieg (1999).

by Bartik (1987) and Epple (1987) and reiterates the intuition for why that problem has been so difficult to solve with standard exclusion restrictions. Section 3 describes our alternative estimation procedure in detail, and Section 4 illustrates its properties with a series of Monte Carlo experiments. Section 4 describes the data used in our application – housing transactions data from the Los Angeles and San Francisco metropolitan areas between 1994 and 2007, combined with violent and property crime data from the RAND California Database. Section 5 reports the results of applying our estimator, as well as several alternative procedures from the literature, to these data. Finally, Section 6 concludes.

2 Why Has It Been So Difficult To Recover The MWTP Function?

In their respective 1987 articles, Epple and Bartik each discuss the econometric problems induced by the equilibrium sorting process that underlies the formation of the hedonic price function. In particular, unobserved determinants of tastes affect both the quantity of an amenity that an individual consumes and (if the hedonic price function is not linear) the hedonic price of the attribute.[5] In a regression like that described in the second stage of Rosen's two-step procedure, the quantity of the amenity that an individual consumes will therefore be endogenous. Moreover, the exclusion restrictions typically used to estimate a demand system (i.e., using supplier attributes as instruments) will not work because, in addition to affecting the quantity of amenity and the hedonic price paid for it, the unobservable component of preferences also determines the supplier from whom the individual purchases. Supplier attributes, which might naturally be used to trace-out the demand function, are therefore correlated with the unobserved determinants of MWTP because of the sorting process underlying the hedonic equilibrium.

To make these ideas concrete, consider the following simple example, which is based on Epple's model. A quadratic hedonic price function is given by:

$$P_i = \beta_0 + \beta_1 Z_i + \frac{\beta_2}{2} Z_i^2 + \epsilon_i \tag{1}$$

where $i = 1, \ldots, N$ indexes houses, P_i measures the price of house i, and Z_i measures the level of the amenity associated with that house (for the sake of illustration, we ignore other

[5] The linear hedonic price function assumes that attributes can be unbundled and repackaged in any combination without affecting their marginal value (e.g., the marginal value of another bedroom is the same regardless of how many bedrooms a house already has). In most empirical settings, this assumption is unrealistic.

amenities and house attributes). For now, we consider data from just a single market, but allow for multi-market data below. The linear price gradient associated with this hedonic price function is:

$$P_i^Z \equiv \frac{\partial P_i}{\partial Z_i} = \beta_1 + \beta_2 Z_i \tag{2}$$

where we define P_i^Z as the implicit price of Z_i at house i. The second stage of Rosen's procedure seeks to recover the coefficients of demand (or marginal willingness-to-pay) and supply functions for the attribute Z from the first-order conditions of the equilibrium relationships:

$$P_i^Z = \alpha_0 + \alpha_1 Z_i^d + \alpha_2 X_i^d + \nu_i^d \quad \text{(demand)} \tag{3}$$

$$P_i^Z = \gamma_0 + \gamma_1 Z_i^s + \gamma_2 X_i^s + \nu_i^s \quad \text{(supply)} \tag{4}$$

where X_i^d and X_i^s represent attributes of the buyers and sellers of house i, respectively. ν_i^d and ν_i^s similarly represent unobserved idiosyncratic shocks to tastes and marginal costs, respectively.

The problem we consider in this paper arises from the fact that Z_i^d must necessarily be correlated with ν_i^d because of the hedonic sorting process. This is easily shown in the following equation. Noting that $Z_i = Z_i^d$ in hedonic equilibrium and combining equations (2) and (3) yields (with some re-arranging):

$$Z_i = \frac{1}{\beta_2 - \alpha_1}[(\alpha_0 - \beta_1) + \alpha_2 X_i^d + \nu_i^d] \tag{5}$$

Equation (5) makes explicit that Z_i will be correlated with ν_i^d. Therefore, in order to estimate equation (3) directly, the literature has sought an instrument for Z_i^d.

The typical approach to estimating demand functions with endogenous quantities uses supply function shifters. The problem with that approach in this context, however, is that hedonic sorting induces a correlation between ν_i^d and X_i^s. Put differently, ν_i^d determines the supplier from whom individual i purchases, so that X_i^s cannot be used to instrument for Z_i^d.[6]

[6] To see this explicitly, derive an equation similar to (5) based on the supply relationship in (4). Noting that $Z_i^s = Z_i^d$ in hedonic equilibrium, set this equation equal to equation (5). Solve this equation for X_i^s, and it becomes apparent that, as long as suppliers are heterogeneous (i.e., $\beta_2 \neq \gamma_1$), X_i^s will be a function of ν_i^d.

In their respective papers, Epple and Bartik propose alternative instrumental variables strategies to deal with this problem. Bartik, for example, suggests instrumenting for Z_i^d with market indicator variables. The intuition for this strategy is that differences in the distribution of suppliers across markets will provide an exogenous source of variation in the equilibrium quantity of the amenity chosen by each individual. The problems with this approach are that it requires strong assumptions about cross-market preference homogeneity and that the instrument may not induce sufficient variation in the endogenous variable. We return to this IV strategy, along with several other commonly used estimation procedures, later in the paper.

3 Model and Estimation

In this section, we describe an alternative econometric approach, which avoids this difficult endogeneity problem altogether while not imposing strong assumptions on the shape of preferences. Beginning with Rosen, the traditional approach has been to equate the implicit price of an amenity Z (read off of the hedonic price function) to its marginal benefit (a function of Z) and use the resulting expression as the estimating equation. The literature that followed Rosen has retained this framework while proposing corrective strategies to deal with the endogeneity of Z. We note that, while the first-order conditions for hedonic equilibrium provide a set of equations that will hold in equilibrium, nothing requires us to write those conditions in this manner. While it does provide an intuitive interpretation of utility maximization, it is the "implicit price equals marginal benefit" specification which has created the endogeneity problem that has plagued this literature for decades.

Returning to the basic structure of the hedonic model, there is no fundamental endogeneity problem. When choosing how much of the amenity Z to consume, individuals take the hedonic price function (i.e., a flexible function of Z) as given and choose Z_i^* to maximize their utility based on their individual preferences. These preferences are determined by a vector of observed individual characteristics, X_i^d, and unobserved taste shifters, ν_i^d. As ν_i^d and X_i^d are typically assumed to be orthogonal in the hedonic model, we are left with a familiar econometric modeling environment: a single endogenous outcome variable, Z, which is a function of a vector of exogenous variables, X_i^d, and an econometric error, ν_i^d. Intuitively, our approach finds the parameters of the MWTP function that maximize the likelihood of observing each individual's chosen Z_i^*.

We first consider the case in which a closed-form solution for Z exists and the estimation approach is intuitive and simple. In the more general case where a closed-form for Z does not exist, we show that by using a simple change of variables technique, it is still straightforward to compute the likelihood of observing Z.

3.1 Identification – Common MWTP Intercept Across Markets

Consider first the simple model described above, where data are taken from multiple markets indexed by k. After having estimated a different hedonic price function for each market, equation (5) can be re-written as:

$$Z_{i,k} = (\frac{\alpha_0 - \widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}} - \alpha_1}) + (\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}} - \alpha_1})X^d_{i,k} + (\frac{1}{\widehat{\beta_{2,k}} - \alpha_1})\nu^d_{i,k} \tag{6}$$

where$\widehat{\ }$s are used to indicate that a parameter was recovered in a previous stage, and we allow α_2 to vary by market. In this case, two sources of variation identify the slope of the MWTP function. The first source is that we observe different hedonic prices for Z across markets with different *average* levels of consumption of Z. Markets with higher hedonic prices (i.e., higher values of $\beta_{1,k}$ and $\beta_{2,k}$) should have lower consumption, all else equal. The sensitivity of mean Z across markets to changes in price is what identifies the slope of the MWTP curve. The second source is the variation across markets in the *variance* of Z, conditional on the known parameters. Markets with steeper hedonic price gradients (i.e., higher values of $\beta_{2,k}$) should have lower variance of observed Z. The sensitivity of the variance of observed Z across markets to changes in the slope of the price gradient also helps to identify the slope of the MWTP curve. The intercept, α_0, and the coefficients on X ($\alpha_{2,k}$) are identified by mean Z and the covariance between Z and X, respectively.

3.2 Identification – Variation in MWTP Intercept Across Markets

Next consider the MWTP function specified in (3), but allow α_0 to vary across markets. We arrive at the following first-order condition:

$$P^Z_{i,k} = \alpha_{0,k} + \alpha_1 Z_{i,k} + \alpha_{2,k} X^d_{i,k} + \nu^d_{i,k} \tag{7}$$

Using the information found in the first-stage estimation of the hedonic price function for each market k, we can rearrange equation (7) to arrive at the following equation, which describes how the consumption of amenity Z varies with observable individual attributes X^d as a result of equilibrium sorting.

$$Z_{i,k} = (\frac{\alpha_{0,k} - \widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}} - \alpha_1}) + (\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}} - \alpha_1})X^d_{i,k} + (\frac{1}{\widehat{\beta_{2,k}} - \alpha_1})\nu^d_{i,k} \tag{8}$$

In particular, equation (8) contains all of the information necessary to recover the parameters describing individual preferences. Making the distributional assumption that $\nu_{i,k}^d \sim N(\mu, \sigma^2)$, Z is then distributed normally with mean $((\frac{\alpha_{0,k}-\widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}}-\alpha_1}) + (\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}}-\alpha_1})X_{i,k}^d))$ and standard deviation $(\frac{\sigma}{\beta_{2,k}-\alpha_1})$. This reveals a straightforward maximum likelihood estimation approach to estimating the remaining parameters. In particular, we find the vector of parameters, $\{\alpha_{0,k}, \alpha_1, \alpha_{2,k}, \sigma\}$, that maximizes the likelihood of the observed vector $\{Z_i\}_{i=1}^N$, $\Pi_{i=1}^N \, \ell(Z_i, X_{i,k}^d; \alpha, \sigma)$, where:

(9)
$$\ell(Z_i, X_{i,k}^d; \alpha, \sigma) = \frac{1}{(\frac{\sigma}{\widehat{\beta_{2,k}}-\alpha_1})\sqrt{2\pi}} \exp\{-\frac{1}{2(\frac{\sigma}{\widehat{\beta_{2,k}}-\alpha_1})^2}(Z_{i,k} - ((\frac{\alpha_{0,k}-\widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}}-\alpha_1}) + (\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}}-\alpha_1})X_{i,k}^d))^2\}$$

The intuition behind this estimator is straightforward, as we are simply maximizing the likelihood of each individual's Z_i that is observed in the data. α_1 is identified by one source of variation in the data - the difference in variances of the optimally chosen Z's across markets, following the intuition above. The market-specific intercepts of the MWTP function are identified by mean differences in consumed Z across markets, with higher levels of observed Z associated with higher values for $\alpha_{0,k}$. The coefficients on attributes ($\alpha_{2,k}$) are identified in the manner described in the previous sub-section.

3.3 Identification With Exactly Two Markets – Indirect Least Squares

It is possible to estimate a closed-form version of the model described by equation (8) using a simple GMM approach. In fact, in the special case with exactly two markets, equation (8) can be estimated using the extremely transparent indirect least squares (ILS) procedure. With six equations and six unknowns, it becomes a simple matter to recover the structural parameters $\{\alpha_{0,k},\, \alpha_1,\, \alpha_{2,k},\, \sigma\}$ from the reduced-form parameters $\{\theta_{0,k},\, \theta_{1,k},\, \sigma_{u,k}\}$, by exploiting a unique mapping between the two sets:

(10)
$$Z_{i,k} = \underbrace{(\frac{\alpha_{0,k}-\widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}}-\alpha_1})}_{\theta_{0,k}} + \underbrace{(\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}}-\alpha_1})}_{\theta_1} X_i^d + \underbrace{(\frac{1}{\widehat{\beta_{2,k}}-\alpha_1})\nu_{i,k}^d}_{u_{i,k}}$$

In the case of more than two markets, one might add richer heterogeneity to the MWTP function (e.g., by parameterizing the slope of MWTP or the variance of ν) in order to take advantage of all available information. Alternatively, one may simply use that additional information to over-identify model parameters.

3.4 The General Model – When a Closed-Form Solution for Z Does Not Exist

We conclude by considering the general form of our model, in which there is not a closed-form solution for Z. This will be the case for many non-linear gradient specifications like the one we use in our application.[7] In this case, we are still able to estimate the model using maximum likelihood with a simple change-of-variables technique.

As $\nu_{i,k}$ is an additively-separable error that enters individuals' utility functions and does not enter the hedonic price function, it is trivial to find a closed-form solution for it. In this subsection, we show that by employing a basic change-of-variables (from Z to ν), a closed-form solution for ν is sufficient for forming a likelihood for Z.

Consider the following example where we impose no parametric assumption on the price function, $P(Z, X; \beta)$. As the gradient is now an implicit function of Z, $P'(Z, X; \beta)$, the first-order condition for utility maximization, can no longer be rearranged to find a closed-form solution for Z:

$$\alpha_{0,k} + \alpha_1 Z_{i,k} + \alpha_{2,k} X_i^d + \nu_{i,k}^d - P'(Z, X; \beta) = 0 \tag{11}$$

However, we are still able to find a closed-form solution for $\nu_{i,k}^d$:

$$\nu_{i,k}^d = -\alpha_{0,k} - \alpha_1 Z_{i,k} - \alpha_{2,k} X_i^d + P'(Z, X; \beta) \tag{12}$$

Making the same distributional assumption – i.e., that $\nu_{i,k}^d \sim N(\mu, \sigma^2)$ – and using a textbook application of change-of-variables, it is straightforward to form the likelihood, $\Pi_{i=1}^N \ \ell(Z_i, X_{i,k}^d; \alpha, \sigma)$, where:

$$\ell(Z_i, X_{i,k}^d; \alpha, \sigma) = \frac{1}{(\frac{\sigma}{\widehat{\beta_{2,k}} - \alpha_1})\sqrt{2\pi}} \exp\{-\frac{1}{2\sigma^2}(\nu_{i,k}^d)^2\} |\frac{\partial \nu_{i,k}^d}{\partial Z_i}| \tag{13}$$

To implement this maximum likelihood procedure, we need only calculate the value of $\nu_{i,k}^d$ consistent with the observed value of $Z_{i,k}$ (given α and $P'(Z, X; \beta)$) and the determinant of the Jacobian associated with the change of variables. These terms are, respectively, given by:

[7] As a general rule, one should not expect the hedonic gradient to be linear (Heckman, Ekeland, and Nesheim (2004)).

$$\nu_{i,k}^d = P'(Z_i, X_{i,k}; \widehat{\beta}_k) - \alpha_{0,k} - \alpha_1 Z_i - \alpha_{2,k} X_{i,k}^d \tag{14}$$

$$|\frac{\partial \nu_i^d}{\partial Z_i}| = |P''(Z_i, X_{i,k}; \widehat{\beta}_k) - \alpha_1| \tag{15}$$

3.5 Monte Carlo Evidence

In this section, we provide Monte Carlo evidence on the performance of our proposed estimator. We begin with Monte Carlo simulations of the simplest two-market model. From this starting point, we increase the number of markets (k), introduce heterogeneity in the slope of the gradients, and increase the level of heterogeneity in both the market-specific gradient intercepts and slopes.

In all cases, we keep the total number of observations fixed at $n = 5,000$ with observations per market given by $\frac{n}{k}$. The number of Monte Carlo runs per experiment is $1,000$. We set the structural parameters to the following values: α_0=3, $\alpha_1 = -0.3$, and σ=0.5.

Over different experiments, we vary the data generating process in two ways: (i) by increasing the number of markets and (ii) by increasing the variance of the gradient parameters across markets. We allow the number of markets to take on the following values: $k = \{2, 5, 10, 50\}$. Finally, we specify that $\beta_{1,k} = 2 + \eta_1$ and $\beta_{2,k} = 0.7 + \eta_2$ where $\eta_1 \sim \gamma_1 * U(-0.3, 0.3)$ and $\eta_2 \sim \gamma_2 * U(-0.15, 0.15)$. We allow γ to take on the following values: $\gamma_1 = 1, 2, 3$ and $\gamma_2 = 0, 1, 2, 3$.

Table 1 presents the results from the Monte Carlo experiments. These results show that there is very little bias in the finite samples, even in the case of only two markets with limited information coming from each market. The standard deviations of the estimated parameters are small relative to the parameters and, more importantly, we find the efficiency of the estimator increasing in both market size and gradient information. The "% fail to reject" statistic is calculated by computing a 95% confidence interval for each estimate of α_0, α_1, and σ and seeing if the true value lies outside of that range. As expected, we find that the true parameter would be rejected approximately 5% of the time (although, in some cases, the true parameter is rejected less than 5% of the time, indicating that the distribution is not exactly normal in small samples).

For comparison, we run the same set of Monte Carlo experiments using the traditional two-step Rosen framework. Results are presented in Table 2. As expected, the estimator performs poorly, particularly when it comes to recovering the slope of the MWTP function (*i.e.*, α_1). In all cases (even with 50 markets and maximum variation across markets), both the MWTP intercept (α_0) and the standard deviation of the preference shock (σ) are significantly

Table 1: Bishop-Timmins Results (common α_0 across markets)

	mean(α_0)	mean(α_1)	mean(σ)	std(α_0)	std(α_1)	std(σ)	% fail α_0	% fail α_1	% fail σ
$k = 2, \gamma_1 = 1, \gamma_2 = 0$	3.0035	-0.3036	0.5015	0.0709	0.0706	0.0357	0.0320	0.0330	0.0340
$k = 2, \gamma_1 = 2, \gamma_2 = 0$	3.0004	-0.3006	0.5000	0.0354	0.0347	0.0182	0.0500	0.0460	0.0460
$k = 2, \gamma_1 = 3, \gamma_2 = 0$	3.0000	-0.3001	0.4998	0.0241	0.0231	0.0127	0.0490	0.0480	0.0450
$k = 2, \gamma_1 = \gamma_2 = 1$	3.0015	-0.3016	0.5005	0.0460	0.0452	0.0233	0.0410	0.0420	0.0440
$k = 2, \gamma_1 = \gamma_2 = 2$	3.0002	-0.3003	0.4999	0.0240	0.0222	0.0124	0.0470	0.0470	0.0500
$k = 2, \gamma_1 = \gamma_2 = 3$	3.0000	-0.3001	0.4997	0.0171	0.0146	0.0091	0.0450	0.0480	0.0460
$k = 5, \gamma_1 = \gamma_2 = 1$	3.0002	-0.3003	0.4999	0.0342	0.0331	0.0175	0.0450	0.0540	0.0560
$k = 5, \gamma_1 = \gamma_2 = 2$	2.9998	-0.2999	0.4997	0.0182	0.0159	0.0097	0.0430	0.0570	0.0560
$k = 5, \gamma_1 = \gamma_2 = 3$	2.9998	-0.2999	0.4997	0.0133	0.0100	0.0074	0.0500	0.0560	0.0540
$k = 10, \gamma_1 = \gamma_2 = 1$	3.0002	-0.3003	0.4998	0.0309	0.0296	0.0158	0.0510	0.0520	0.0540
$k = 10, \gamma_1 = \gamma_2 = 2$	2.9998	-0.2999	0.4997	0.0166	0.0141	0.0089	0.0510	0.0540	0.0500
$k = 10, \gamma_1 = \gamma_2 = 3$	2.9998	-0.2999	0.4997	0.0123	0.0087	0.0069	0.0500	0.0530	0.0470
$k = 50, \gamma_1 = \gamma_2 = 1$	3.0000	-0.3001	0.4998	0.0285	0.0271	0.0147	0.0510	0.0520	0.0530
$k = 50, \gamma_1 = \gamma_2 = 2$	2.9998	-0.2999	0.4996	0.0155	0.0128	0.0084	0.0460	0.0510	0.0530
$k = 50, \gamma_1 = \gamma_2 = 3$	2.9998	-0.2999	0.4996	0.0117	0.0078	0.0066	0.0490	0.0540	0.0470

biased downwards. In addition, the MWTP slope is always biased upwards (as expected); in all but two of the experiments, the mean value of the slope takes on a positive value (implying an upward sloping demand curve). Finally, the standard error of each estimate is small, causing our estimated 95% confidence intervals to reject the true parameters in all of cases.

Finally, we run a set of experiments where the MWTP intercept varies by market. In particular, we specify $\alpha_{0,k} \sim U(2,4)$, while keeping $\alpha_1 = -0.3$ and $\sigma = 0.5$. Note that in this specification, we require heterogeneity in the the slope of the gradients. Our estimator performs well in each case, including the case with only two markets and minimum gradient heterogeneity. The results from these experiments are presented in Table 3.

4 Data

In our application, we estimate a series of hedonic price functions for each of two housing markets – the Los Angeles Metropolitan and San Francisco Bay Areas. Our primary variable of interest is the rate of violent crime, although we also control for house attributes, local property crime rates, and all other neighborhood attributes at the level of the census tract with a vector of fixed effects. Moreover, we allow the hedonic price function to vary over time. The data used to estimate these hedonic relationships are summarized in Table 4.

Table 2: Rosen Results (common α_0 across markets)

	mean(α_0)	mean(α_1)	mean(σ)	std(α_0)	std(α_1)	std(σ)	% fail α_0	% fail α_1	% fail σ
$k = 2, \gamma_1 = 1, \gamma_2 = 0$	2.0385	0.6615	0.0980	0.0026	0.0026	0.0003	1	1	1
$k = 2, \gamma_1 = 2, \gamma_2 = 0$	2.1381	0.5619	0.1857	0.0044	0.0042	0.0009	1	1	1
$k = 2, \gamma_1 = 3, \gamma_2 = 0$	2.2649	0.4350	0.2572	0.0053	0.0049	0.0017	1	1	1
$k = 2, \gamma_1 = \gamma_2 = 1$	2.0802	0.6129	0.1455	0.0035	0.0036	0.0007	1	1	1
$k = 2, \gamma_1 = \gamma_2 = 2$	2.2557	0.4224	0.2598	0.0055	0.0049	0.0019	1	1	1
$k = 2, \gamma_1 = \gamma_2 = 3$	2.4299	0.2332	0.3369	0.0068	0.0050	0.0029	1	1	1
$k = 5, \gamma_1 = \gamma_2 = 1$	2.1492	0.5381	0.1984	0.0048	0.0047	0.0012	1	1	1
$k = 5, \gamma_1 = \gamma_2 = 2$	2.4131	0.2525	0.3299	0.0068	0.0052	0.0028	1	1	1
$k = 5, \gamma_1 = \gamma_2 = 3$	2.6150	0.0358	0.4022	0.0079	0.0047	0.0038	1	1	1
$k = 10, \gamma_1 = \gamma_2 = 1$	2.1774	0.5076	0.2163	0.0050	0.0049	0.0014	1	1	1
$k = 10, \gamma_1 = \gamma_2 = 2$	2.4654	0.1963	0.3501	0.0071	0.0051	0.0031	1	1	1
$k = 10, \gamma_1 = \gamma_2 = 3$	2.6669	-0.0187	0.4185	0.0081	0.0045	0.0040	1	1	1
$k = 50, \gamma_1 = \gamma_2 = 1$	2.2022	0.4807	0.2309	0.0053	0.0050	0.0015	1	1	1
$k = 50, \gamma_1 = \gamma_2 = 2$	2.5067	0.1519	0.3652	0.0073	0.0050	0.0033	1	1	1
$k = 50, \gamma_1 = \gamma_2 = 3$	2.7046	-0.0582	0.4299	0.0082	0.0043	0.0042	1	1	1

Table 3: Bishop-Timmins Results (Market-specific $\alpha_{0,k}$)

	mean(α_1)	mean(σ)	std(α_1)	std(σ)
$k = 2, \gamma_1 = \gamma_2 = 1$	-0.3531	0.5263	0.2406	0.1209
$k = 2, \gamma_1 = \gamma_2 = 2$	-0.3139	0.5066	0.1028	0.0524
$k = 2, \gamma_1 = \gamma_2 = 3$	-0.3068	0.5031	0.0662	0.0345
$k = 5, \gamma_1 = \gamma_2 = 1$	-0.3277	0.5134	0.1535	0.0775
$k = 5, \gamma_1 = \gamma_2 = 2$	-0.3084	0.5037	0.0693	0.0359
$k = 5, \gamma_1 = \gamma_2 = 3$	-0.3045	0.5018	0.0431	0.0233
$k = 10, \gamma_1 = \gamma_2 = 1$	-0.3221	0.5103	0.1335	0.0675
$k = 10, \gamma_1 = \gamma_2 = 3$	-0.3068	0.5027	0.0606	0.0316
$k = 10, \gamma_1 = \gamma_2 = 3$	-0.3036	0.5012	0.0370	0.0204
$k = 50, \gamma_1 = \gamma_2 = 1$	-0.3193	0.5069	0.1220	0.0616
$k = 50, \gamma_1 = \gamma_2 = 2$	-0.3061	0.5003	0.0554	0.0290
$k = 50, \gamma_1 = \gamma_2 = 3$	-0.3033	0.4990	0.0333	0.0186

4.1 Property Transactions Data

The real estate transactions data we employ cover the five core counties of the San Francisco Bay Area (Alameda, Contra Costa, San Francisco, San Mateo, and Santa Clara) and the five counties that comprise the Los Angeles Metropolitan Area (Los Angeles, Ventura, San Bernadino, Riverside, and Orange) over the period 1994 to 2007. The data were purchased from DataQuick Inc. and include transaction dates, prices, loan amounts, and buyers', sellers', and lenders' names for all transactions. In addition, the data for the final observed transaction for each house include characteristics such as exact street address, square footage, year built, lot size, number of bedrooms, and number of bathrooms.

The process of cleaning the data involves a number of cuts. Many of these are made in order to deal with the fact that we only see housing characteristics at the time of the last sale, but we need to use housing characteristics from all sales as controls in our hedonic price regressions. We therefore seek to eliminate any observations where houses underwent major improvement or degradation. First, to control for land sales or re-builds, we drop all transactions where "year built" is missing or with a transaction date that is prior to "year built". Second, in order to control for property improvements (e.g., an updated kitchen) or degradations (e.g., water damage) that do not present as re-builds, we drop any house that ever appreciates or depreciates in excess of 50 percentage points of the county-year mean price change. We also drop any house that moves more than 40 percentiles between sales in the county-year distribution. Additionally, we drop transactions where the price is missing, negative, or zero. After using the consumer price index to convert all transaction prices into 2000 dollars, we drop one percent of observations from each tail to minimize the effect of outliers. Finally, as we merge in the pollution data using the property's geographic coordinates, we drop properties where latitude and longitude are missing.

This yields a final sample of 682,658 transactions in the San Francisco Bay Area and 1,696,981 transactions in the Los Angeles metropolitan area. Table 4 reports summary statistics for each housing market.

Table 4: Housing Data Summary Statistics

	Los Angeles Metro Area ($n = 1,696,981$)		San Francisco Metro Area ($n = 682,658$)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Price (constant 2000 dollars)	276,179	172,622	442,767	235,717
Year Built	1971.02	20.86	1967.74	23.49
Lot Size (sq. ft)	7,680.29	10,190.72	6,447.11	7,696.38
Square Footage	1,673.77	684.46	1682.87	686.34
Number Bathrooms	2.21	0.77	2.09	0.74
Number Bedrooms	3.08	0.91	3.04	1.09
Property Crimes (per 100,000 residents)	1,913.29	672.74	1,756.31	706.47
Violent Crimes (per 100,000 residents)	521.18	248.50	385.41	208.09

4.2 Home Buyers

We use information on the race and income of home buyers recorded on mortgage applications and published in accordance with the Home Mortgage Disclosure Act (HMDA) of 1975. HMDA data describe the race, gender, and income of the mortgage applicant along with the loan amount, mortgage lender's name, and census tract where the property is located. Because of the overlap between these variables and those provided by DataQuick, we are able to merge these two data sets. Bayer, McMillan, Murphy, and Timmins (2011) describes this merging procedure in detail and provides information on the quality of the merge. The merged HMDA-DataQuick data set is used to estimate the second stage of our analysis.

Table 5 reports summary statistics for the full sample of home buyers in each city. Compared with Los Angeles, the San Francisco Bay Area has a higher percentage of Whites and Asian-Pacific Islanders but a lower percentage of Hispanics. San Francisco also has a higher average income. The table also reports summary statistics for a sub-sample of individuals in each city who purchased a house in 1994 – this group will be used below to demonstrate the implications of our model for valuing non-marginal changes in crime rates.

Table 5: Home Buyer Summary Statistics (Full- and 1994- Samples)

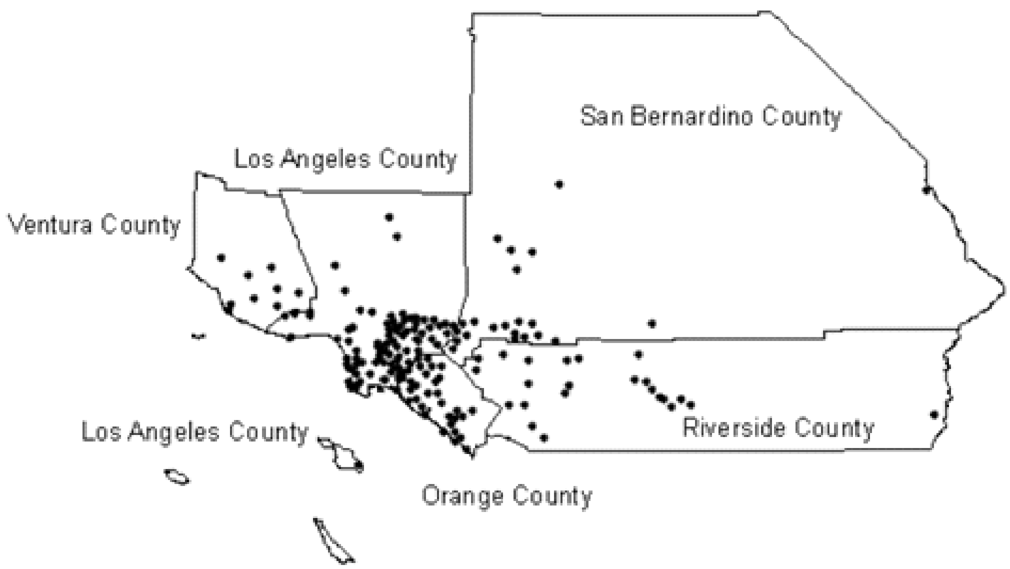
	Los Angeles Metro Area				San Francisco Metro Area			
	Full Sample ($n = 996,747$)		1994 Sample ($n = 59,108$)		Full Sample ($n = 468,598$)		1994 Sample ($n = 28,646$)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Price	297,153.3	176,412.91	230,667.14	136,460.35	450,207.27	230,459.33	325,777.5	172,249.44
Violent Crime	505.8	241.19	828.61	392.3	379.72	206.1	523.88	327.03
Income	96,440.99	115,703.8	85,332.61	101,193.76	122,674.35	109,641.99	102,537.5	96,038.61
White	0.57	0.5	0.59	0.49	0.58	0.49	0.66	0.47
Asian	0.13	0.33	0.13	0.33	0.26	0.44	0.21	0.41
Black	0.05	0.21	0.05	0.22	0.03	0.18	0.04	0.19
Hispanic	0.25	0.43	0.24	0.43	0.13	0.33	0.09	0.29

Prices and incomes are expressed in constant 2000 dollars. The violent crime rate is per 100,000 residents.

4.3 Crime Data

Crime statistics come from the RAND California data base, are organized by "city", and measure incidents per 100,000 residents. The data describe property and violent crime rates for 80 cities in the San Francisco metropolitan area and 175 cities in the Los Angeles metropolitan area between 1986 and 2008. Figures 1 and 2 illustrate the locations of these cities. Property crime is defined as "crimes against property, including burglary and motor vehicle theft", while violent crime is defined as "crimes against people, including homicide, forcible rape, robbery, and aggravated assault." Crime rates are imputed for each house in our data set using an inverse-distance weighted average of the crime rate in each city. We use the property crime rate as a control in our hedonic estimation and focus attention on violent crimes in our valuation exercise, as these crimes are less likely to be subject to systematic under-reporting (Gibbons (2004)).

Figure 1: Locations of Crime-reporting Cities within the Los Angeles Metro Area



Figures 3 and 4 illustrate the distribution of violent crime rates within each metropolitan area, and how average crime rates in each have declined over time. These downward trends are consistent with drops in violent crime rates over the same period in many parts of the US. Table 4 provides summary statistics for crime in each city, measured at the level of the house transaction. Table 5 reports mean violent crime rates measured at the level of the home buyer.

Figure 2: Locations of Crime-reporting Cities within the San Francisco Metro Area

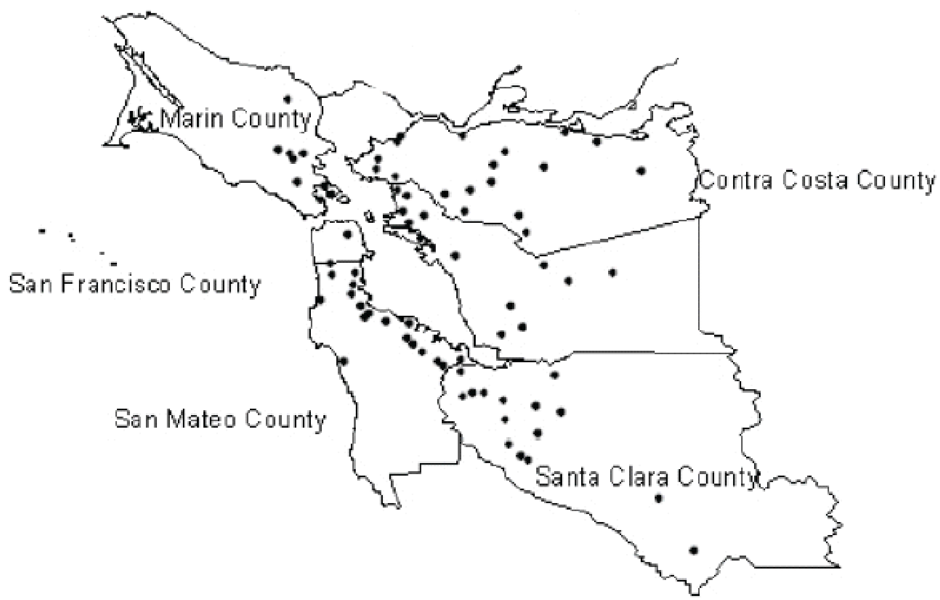


Figure 3: Distribution of Violent Crime Rates (Incidents per 100,000 Residents)

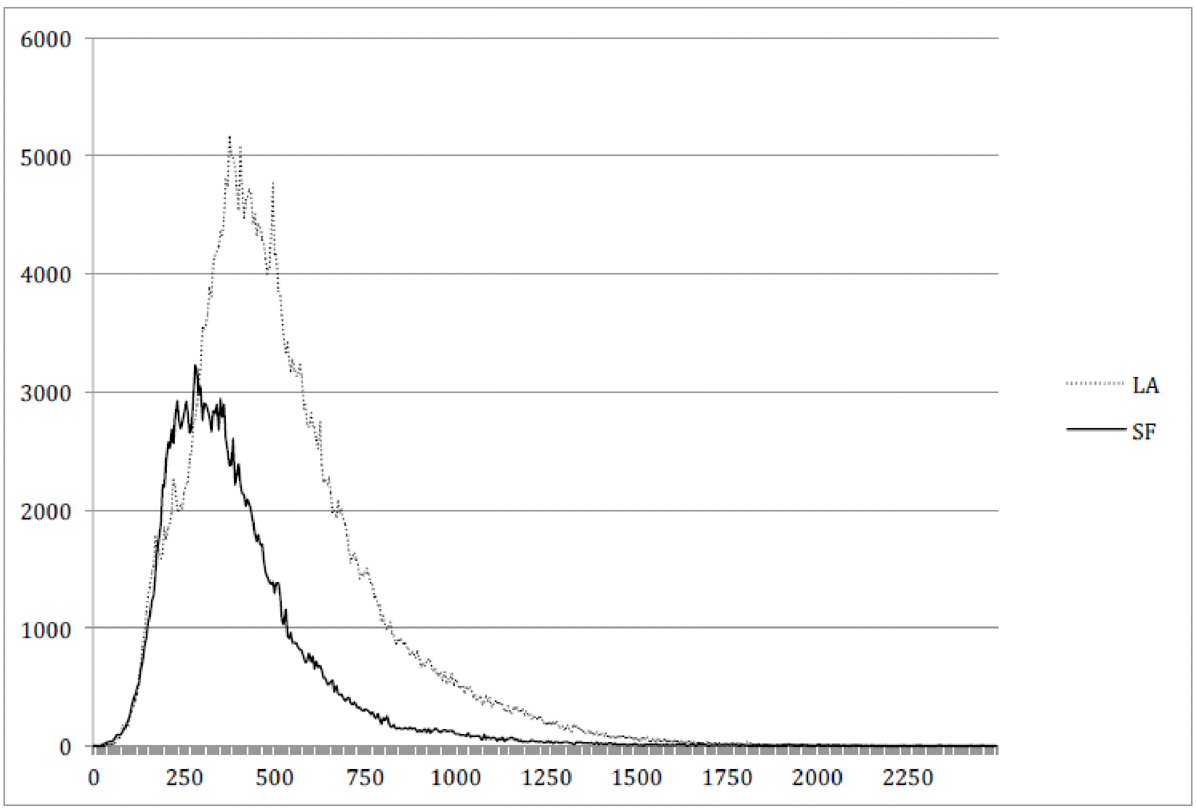
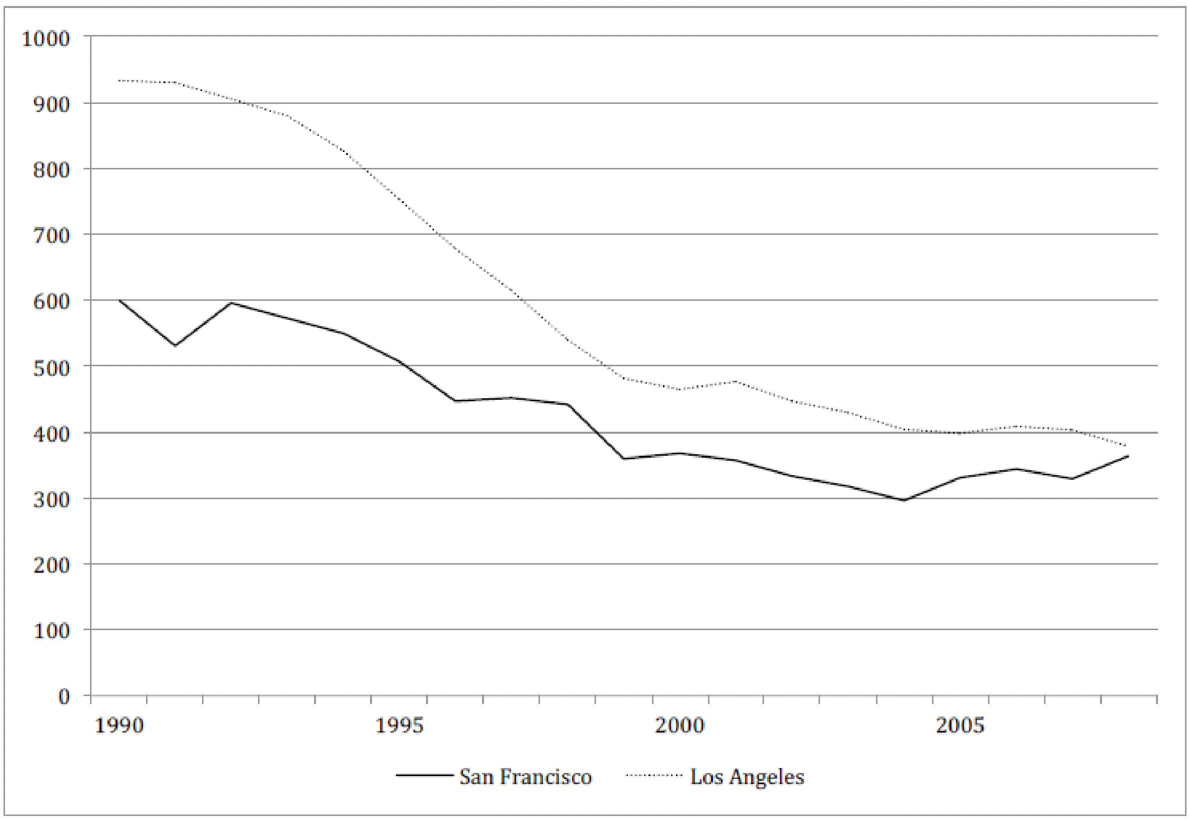


Figure 4: Time Variation in Violent Crime Rates (Incidents per 100,000 Residents)



5 Results

5.1 Hedonic Price Function

In order to allow for flexibility in recovering the hedonic price of violent crime, we estimate a separate log-linear hedonic specification for each year (1994 - 2007), controlling for house attributes (year built, lot size, square footage, number of bathrooms, number of bedrooms), crime rates (violent and property), and a vector of census tract fixed effects. The latter serve as controls for any amenities that vary at the level of the neighborhood. Moreover, because we estimate a separate hedonic price function for each year, we allow for those neighborhood amenities to vary over time, along with the hedonic prices of the observed housing attributes. In all specifications, house prices are annualized by multiplying them by 5%.

Results with standard errors based on 200 random bootstrap draws are reported in Tables 6 and 7. Each row represents a separate regression specification. By looking down a column, it is easy to see how the implicit price of a housing or neighborhood attribute varies over time. For the most part, hedonic price estimates have the expected sign and magnitude. For example, at the mean housing price in Los Angeles ($276,179), households would be willing to pay 3.6 cents per year for an additional square foot of lot size in 1994. Similarly, they would be willing to pay $5.22 for an additional square foot of housing. These values vary somewhat, but are relatively stable over time. Looking again at 1994, the values of lot size and square footage in San Francisco are higher (13.9 cents and $7.55, respectively). In that same year, an additional bathroom is worth $277.56 a year in Los Angeles, while an additional bedroom is worth $604.83.[8] The value of bedrooms and bathrooms varies somewhat over time in both San Francisco and Los Angeles, while the effect of year built varies a great deal over time (both in magnitude and sign).

We include property crime as a control in order to avoid confounding effects on violent crime that could arise if it were left as an unobservable.[9] That said, we expect that property crime may be measured with error and therefore focus our attention on violent crime for the remainder of the empirical application. The hedonic price of property crime may be biased upward if under-reporting is more of a problem in neighborhoods with low housing prices. Indeed, this appears to be the case in Los Angeles, where property crime exhibits a counterintuitive positive hedonic price in every year. In San Francisco, the hedonic coefficient

[8]Note that this marginal effect ignores the adjustment for the discreteness of bathrooms and bedrooms described in Kennedy (1981). Given our large sample size and subsequently small standard errors, this adjustment has little practical impact.

[9]The correlations between violent crime and property crime across our full sample period in Los Angeles and San Francisco are 0.74 and 0.71, respectively.

Table 6: Hedonic Price Function Estimates - Los Angeles Metro Area

	Year Built	Lot Size	Sq. Footage	Bathrooms	Bedrooms	Prop. Crime	Violent Crime
1994	1.25E-03***	2.58E-06***	3.78E-04***	0.0201***	0.0438***	1.40E-04***	-3.56E-04***
	(9.20E-05)	(1.00E-07)	(3.90E-06)	(2.40E-03)	(1.50E-03)	(4.80E-06)	(9.50E-06)
1995	9.75E-04***	2.82E-06***	3.94E-04***	0.0135***	0.0504***	1.62E-04***	-4.26E-04***
	(9.90E-05)	(1.20E-07)	(4.30E-06)	(3.00E-03)	(1.70E-03)	(5.20E-06)	(1.10E-05)
1996	1.12E-04	2.96E-06***	3.99E-04***	0.0151***	0.0585***	1.75E-04***	-4.36E-04***
	(1.00E-04)	(1.30E-07)	(5.20E-06)	(3.10E-03)	(1.80E-03)	(6.90E-06)	(1.20E-05)
1997	-2.67E-04***	2.72E-06***	4.05E-04***	0.0201***	0.0570***	1.36E-04***	-3.07E-04***
	(9.00E-05)	(1.20E-07)	(4.80E-06)	(3.10E-03)	(1.90E-03)	(7.40E-06)	(1.30E-05)
1998	-2.92E-04***	3.29E-06***	4.13E-04***	0.0215***	0.0532***	1.60E-04***	-5.70E-04***
	(7.90E-05)	(1.20E-07)	(5.00E-06)	(2.70E-03)	(1.60E-03)	(8.20E-06)	(1.70E-05)
1999	-4.06E-04***	3.11E-06***	4.27E-04***	0.0256***	0.0493***	8.45E-05***	-3.64E-04***
	(7.80E-05)	(1.10E-07)	(3.40E-06)	(2.40E-03)	(1.30E-03)	(1.00E-05)	(1.80E-05)
2000	-2.7E-04***	3.50E-06***	3.96E-04***	0.0354***	0.0566***	3.55E-04***	-9.54E-04***
	(7.30E-05)	(1.10E-07)	(3.30E-06)	(2.10E-03)	(1.40E-03)	(1.10E-05)	(2.40E-05)
2001	-1.78E-04**	3.63E-06***	3.58E-04***	0.0390***	0.0537***	2.69E-04***	-7.01E-04***
	(7.40E-05)	(1.20E-07)	(3.30E-06)	(2.10E-03)	(1.30E-03)	(1.10E-05)	(2.10E-05)
2002	-2.63E-04***	3.36E-06***	3.35E-04***	0.0332***	0.0531***	2.98E-04***	-7.13E-04***
	(5.90E-05)	(9.40E-08)	(3.10E-06)	(1.80E-03)	(1.20E-03)	(8.20E-06)	(1.90E-05)
2003	-5.82E-04***	3.56E-06***	3.17E-04***	0.0329***	0.0516***	2.74E-04***	-8.05E-04***
	(6.20E-05)	(1.00E-07)	(3.00E-06)	(1.90E-03)	(1.20E-03)	(8.90E-06)	(2.10E-05)
2004	-1.69E-04**	3.21E-06***	3.13E-04***	0.0270***	0.0618***	1.86E-04***	-5.92E-04***
	(6.70E-05)	(1.20E-07)	(3.20E-06)	(2.30E-03)	(1.30E-03)	(9.80E-06)	(2.40E-05)
2005	-5.32E-04***	3.57E-06***	3.03E-04***	0.0235***	0.0611***	1.87E-04***	-5.47E-04***
	(6.70E-05)	(1.00E-07)	(3.30E-06)	(2.20E-03)	(1.30E-03)	(9.10E-06)	(3.20E-05)
2006	-1.11E-03***	3.94E-06***	2.96E-04***	0.0147***	0.0619***	1.84E-04***	-3.47E-04***
	(7.70E-05)	(1.30E-07)	(3.90E-06)	(2.40E-03)	(1.50E-03)	(9.90E-06)	(3.10E-05)
2007	-1.24E-03***	4.44E-06***	2.95E-04***	0.0182***	0.0645***	1.35E-04***	-1.11E-04***
	(1.00E-04)	(1.70E-07)	(4.00E-06)	(2.90E-03)	(1.80E-03)	(9.70E-06)	(3.40E-05)

*Data are mean-differenced to remove 578 tract fixed effects. Significance is indicated by *** (0.01), ** (0.05), and * (0.10).*

on property crime is smaller, sometimes insignificant, and exhibits a sign that varies over time.

In contrast to property crime, violent crime exhibits an intuitive effect on housing prices that is both statistically significant and relatively stable over time for both Los Angeles and San Francisco. In Los Angeles, a simple measure of the MWTP in 2000 based on the hedonic

Table 7: Hedonic Price Function Estimates - San Francisco Metro Area

	Year Built	Lot Size	Sq. Footage	Bathrooms	Bedrooms	Prop. Crime	Violent Crime
1994	8.54E-04***	6.30E-06***	3.41E-04***	2.74E-03	0.0322***	-4.02E-05***	-2.65E-04***
	(9.40E-05)	(2.80E-07)	(3.50E-06)	(3.00E-03)	(1.60E-03)	(5.20E-06)	(2.30E-05)
1995	8.13E-04***	6.40E-06***	3.43E-04***	7.23E-03*	0.0329***	-1.00E-05	-4.80E-04***
	(1.10E-04)	(3.30E-07)	(5.30E-06)	(4.00E-03)	(1.90E-03)	(8.00E-06)	(3.10E-05)
1996	7.18E-04***	6.25E-06***	3.56E-04***	9.95E-03***	0.0380***	-5.28E-06	-4.79E-04***
	(9.00E-05)	(2.90E-07)	(4.50E-06)	(3.40E-03)	(1.80E-03)	(8.20E-06)	(2.90E-05)
1997	5.14E-04***	6.69E-06***	3.52E-04***	0.0161***	0.0387***	7.45E-06	-5.96E-04***
	(8.30E-05)	(2.90E-07)	(4.80E-06)	(3.40E-03)	(1.70E-03)	(7.80E-06)	(2.80E-05)
1998	2.67E-04***	6.68E-06***	3.56E-04***	0.0178***	0.0397***	1.14E-04***	-9.55E-04***
	(8.30E-05)	(2.80E-07)	(5.20E-06)	(3.60E-03)	(1.90E-03)	(9.50E-06)	(4.00E-05)
1999	4.59E-05	6.63E-06***	3.54E-04***	0.0168***	0.0424***	7.55E-05***	-1.04E-03***
	(7.80E-05)	(2.40E-07)	(3.00E-06)	(2.70E-03)	(1.50E-03)	(8.40E-06)	(3.50E-05)
2000	2.32E-04***	7.56E-06***	3.35E-04***	0.0236***	0.0394***	1.29E-04***	-1.19E-03***
	(8.70E-05)	(3.00E-07)	(4.23E-06)	(3.20E-03)	(1.80E-03)	(8.90E-06)	(4.60E-05)
2001	3.38E-04***	8.60E-06***	3.12E-04***	0.0236***	0.0359***	7.19E-05***	-1.04E-03***
	(8.90E-05)	(4.80E-07)	(5.90E-06)	(3.40E-03)	(1.90E-03)	(8.10E-06)	(5.10E-05)
2002	-1.30E-04*	8.56E-06***	3.00E-04***	0.0253***	0.0405***	9.38E-05***	-1.23E-03***
	(7.40E-05)	(3.30E-07)	(3.70E-06)	(2.70E-03)	(1.70E-03)	(9.50E-06)	(4.00E-05)
2003	-4.51E-04***	8.33E-06***	2.89E-04***	0.0276***	0.0437***	-3.29E-05***	-7.95E-04***
	(6.90E-05)	(3.6E-07)	(4.70E-06)	(2.60E-03)	(1.70E-03)	(6.80E-06)	(2.90E-05)
2004	-8.93E-04***	8.57E-06***	2.75E-04***	0.0317***	0.0495***	-5.95E-05***	-6.99E-04***
	(6.90E-05)	(3.10E-07)	(3.50E-06)	(2.80E-03)	(1.50E-03)	(1.10E-05)	(4.10E-05)
2005	-9.94E-04***	9.02E-06***	2.69E-04***	0.0350***	0.0488***	-7.19E-06	-6.52E-04***
	(7.40E-05)	(3.80E-07)	(2.90E-06)	(2.30E-03)	(1.40E-03)	(1.40E-05)	(5.70E-05)
2006	-1.24E-03***	8.84E-06***	2.85E-04***	0.0293***	0.0489***	-3.82E-05***	-4.68E-04***
	(7.70E-05)	(4.10E-07)	(3.70E-06)	(2.80E-03)	(1.60E-03)	(9.10E-06)	(3.90E-05)
2007	-1.38E-03***	8.45E-06***	2.97E-04***	0.0311***	0.0443***	2.49E-05*	-8.30E-04***
	(9.50E-05	(4.90E-07)	(4.30E-06)	(3.30E-03)	(1.90E-03)	(1.50E-05)	(5.80E-05)

*Data are mean-differenced to remove 833 tract fixed effects. Significance is indicated by *** (0.01), ** (0.05), and * (0.10).*

price function estimates and evaluated at the mean housing price for that city is $13.17.[10]. In San Francisco, it is $26.34. Table 8 reports the willingness to pay, evaluated at the mean housing price in each city, for a marginal reduction in violent crime in each year. Multiplying this number by 100,000 converts it into the "value of a statistical case of violent crime" (VSCVC). Analogous to the value of a statistical life (VSL), the VSCVC scales up the value of a marginal reduction in violent crime risk to reflect willingness to pay for avoidance of a case with certainty. This simple VSCVC ranges between $153,000 and $2.6 million (in 2000 dollars). This corresponds to prior literature; see, for example, Linden and Rockoff (2008), who find that avoiding a sexual offense is worth between $600,000 and $2.5 million (in 2004 dollars). For the sake of comparison, the VSL currently used by the EPA is $7.4 million (in 2006 dollars).[11]

Table 8: Simple Estimates of MWTP to Avoid Violent Crime

Year	Los Angeles Metro Area	San Francisco Metro Area
1994	-4.92	-5.87
1995	-5.88	-10.63
1996	-6.02	-10.60
1996	-4.24	-13.19
1998	-7.87	-21.14
1999	-5.03	-23.02
2000	-13.17	-26.34
2001	-9.68	-23.02
2002	-9.85	-27.23
2003	-11.12	-17.60
2004	-8.17	-15.47
2005	-7.55	-14.43
2006	-4.79	-10.36
2007	-1.53	-18.37

[10] This figure is derived by taking $(\frac{dP}{dVC}) \times 0.05$, evaluated at the mean price for Los Angeles.
[11] http://yosemite.epa.gov/ee/epa/eed.nsf/pages/MortalityRiskValuation.html#whatisvsl.

5.2 MWTP Function

In this subsection, we report the results of the Bishop-Timmins, Rosen, and Bartik procedures for recovering estimates of the MWTP function using the hedonic price function estimates and data on individual home buyers described above. We estimate a simple linear MWTP function for each metropolitan area, treating each year as a separate '"market":[12]

$$(16)\quad P_{i,t}^{VC} = \alpha_0+\alpha_1 VC_{i,t}+\alpha_2 INC_{i,t}+\alpha_3 API_{i,t}+\alpha_4 BLACK_{i,t}+\alpha_5 HISP_{i,t}+YEAR_{i,t}'\Omega+\nu_{i,t}^d$$

$$(17)\quad \nu_{i,t}^d \sim N(\mu,\sigma^2)$$

where API, $BLACK$, and $HISP$ refer to Asian-Pacific Islander, Black, and Hispanic dummy variables ($WHITE$ is the excluded category), INC measures annual income (in 1,000's of year 2000 dollars), and $YEAR$ represents a vector of year dummies.

Table 9 reports results for each of the three models separately for each metropolitan area. The difference in the estimates is striking. First, consider the coefficient on violent crime, α_1, which reveals the amount by which the individual's MWTP to avoid violent crime increases (or decreases) with an increase in that disamenity. Intuitively, this coefficient should be negative, indicating that the MWTP to avoid violent crime increases as the rate of violent crime increases – this would be consistent with a downward sloping demand curve for public safety. We find this to be the case with our model. In particular, each additional case of violent crime per 100,000 residents raises MWTP to avoid it by 29 cents in Los Angeles and 22 cents in San Francisco. As we will show below, this has important implications for the value ascribed to large reductions in crime rates like those witnessed in California during the 1990's. In contrast, estimates from the Rosen model suggest that increases in violent crime *reduce* the MWTP to avoid violent crime (i.e., consistent with an upward sloping demand curve for public safety). This is exactly the direction of the bias suggested by Bartik and Epple, and it leads to upwardly biased estimates of the value of non-marginal reductions in violent crime (which we show below). While the point estimates of the MWTP function derived with the Bartik model are also consistent with an upward sloping demand curve, the magnitude of that slope is smaller than in the case of the Rosen model and is not statistically significantly different from zero.

Looking at the the remaining coefficient estimates derived with our model, an increase in

[12]We implement Bartik's IV procedure by first regressing violent crime on income, race dummies, year dummies, and interactions between year dummies and the race and income variables. Fitted values of violent crime are then used in a second stage to recover estimates of the MWTP function parameters.

Table 9: MWTP Function Estimates

	Bishop-Timmins		Rosen		Bartik	
	LA	SF	LA	SF	LA	SF
Constant	227.16***	116.57***	-6.4184***	-5.5894***	-4.2538***	-2.3214
	(7.203)	(3.384)	(0.13)	(0.489)	(1.305)	(5.557)
Vio. Crime	-0.2896***	-0.2167***	3.50E-03***	7.30E-03***	7.86E-04	1.32E-03
	(9.18E-03)	(6.99E-03)	(5.01E-05)	(1.52E-04)	(1.60E-03)	(9.79E-03)
Income (/1000)	-0.0362***	-0.0651***	-0.0134***	-0.0315***	-0.0136***	-0.0324***
	(1.54E-03)	(3.44E-03)	(6.35E-04)	(2.16E-03)	(7.12E-04)	(3.26E-03)
Asian	5.6257***	4.9090***	0.1542***	0.2586***	0.2049***	0.3821**
	(0.263)	(0.239)	(0.015)	(0.043)	(0.03)	(0.188)
Black	58.421***	41.430***	1.4251***	3.4396***	1.9529***	4.4512***
	(1.869)	(1.368)	(0.027)	(0.081)	(0.308)	(1.635)
Hispanic	34.413***	21.357***	1.9458***	3.5781***	2.2466***	4.0520***
	(1.046)	(0.674)	(0.034)	(0.092)	(0.175)	(0.741)
σ_ν	57.790***	42.844***				
	(1.785)	(1.288)				

Year dummies are included in all specifications. Significance is indicated by ****(0.01),* ***(0.05), and* **(0.10).* $n_{LA} = 996,747$ *and* $n_{SF} = 468,598$.

income of $1,000 per year increases MWTP to avoid violent crime by 3.6 cents in Los Angeles and 6.5 cents in San Francisco; i.e., public safety is a normal good. The signs are the same but the magnitudes of this income effect are smaller in the Rosen and Bartik models.

Considering differences by race, the excluded group (Whites) have the highest mean MWTP to avoid violent crime. Our model suggests that Asian-Pacific Islanders have a slightly lower mean MWTP (as indicated by their positive intercept shifts of $5.63 in Los Angeles and $4.91 in San Francisco). Blacks have the lowest mean MWTP to avoid violent crime, followed by Hispanics. While statistically significant, race does not play an economically important role in the estimates derived from the Rosen and Bartik models.

6 Measuring the Benefits of a Non-Marginal Reduction in Crime

As is clear from our data description, both the San Francisco Bay and Los Angeles Metropolitan Areas experienced large and persistent reductions in crime rates over the course of the 1990's. Similar reductions have been observed in numerous other cities across the US. Out of the 25 cities that he considers, Levitt (2004) provides the following ranks for the reductions in homicides between 1991 - 2001: San Jose (4th), San Francisco (12th), and Los Angeles (15th).

The changes in California crime rates experienced during the 1990's represent a significant improvement and are, importantly, *non-marginal*.[13]

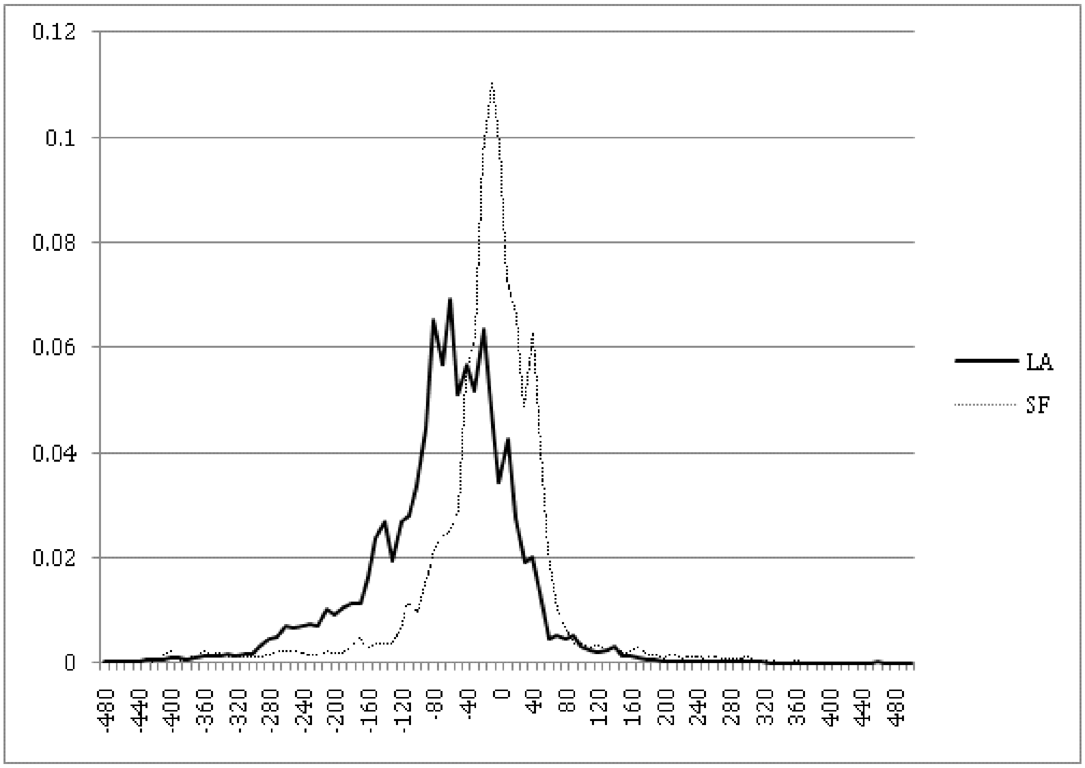
There is a large and growing literature aimed at valuing the benefits of crime reductions (particularly with the goal of conducting cost-benefit analysis of, for example, police force expansions). This literature was recently surveyed by Heaton (2010). He notes that the property value hedonic technique (along with a variety of stated preference techniques) is particularly valuable for recovering the intangible costs of crime (i.e., lost quality of life from fear of victimization, effective loss of public space). As opposed to tangible costs (i.e., the value of lost property), such intangibles are likely to be particularly important for measuring the costs of violent crime (a point emphasized by Linden and Rockoff (2008) with respect to sexual offenses).

With this as a backdrop, we consider the reductions in crime that occurred in the San Francisco Bay and Los Angeles Metropolitan Areas in the early 1990's. Recognizing that the hedonic method does not allow individuals to re-optimize in response to a non-marginal change in amenities, we consider a group for whom this is less likely to be a concern. In particular, we consider the set of all individuals who purchased a house in 1994 in each city (described in Table 5). We then measure the value of the crime reductions they experience between 1994 and 1995. It is likely that these individuals will still occupy the same residence in 1995 and, as we will see below, the changes that occurred over this year were substantial enough that proper identification of the MWTP function becomes important in measuring their value. In particular, Figure 5 illustrates the distribution of changes in crime rates experienced by this set of households in each metropolitan area.

For the purposes of illustration, we report valuations based on five different modeling strategies: (i) Bishop-Timmins; (ii) simple linear – this approach assigns marginal willingness to pay based on the simple log-linear hedonic price function evaluated at the mean housing price for the city in question (i.e., using the marginal willingness to pay reported in Table 8); (iii) Bajari-Benkard – this approach is based on the "inversion" procedure outlined in Bajari and Benkard (2004) under a linear utility specification; put simply, the approach assigns a constant (i.e., horizontal) MWTP function to each individual with a value equal to the slope of the hedonic price function evidenced at her observed housing choice; (iii) Rosen; and (iv) Bartik. In order to clarify how this procedure works, Figures 6, 7, and 8 illustrate the hedonic price gradient and MWTP function estimates for the Bishop-Timmins, Rosen, and Bartik

[13] Levitt (2004) discusses six factors that he argues were *not* responsible for these declines, including economic growth and reduced unemployment, shifting age and racial demographics, changes in policing strategies, changes in gun control laws and laws controlling concealed weapons, and changes in capital punishment. He argues instead that there is a strong case to be made for the role of increasing size of the police force, increased incarceration rats, declines in the crack epidemic, and the legalization of abortion twenty years prior. The relative importance of each of these factors is still a contentious topic. See, for example, Blumstein and Wallman (2006).

Figure 5: Distribution of One-Year Violent Crime Rate Changes for 1994 Buyers



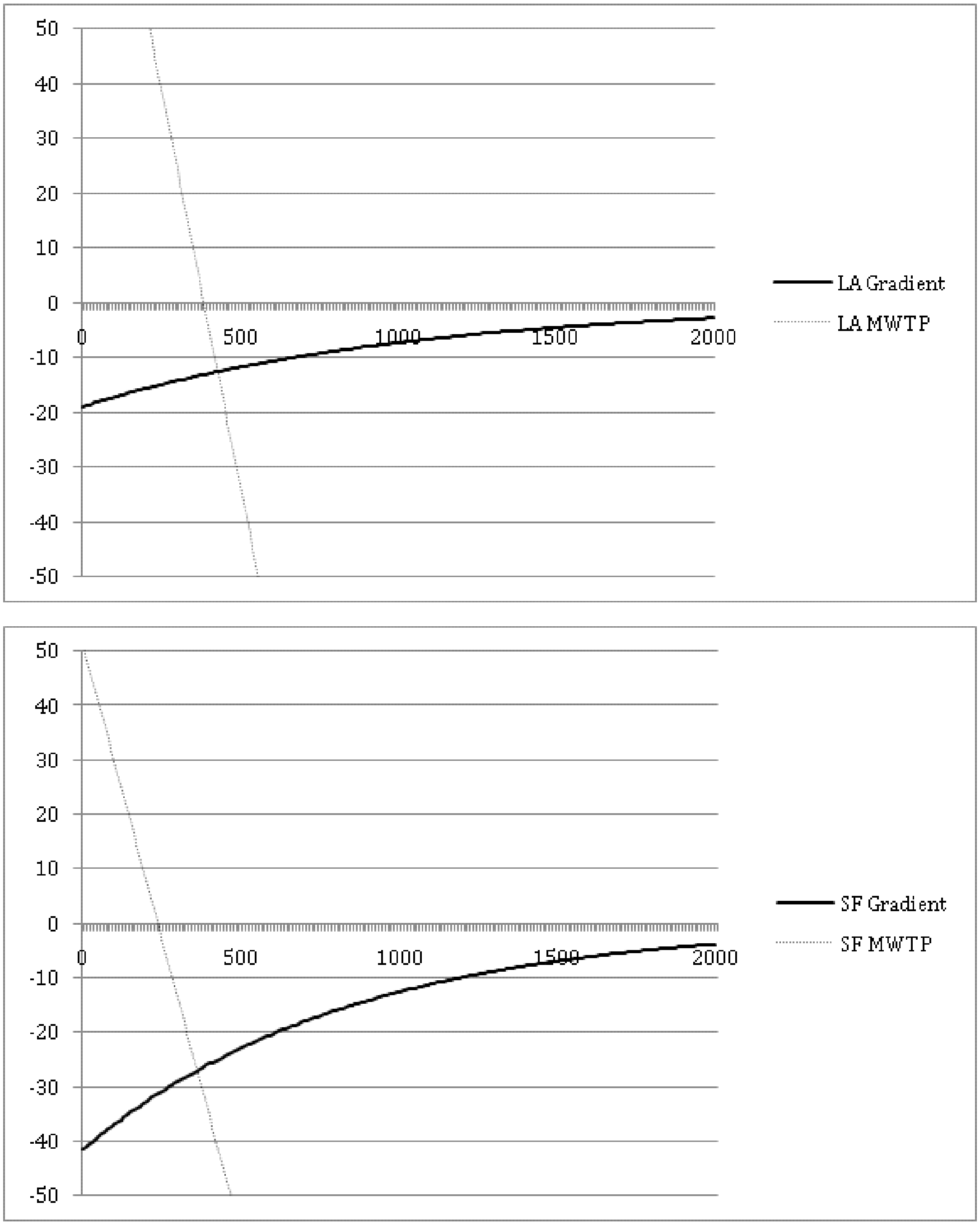
models for the year 2000. The value of a reduction in crime is taken as the area between the horizontal axis and the MWTP function between the starting and finishing levels of violent crime. Values associated with reductions are reported as positive magnitudes; increases in violent crime rates yield negative values. Finally, when the MWTP function intersects the horizontal axis, we assume that it's value is zero from that point on (i.e., we do not allow for negative MWTP's to avoid violent crime).[14]

To simplify the exposition, we report results separately for the 77% of buyers who experienced a reduction in violent crime rates and for the remaining buyers who experienced an increase. Tables 10 and 11 report results for each of these groups, respectively.

The bias from improperly accounting for the effect of a non-marginal change in violent

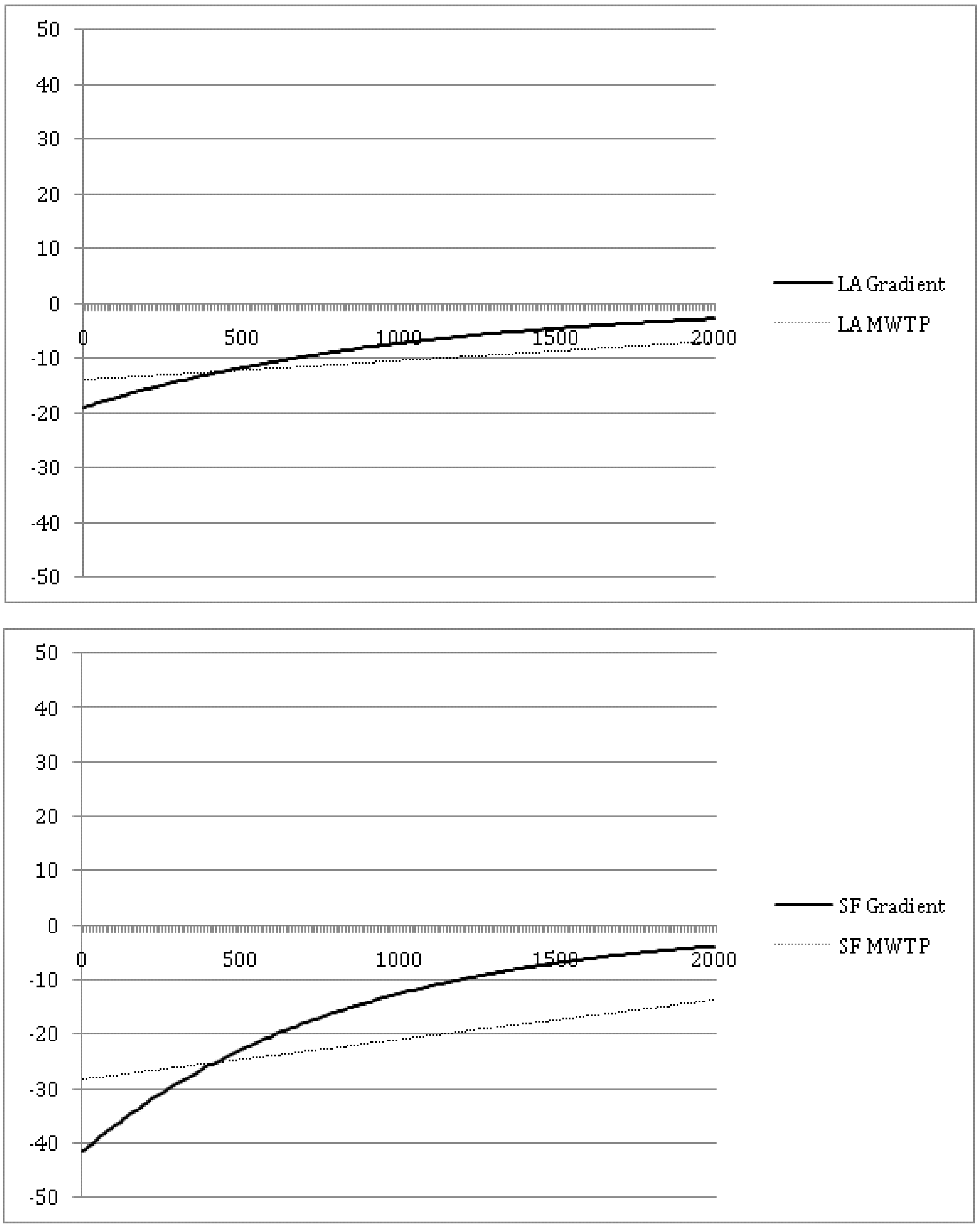
[14]A negative willingness to pay to avoid violent crime would, for example, occur at very low violent crime rates along the MWTP function described in Figure 6. However, we see no actual hedonic prices for violent crime lying above the horizontal axis, and the fact that the MWTP function extends into the positive quadrant is purely a result of the assumed linear functional form. We therefore constrain MWTP functions to lie in the 4th quadrant (i.e., positive violent crime, negative MWTP) by setting the MWTP to zero for these low violent crime rates.

Figure 6: Gradient and MWTP Function (Year 2000) from the Bishop-Timmins Model



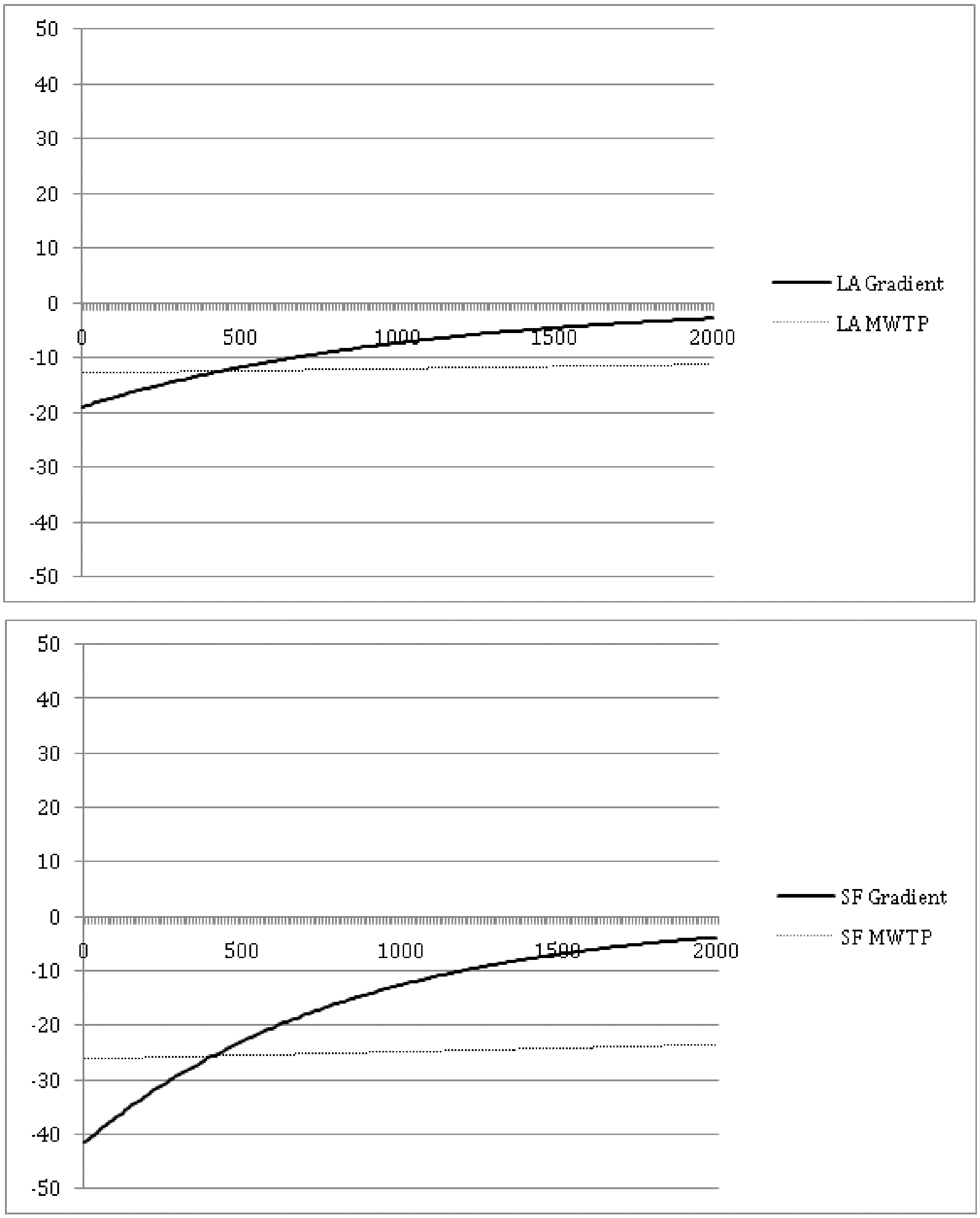
crime on MWTP is evident. Consider first the case of crime reductions. The simple linear, Bajari-Benkard, Rosen and Bartik models all yield an estimate of the average WTP for observed crime reductions that is 9.48 to 12.29 times greater than our model in Los Angeles,

Figure 7: Gradient and MWTP Function (Year 2000) from the Rosen Model



and 5.98 to 7.97 times greater in San Francisco. On a "WTP per avoided case" basis, the alternative models yield results that are 4.7 to 5.53 times greater in Los Angeles and 2.35 to 3.16 times greater in San Francisco. The direction of the bias from improperly measuring the

Figure 8: Gradient and MWTP Function for the Year 2000 from the Bartik Model



MWTP function is reversed when we consider increases in the rate of violent crime. Here, the alternative models yield estimates of average WTP for observed crime reductions that are only 0.15 to 0.26 of our estimate in Los Angeles, and 0.22 to 0.37 in San Francisco. On a "WTP per

Table 10: WTP for Non-Marginal Reductions in Violent Crime

	Los Angeles Metro Area ($n = 49,439$)			San Francisco Metro Area ($n = 18,002$)		
	Average WTP	Std. Dev. WTP	Average WTP per crime	Average WTP	Std. Dev. WTP	Average WTP per crime
Bishop-Timmins	39.02	60.86	0.89	48.36	66.52	1.86
Simple Linear	479.72	400.61	4.92	385.55	701.72	5.87
Bajari-Benkard	370.01	343.09	4.18	289.01	559.69	4.37
Rosen	398.32	381.2	4.36	356.83	871.43	4.61
Bartik	376.37	351.11	4.22	301.26	605.97	4.42

Table 11: WTP for Non-Marginal Increases in Violent Crime

	Los Angeles Metro Area ($n = 9,669$)			San Francisco Metro Area ($n = 10,644$)		
	Average WTP	Std. Dev. WTP	Average WTP per crime	Average WTP	Std. Dev. WTP	Average WTP per crime
Bishop-Timmins	-816.39	2221.47	-9.92	-679.35	1667.56	-8.89
Simple Linear	-211.27	263.81	-4.92	-252.31	313.54	-5.87
Bajari-Benkard	-131.63	149.75	-3.70	-170.88	196.76	-4.23
Rosen	-122.95	135.78	-3.62	-152.45	161.55	-4.07
Bartik	-129.39	151.97	-3.51	-168.04	208.29	-4.11

additional case" basis, the alternative models yield cost increases that are only 0.35 to 0.50 as large in Los Angeles, and 0.46 to 0.66 as large in San Francisco. These differences, both for increases and decreases in crime rates, are far from trivial and would have an important impact on any cost-benefit analysis.

7 Conclusion

Researchers regularly ascribe to individuals downward sloping demand curves for goods ranging from breakfast cereals to BMW's. Indeed, recovering the price elasticity of demand for goods like these constitutes one of the main activities undertaken by applied microeconomists. But, because of the difficult endogeneity problems associated with the recovery of the MWTP function with the hedonic technique, the same flexibility has not generally been ascribed to individual demand for local public goods and amenities. Rather, applications of the hedonic method have tended to focus only on the first-stage hedonic price regression - this approach is quite limited, in that these results will only yield valid welfare estimates of marginal policies. Very few changes in local public goods or amenities are, in fact, marginal. In order to properly evaluate the welfare effects of larger changes, the researcher must recover structural preference parameters - i.e., the MWTP function. In this paper, we propose a method for doing just that, while avoiding the endogeneity problems so commonly associated with the hedonic model.

We avoid these problems by recognizing that they are largely manufactured - a result of framing Rosen's second stage regression equation in terms of marginal cost (implicit attribute price) equaling marginal benefit (marginal utility from consuming the amenity in question). We show that one can instead write down the information provided by hedonic equilibrium in a simple modeling environment with no fundamental endogeneity problems (i.e., a single endogenous outcome variable, which is a function of a vector of exogenous variables, and an econometric error).

In the most general form of our model, estimation is straightforward, consisting of a standard maximum likelihood procedure employing a textbook change-of-variables technique. In a restricted version of the model, a closed-form solution for the amenity may be found analytically. In this case, the likelihood can be written in terms of the amenity and the change of variables is not required. Estimation in the simplest, two-market linear-quadratic model can even be reduced to an indirect least squares procedure, exploiting a one-to-one mapping between the structural and reduced-form parameters. Like the Rosen model, our approach (i) derives from the first-order condition for utility maximization and is, therefore, quite intuitive, (ii) is able to incorporate rich individual- and market-level heterogeneity, and (iii) is computationally light and easy to implement. Additionally, our model requires no more in terms of data than the standard hedonic model.

Using a series of Monte Carlo experiments, we demonstrate that our proposed model presents very little bias in finite samples. Applying our model to data on crime rates in California's two largest metropolitan areas, we arrive at a number of important conclusions. First, properly accounting for the shape of the MWTP function has important implications for measuring the welfare effects of non-marginal changes in violent crime. Considering the welfare effects of the reductions in violent crime between 1994-1995 experienced by those individuals who bought houses in 1994, we find that alternative modeling procedures overstate average benefits of observed crime reductions by a factor of 6 to 10 times relative to our approach. Conversely, they understate the costs of increases in the crime rate, recovering estimates that are only 15 to 30% as large as those we obtain. These differences are both statistically and economically significant, and consequential for cost-benefit analysis of policies that would have large impacts on future crime rates (Heaton (2010)).

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