Hedonic Prices and Implicit Markets: Estimating Marginal Willingness to Pay for Differentiated Products 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. In this paper, we propose a new econometric approach to recover the marginal willingness-to-pay function that avoids these endogeneity problems. With a parametric specification for the marginal willingness-to-pay function, our approach is both 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' MWTP functions 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 employing data from multiple markets or by allowing for non-linearity in the hedonic price function) to identify the 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

[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).

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 of 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 (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 estimable Tiebout sorting models.[4] Our proposed method is identified even in a single-market setting, given a flexible representation of the hedonic price function and a parametric representation of the MWTP function. Impor-

[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).

[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).

tantly, 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 violent crime rates in the San Francisco Bay and Los Angeles Metropolitan Areas over the period 1994 to 2007. We find that recovering the full MWTP function is economically important; 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 1990s 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, and hazardous waste site remediation.

This paper proceeds as follows. Section 2 describes the endogeneity problem discussed by Bartik (1987) and Epple (1987) and reiterates the intuition for why the problem has been so difficult to solve with standard exclusion restrictions. Section 3 describes our alternative estimation procedure in detail. 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 to these data. Section 6 calculates the welfare effects from the actual non-marginal changes in crime faced by a subset of homeowners and compares these welfare effects with those calculated with alternative procedures in the existing literature. Finally, Section 7 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. Consider the quadratic hedonic price function 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 house i (for the sake of illustration, we ignore other amenities

[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.

and house attributes). For now, we consider data from just a single market, but allow for multi-market data in the following section. 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]

In three respective papers, Epple, Bartik, and Kahn and Lang (1988) propose alternative instrumental variables strategies to deal with this problem. Bartik, for example, suggests instrumenting for Z_i^d with market indicator variables. Kahn and Lang suggest a similar instrument of market indicators interacted with household demographic attributes. The intuition for these strategies 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 problem with these approaches is that they require strong assumptions about cross-market preference homogeneity and the instrument may not induce sufficient variation in the endogenous variable. Ekeland, Heckman, and Nesheim (2004) propose an alternative instrumental variables approach to overcome the endogeneity problem. They show that due to the non-linearity of the hedonic model, the conditional expectation of Z_i^d given X_i^d may be used to instrument for Z_i^d. This instrumentation strategy does not require assumptions about cross-market preference homogeneity and may be used in a single-market setting. Our proposed estimation strategy differs from these previous approaches as we avoid instrumental variables altogether. Our strategy is the subject of Section 3.

[6] To see this explicitly, derive an equation similar to Equation (5) based on the supply relationship in Equation (4). Noting that $Z_i^s = Z_i^d$ in hedonic equilibrium, set this equation equal to Equation (5). Solving for X_i^s, 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.

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 the amenity Z (from the estimation of the hedonic price function) to its marginal benefit (which is a function of Z) and use the resulting expression as the estimating equation. The literature following 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 these conditions in this manner. While this representation does provide an intuitive interpretation of utility maximization, it is the "implicit price equals marginal benefit" specification itself 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 as given and choose Z_i^* to maximize 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: an endogenous outcome variable, Z_i, 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 household'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 general case of our model, where a closed-form for Z may not exist, we show that by using a simple change-of-variables technique it is still straightforward to compute the likelihood of observing Z. Also in this section, we provide evidence of our estimator's small sample properties with Monte Carlo simulation results.

3.1 The Simple Model: When a Closed-Form Solution for Z Exists

In this sub-section, we consider a special case of the general model in which Z may be easily isolated in the first-order condition for utility maximization. While our proposed estimator is applicable to a much richer specification of the model (as discussed in Section (3.2)), we present this simplified case first as the estimation strategy is extremely transparent.

Consider the simple, linear-quadratic model where the hedonic price function is given by:

$$P_{i,k} = \beta_0 + \beta_{1,k} Z_{i,k} + \frac{\beta_{2,k}}{2} Z_{i,k}^2 + \epsilon_{i,k} \tag{6}$$

where i indexes houses and k indexes markets (defined by space or time). The price gradient for market k is therefore:

$$P_{i,k}^Z = \beta_{1,k} + \beta_{2,k} Z_{i,k} \tag{7}$$

Specifying the MWTP function as:

$$P_{i,k}^Z = \alpha_{0,k} + \alpha_1 Z_{i,k} + \alpha_{2,k} X_{i,k}^d + \nu_{i,k}^d \tag{8}$$

we arrive at the following first-order condition describing the equilibrium relationship:

$$\alpha_{0,k} + \alpha_1 Z_{i,k} + \alpha_{2,k} X_{i,k}^d + \nu_{i,k}^d - P_{i,k}^Z = 0 \tag{9}$$

The traditional estimation strategy associated with Rosen would first recover an estimate of $\widehat{P^Z_{i,k}}$ from the estimated price gradient, isolate this term on the left hand side of Equation (9), and estimate the resulting regression equation (treating $\nu^d_{i,k}$ as the regression error) in a separate second stage. Our approach, is to alternatively rearrange Equation (9) such that the single endogenous variable, $Z_{i,k}$, is isolated on the left:

$$Z_{i,k} = (\frac{\alpha_{0,k} - \beta_{1,k}}{\beta_{2,k} - \alpha_1}) + (\frac{\alpha_{2,k}}{\beta_{2,k} - \alpha_1})X^d_{i,k} + (\frac{1}{\beta_{2,k} - \alpha_1})\nu^d_{i,k} \tag{10}$$

Equation (10) describes how the consumption of the amenity Z varies with observable household characteristics, $X^d_{i,k}$, unobservable preference shocks, $\nu^d_{i,k}$, and parameters of the hedonic price function, $\{\beta_{1,k}, \beta_{2,k}\}$. This equation contains all of the information necessary to recover the parameters describing individual preferences, $\{\alpha_{0,k}, \alpha_1, \alpha_{2,k}, \sigma\}$. Using hats to indicate that $\{\widehat{\beta_{i,k}}, \widehat{\beta_{2,k}}\}$ are known from the first-stage estimation of the hedonic price function, we may write:

$$Z_{i,k} = (\frac{\alpha_{0,k} - \widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}} - \alpha_1}) + (\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}} - \alpha_1})X^d_{i,k} + (\frac{1}{\widehat{\beta_{2,k}} - \alpha_1})\nu^d_{i,k} \tag{11}$$

Making the distributional assumption that $\nu^d_{i,k} \sim N(0, \sigma^2)$, $Z_{i,k}$ is then distributed normally with mean $((\frac{\alpha_{0,k} - \widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}} - \alpha_1}) + (\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}} - \alpha_1})X^d_{i,k}))$ and standard deviation $(\frac{\sigma}{\widehat{\beta_{2,k}} - \alpha_1})$. This reveals a straightforward Maximum Likelihood approach for estimating the remaining parameters.[7] In particular, we find the vector of parameters, $\{\alpha_{0,k}, \alpha_1, \alpha_{2,k}, \sigma\}$, that maximizes the likelihood

[7] Kahn and Lang (1988) suggest estimating a restricted version of Equation (11) via non-linear least squares. However, their estimator requires the strong cross-market homogeneity assumption that all of the utility parameters are constant across markets. Additionally, their proposed estimator is only applicable for the subset of cases where a closed-form solution for Z exists and does not generalize to the cases we present in Section (3.2).

of the observed vector $\{Z_{i,k}\}_{i=1}^{N}$. This likelihood is given by $\Pi_{i=1}^{N}\, \ell(Z_{i,k}, X_{i,k}^{d}; \alpha, \sigma)$ where:

(12)

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

3.1.1 Indirect Least Squares

It is worth considering the very special case of this model when estimation is particularly straightforward: the case where the structural parameters may be recovered using a least-squares estimation.

As an example, consider the specification above with exactly two markets. In this case, Equation (11) may be estimated using an extremely transparent indirect least squares (ILS) procedure. With the same number of equations as unknown structural parameters,[8] it becomes a simple matter to recover the structural parameters $\{\alpha_{0,k},\ \alpha_1,\ \alpha_{2,k},\ \sigma\}$ from the reduced-form parameters $\{\theta_{0,k},\ \theta_{1,k},\ \sigma_{u,k}\}$ (which are recovered using OLS) by exploiting the unique mapping between the two sets:

$$Z_{i,k} = \underbrace{(\frac{\alpha_{0,k} - \widehat{\beta_{1,k}}}{\widehat{\beta_{2,k}} - \alpha_1})}_{\theta_{0,k}} + \underbrace{(\frac{\alpha_{2,k}}{\widehat{\beta_{2,k}} - \alpha_1})}_{\theta_{1,k}} X_i^d + \underbrace{(\frac{1}{\widehat{\beta_{2,k}} - \alpha_1})\nu_{i,k}^{d}}_{u_{i,k}} \tag{13}$$

With more than two markets, one could add richer heterogeneity to the MWTP function (e.g., by parameterizing either the slope of the MWTP function or the variance of ν) in order to take advantage of all available information.[9]

[8] Let L denote the number of elements in X and K denote the number of markets. The reduced-form estimation returns $\big(K*(L+1)+K\big)$ parameters. The number of structural parameters in Equation (11) is $\big(K*(L+1)+2\big)$. Therefore, for $K=1$, this model is underidentified (given the linear price gradient). For $K=2$, it is exactly identified. For $K=3$, the model is overidentified.

[9] One could also use this additional information with a more general estimation strategy to overidentify the model's parameters.

3.2 The General Model: When a Closed-Form Solution for Z May Not Exist

We now consider a more general form of the model, in which we do not rely on finding a closed-form solution for Z. The lack of a closed-form solution will be the case for most non-linear gradient specifications (including the log-linear gradient specification that use in our application in Section (5)).[10] In this case, we are still able to estimate the model using Maximum Likelihood with a simple change-of-variables technique.

Consider first the case where $\nu_{i,k}^d$ is an additively-separable error that enters households' linear MWTP functions and does not enter the hedonic price function. In this case, finding a closed-form solution for $\nu_{i,k}^d$ is trivial. We show that by employing a basic change of variables (from Z to ν), a closed-form solution for ν is sufficient for forming the likelihood of observing Z.

In the following example, we impose no parametric assumption on the price function, $P(Z, X; \beta)$, and show how it may no longer be possible to find a closed-form solution for Z by rearranging the first-order condition for utility maximization given by:

$$\alpha_{0,k} + \alpha_1 Z_{i,k} + \alpha_{2,k} X_i^d + \nu_{i,k}^d - P'(Z, X; \beta) = 0 \tag{14}$$

[10] As a general rule, one should not expect the hedonic price gradient to be linear. Additionally, specifying the MWTP to be linear is not inconsistent with a nonlinear price gradient in equilibrium; as clearly demonstrated by Ekeland, Heckman, and Nesheim (2004), a linear MWTP function alone does not imply a linear price gradient. For the equilibrium price gradient to be linear, it would not only require that consumers have a perfectly linear MWTP function, but also that suppliers have a perfectly linear marginal willingness-to-accept function and that shocks to both preferences and profits are exactly normal. A key insight of the Ekeland, Heckman, and Nesheim paper is that very minor perturbations of any of these conditions will lead to substantial non-linearity in the resulting equilibrium price gradient.

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

$$\nu_{i,k}^d = P'(Z, X; \beta) - \alpha_{0,k} - \alpha_1 Z_{i,k} - \alpha_{2,k} X_i^d \tag{15}$$

Making the distributional assumption that $\nu_{i,k}^d \sim N(0, \sigma^2)$ and using a textbook application of a change of variables, it is straightforward to form the likelihood $\Pi_{i=1}^N \ell(Z_i, X_{i,k}^d; \alpha, \sigma)$ where:

$$\ell(Z_i, X_{i,k}^d; \alpha, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\{-\frac{1}{2\sigma^2}(\nu_{i,k}^d)^2\} |\frac{\partial \nu_{i,k}^d}{\partial Z_i}| \tag{16}$$

To implement this Maximum Likelihood procedure, we only need to calculate the value of $\nu_{i,k}^d$ consistent with the observed value of $Z_{i,k}$ (given α, $\widehat{\beta}$, and X) and the determinant of the Jacobian associated with the change of variables. Respectively, these terms are given by:

$$\nu_{i,k}^d = P'(Z, X; \widehat{\beta}) - \alpha_{0,k} - \alpha_1 Z_{i,k} - \alpha_{2,k} X_{i,k}^d \tag{17}$$

and:

$$|\frac{\partial \nu_{i,k}^d}{\partial Z_{i,k}}| = |P''(Z, X; \widehat{\beta}) - \alpha_1| \tag{18}$$

While the MWTP function specified thus far has been both linear and additively separable in the idiosyncratic shock, $\nu_{i,k}^d$, richer specifications of the MWTP function may be estimated using our framework. Our estimator simply requires that one is able to isolate the idiosyncratic shock, $\nu^d_{i,k}$. For example, if the MWTP function were given by:[11]

$$P'(Z,X;\beta) = Z_{i,k}^{\alpha_1}\; X_{i,k}^{\alpha_{2,k}}\; \nu^d_{i,k} \tag{19}$$

then $\nu^d_{i,k}$ may be recovered as:

$$\nu_{i,k} = \frac{P'(Z,X;\widehat{\beta})}{Z_{i,k}^{\alpha_1}\; X_{i,k}^{\alpha_{2,k}}} \tag{20}$$

$|\frac{\partial \nu^d_{i,k}}{\partial Z_{i,k}}|$ as:

$$|\frac{\partial \nu^d_{i,k}}{\partial Z_{i,k}}| = |\frac{P''(Z,X;\widehat{\beta}) - \alpha_1 Z_{i,k}^{-1} P'(Z,X;\widehat{\beta})}{Z_{i,k}^{\alpha_1} X_{i,k}^{\alpha_2}}| \tag{21}$$

and the likelihood could be formed using the change of variables technique.

The contribution of this paper is to illustrate a new estimation approach that avoids the traditional endogeneity problems that have plagued the literature. As the formal identification of the hedonic model has been discussed in detail in Brown and Rosen (1982), Mendelsohn (1985), Ekeland, Heckman, and Nesheim (2004), and, particularly, Heckman, Matzkin, and Nesheim (2010), we instead provide an informal discussion of identification, as the nature of our estimator allows for easy illustration of what features of the data pin down the parameters of the MWTP function.

Consider the model with linear MWTP outlined earlier in this section. When the MWTP intercept (α_0), the coefficients on X (α_2), and the MWTP variance (σ^2) are common across markets, they are identified by the mean Z, the covariance between Z and X, and the variance of Z, respectively. Four sources of variation identify the slope of the MWTP function. The first source is the sensitivity of mean Z to changes in price across markets. The second source

[11]In this case, the underlying utility function would be given by: $U(Z,X;\alpha) = (\frac{1}{\alpha_1+1})\; Z_{i,k}^{\alpha_1+1}\; X_{i,k}^{\alpha_{2,k}}\; \nu^d_{i,k}$.

is the sensitivity of the variance of Z to changes in the slope of the price gradient across markets. The third source is the sensitivity of the covariance of Z and X to changes in the slope of the price gradient across markets. The final, fourth source is the nonlinearity of the price gradient; Z will not be distributed normally when the gradient is nonlinear creating additional identifying variation (particularly if Z is allowed to have market-specific distributions).

When the intercept of the MWTP function is allowed to vary by market, the variation in mean Z across markets is used to identify the market-specific intercepts of the MWTP function and is no longer available to identify the slope of MWTP. In this case, higher levels of mean Z are associated with higher market-specific values for $\alpha_{0,k}$, all else equal. A similar logic applies when the coefficients on X are allowed to vary by market and differences in the covariance between Z and X are used to identify $\{\alpha_{2,k}\}_{k=1}^{K}$ or when the variance of ν is allowed to vary by market and variance of Z is used to identify $\{\sigma_k^2\}_{k=1}^{K}$. Finally, when all of the parameters of the MWTP function are allowed to vary by market, this is analogous to multiple single-market cases and the non-linearity of the price gradient is the only remaining source of identification of the MWTP slope. This is consistent with the established wisdom in the hedonic literature - one either needs a non-linear hedonic price gradient or multi-market data to recover the full MWTP function.

3.3 Monte Carlo Evidence

In this subsection, 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 and increase the level of heterogeneity in both the market-specific gradient intercepts and slopes. Finally, we allow the MWTP intercept to vary by market.

For the first simulations, the hedonic gradient and MWTP function are respectively given by:

$$P^{Z}_{i,k} = \beta_{1,k} Z_{i,k} + \beta_{2,k} Z_{i,k} + \epsilon_{i,k} \tag{22}$$

$$P^{Z}_{i,k} = \alpha_0 + \alpha_1 Z_{i,k} + \nu^{d}_{i,k} \tag{23}$$

We allow the number of markets to take on the following values: $k = \{2, 5, 10, 50\}$. 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 $\eta_2 \sim \gamma_2 * U(-0.15, 0.15)$. γ is allowed to take on the following values: $\gamma_1 = \{1, 2, 3\}$ and $\gamma_2 = \{0, 1, 2, 3\}$.

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 repetitions per experiment is $1,000$. We set the structural parameters to the following "true" values: α_0=3, α_1=$-$0.3, and σ=0.5.

The results in Table 1 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, the efficiency of the estimator is increasing in both market size and level of gradient heterogeneity. 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 respective "true" value would lie outside of this interval. 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 finite samples).

For comparison, we run the same set of Monte Carlo experiments using the traditional

Table 1: Bishop-Timmins Results (common α_0)

	mean(α_0)	mean(α_1)	mean(σ)	std(α_0)	std(α_1)	std(σ)	% fail α_0	% fail α_1	% fail σ
true parameter value	3	-0.3	0.5	0	0	0	0.05	0.05	0.05
$k = 2, \gamma_1 = 1, \gamma_2 = 0$	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

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, α_1. In all cases (even with 50 markets and maximum gradient heterogeneity across markets), both the MWTP intercept (α_0) and the standard deviation of the preference shock (σ) are significantly 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 cases.

Finally, we return to our estimator and run a set of experiments where the MWTP intercept is allowed to vary across markets, with the MWTP function given by:

$$P^Z_{i,k} = \alpha_{0,k} + \alpha_1 Z_{i,k} + \nu^d_{i,k} \tag{24}$$

Table 2: Rosen Results (common α_0)

	mean(α_0)	mean(α_1)	mean(σ)	std(α_0)	std(α_1)	std(σ)	% fail α_0	% fail α_1	% fail σ
true parameter value	3	-0.3	0.5	0	0	0	0.05	0.05	0.05
$k = 2, \gamma_1 = 1, \gamma_2 = 0$	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

and we specify that $\alpha_{0,k} \sim U(2,4)$, 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 across markets and do not estimate the cases where $\gamma_2 = 0$. 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

4.1 Application Overview

In our application, we apply our estimator to valuing the willingness to pay to avoid violent crime in the Los Angeles and San Francisco metropolitan areas for the period 1994 to 2007. Further details and results of this application are discussed in Section (5).

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

	mean(α_1)	mean(σ)	std(α_1)	std(σ)
true parameter value	-0.3	0.5	0	0
$k = 2, \gamma_1 = \gamma_2 = 1$	-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

In the first stage of our estimation, we recover the parameters of the hedonic price function (one for each metropolitan area in each year). We specify a log-linear hedonic price function that is quadratic in our variable of interest, violent crime, and includes the following house attributes as controls: year built, lot size, square footage, number of bathrooms, number of bedrooms, and rate of property crime. We additionally control for a full set of Census tract-level fixed effects. Also, as we estimate a separate price function for each year, we allow both the hedonic prices of each amenity and the tract-level fixed effects to vary through time.

In the second stage of our estimation, we recover the structural parameters of the MWTP function. We specify a separate linear MWTP function for each metropolitan area and treat each year as a separate "market". We allow MWTP to vary with the rate of violent crime, household race, and household income. We additionally control for a full set of year fixed effects.

To demonstrate the policy implications of various hedonic estimators, we consider the non-marginal policy analysis of the observed changes in crime for the one year period of 1994 to 1995. In particular, we take all households that purchased a house in 1994 and compute their willingness to pay for (or to avoid) the decrease in crime (or increase in crime) that they experienced during their first year in the house.[12] Further details and results from this analysis are presented in Section (6).

To estimate these specifications, we employ a varied set of data from multiple sources. These data and our sample cuts are discussed below.

4.2 Property Transactions Data

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

Additional data cuts are made in order to deal with the fact that DataQuick only reports housing characteristics at the time of the final observed transaction, but we need to use housing characteristics from all transactions as controls in our hedonic price regressions. First, to control for land sales or total re-builds, we drop all transactions where "year built" is missing or later than the observed transaction date. Second, to control for major improvements or degradations, we drop any property with an observed annual appreciation or depreciation rate exceeding the county- and year- specific mean price change by more than 50 percentage points (in either direction). Additionally, we drop any property that moves more than 40 percentiles (in either direction) between transactions in the overall county- and year- specific

[12]Note that 77 percent of households experienced a decrease in crime during 1994-1995.

distribution of price. We also drop transactions where the price is missing, negative, or zero. As we merge-in the pollution data using the property's geographic coordinates, we drop properties where latitude and longitude are missing. Finally, drop houses with more than five observed transactions over the 14 year sample.

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

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

4.3 Household Demographic Data

For our demographic characteristics, we use information on the race and income of buyers recorded on mortgage applications and published in accordance with the Home Mortgage Disclosure Act (HMDA) of 1975. The HMDA data also describe the mortgage lender's name, the property's price, and the property's census tract. As the variables of lender name, price, and census tract are also available in the DataQuick data, we are able to merge the buyer characteristics data with the property transactions data using the algorithm described in

Bayer, McMillan, Murphy, and Timmins (2011).

Table (5) reports the summary statistics for the sample of buyers in each city. Compared with Los Angeles, San Francisco 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 the summary statistics for a sub-sample of buyers in each city who purchased a house in 1994. This group will be used in the policy analysis that demonstrates the implications of valuing non-marginal changes in violent crime rates.

Table 5: 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.

4.4 Violent Crime Data

The violent crime rate that we employ comes from the RAND California database and is defined as the number of incidents per 100,000 residents.[13] Violent crime is reported for each of the 80 cities in the San Francisco metropolitan area and 175 cities in the Los Angeles metropolitan area for each year of our data. Figures (1) and (2) illustrate the locations of these cities.

[13]In the data, violent crime is defined as "crimes against people, including homicide, forcible rape, robbery, and aggravated assault."

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

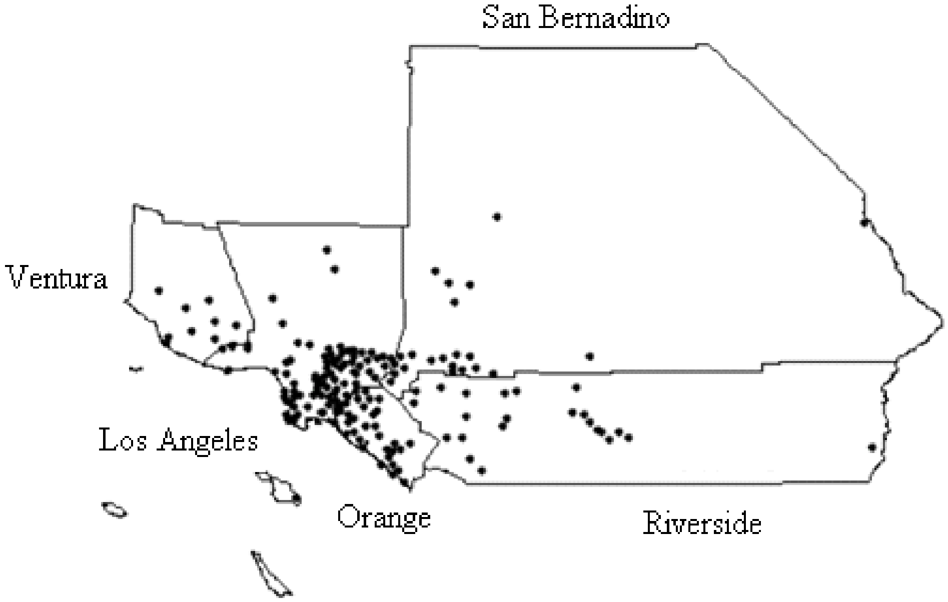
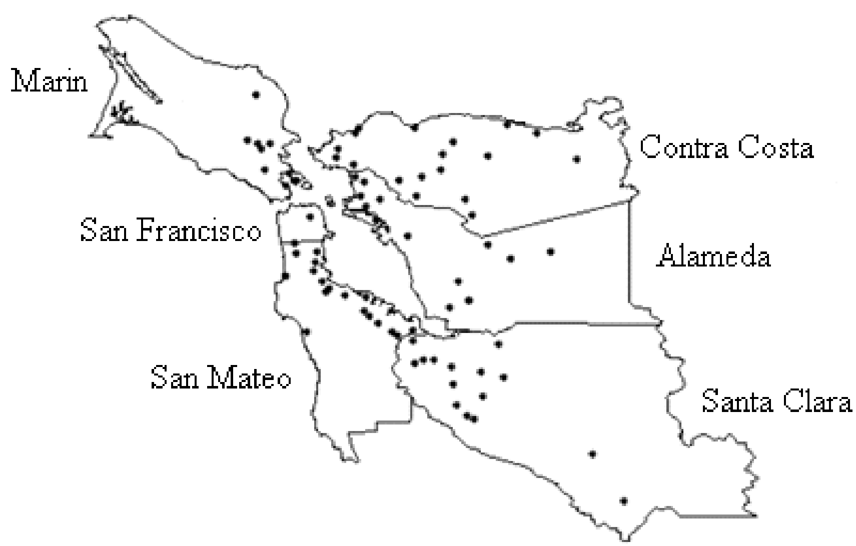


Figure 2: Locations of Crime-reporting Cities within the San Francisco Metro Area



For our analysis, we impute a violent crime rate for each individual house using an inverse distance-squared weighted average of the crime rate in each city.[14] As a control in our hedonic regressions, we also create an analagous measure of property crime rates using RAND California database and this algorithm.[15,16] Table (4) provides summary statistics for both violent crime and property crime at the level of the house. Table (5) provides summary statistics for our variable of interest, violent crime, at the level of the buyer.

We see a significant amount of variation (cross-sectional and time-series) in our key variable of interest, violent crime. Figures (3) and (4) illustrate the distribution of violent crime rates and the time-trend of mean violent crime rates for each metropolitan area, respectively. The declining trends observed in both Los Angeles and San Francisco are consistent with the decreases in violent crime observed in most of the US over the same period.

[14]Distance is computed using the Great Circle estimator, geographic coordinates of city centroids, and geographic coordinates of each house.

[15]Property crime is defined as "crimes against property, including burglary and motor vehicle theft."

[16]We use the property crime rate as a control in our hedonic estimation and focus attention on violent crimes in our valuation exercise, as violent crimes are less likely to be subject to systematic under-reporting (Gibbons (2004)).

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

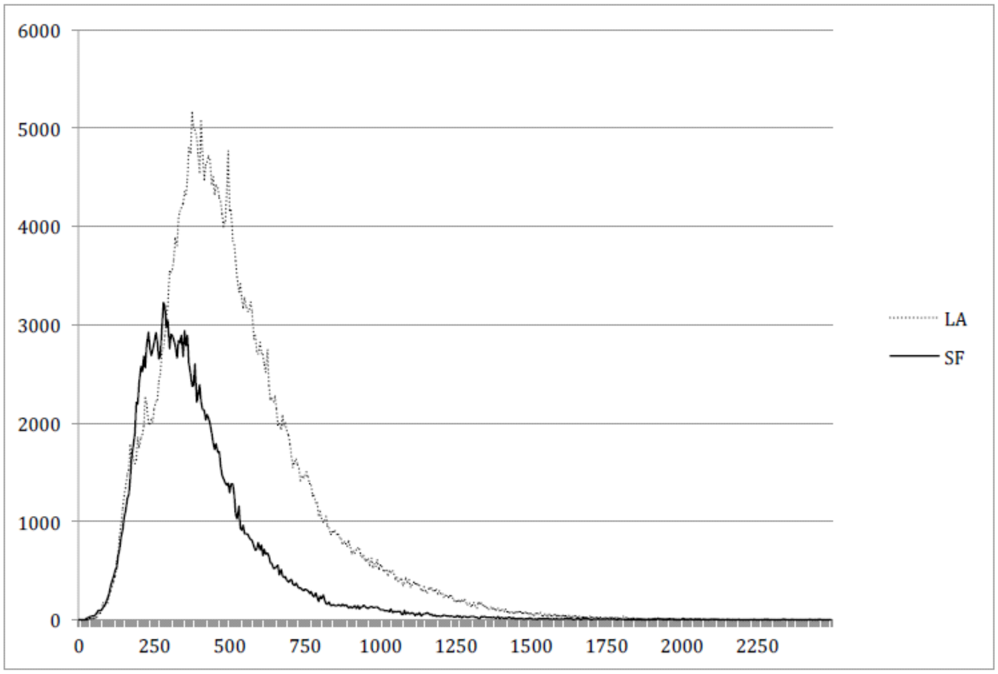
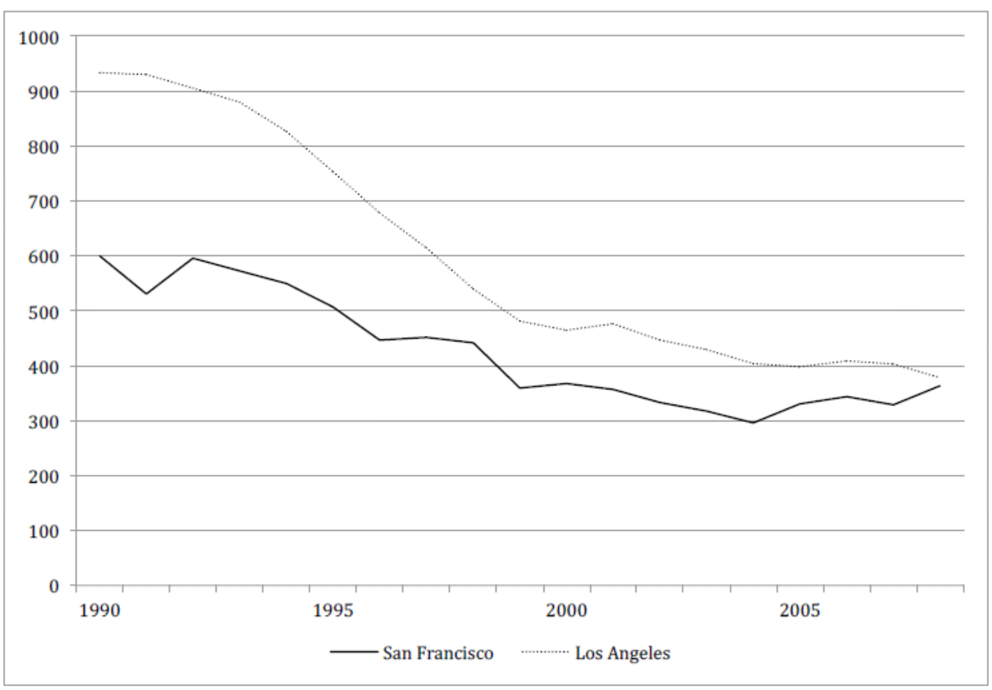


Figure 4: Time Variation in Violent Crime Rates (Incidents per 100,000 Residents)



5 Results

5.1 Hedonic Price Function

In this subsection, we discuss the results from the estimation of a log-linear hedonic price function for each metropolitan area and each year (1994 - 2007). Regression results are reported in Tables (A.1) and (A.2) in the Appendix, with each row representing a separate annual regression. In the vast majority of cases, hedonic price estimates have the expected sign and magnitude.[17] For discussion purposes, we calculate a simple measure of willingness to pay, given only by the derivative of the price function. In this case, MWTP is calculated at the mean housing prices of $\$276,179$ for Los Angeles and $\$442,767$ for San Francisco. The figures are annualized by multiplying them by 0.05.

Looking down each column of Tables (A.1) and (A.2), it is easy to see how the implicit price of a housing or neighborhood attribute varies over time. In Los Angeles, households are willing to pay 3.6 cents per year for an additional square foot of lot size in 1994. Similarly, they are 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 this same year, an additional bathroom is worth $277.56 per year in Los Angeles, while an additional bedroom is worth $604.83.[18] 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).

[17] An exception is the sign on property crime, which often exhibits a counterintuitive positive sign. This is not surprising as property crime is usually considered to be under-reported (unlike violent crime, which we focus on in our analysis). This underreporting would lead the coefficient to be biased upwards.

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

Our amenity of interest, 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, the simple measure of annual MWTP is $13.17, while in San Francisco, it is $26.34. Table (6) reports these simple (marginal) measures of willingness to pay for each year.

Table 6: Simple Estimates of MWTP to Avoid Violent Crime

Year	Los Angeles	San Francisco
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

Multiplying these numbers by 100,000 converts them into "values of a statistical case of violent crime" (VSCVC) (i.e., the joint willingness to pay of $100,000$ residents to avoid a single case of violent crime with certainty). Our simple estimates of VSCVC range between $\$153,000$ and $2.6 million (in 2000 dollars). This corresponds to the prior literature; see, for example the paper by Linden and Rockoff (2008) which finds that avoiding a sexual offense is worth between $600,000 and $2.5 million (in 2004 dollars). For the sake of comparison, the value of statistical life currently used by the EPA is $7.4 million (in 2006 dollars).[19]

[19] http://yosemite.epa.gov/ee/epa/eed.nsf/pages/MortalityRiskValuation.html#whatisvsl.

5.2 MWTP Function

In this subsection, we report the results from our procedure for recovering estimates of the MWTP function using the first-stage hedonic price function estimates and data on individual home buyers. With the log-linear specification for the hedonic price function, a closed-form solution for Z may not be recovered and we employ a likelihood-based estimation approach employing a change of variables from Z to ν.

We specify a linear MWTP function for each metropolitan area, i.e., we run the model separately for Los Angeles and for San Francisco.[20] For each metropolitan area, we allow the intercept of the MWTP function to vary by year by including a set of year dummies in our estimation. Given this framework, one could additionally allow the coefficients on demographic characteristics to vary by year without additional assumptions or variation coming from the first-stage estimates.[21]

$$P_{i,t}^{VC} = \alpha_{0,t} + \alpha_1 VC_{i,t} + X_{i,t}^{d\,\prime}\alpha_2 + \nu_{i,t}^d \tag{25}$$

where:

$$\nu_{i,t}^d \sim N(0, \sigma^2) \tag{26}$$

and $X_{i,t}^d$ is a vector comprised of income (in thousands of 2000 dollars) and a vector of race dummies (Asian-Pacific Islander, Black, Hispanic, and White).[22]

[20] To be clear, we do not treat Los Angeles and San Francisco as separate "markets" for identification purposes (i.e., there is no homogeneity assumption regarding preferences across the two metropolitan areas). Rather, we show how our estimator performs using two fully separate datasets: one for Los Angeles and one for San Francisco.

[21] With greater variation in the hedonic price function estimates, one could allow all coefficients to vary by year in the single-market setting.

[22] White is the excluded race.

Columns I and II of Table (7) reports results from our estimator separately for each metropolitan area. We recover a separate set of coefficients for Los Angeles and for San Francisco. First, consider the coefficient on violent crime, α_1, which reveals the amount by which the individual's MWTP to avoid violent crime changes with an increase in this disamenity. Intuitively, this coefficient should be negative, indicating that the MWTP to avoid violent crime increases as the rate of violent crime increases (consistent with a demand curve for public safety that is downward sloping). We find this to be the case with our model; each additional incident per 100,000 residents raises MWTP to avoid violent crime by 29 cents in Los Angeles and by 22 cents in San Francisco. As we show in Section (6), this has important implications for the value ascribed to large reductions in violent crime rates like those witnessed in California over the period of our sample.

Looking at the the remaining coefficient estimates derived using our model, an increase in 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 (consistent with public safety being a normal good). Considering differences in MWTP by race, the excluded group (Whites) has 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.

For the sake of comparison, Columns III and IV of Table (7) report the results from the traditional Rosen estimation approach separately for each metropolitan area. These results are strikingly different from the results presented in Columns I and II. In contrast to our estimator, estimates from the Rosen model suggest that increases in violent crime reduce the MWTP to avoid violent crime (indicating that the demand curve for public safety is upward sloping). This is exactly the direction of bias suggested by both Bartik and Epple and leads to upwardly biased estimates of the welfare associated with non-marginal reductions in violent crime (which we show in Section(6)). Additionally, while the coefficient on income is of the same sign, the magnitude is much smaller. Finally, race does not appear to play an economically significant role in the estimates derived using the Rosen estimation approach (although the coefficients are statistically significant).

Table 7: MWTP Function Estimates

	Bishop-Timmins		Rosen	
	Los Angeles	San Francisco	Los Angeles	San Francisco
Constant	227.16	116.57	-6.4184	-5.5894
	(7.203)	(3.384)	(0.13)	(0.489)
Violent Crime	-0.2896	-0.2167	3.50E-03	7.30E-03
	(9.18E-03)	(6.99E-03)	(5.01E-05)	(1.52E-04)
Income (/1000)	-0.0362	-0.0651	-0.0134	-0.0315
	(1.54E-03)	(3.44E-03)	(6.35E-04)	(2.16E-03)
Asian	5.6257	4.9090	0.1542	0.2586
	(0.263)	(0.239)	(0.015)	(0.043)
Black	58.421	41.430	1.4251	3.4396
	(1.869)	(1.368)	(0.027)	(0.081)
Hispanic	34.413	21.357	1.9458	3.5781
	(1.046)	(0.674)	(0.034)	(0.092)
σ_ν	57.790	42.844	–	–
	(1.785)	(1.288)	–	–
$YearDummies?$	*yes*	*yes*	*yes*	*yes*
N	996,747	468,598	996,747	468,598

All coefficients are significant at the 1% level of significance.

6 Measuring the Welfare Implications of a Non-Marginal Change in Violent Crime Rates

As is clear from our data description, both the Los Angeles and the San Francisco Metropolitan Areas experienced large and persistent reductions in average violent crime rates over the course of our sample period. 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). These changes in California crime rates represent a significant improvement on average and are, importantly, non-marginal.[23]

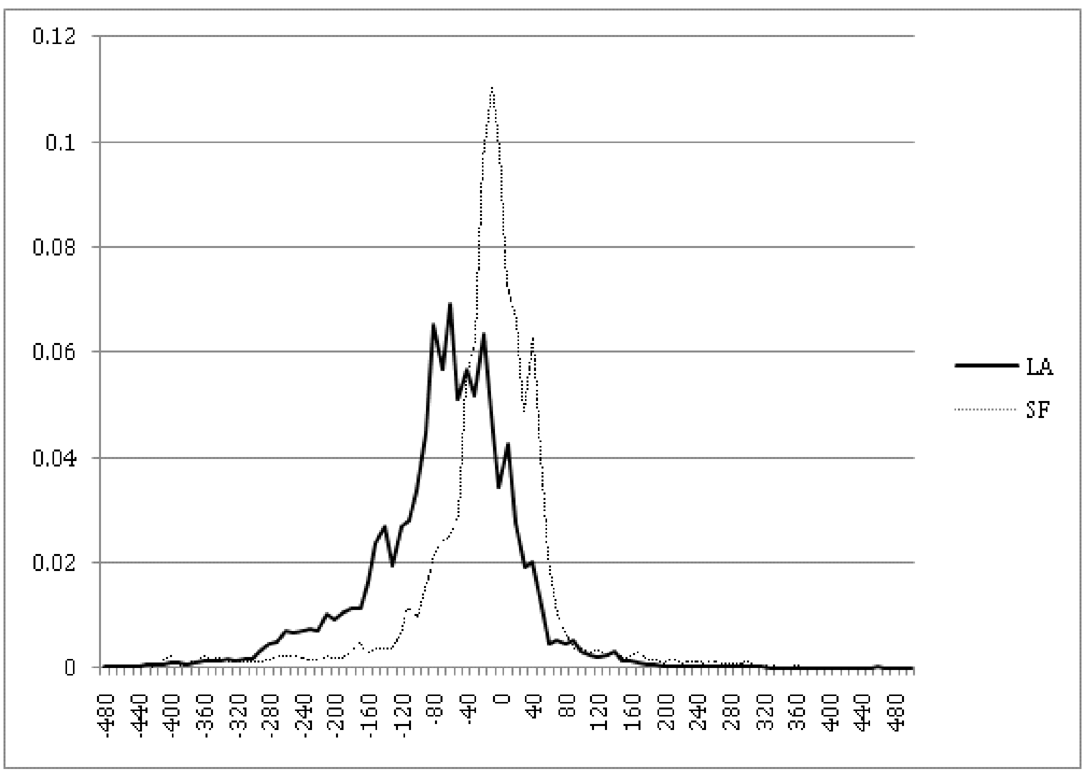
There is a large and growing literature aimed at valuing the benefits of crime reductions (particularly with the goal of conducting cost-benefit analysis of police force expansions, for example). This literature was recently surveyed by Heaton (2010). He notes that the property value hedonic technique (along with a variety of stated preference techniques) is particularly valuable for recovering the intangible costs of crime (e.g., lost quality of life for fear of victimization or effective loss of public space). 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).

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

[23]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).

1994 (summary statistics describing these individuals is given in Table (5)). We then measure the value of the crime changes that these individuals actually experienced between 1994 and 1995. It is highly likely that these individuals still occupy the same residence in 1995 and, as we show in this section, the changes that occurred over this year were substantial enough that proper identification of the MWTP function becomes important in measuring their change in welfare. In particular, Figure (5) illustrates the distribution of changes in violent crime rates experienced by this set of households in each metropolitan area. 77% of these households experienced reductions in violent crime during this period while the remainder experienced increases in violent crime. This allows us to illustrate the welfare changes associated with both reductions and increases in crime.

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



For the purposes of illustration, we report valuations based on three different estimation strategies: (i) Bishop-Timmins, (ii) Rosen, and (iii) horizontal MWTP. The third approach assigns a constant willingness to pay to each individual with the value equal to the slope of the hedonic price function at their observed housing choice. As the utility function is assumed to be linear in Z, this approach corresponds to either the "inversion" procedure outlined in Bajari and Benkard (2005) or to the Rosen (1974) model where the endogeneity problem is trivially solved by assuming that the MWTP function doesn't depend on Z. In this case, the welfare effects may be calculated as the area of the rectangle under the horizontal MWTP, with the width given by the experienced change in violent crime.

For the first two strategies, the value associated with a change in the violent crime rate is calculated as the area of the trapezoid under the downward-sloping MWTP function over the width of the experienced change in violent crime. Figures (6) and (7) illustrate the hedonic price gradient and MWTP function estimates for the Bishop-Timmins and Rosen models for the year 1994. Values associated with reductions in crime are reported as positive magnitudes; values associated with increases yield negative magnitudes.[24]

To simplify the exposition, we report results separately for the 77% of buyers who experienced a reduction in their violent crime rate and for the remaining buyers who experienced an increase. Tables (8) and (9) report results for each of these groups, respectively. Note that the large standard deviations of WTP illustrate skewness of the distributions, versus individuals experiencing counterintuitive signs on their WTP.

The bias from improperly accounting for the effect of a non-marginal change in violent crime on MWTP is evident. Consider first the case of crime reductions. The Rosen model and horizontal MWTP yield estimates of the average WTP for observed reductions that are 10.21 and 9.48 times greater than our model in Los Angeles and 7.37 and 5.98 times greater

[24]A negative willingness to pay to avoid violent crime would 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 specification. 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 from the Bishop-Timmins Model

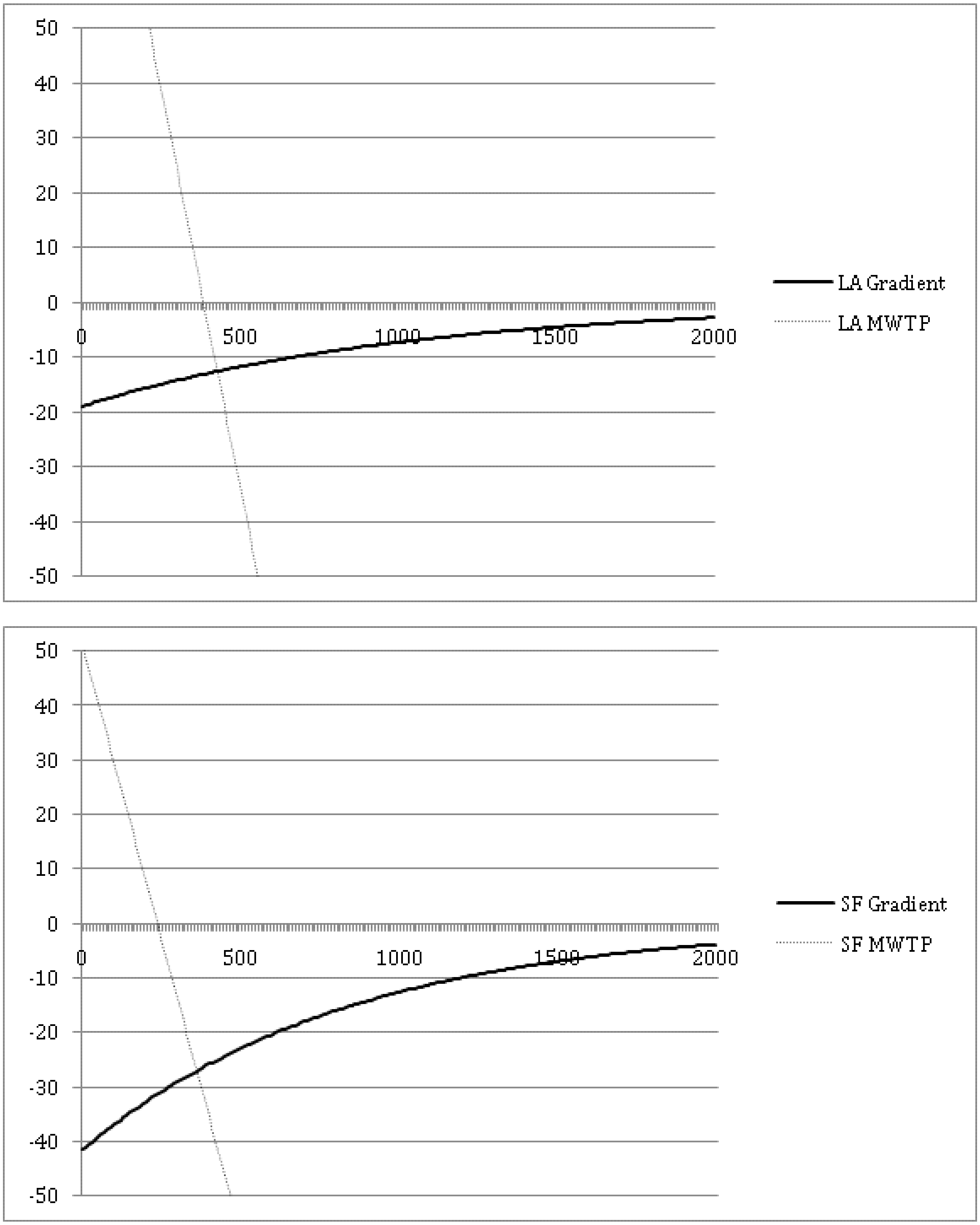
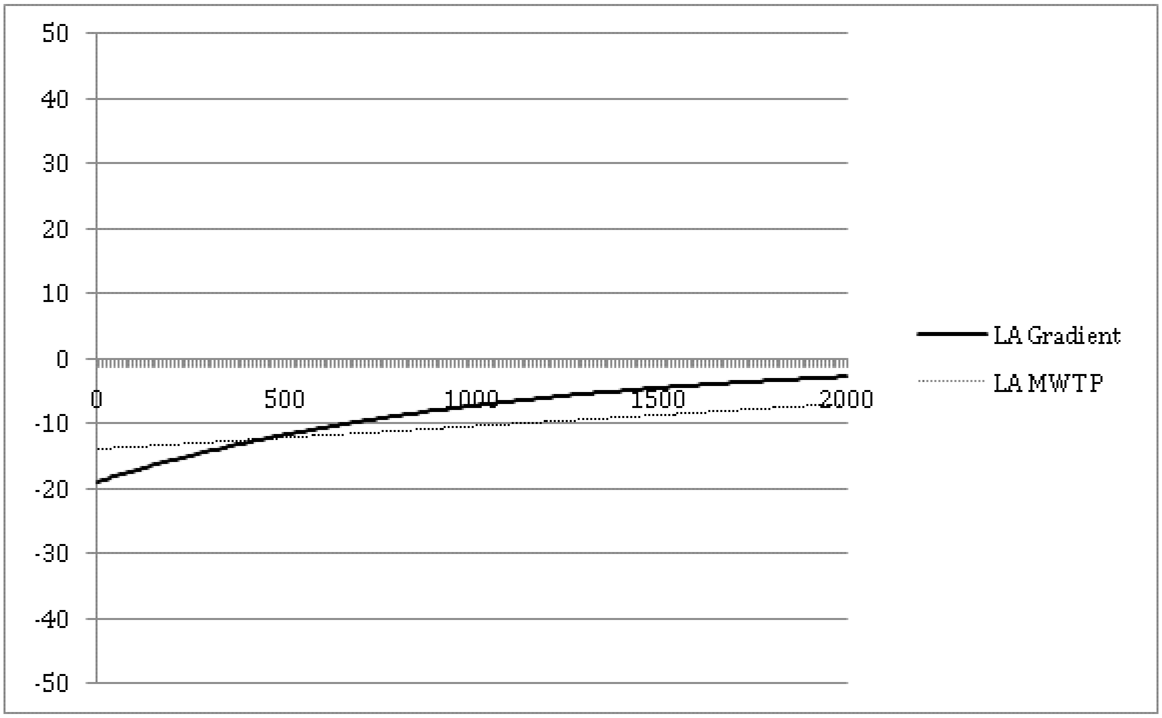


Figure 7: Gradient and MWTP Function from the Rosen Model



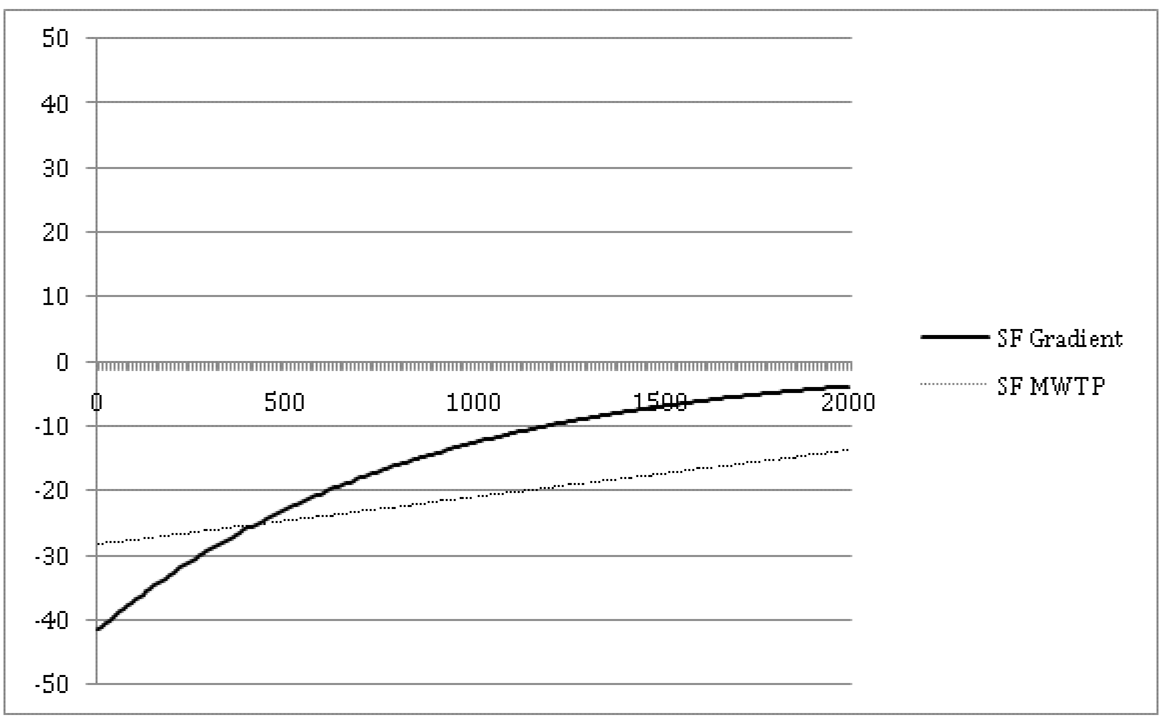


Table 8: WTP for Non-Marginal Reductions in Violent Crime

	Los Angeles ($n = 49,439$)		San Francisco ($n = 18,002$)	
	Average WTP	Std. Dev. WTP	Average WTP	Std. Dev. WTP
Bishop-Timmins	39.02	60.86	48.36	66.52
Rosen	398.32	381.2	356.83	871.43
Horizontal MWTP	370.01	343.09	289.01	559.69

Table 9: WTP for Non-Marginal Increases in Violent Crime

	Los Angeles ($n = 9,669$)		San Francisco ($n = 10,644$)	
	Average WTP	Std. Dev. WTP	Average WTP	Std. Dev. WTP
Bishop-Timmins	-816.39	2221.47	-679.35	1667.56
Rosen	-122.95	135.78	-152.45	161.55
Horizontal MWTP	-131.63	149.75	-170.88	196.76

in San Francisco. The direction of the bias is reversed when we consider increases in the rates of violent crime. Here, the alternative models yield estimates of average WTP for observed crime reductions that are only 0.15 and 0.16 of our estimate in Los Angeles and 0.22 and 0.25 in San Francisco. These differences are far from trivial and would have an important impacts on any cost-benefit analysis.

7 Conclusion

Researchers regularly ascribe downward sloping demand curves to households for goods ranging from breakfast cereals to BMWs. Indeed, recovering the price elasticity of demand for such goods constitutes one of the main activities undertaken by applied microeconomists. However, because of the difficult endogeneity problems associated with the recovery of the MWTP function using the hedonic technique, the same flexibility has generally not been ascribed to household demand for local public goods and amenities. Instead, applications of the hedonic method have tended to focus only on the first-stage hedonic price regression; recovering parameters that only yield valid welfare estimates of marginal policies. In order to properly evaluate the welfare effects associated with larger policies (of which most changes in local public goods are), the researcher must recover the structural parameters of the MWTP function. In this paper, we propose an estimation approach for the recovery of these parameters, while avoiding the endogeneity problems so commonly associated with the hedonic model.

We show that there is no fundamental endogeneity problem in the hedonic model; the endogeneity problems are largely manufactured and are 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 instead rearrange the information provided by hedonic equilibrium and arrive in a simple modeling environment with a single endogenous outcome variable, a vector of exogenous variables, and an econometric error.

Starting with a parametric specification for utility, estimation is straightforward and consists of a standard Maximum Likelihood procedure which employs a textbook change-of-variables technique. In a restricted version of the model, a closed-form solution for the amenity of interest may be found analytically and the change of variables is not required.

Estimation in the simplest version of the model may even be reduced to an indirect least squares procedure, exploiting the one-to-one mapping between the structural and reduced-form parameters. Like the Rosen model, our approach (i) is quite intuitive, as it is derived from the first-order condition for utility maximization, (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 estimator presents very little bias in finite samples. Applying our model to data to violent crime rates in California's two largest metropolitan areas, we find that 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 associated with the observed one-year change in crime for those households that purchased a house in 1994, we find that alternative modeling procedures overstate benefits (for those households which experienced a decrease in violent crime) by a factor of 6 to 10, relative to our approach, and understate costs (for those households which experienced an increase in violent crime) by a factor of 3 to 6, relative to our approach. These differences are both statistically and economically significant and consequential for cost-benefit analyses of policies that may have large impacts on future crime rates.

Appendix - Hedonic Price Function Results

Table A.1: 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-level fixed effects. Significance is indicated by ***(0.01), **(0.05), and *(0.10).*

Table A.2: 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-level fixed effects. Significance is indicated by ***(0.01), **(0.05), and *(0.10).*

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