Difference-in-Differences Hedonics

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Cross-sectional estimates of hedonic price functions theoretically recover marginal values for characteristics but face endogeneity problems. Consequently, economists have introduced difference-in-differences and other quasi-experimental econometric methods into hedonic models. Unfortunately, the welfare interpretation of these estimands has not been clear. This paper shows that quasi-experimental hedonics can identify the movement along the ex post price function. It further shows that this effect is a lower bound on general equilibrium welfare. Thus, nonmarginal welfare can be recovered using transparent designs without Rosen's second stage or more structural models. The paper illustrates these results with an application to toxic facilities and housing prices.

I. Introduction

For more than half a century, economists have used hedonic price functions as a simple way to model quality-differentiated products. The standard hedonic model uses cross-sectional data and the insight that the derivative of the price function with respect to an attribute equals households' marginal willingness to pay (WTP; Rosen 1974). While working with

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cross sections was the standard hedonic project for decades, recently economists have drawn attention to the problem of unobserved attributes that may be correlated with the attribute of interest (Greenstone 2017). To overcome this endogeneity problem, they have applied difference-in-differences (DD) and other quasi-experimental methods to the hedonic econometric model.[1]

While the new approach has definite econometric advantages, it seemingly has come at the cost of clarity about the estimand: what economic question it answers is not always clear or at least has not been perceived clearly in the literature. For example, if we first-difference the data, the dependent variable becomes a change in prices, which mixes information from two equilibria. Yet households face a trade-off among products at a point in time, not across time.

In the housing context, the literature has begun to refer to such changes in prices over time as capitalization (e.g., Chay and Greenstone 2005; Klaiber and Smith 2013; Kuminoff and Pope 2014). The link between such capitalization and the underlying economic model is not immediately clear. For changes to the characteristics of a small subset of houses, the equilibrium price function can be taken as constant over a short time period, so DD models can be interpreted within a single equilibrium (Palmquist 1992). But in general, a large change in the supply of an amenity will endogenously shift the hedonic price function. In addition, other changes in the economic environment taking place over longer time periods would also shift the price function. In these cases, panel data studies compare prices at two different equilibria in potentially confusing ways. The confusion is compounded by ambiguity about the meaning of language borrowed from the program evaluation literature, such as "*the* capitalization effect," when in fact there are various such effects with differing interpretations.

Klaiber and Smith (2013), Parmeter and Pope (2013), and Kuminoff and Pope (2014) have argued that because it combines two equilibria, the capitalization effect answers an ill-defined economic question. Taken together, these papers make two key points. First, the total change in prices from an exogenous change in characteristics is not the same as WTP. Instead, it conflates WTP (defined within the context of one equilibrium) with changes in the price function. Second, estimated cross-sectional price functions are biased if they ignore changes in the function. Both points are correct.

[1] Examples include Davis (2004, 2011), Chay and Greenstone (2005), Greenstone and Gallagher (2008), Linden and Rockoff (2008), Pope (2008), Cellini, Ferreira, and Rothstein (2010), Bento, Freedman, and Lang (2015), Currie et al. (2015), Mastromonaco (2015), Muehlenbachs, Spiller, and Timmins 2015, Haninger, Ma, and Timmins (2017), and Lang (2018). Parmeter and Pope (2013) review this literature. Kuminoff, Parmeter, and Pope (2010) illustrate the importance of using DD hedonic techniques to control for unobservables.

Nevertheless, as I show in this paper, DD hedonic studies can provide meaningful welfare measures. This paper clarifies the issue by introducing distinctions made in the treatment effect literature when the stable unit treatment value assumption (SUTVA) is violated (sec. II). When the hedonic price function shifts endogenously, there are indirect effects (IEs) on the price of all units regardless of treatment status, which violates the usual SUTVA condition.

Using this framework, I first show in section III that if they allow for changes in the price function over time, quasi-experimental hedonic studies can identify what this literature calls the direct effect (DE) of treatment, or the effect of treatment on a given unit, conditional on the treatment program going forward for all other units. This DE has the simple interpretation as the movement along the ex post hedonic price function.

Second, in section IV I show that this effect can be interpreted as a lower bound on Hicksian equivalent surplus (ES) for a nonmarginal change in characteristics of interest, even in the presence of endogenous general equilibrium shifts in the price function, shifts in the price function from other exogenous factors, and endogenous adjustments to other characteristics. The bound is similar to one discussed many years ago by Bartik (1988). For truly marginal changes, it collapses to marginal WTP. These results are quite general. Demands and other aspects of the economic environment may change between periods, there are no restrictions on heterogeneity in demands, household data are not required, and even repeated cross sections can be used. Thus, quasi-experimental estimates of the hedonic price function alone are sufficient to yield at least a bound on nonmarginal changes, even accounting for general equilibrium effects, without requiring economists to estimate Rosen's (1974) difficult second stage or other more structural models.

Section V illustrates these results with an application to the value of reduced toxic emissions in Los Angeles between 1995 and 2000. Although a lower bound on general equilibrium welfare, the estimates are substantial, at about \$6.7–\$7.5 billion for the present value of the realized decrease in emissions, or about \$62–\$69 per household annually. In contrast, the conventional approach to capitalization with a time-invariant function gives values about 14%–20% lower. Simply linearizing marginal WTP gives estimates that are lower still. Thus, besides clarifying the interpretation of quasi-experimental hedonics, the method suggested here can tighten the lower bound.

II. Hedonic Capitalization Effects

A. *The Hedonic Model*

Although the results of this paper apply to any hedonic context, for concreteness, consider the specific application of housing price functions.

Let $\mathcal{H}$ denote the set of houses in a region with typical element h and let $\mathcal{I}$ denote the set of households with typical element i. For ease of exposition, assume for now that the region is closed, so there is no migration in or out. (The extensions in online app. A show that this assumption can be relaxed without affecting the interpretation.) Equilibrium in each time period consists of a one-to-one correspondence of households to houses (all households occupy a house, and all houses are occupied by a household). Households may rent or own their house, and owners rent from themselves.

At time t, households differ by their income y and their current-period preferences, which are represented by a twice differentiable conditional indirect utility function over prices, an amenity of interest g, and other characteristics $\mathbf{x}$, $v_i^t(y_i^t - p_h, g_h, \mathbf{x}_h)$, with $\partial v_i^t/\partial y_i^t > 0$. On the supply side, the profit function for house h is $\pi_h = p_h - c_h(\mathbf{x}_h)$, where the cost function $c_h()$ is twice differentiable. For simplicity, assume that $c_h()$ is constant over time, although this assumption could be relaxed.

Consider two points in time, denoted $t = 0$ for an initial situation and $t = 1$ in a later situation. In each period, prices of houses are determined by the level of the amenities evaluated on the time-specific equilibrium price function: $p_h^t = p^t(g_h^t, \mathbf{x}_h^t)$. The time superscript on the price function indicates that equilibrium hedonic prices may shift. In each period, households maximize utility over a continuous choice set defined by the continuously differentiable price function.

I make the standard hedonic assumption that households have perfect information and are in a static equilibrium in each time period.[2] When we maximize utility in period t, the household satisfies the first-order condition for g:

$$\frac{\partial v_i^t}{\partial g} = -\frac{\partial v_i^t}{\partial p}\frac{\partial p^t}{\partial g}.$$

Using $-\partial v_i^t/\partial p = \partial v_i^t/\partial y$, we find that this is equivalent to

$$\frac{\partial v_i^t/\partial g}{\partial v_i^t/\partial y} = \frac{\partial p^t}{\partial g}. \tag{1}$$

[2] This assumption continues to underlie the majority of work on hedonic markets (Ekeland, Heckman, and Nesheim 2004; Bajari and Benkard 2005; Heckman, Matzkin, and Nesheim 2010; Bishop and Timmins 2019) as well as structural models of locational choice (Epple, Quintero, and Sieg 2020). More recent work increasingly addresses dynamic optimization in the presence of transactions costs, which may be substantial in applications to housing (Kennan and Walker 2011; Bayer et al. 2016; Bishop and Murphy 2019; Ouazad and Rancière 2019). These models help explain how the hedonic function may shift over time with the business cycle.

Equation (1) is the standard tangency condition from Rosen (1974), with the derivative of the hedonic function with respect to an amenity equal to marginal WTP at the optimal point.

Similarly, a landlord's first-order condition for profit maximization for characteristic x_r is

$$\frac{\partial c_h}{\partial x_r} = \frac{\partial p^t}{\partial x_r}. \tag{2}$$

The endogenous amenities $\mathbf{x}$ are supplied according to similar tangency condition, with marginal cost equal to marginal revenue.

The basic problem is (1) to estimate these primitive conditions when g or $\mathbf{x}$ are endogenous and (2) to make inferences about nonmarginal welfare effects from these primitive conditions.

B. *Defining Capitalization Effects*

To overcome the first issue, related to estimation, researchers have applied DD and related quasi-experimental approaches to the hedonic model to identify the effects of exogenous changes in g. While effectively addressing an econometric problem, these methods have raised other questions about what precisely they identify (Klaiber and Smith 2013; Kuminoff and Pope 2014).

If the equilibrium hedonic price function for a housing market changes endogenously because of a shock to amenities, then the price of a house will change even if its amenities have not. In the vocabulary of the program evaluation literature, this is a violation of SUTVA, particularly the no-interference assumption: the outcome (price) of an untreated housing unit in the market is affected by the fact that other housing units were treated with changes to their amenities. In the presence of interference, a policy scenario has an IE even on untreated units plus a DE of treatment on the treated. Consequently, we must make a distinction between the effect of a treatment scenario and the effect of treatment status for a unit, given the scenario. To analyze such effects, we can draw on extensions to the potential outcome framework to consider effects defined by an entire policy—that is, by a change in g anywhere.

In theory, changing the treatment status of just house h by itself could itself have general equilibrium effects, which would muddle the distinction between the DE and the IE. Assumption 1 rules out this problem:

Assumption 1 (Local noninterference). Let $\mathbf{p}_{-h}$ be the vector of prices for all houses except some house h. For all treatment scenarios and $\forall\ h$, $\mathbf{p}_{-h}$ is invariant to whether h is treated.

This assumption—which can be taken as a limiting case of Palmquist's (1992) localized externality—facilitates the distinction between the effect status of treatment on a particular house and the general equilibrium effects of the program.[3]

Let g_h^a be the value of g at house h, which is realized under some potential scenario a at $t = 1$, and let $\mathbf{g}_{-h}^a$ be the $(H - 1)$-dimensional vector of g at all houses except h in scenario a. Let $\mathbf{x}_h^a(g_h^a)$ be the value of $\mathbf{x}$ at house h in scenario a, which itself is a function of g_h^a. Let a^* be the scenario that was actually implemented, such as a program to clean up toxic waste. Likewise, let a' be some alternative counterfactual scenario that could have prevailed at $t = 1$, the outcomes under which one wants to compare to the outcomes under a^*. With this notation, different scenarios a describe different possible distributions of g at $t = 1$.

I incorporate the violation of SUTVA by allowing for different potential prices at house h based not only on g_h but also on the entire policy vector $\mathbf{g}$. Under assumption 1, we can write the potential outcome for house h if we were in the counterfactual state (with no houses treated) as $p_h^{a'}(g_h^{a'}, \mathbf{x}_h^{a'}(g_h^{a'}))$. The a' superscript on p indicates that the functional relationship depends on the state of the world (in this case, the counterfactual state). In figure 1, this price is illustrated by p_A, from the counterfactual price function evaluated at $g_h^{a'}$. The potential outcome for house h, if the rest of the market were under policy a^*, can be written as $p_h^{a^*}(g_h^{a'}, \mathbf{x}_h^{a^*}(g_h^{a'}))$ if house h were not treated (receiving its counterfactual $g_h^{a'}$) and as $p_h^{a^*}(g_h^{a^*}, \mathbf{x}_h^{a^*}(g_h^{a^*}))$ if house h were treated (receiving $g_h^{a^*}$). These are depicted in figure 1 by prices p_B and p_C respectively.

As always, causal effects of a policy must compare the policy scenario, a^*, with a counterfactual, a'. Two distinctions here should be emphasized about this comparison that differ from other common settings. First, there may be exogenous changes over time. Thus, in general, the equilibrium under a' is not the same as in $t = 0$. Even if a' is no program to change g, the distribution of g may be evolving. Also, even if g would not have changed, p_A is not necessarily equal to p_h^0, as there could be other changes in the economic environment affecting the price function or $\mathbf{x}_h$. Second, with interference, there are endogenous changes from the policy that require untreated units to be evaluated in the policy scenario as well as the counterfactual. Despite the fact that house h is untreated, $p_B = p_h^{a^*}(g_h^{a'}, \mathbf{x}_h^{a^*}(g_h^{a'}))$ is not necessarily equal to $p_A = p_h^{a'}(g_h^{a'}, \mathbf{x}_h^{a'}(g_h^{a'}))$ because the treatments at the other houses affect equilibrium prices at all houses, including h.

[3] For similar reasons, Hudgens and Halloran (2008) impose a randomization assumption fixing the number of treated units, and VanderWeele and Tchetgen Tchetgen (2011) propose an alternative definition of the DE that no longer decomposes the total effect. The local noninterference assumption provides an alternative way to address this issue.

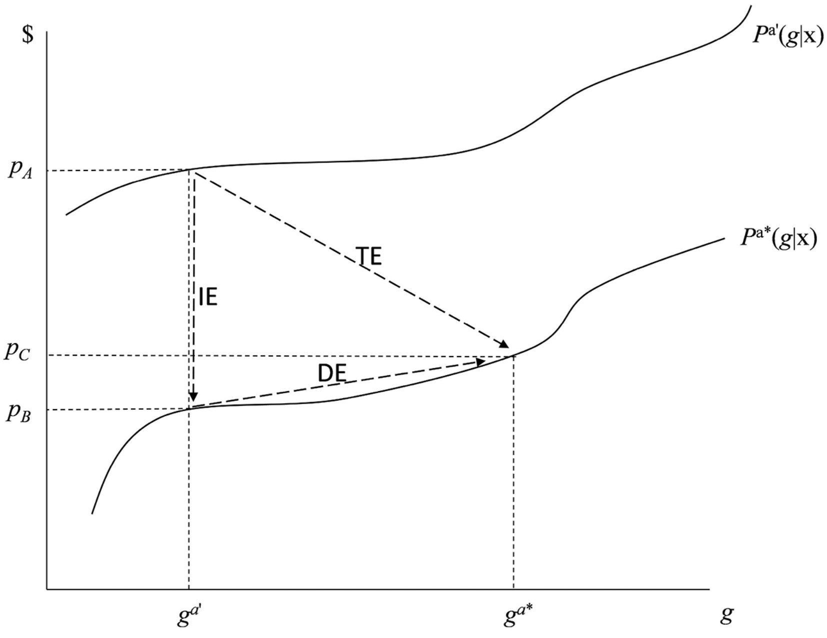

FIG. 1.—Defining capitalization effects. The figure illustrates the IE, DE, and TE of a policy shifting the distribution of an amenity g. The policy shifts the hedonic price function from $p^{a'}()$ to $p^{a^*}()$. Even the prices of untreated houses are affected by this shift, moving from p_A to p_B, which is an IE. Treated houses move from p_A to p_C, which is a TE for these units. This TE can be decomposed into IE + DE.

Following Hudgens and Halloran (2008) and VanderWeele and Tchetgen Tchetgen (2011), define the individual *total effect* (TE) of policy a^* for some house h as

$$\mathrm{TE}_h(a^*) = p_h^{a^*}\left(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*}\left(\mathrm{g}_h^{a^*}\right)\right) - p_h^{a'}\left(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\left(\mathrm{g}_h^{a'}\right)\right).$$

The TE is the overall effect of treatment by the policy at house h. In figure 1, it is equal to $p_C - p_A$. It can be decomposed into two parts. The individual *indirect effect* (IE) of treatment a^* is

$$\mathrm{IE}_h(a^*) = p_h^{a^*}\left(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\left(\mathrm{g}_h^{a'}\right)\right) - p_h^{a'}\left(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\left(\mathrm{g}_h^{a'}\right)\right).$$

IE_h represents the effect on the price of untreated houses due to the shifting price function between scenarios a' and a^*. It is the result of interference: even if house h is untreated, its price may be affected by spillovers from treatments elsewhere. IE_h is depicted in figure 1 by $p_B - p_A$.

The individual *direct effect* (DE) of treatment a^* for h, conditional on the program going forward in the rest of the market, is defined as

$$\mathrm{DE}_h(a^*) = p_h^{a^*}\left(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*}\left(\mathrm{g}_h^{a^*}\right)\right) - p_h^{a^*}\left(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\left(\mathrm{g}_h^{a'}\right)\right).$$

DE_h represents the effect of reassigning house h from an untreated to a treated state while holding constant the treatment status of the other houses. It is depicted in figure 1 by $p_C - p_B$.

As written, TE, IE, and DE all include any effects mediated through changes in $\mathbf{x}$. For example, improvements in g might motivate households to improve the house in other (observable) ways or trigger resorting, with new households changing the house. Variants of these treatment effects that net out the portions mediated through changes in $\mathbf{x}$ can be defined for all three. Define the *total unmediated effect* (TUE) and the *direct unmediated effect* (DUE) at $\tilde{\mathbf{x}}_h$ as

$$\mathrm{TUE}_h(a^*) = p_h^{a^*}\left(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*} = \tilde{\mathbf{x}}_h\right) - p_h^{a'}\left(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'} = \tilde{\mathbf{x}}_h\right),$$

$$\mathrm{DUE}_h(a^*) = p_h^{a^*}\left(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*} = \tilde{\mathbf{x}}_h\right) - p_h^{a^*}\left(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'} = \tilde{\mathbf{x}}_h\right).$$

TUE and DUE are the same as TE and DE, respectively, except they hold $\mathbf{x}_h$ constant. DUE and DE can both be identified by DD hedonic methods. As I show below, DUE is the causal concept with the clearest welfare interpretation as a lower bound on welfare. It represents moving h from an untreated to a treated state while otherwise holding constant the treatment program and holding constant $\mathbf{x}_h$. Accordingly, henceforth I shall focus primarily on DUE.

These individual effects have their respective group averages. Define the average TUE and DUE as

$$\overline{\mathrm{TUE}(a^*)} = \frac{1}{H}\sum_h \mathrm{TUE}_h(a^*),$$

$$\overline{\mathrm{DUE}(a^*)} = \frac{1}{H}\sum_h \mathrm{DUE}_h(a^*).$$

More generally, we could define similar averages over any subset of houses $\mathcal{H}'$. In the case of the DUE, we then write

$$\overline{\mathrm{DUE}_{\mathcal{H}'}(a^*)} = \frac{1}{\sum_h 1(h \in \mathcal{H}')}\sum_{h\in\mathcal{H}'} \mathrm{DUE}_h(a^*).$$

A particular special case is where $\mathcal{H}'$ is simply the subset of treated houses. Then $\overline{\mathrm{DUE}_{\mathcal{H}'}(a^*)}$ is the average DUE on the treated, or $\overline{\mathrm{DUET}(a^*)}$.

III. Difference-in-Differences Hedonic Models Identify the Direct Effect

Either $\overline{\mathrm{TE}(a^*)}$ or $\overline{\mathrm{DE}(a^*)}$—or their unmediated variants—could be defined as a capitalization effect. $\overline{\mathrm{TE}(a^*)}$ captures both the treatment on h

and the shifting hedonic price function. If we wanted to forecast the effects of the program on prices relative to a counterfactual of no program, either $\overline{\text{TE}(a^*)}$ or $\overline{\text{TUE}(a^*)}$ would be useful measures. However, the impact on prices qua prices are of limited interest for measuring welfare, except for understanding distributional effects on individuals who pay them or receive them as income. As Klaiber and Smith (2013) and Kuminoff and Pope (2014) have emphasized, $\overline{\text{TUE}(a^*)}$ is not the average WTP for program a^*. It conflates the DUE and the indirect unmediated effect. Indeed, it is hard to give it any welfare interpretation except in the special case where the hedonic function does not shift.

Moreover, without additional assumptions, $\overline{\text{TE}(a^*)}$ and $\overline{\text{TUE}(a^*)}$ cannot be identified anyway. Because $p_h^{1,a'}$ is not observed, we cannot know the IEs.[4] However, $\overline{\text{DUE}(a^*)}$ can still be identified because by definition it does not reference scenario a'. It requires only the weaker assumption, typical of DD estimators, that changes from p_h^0 to p_h^{1,a^*} for untreated units are the same on average as what they would have been for treated units were they left untreated, but the policy went forward. In practice, it allows researchers to use data on observed changes.

The basic argument can be seen in figure 1, if we replace $p^{a'}()$ with $p^0()$. A treated unit and its matched control both start at p_A. In scenario a^*, the untreated unit moves to p_B, and under the identifying assumption so would the treated unit (in expectation). In this example, at untreated units g does not change, but that assumption is unnecessary.[5] Treated units have an additional shock to g, ending up at p_C. Thus, the identified effect from DD is $(\text{P}_\text{C} - \text{P}_\text{A}) - (\text{P}_\text{B} - \text{P}_\text{A}) = (\text{P}_\text{C} - \text{P}_\text{B})$, which is the movement along the ex post hedonic price function from treatment, or DUE. As shown in section IV, this effect is a lower bound on general equilibrium welfare.

A. Identification and Estimation of Capitalization Effects: The Linear Case

For simplicity, consider first a linear model. For any individual house h, the ex ante and a^* hedonic price functions and their difference are

[4] That is not to say that if it were of interest, TE could not be identified with additional assumptions or data. One possible assumption is that there are no other changes, so that if a' were no policy, then p_h^0 could be substituted for $p_h^{a'}(\text{g}_h^{a'})$ in the expression for TE. This may be especially plausible under RD designs. Another assumption is that observations are available at other untreated markets that can identify the counterfactual time trend. See Hudgens and Halloran (2008) and Manski (2013). Crépon et al. (2013) illustrate the idea.

[5] The term g can change for the untreated, so long as it would have changed in the same way for the treated absent treatment. For example, Chay and Greenstone (2005) and Bento, Freedman, and Lang (2015) consider price effects of air quality improvements triggered by regulatory thresholds. One can identify the DEs of the regulations, still allowing for national time trends.

$$p_h^0 = \alpha^0 + \beta^0 g_h^0 + \gamma^{0\prime}\mathbf{x}_h^0 + \xi_h + \varepsilon_h^0, \tag{3a}$$

$$p_h^{a^*} = \alpha^{a^*} + \beta^{a^*} g_h^{a^*} + \gamma^{a^{*\prime}}\mathbf{x}_h^{a^*} + \xi_h + \varepsilon_h^{a^*}, \tag{3b}$$

$$dp_h^{a^*} = d\alpha^{a^*} + d\beta^{a^*} g_h^0 + \beta^{a^*} dg_h^{a^*} + d\gamma^{a^{*\prime}}\mathbf{x}_h^0 + \gamma^{a^{*\prime}} d\mathbf{x}_h^{a^*} + d\varepsilon_h^{a^*}, \tag{3c}$$

where in equation (3c) the differences are taken from the baseline, not from the unobserved counterfactual. This model is a variant of the generalized DD estimator recommended by Kuminoff, Parmeter, and Pope (2010). Note that the local noninterference assumption 1 is implicitly embedded in equation (3b), as the parameters are independent of $g_h^{a^*}$.

As written, this model assumes true panel data at the micro level, which in the case of housing is the repeat-sales model. However, in practice, it could be applied to repeated cross sections, essentially treating the panel as being at the level of some group (e.g., communities) and using fixed effects in lieu of first differencing.[6] The application in section V illustrates the approach.

In any case, if the hedonic price function does not change between (3a) and (3b), then we can suppress time scenario superscripts in the parameters and equation (3c) collapses to

$$dp_h^{a^*} = \beta dg_h^{a^*} + \gamma' d\mathbf{x}_h^{a^*} + d\varepsilon_h^{a^*}. \tag{4}$$

In this case, it is clear that DD hedonic regressions identify β, the marginal effect of a change in the attribute, if $d\varepsilon$ is independent of dg after conditioning on $d\mathbf{x}$.

However, when the hedonic function does shift, the true model is (3c), so (4) of course is misspecified. Kuminoff and Pope (2014) refer to this problem as conflation bias, as the estimates conflate marginal WTP at a point in time (i.e., β^0 or β^{a^*}) with changes in the price function. As they show, conflation bias is an example of omitted variable bias. Clearly, if g^0 and $\mathbf{x}^0$ are included in the model, as in equation (3c), the linear model potentially can identify β^{a^*}, the ex post marginal WTP under the scenario. Thus, any flaw in the model arises from failure to properly condition on baseline observables, not with the economic logic of differencing prices from two equilibria per se.

Of course, including g^0 and $\mathbf{x}^0$ in a linear model may raise additional estimation issues. While allowing for an unobserved time-invariant effect, ξ_h, equations (3) still require a conditional zero mean assumption on $d\varepsilon$

[6] In that case, we would simply replace eq. (3c) with the following fixed effects variant:

$$p_h^t = \alpha^0(1 - D^1) + \alpha^{a^*}D^1 + \beta^0 g_h^0(1 - D^1) + \beta^{a^*} g_h^{a^*} D^1 + \gamma^{0\prime}\mathbf{x}_h^0(1 - D^1)$$
$$+ \gamma^{a^{*\prime}}\mathbf{x}_h^{a^*} D^1 + \xi_c + \varepsilon_h^t,$$

where D^1 is an indicator for an observation from the second period. The equation simply stacks eqq. (3a) and (3b) with period-specific coefficients and a fixed effect for community c.

to estimate the full set of parameters. Unfortunately, $d\varepsilon$ may well be correlated with g^0: for example, houses near landfills may be depreciating in unobserved ways. However, important (if incomplete) information can still be identified under a weaker conditional independence assumption, in which dg^{a^*} is independent of $d\varepsilon^{a^*}$ conditional on g^0 and the other observables: $(d\varepsilon \perp dg | g^0, \mathbf{x}^0, d\mathbf{x})$. This would allow identification of β^{a^*}, even if β^0 were biased.

The fact that it is the ex post hedonic price parameter, β^{a^*}, that is identified under the weaker assumptions is the crucial point here. In the context of the linear model, this parameter represents $\overline{\text{DUET}}$ (per unit g), the DE netting out the mediated effect of any changes in $\mathbf{x}$. The product $\beta^{a^*} \cdot dg^{a^*}$ is the movement along the ex post hedonic price function in the dimension of g.

B. Estimating Direct Effects without Linearity

The preceding insight extends to nonlinear models, like matching estimators, as well. To simplify the exposition, consider the case of a binary treatment, which occurs only in the second period: $\mathrm{g}^0 = 0$, $\mathrm{g}^{a^*} \in \{0, 1\}$.[7] Examples might include cleanup of Superfund sites (Greenstone and Gallagher 2008; Gamper-Rabindran and Timmins 2013), discovery of a cancer cluster (Davis 2004), closure of large polluting facilities (Currie et al. 2015; Mastromonaco 2015), arrival of a sex offender (Linden and Rockoff 2008), and so forth. Relaxing the linearity inherent in equations (3), we can define the potential outcomes using the following semiparametric assumptions:

$$p_h^0 = \boldsymbol{\gamma}^{0\prime}\mathbf{x}_h^0 + \varepsilon_h^0, \tag{5a}$$

$$p^{a^*}\left(\mathrm{g}_h^{a^*} = 0\right) = \boldsymbol{\gamma}_{\mathrm{g}^1=0}^{a^*\prime}\mathbf{x}_h^{a^*} + \varepsilon_{\mathrm{g}^{a^*}=0,h}^{a^*}, \tag{5b}$$

$$p^{a^*}\left(\mathrm{g}_h^{a^*} = 1\right) = \boldsymbol{\gamma}_{\mathrm{g}^1=1}^{a^*\prime}\mathbf{x}_h^{a^*} + \varepsilon_{\mathrm{g}^{a^*}=1,h}^{a^*}, \tag{5c}$$

where the $\boldsymbol{\gamma}$ vectors include an intercept term and $\mathrm{E}[\varepsilon_{\mathrm{g}',h}^{a^*} | \mathbf{x}]$ need not be zero. Equation (5b) represents houses that are not treated ex post, and equation (5c) represents those that are. This model controls for $\mathbf{x}$ with regressions that differ by treatment status but allows the effect of g, which is embedded in the ε's, to have any arbitrary form (e.g., Heckman, Ichimura, and Todd 1997). It again implicitly relies on the local noninterference assumption 1, as $\boldsymbol{\gamma}_{\mathrm{g}}^{a^*}$ does not depend on whether any one house h is treated.

[7] The model of this subsection could be extended to include multivalued or even continuous treatments, as suggested by Imbens (2000) and Hirano and Imbens (2004). See, e.g., Muehlenbachs, Spiller, and Timmins (2015) for a hedonic application.

This model requires a conditional mean independence assumption on differences in unobservables, slightly weaker than the linear model. For example, if we want to know the effect of the observed policy a^* relative to some counterfactual, then we want to estimate the average treatment on the treated, and we require the following assumption.

ASSUMPTION 2 (Conditional mean independence in differences for the treated).

$$\mathrm{E}[\varepsilon^{a^*}_{g^1=0} - \varepsilon^0 \mid \mathbf{x}^0, g^{a^*} = 1] = \mathrm{E}[\varepsilon^{a^*}_{g^1=0} - \varepsilon^0 \mid \mathbf{x}^0, g^{a^*} = 0]\,. \tag{6}$$

In words, after conditioning on $\mathbf{x}^0$, the houses that are actually treated by the policy ($g^{a^*} = 1$) would have had the same trend (on average) in unobserved time-varying effects, had they not been treated, as the untreated houses ($g^{a^*} = 0$). Under these conditions plus the usual requirement of overlapping support, a conditional DD estimator can identify the $\overline{\mathrm{DUE}}$ for the treated. This is stated in the following lemma.

LEMMA. Given assumption 1, assumption 2, and the model of equations (5),

$$\begin{aligned}
&\mathrm{E}\Big[\Big(p^{a^*}\Big(g^{a^*} = 1\Big) - \gamma^{a^*\prime}_{g^1=0}\mathbf{x}^{a^*}\Big) - \Big(p^0 - \gamma^{a^*\prime}_{g^1=0}\mathbf{x}^0\Big)|\mathbf{x}^0, g^{a^*} = 1\Big)\Big] \\
&\quad - \mathrm{E}\Big[\Big(p^{a^*}(g^1 = 0) - \gamma^{a^*\prime}_{g^1=0}\mathbf{x}^{a^*}\Big) - \Big(p^0 - \gamma^{a^*\prime}_{g^1=0}\mathbf{x}^0\Big)|\mathbf{x}^0, g^{a^*} = 0\Big)\Big] \\
&= \mathrm{E}\Big[\Big(\Big(p^{a^*}\Big(g^{a^*} = 1\Big) - p^{a^*}(g^1 = 0)\Big)|\mathbf{x}^0, g^{a^*} = 1\Big) \\
&\quad - \gamma^{a^*\prime}_{g^1=0}\Big((d\mathbf{x} \mid \mathbf{x}^0, g^{a^*} = 1) - (d\mathbf{x} \mid \mathbf{x}^0, g^{a^*} = 0)\Big)\Big] = \overline{\mathrm{DUET}(a^*)}.
\end{aligned} \tag{7}$$

Proof.—The first equality follows immediately from equations (5) and assumption 2. The second follows from equations (5) and assumption 1. The third follows from the definition of DUET.

$\overline{\mathrm{DUET}(a^*)}$ might be estimated using a regression-adjusted DD matching estimator (e.g., Heckman, Ichimura, and Todd 1997). Muehlenbachs, Spiller, and Timmins (2015) and Haninger, Ma, and Timmins (2017) use this approach in hedonic applications. For the linear case, the parameter β^1 represents the marginal contribution of g along the ex post hedonic function, holding constant any effects mediated through $\mathbf{x}$. The estimand defined in the lemma recovers an analogous effect for those houses treated by the policy but using weaker econometric assumptions.

C. *Extensions*

The following section is devoted to the economic interpretation of this estimand. Before turning to that discussion, two comments are in order.

First, $\overline{\text{DUE}}$ on the treated, which is identified using DD hedonics, arguably identifies effects at the most salient part of the distribution, certainly when evaluating the policy that went into effect. Nevertheless, as shown in online appendix section A.1, we also can identify treatment effects at untreated units, which would be useful for evaluating counterfactual policies—so long as the observed price function is still representative of the ex post equilibrium. For example, we can always compare the actual policy to an alternative counterfactual.

Second, in some cases, one may not want to impose the conditional mean independence assumption. Although it is weaker than those required for the standard ordinary least squares model, one may be concerned that changes in unobservables are correlated with changes in g. If so, one could invoke additional exclusion restrictions and use instrumental variables. For example, Chay and Greenstone (2005) and Bento, Freedman, and Lang (2015), considering hedonic regressions of housing prices on air quality, argue that recessions or local economic shocks can simultaneously reduce housing prices in unobserved ways while improving air quality by dampening economic activity, thus biasing DD (or fixed effects) hedonic estimates of air quality downward. They argue that national ambient air quality thresholds are a plausible source of exogenous variation in air quality.

Similarly, the exogeneity of g can be made more credible using regression discontinuity (RD) designs (e.g., Chay and Greenstone 2005; Greenstone and Gallagher 2008; Cellini, Ferreira, and Rothstein 2010; Gamper-Rabindran and Timmins 2013; Lang 2018). In principle, RD designs can be used in either panel or cross-sectional settings. In the neighborhood of the discontinuity, treatment is as good as randomly assigned, as in a controlled experiment (Lee and Lemieux 2010). This has two key implications for interpreting hedonics. First, the local average treatment effect is the same as the average treatment effect on the treated, so RD designs identify either. Second, RD estimates are unbiased even when researchers do not include a full set of controls, so long as they do not jump discretely along with the policy (Bayer, Ferreira, and McMillan 2007), though they are less efficient. This suggests that it may not always be necessary to control for changes in $\mathbf{x}$ not caused by the policy.

IV. The Welfare Interpretation of Capitalization Effects

A. *Interpreting the Direct Unmediated Effect*

Section III showed that quasi-experimental hedonic studies can identify $\text{DUET}(a^*)$, the DUE on the treated, if they allow for changing hedonic functions. $\text{DUET}(a^*)$ is a well-defined economic concept. It is the difference along the ex post hedonic price function between the values of a house at the new and old levels of the amenity or, equivalently, the cumulated marginal values along the price function (not demand function), netting out effects mediated through $d\mathbf{x}$: $p^{a^*}(g^{a^*}, \mathbf{x}^0) - p^{a^*}(g^0, \mathbf{x}^0) = \int_{g^0}^{g^{a^*}} (\partial p^{a^*}(g, \mathbf{x}^0)/\partial g)\, dg$.

What is the economic interpretation of this estimand? In this section, I show that, summed over houses, it represents a lower bound on the total welfare effects of the policy for all households, accounting for nonmarginal changes in g and general equilibrium price effects, mobility responses, and endogenous responses to $\mathbf{x}$. The specific measure bounded is the Hicksian ES for all these effects. ES is similar to the equivalent variation but differs insofar as it measures the willingness to accept to forego the realized change in g, in contrast to the g's that would be chosen when foregoing the price change.[8]

The argument for this lower bound on ES is quite simple in a partial equilibrium context where there are no supply or implicit price effects on $\mathbf{x}$ and no effects on profits, so that the only effects are the change in the distribution of g (Griffith and Nesheim 2013). By a simple revealed preference argument, the household consuming g^1 could save expenditures amounting to $\int_{g^0}^{g^{a^*}} (\partial p^{a^*}/dg)\, dg$ by consuming g^0 instead. But because it does not choose to do this, the household's minimum willingness to accept must be greater than this amount.

This intuition can be seen in figure 2, which depicts a Marshallian bid function for g intersecting the two marginal price functions at the chosen quantities g^0 and g^1. It also depicts a Hicksian demand function evaluated at u^1, which intersects the Marshallian function at g^1. Hicksian ES is the entire shaded area under the Hicksian demand function from g^0 to g^1. (In contrast, equivalent variation would be the area under the function from the level of g chosen under p^0 to achieve u^1, depicted here as $g(p^0(), u^1)$, up to g^1.) Clearly, $\int_{g^0}^{g^{a^*}} (\partial p^{a^*}/dg)\, dg$, in darker shading, is a lower bound on ES $= \int_{g^0}^{g^{a^*}} h(g, u^1)\, dg$. The argument is analogous to the fact that a Paasche index is a lower bound on the value of a quantity change.

In fact, under assumption 1 (local noninterference) and an additional assumption of nonnegative profits, this bound remains true even in general equilibrium with an endogenous change in the entire hedonic price function, endogenous changes in the supply of $\mathbf{x}$, and resorting of households. The required assumption on profits is as follows.

[8] In other words, it is the change in money that holds utility constant at ex post levels for a change in g, or, equivalently, the area under the Hicksian demand curve for g (evaluated at ex post utility) between g^0 and g^1. Whereas equivalent variation is more appropriate for price changes, ES is often used for exogenous changes in quantities or qualities (see Hicks 1943 or Freeman, Herriges, and Kling 2014, ch. 3).

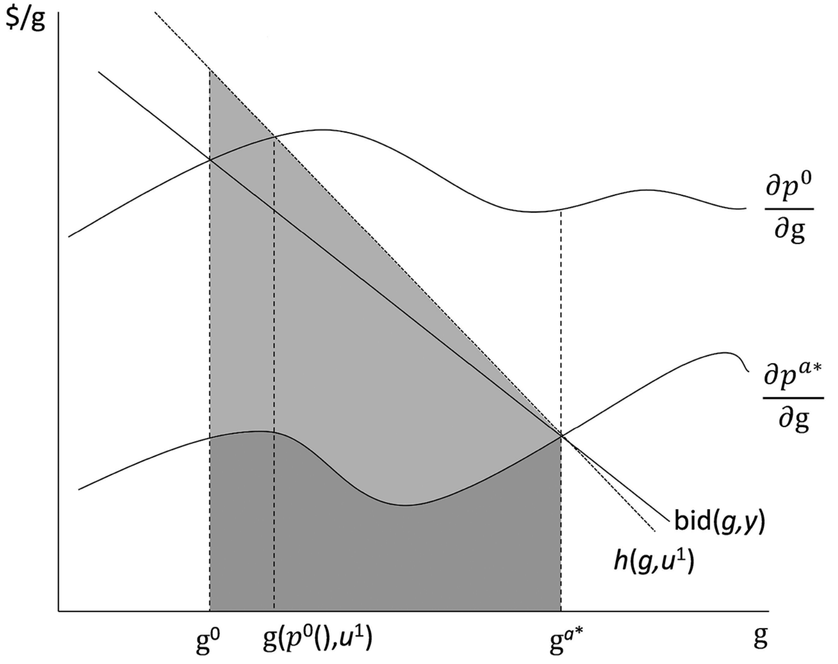

FIG. 2.—Bounds for ES for changes in characteristics. The figure shows the Hicksian ES as the area under the Hicksian demand curve $h()$ from g^0 to g^{a^*}. A partial equilibrium version of the lower bound is illustrated by the fact that this area exceeds the movement along the price function, or the area $\int_{g^0}^{a^*}(\partial p^{a^*}/dg)dg$. The text shows that this bound extends to general equilibrium.

ASSUMPTION 3 (Nonnegative profits). The change in aggregate profits due to adjustments in **x** from their counterfactual level are nonnegative when evaluated at the counterfactual level of g:

$$\sum_h\Big[\Big(p^{a^*}\Big(g_h^{a\prime},\mathbf{x}_h^{a^*}\Big)-p^{a^*}(g_h^{a\prime},\mathbf{x}_h^{a\prime})\Big)-\Big(c\Big(g_h^{a\prime},\mathbf{x}_h^{a^*}\Big)-c(g_h^{a\prime},\mathbf{x}_h^{a\prime})\Big)\Big]\geq 0.$$

This assumption, which nests a zero-profit condition, seems intuitive: landlords would not make the investment to change **x** unless it increased profits.Defining H^T as the number of treated houses, we can state the following proposition, the key result of this section.

PROPOSITION 1. Given assumptions 1 and 3, $H^T\cdot\overline{\mathrm{DUET}(a^*)}\leq(\mathrm{ES}+\Delta\mathrm{profits})$ for an exogenous change in the distribution of g. The result holds even when hedonic prices, households, and landlords adjust to the change endogenously, with these effects included in the welfare measure. It also holds when there are other changes in the economic environment potentially shifting the price function or **x** over time but does not include these in the welfare measure.

Proof.—See the appendix.

The proposition states that $\overline{\text{DUET}(a^*)}$ times the number of treated units is a lower bound on welfare for all households, whether affected directly or indirectly (by the changing price function). Note that although panel data are used to control econometrically for unobservables, $\overline{\text{DUET}(a^*)}$ is the average movement along the ex post hedonic function and ES uses the ex post expenditure function. Thus, only the ex post situation is relevant for the interpretation. If demands or tastes change, the result remains valid, but the evaluation is from the perspective of ex post preferences.

The formal proof follows the outline of a verbal argument in Bartik (1988), clarifying a few ambiguous points.[9] Denote the expenditure function for household i as $e_i(p(), u)$, where $p()$ is the hedonic price function and the price of other goods is normalized to 1. It is the solution to the expenditure minimization problem when the household faces hedonic price function $p()$. Denote the restricted expenditure function as $\tilde{e}_i(p(\mathrm{g}, \mathbf{x}), \mathrm{g}, \mathbf{x}, u)$; it is the solution to the expenditure minimization problem when the household is constrained to choose the bundle $(\mathrm{g}, \mathbf{x})$. The basic idea is to define the welfare measure as follows:

$$dW = \sum_i \left[\tilde{e}_i\left(p^{a'}\left(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\right), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u^{a^*}_i\right) - e_i\left(p^{a^*}(), u^{a^*}_i\right)\right] + \sum_h \left[\left(p^{a^*}\left(\mathrm{g}^{a^*}_h, \mathbf{x}^{a^*}_h\right) - p^{a'}\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a'}_h\right)\right) - \left(c\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a^*}_h\right) - c\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a'}_h\right)\right)\right], \tag{8}$$

where $(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')})$ represent the characteristics, in the counterfactual scenario a', of a house actually occupied by household i in the counterfactual scenario. The first term in square brackets is, by definition, ES for the change in g. The second term in square brackets is the change in landlord profits. It is the change in rents, from the shift in the hedonic price function, adjustments in $\mathbf{x}$ and exogenous changes in g, minus the change in costs, evaluated at baseline levels of g.

As shown in the appendix, using assumption 3, we find that this measure is equivalent to

[9] Bartik's argument actually was that the movement along the ex ante price function would be an upper bound on welfare. He does not link this measure to what can be identified econometrically. As noted in sec. III, it is the ex post price function that is identified with panel data, which provides a lower bound by similar logic. Additionally, Bartik (1988) does not provide a mathematical proof. Kanemoto (1988) provided another related bounding proof. However, his model is quite different, involving capitalization into land values in long-run equilibrium. Furthermore, he shows that prepolicy prices are a lower bound on a rather unusual version of compensating variation for a subset of the economy, whereas my bound uses the identified ex post prices as a bound on conventional ES.

$$
\begin{aligned}
dW = & \sum_i \Big[\tilde{e}_i\Big(p^{a^*}\big(g^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), g^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*}\Big) - e_i\Big(p^{a^*}(), u_i^{a^*}\Big)\Big] \\
& + \sum_h \Big[\Big(p^{a^*}\Big(g_h^{a'}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\big(g_h^{a'}, \mathbf{x}_h^{a'}\big)\Big) - \Big(c\Big(g_h^{a'}, \mathbf{x}_h^{a^*}\Big) - c\big(g_h^{a'}, \mathbf{x}_h^{a'}\big)\Big)\Big] \\
& + \sum_h \Big(p^{a^*}\Big(g_h^{a^*}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\Big(g_h^{a'}, \mathbf{x}_h^{a^*}\Big)\Big). \qquad (9)
\end{aligned}
$$

Now, in the first line, the term in square brackets is nonnegative for each i: the value of a constrained expenditure minimization problem is no less than the value of an unconstrained expenditure minimization problem at the same prices and utility. Additionally, the second line is nonnegative by assumption 3. Meanwhile, the third line is the observed measure, the sum of price changes along the ex post price function holding $\mathbf{x}$ constant. As the desired welfare measure is the observed value plus a positive number, the observed value is less than the change in welfare.

Thus, there is a clear welfare interpretation of capitalization effects in a DD framework. They can identify a lower bound on ES for changes in g. (For decreases in g, the lower bound means the estimate is too negative, which is the same as an upper bound on the welfare loss, in absolute values.) In general, the gap represented by the bound is unknown. However, we can expect that it better approximates the true value for smaller shocks. Indeed, for truly marginal changes, the movement along the price function is the derivative, which is equal to marginal WTP by the tangency condition (eq. [2]). In online appendix C, I present simulations finding that the lower bound welfare estimates for improvements in g range from 75% of ES for large changes to 92% for smaller (but nonmarginal) changes. This evidence suggests that the bound is meaningful.

B. *Additional Extensions*

Moreover, in online appendix A, I show that this welfare interpretation extends to more general settings than those used in the main text of the paper. First, in online appendix section A.2, I show that, though for expositional simplicity it was easier to develop the model as a closed city, all the results extend to open cities. The basic logic is that while immigration into and out of the study area may alter the true value being bounded, it does not alter the computation of the bound itself, which remains valid. Second, in online appendix section A.3, I show that it also extends to a world with transactions costs, as long as those costs are superadditive in a network of multiple moves.

C. *The Direct Mediated Effect*

Finally, the unmediated effect considered so far requires controlling for changes in $\mathbf{x}$ if they are either correlated with g or caused by the policy. But some characteristics may be unobserved, and some recent hedonics papers have intentionally omitted contemporaneous characteristics (while controlling for baseline levels) to include mediated effects. Accordingly, it is useful to consider the importance of such controls over a wider range of study designs and policy questions. First, if the changes in unobservables are simply correlated with the change in g globally but not actually caused by it, then we would still want to control for changes in $\mathbf{x}$, as they have no causal relationship to the changes of interest. This obviously requires either explicitly controlling for $\mathbf{x}$ or using some quasi-experimental design where the source of variation in dg is exogenous to unobserved changes in $\mathbf{x}$, such as an RD or other instrumental variable design.

What if changes in $\mathbf{x}$ are actually caused by the policy-induced changes in g either through resorting (Bayer, Ferreira, and McMillan 2007) or through changes in the housing stock induced by changes in g? Unfortunately, in that case, the observed measure would incorporate the gross benefits of general equilibrium adjustments to $\mathbf{x}$ without netting out the costs of providing them. Failing to net out costs can undermine the lower bound interpretation, although it still holds under additional conditions. To see this, rewrite equation (9) as

$$\begin{aligned} dW = & \sum_i \left[\tilde{e}_i\left(p^{a^*}\left(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\right), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*}\right) - e_i\left(p^{a^*}(), u_i^{a^*}\right)\right] \\ & - \sum_h \left(c\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a^*}_h\right) - c\left(\mathrm{g}^{a'}_h, \mathbf{x}_h{}^{a'}\right)\right) \\ & + \sum_h \left(p^{a^*}\left(\mathrm{g}^{a^*}_h, \mathbf{x}^{a^*}_h\right) - p^{a^*}\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a'}_h\right)\right). \end{aligned} \tag{10}$$

Here, the first set of terms remains the same as inequation (9), as do the change in costs, while the last set of terms is the DE gross of any change in $\mathbf{x}$, which is now what we observe. For the lower bound to still hold (i.e., for the last set of terms to be less than dW), we would need

$$\begin{aligned} & \sum_h \left(c\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a^*}_h\right) - c\left(\mathrm{g}^{a'}_h, \mathbf{x}^{a'}_h\right)\right) \leq \\ & \sum_i \left[\tilde{e}_i\left(p^{a^*}\left(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\right), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*}\right) - e_i\left(p^{a^*}(), u_i^{a^*}\right)\right]. \end{aligned} \tag{11}$$

Essentially, the change in costs from the change in $\mathbf{x}$, which are associated with the change in g, cannot be too big; more precisely, it cannot be bigger than the ES for households from the changes in g. A sufficient but not necessary condition is that they are nonpositive. One plausible example is where the unobserved $\mathbf{x}$ is literally free. For example, g might be transportation infrastructure, which could affect unobserved changes in air quality. In that case, there are no costs to net out, so including the effects mediated through air quality would be valid.

Nevertheless, this analysis suggests that under the most general case, it is important to control for changes in $\mathbf{x}$ whenever possible to have the cleanest welfare interpretation. It is worth emphasizing here that the question centers on changes in $\mathbf{x}$, not levels. Unobserved, unchanging levels of $\mathbf{x}$ cancel out in the comparison, which motivates using DD strategies at the outset.

V. Application to Changes in Toxic Air Emissions

In this section, I illustrate DD hedonic studies with an application to changes in exposure to plants emitting toxic air pollutants, a question also considered by Currie et al. (2015) and Mastromonaco (2015). In particular, I estimate a variant of equation (3c), using two cross sections of individual houses and treating local geographic areas as the panel unit (see n. 6). My strategy resembles that of Currie et al. (2015) in spirit. They treat plants as observations, looking at the effect of plant openings and closings on average property values within a 1-mile ring of the plant relative to the effect at 1–2 miles. In contrast, I have microdata on housing transactions, so I treat houses as observations, looking at the effect of a changing number of plants within a 2-mile ring of the house while controlling for conditions at 1-mile grid cells using fixed effects. I also consider controlling for changing conditions using 2-mile grid cell × year fixed effects. Additionally, whereas Currie et al. (2015) assume constant hedonic coefficients (as in eq. [5]), to avoid conflation bias I allow the hedonic coefficients to evolve between the two time periods, as in equation (3c). Thus, this approach identifies $\overline{\text{DUET}(a^*)}$ and the lower bound on welfare.

The specific application is to the Los Angeles area (all of Los Angeles and Orange Counties and portions of Riverside, San Bernardino, and Ventura Counties) between 1995 and 2000. Data on toxic air emissions come from the US Environmental Protection Agency's Toxics Release Inventory (TRI) database. As discussed by Currie et al. (2015) and Mastromonaco (2015), TRI data are good at identifying polluting plants but exhibit measurement error in emission levels. Accordingly, I focus on the extensive margin of whether a plant is emitting at all rather than emission levels. These comings and goings of plants can also be measured with error if plants fall below the TRI reporting threshold rather than actually shut down. Currie et al. (2015) overcome this problem by merging TRI data to confidential data on plants' operations. Unfortunately, those data are not available to me. However, I approximate their approach by coding a plant as operating at year t if it appears in the TRI database at any point between t and $t - 8$ and t and $t + 8$. Thus, plants that come and go from and return to the TRI reports are assumed to be operating throughout the period. (Eight years takes the 1995 data back to the beginning of the TRI program.)

Exposure to TRI facilities was imputed to a house in two ways. My main approach weights facilities by their distance, with a facility having a weight of $\max\{0, 1 - 1/2Distance\}$, where *Distance* is miles from the facility to a given census block. Thus, for example, a facility two or more miles away from a census block receives a weight of zero, a facility 1 mile away has a weight of 1/2 and a facility colocated in the block has full weight. As an alternative, I use the raw count of facilities within 2 miles. Panel A of table 1 gives summary statistics for these measures by year. It shows a decline in exposure to TRI, with the average house experiencing an 8% reduction in the number of facilities. Finally, I take the square root of these counts plus 1 to allow the computation of derivatives at zero. Within these data, this functional form gives hedonic derivatives that approximate those from a flexible polynomial function while restricting the function to be monotonic in pollution. As discussed below, the main results are not sensitive to this transformation.

Data on real estate transactions were acquired from Fidelity National Data Service, a market research firm providing proprietary data. They include the sales price, date of the sale, number of bedrooms, number of bathrooms, square footage, lot size, year built, and the census block in which it is located. After restricting the data to single family homes and arm's length transactions, and after discarding certain outliers, the data include

TABLE 1
Summary Statistics of Housing Amenities by Year

	1995	2000
	A. Measures of TRI Exposure	
TRI facilities within 2 miles:		
N	2.50	2.29
	(4.31)	(3.80)
Distance-weighted *N*	.74	.68
	(1.44)	(1.3)
	B. Structural Characteristics	
Sale price	193,736	270,914
	(129,691)	(190,782)
Lot size (square feet)	9,617	9,979
	(14,285)	(16,736)
Living area (square feet)	1,672	1,723
	(640)	(701)
Bedrooms	2.05	2.09
	(.73)	(.82)
Bathrooms	3.20	3.22
	(.84)	(.92)
Age (years)	31.13	36.15
	(20.86)	(21.71)

Note.—Data are means with standard deviations in parentheses.

nearly 140,000 observations.[10] Panel B of table 1 summarizes the housing data. Housing values increased over the period and the housing stock aged, but other characteristics remained fairly constant.

Typically, researchers use census tracts or zip codes as geographic units for constructing spatial fixed effects. However, these geographic units may evolve over time. Additionally, they are based on population density, so their sizes vary widely. This is problematic if small geographies are systematically more homogeneous than large ones—so that there is more variation with which to estimate effects from the latter—and if large geographies also vary systematically in unobserved ways from other areas. Finally, geographies creating homogeneous areas (like census tracts) may inflate the spatial scale of very localized effects by systematically aggregating the affected area to similar areas nearby. For all these reasons, arbitrary zones like a 1-mile grid are preferable to census geographies when controlling for spatial effects (see Banzhaf and Walsh 2008). Accordingly, I impose a 1-square-mile grid over the area, using the grid cells for spatial fixed effects.

Identifying $\overline{\mathrm{DUE}(a^*)}$ requires changes in the number of active TRI sites to be orthogonal to changes in unobserved factors affecting prices, after conditioning on baseline conditions and fixed effects. To gauge the plausibility of this assumption, I look at preexisting price trends. In particular, I regress 1990–95 prices on future 1995–2000 changes in exposure interacted with a time trend plus contemporaneous exposure and the hedonic variables listed in table 1. Table 2 shows the results for the coefficient of interest, the interaction between the time trend and the future change in facilities. It shows the change in percentage points in annual housing appreciation over 1990–95 for each additional plant to which the house would become exposed between 1995 and 2000. The coefficients are negative and statistically significant at conventional levels for the unweighted model and marginally so for the weighted model. However, they are not economically meaningful. A one-plant increase in future exposure reduces 1990–95 appreciation by 0.0001–0.0003 percentage points per year, or less than \$1 at the mean of the data. I also consider more flexible variants of this model, interacting cubic time trends with each of four categories of changes in future exposure: increases, no change, a one-plant decrease, and a decrease of two or more plants. Figure 3 shows the results. As seen in the graph, housing prices in Los Angeles were declining in the early 1990s after a long boom, but note that the price levels are not monotonic

[10] I drop all observations with housing prices below \$50,000 or above \$2 million, lot sizes smaller than 1,000 square feet or larger than 10 acres, living areas smaller than 500 square feet or larger than 5,000 square feet, zero bathrooms or more than 7.5 bathrooms, or more than 10 bedrooms. At the low end, these observations likely reflect either coding errors or nonprimary residences; at the high end, they represent extremely grand houses, where misspecification of a linear regression is likely to pose problems. These dropped observations account for about 2.7% of the data.

TABLE 2
Preexisting Trends in Housing Prices

	Facilities within 1 Mile	
	Weighted N (1)	N (2)
Time trend × 1995–2000 change in facilities	−.000272*	−.000123***
	(.000150)	(.0000465)
R^2	.78	.78

Note.—The table shows the coefficients from regressing housing prices between 1990 and 1995 on 1995–2000 changes in the number of TRI facilities within 1 mile interacted with a time trend. The regressions control for time trends (without interaction), contemporaneous TRI exposure, hedonic variables listed in table 1, and 1-mile grid cell fixed effects. Standard errors clustered by grid cell are reported in parentheses.
* Significant at the 10% level.
*** Significant at the 1% level.

by category: prices in areas experiencing no change in pollution are higher than those showing either increases or decreases. More importantly, the trends are fairly parallel—remarkably so for the last 3 years. This evidence reassuringly suggests that TRI sites were not closing in areas that were already gentrifying.

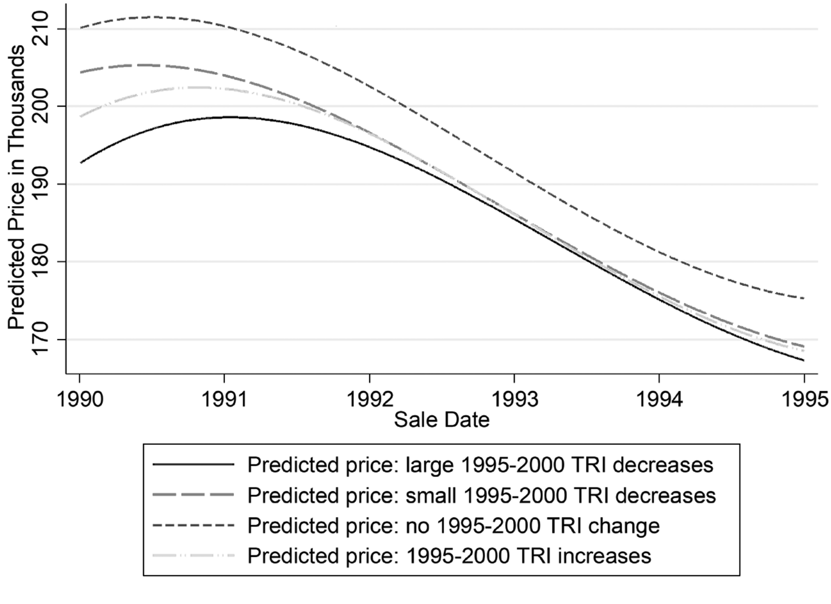

Fig. 3.—Preexisting trends in housing prices. The figure shows 1990–95 mean predicted prices for four categories of houses, those with 1995–2000 decreases in TRI exposure of two or more plants, a decrease of one plant, no change, and increases in exposure. A color version of this figure is available online.

For the main model of interest, I regress log price on the square root of nearby TRI sites, cubic functions of lot area, living area, bathrooms, bedrooms, and age, plus time-invariant fixed effects for the grid cell, and year-quarter dummies to pick up proportionate housing price inflation. Table 3 presents the results using distance-weighted exposure. The table shows results for six separate regressions in separate columns, which can be grouped into three pairs. The three pairs differ by the set of fixed effects: 1-mile grid fixed effects plus year effects, 1-mile grid fixed effects plus county-year effects, and 2-mile grid $\times$ year fixed effects. Within each pair, model A represents the conventional approach with a time-invariant hedonic price function (i.e., eq. [4]), whereas model B uses the time-varying approach advocated in this paper.

Panel A presents the pollution coefficients from the hedonic regressions, with standard errors clustered by grid cell in parentheses. All pollution coefficients are negative and statistically significant. Nevertheless, they should be interpreted with care. As discussed above, the coefficient in the time-invariant model likely suffers from conflation bias. Additionally, in the time-varying model, the 1995 coefficients are identified only under the assumption that changes in unobservables are uncorrelated with baseline conditions and, in any case, are not used to construct the lower bound on ES. The 2000 coefficients are identified under the weaker assumption that changes in unobservables and changes in exposure are independent, conditional on baseline exposure and other variables. Interestingly, for all three models, the time-invariant coefficient falls within the interval bracketed by the corresponding two time-varying coefficients, although as discussed by Kuminoff and Pope (2014), this pattern need not always hold. The 2000 coefficient is higher than the time-invariant model, so in this application it appears conflation bias is downward.

Panel B shows the respective capitalization effects from the 1995–2000 change in TRI exposure, using the 2000 price function in the case of models B. These capitalization effects (in billions of dollars) aggregate the predicted price increases, reweighting the data so as to reflect the number of owner-occupied housing units in each census tract to obtain the total estimated capitalization for the Los Angeles owner-occupied housing stock. When using model B and the ex post function to measure the effects, we find that this measure represents $\overline{\text{DUET}}$ for the observed 1995–2000 change in exposure, which is the lower bound on the general equilibrium ES. The standard errors (in parentheses) and confidence intervals (in square brackets) are based on a cluster bootstrap. The bootstrap accounts for sampling error in estimation, forecasting (i.e., predicting DEs), and reweighting tracts.

Using models A, we find that the conventional approach yields capitalization effects ranging from \$5.8 billion to \$6.5 billion. Using models B, we find that $\overline{\text{DUET}}$ ranges from \$6.7 billion to \$7.5 billion. These estimates

TABLE 3
RESULTS OF APPLICATION TO TRI DATA

	Model 1: 1-Mile Grid Fixed Effects + Year Fixed Effects		Model 2: 1-Mile Grid Fixed Effects + County-Year Fixed Effects		Model 3: 2-Mile Grid × Year Fixed Effects	
	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)
	A. Estimated Coefficients					
Square root of TRI facilities:						
Time invariant	−.1313***		−.1375***		−.1466***	
	(.0137)		(.0137)		(.0111)	
1995		−.1047***		−.0962***		−.0526***
		(.0213)		(.0221)		(.0103)
2000		−.1493***		−.1653***		−.1657
		(.0156)		(.0161)		(.0135)
	B. Capitalization Effects					
Movement along price function (billion $)	5.917***	6.732***	6.200***	7.440***	6.378***	7.495***
	(.569)	(.622)	(.601)	(.710)	(.478)	(.579)
95% CI	4.802–7.033	5.513–7.952	5.023–7.378	6.048–8.831	5.442–7.314	6.360–8.630
Difference from model A		.815**		1.239***		1.117***
		(.367)		(.423)		(.170)
95% CI		.095–1.535		.411–2.068		.784–1.450
R^2	.751	.753	.780	.782	.816	.818

NOTE.—Each column represents a separate regression. Each pair of columns (models 1–3) uses different fixed effects. For each model, model A imposes a time-invariant hedonic price function on TRI facilities and all hedonic controls, while model B allows all coefficients to vary over time. Panel B shows the movement along the hedonic price functions, using the ex post function for the year-specific models, which gives the lower bound. Standard errors in parentheses are clustered by grid cells. Confidence intervals (CI) for welfare measures are cluster bootstrapped.

** Significant at the 5% level.

*** Significant at the 1% level.

represent a present value for what presumably is a permanent shock to amenities. With about 5.4 million owner-occupied housing units in the study area and at a discount rate of 5%, these values for $\overline{\text{DUET}}$ work out to \$62–\$69 per Los Angeles household per year. Thus, in this case, even the lower bound measure is substantial and may be informative for policy. The last row of the panel directly compares the estimates of $\overline{\text{DUET}}$ from columns B to the conventional capitalization approach in columns A. For this application, the conventional approach gives estimates that are \$0.8–\$1.2 billion (or 14%–20%) higher. Moreover, the differences are statistically significant. Thus, not only does the approach suggested in this paper bring clarity to the estimand as a lower bound on welfare, but also in this case it is attended by a tighter bound. Finally, comparing across models, we see that allowing for time-varying fixed effects (as in models 2 and 3) does not appear to close the gap or reduce conflation bias: time-varying coefficients are required.

In online appendix D, tables D2–D6 show the results for alternative functional forms for the pollution variables, including a cubic function, a linear function of pollution (though still in the semilog form), inverse hyperbolic sine transformation, the square root plus an arbitrarily small number (0.01) instead of +1, and, finally, using the raw count of polluting facilities instead of distance-weighted counts. The results are similar to the main specification shown in table 3. All estimates for DUET are within about 20% of the main specification and are statistically significant at the 1% level. Similarly, all differences from the conventional approach are within about one-third of the differences found in the main specification and are statistically significant, with the one exception of model 1 for the cubic function.

Appendix table D1 replicates table 3, adding a third panel that displays another conventional welfare approximation often presented, the linearized marginal WTP. Tables D2–D6 also include these results for the alternative functional forms. The approach computes the derivative of the hedonic function at each point, interpreted as marginal WTP, and simply multiplies this marginal value by the change in g. Because they involve derivatives of functions that are highly nonlinear, especially around zero, these results are more sensitive to functional forms. This is in contrast to the approach suggested in this paper of computing changes along the function rather than derivatives, possibly another advantage. See the appendix for details and additional discussion.

VI. Conclusions

For decades, economists have used the hedonic model to estimate demands for the implicit characteristics of differentiated commodities, including otherwise unpriced local public goods and amenities. The traditional cross-sectional approach to hedonic estimation has recovered marginal WTP for amenities when unobservables are conditionally independent of the amenities but has been criticized as biased when this condition is not met (Greenstone 2017).

In response, economists have introduced panel econometric models using DD and related approaches to identify capitalization effects. Unfortunately, the interpretation of these effects has not been clearly perceived in the literature, perhaps because there is a range of meanings to the words "capitalization" and "causal effect" when the price function shifts. In this paper, I show that DD and related hedonic methods can identify what is known in the causal literature as the average DE on prices of a change in amenities, which in this case can be interpreted as a movement along the ex post hedonic price function. I further show that this is a lower bound measure on Hicksian ES. Simulations suggest that the lower bound provides valuable information on the order of 75%–92% of the actual ES.

These results have two implications for hedonic research. First, researchers can employ DD and other quasi-experimental methods to overcome estimation problems while maintaining a clear connection to the underlying economic model, a point that sometimes has been challenged. Second, from those estimates, they can recover bounds on nonmarginal welfare measures without turning to Rosen's (1974) second stage or more structural approaches.

Future work might consider how quasi-experimental methods might be extended to account for price and distributional effects. For example, Hudgens and Halloran (2008), Crépon et al. (2013), and Manski (2013) propose ways to identify IEs using variation in treatment programs across groups (markets, in the hedonic context) while still identifying DEs from variation in treatment assignment within a group. Such methods might allow researchers to identify total price effects and hence transfers among subpopulations of buyers and sellers. As Sieg et al. (2004) discuss, such price changes can have important distributional welfare effects.

Additional work might consider ways to average different bounds to improve the approximation. Some quasi-experimental strategies can plausibly identify effects in multiple cross sections, especially when they use RD or instrumental variable strategies. Examples include Greenstone and Gallagher (2008), Gamper-Rabindran and Timmins (2013), and Haninger, Ma, and Timmins (2017). When they do, there is at least the potential to identify separate effects in two or more cross sections. If the movement along the hedonic price function can be estimated in the ex ante period as well as the ex post, it would be possible to construct an upper bound analogous to the lower bound discussed here (Bartik 1988). If so, it may be further possible to average these effects to get a second-order approximation to welfare, as suggested by Banzhaf (2020).

Appendix

Proof of Proposition 1

As noted in the main text, our measure of the change in welfare is

$$\begin{aligned} dW = & \sum_i \Big[\tilde{e}_i \Big(p^{a'}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) - e_i \Big(p^{a^*}(), u_i^{a^*} \Big) \Big] \\ & + \sum_h \Big[\Big(p^{a^*}\Big(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*}\Big) - p^{a'}\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) - \Big(c\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) - c\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) \Big]. \end{aligned} \tag{8}$$

The right side of equation (8) can be decomposed as follows:

$$\begin{aligned} dW = & \sum_i \Big[\tilde{e}_i \Big(p^{a^*}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) - e_i \Big(p^{a^*}(), u_i^{a^*} \Big) \Big] \\ & + \sum_i \Big[\tilde{e}_i \Big(p^{a'}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}_{i(a')}{}^{a'}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) - \tilde{e}_i \Big(p^{a^*}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) \Big] \\ & + \sum_h \Big(p^{a^*}\Big(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\Big(\mathrm{g}_h{}^{a'}, \mathbf{x}_h^{a^*}\Big) \Big) + \sum_h \Big(p^{a^*}\Big(\mathrm{g}_h{}^{a'}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\big(\mathrm{g}_h{}^{a'}, \mathbf{x}_h{}^{a'}\big) \Big) \\ & + \sum_h \Big(p^{a^*}\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) - p^{a'}\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) - \sum_h \Big(c\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) - c\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big). \end{aligned} \tag{12}$$

Fixing indexes so that $h = i(a')$, which we can do because of the bijective mapping between houses and households, the expression can be rearranged as

$$\begin{aligned} dW = & \sum_t \Big[\tilde{e}_i \Big(p^{a^*}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) - e_i \Big(p^{a^*}(), u_i^{a^*} \Big) \Big] \\ & + \sum_h \Big[\Big(p^{a^*}\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) - \Big(c\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) - c\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) \Big] \\ & + \sum_h \Big(p^{a^*}\Big(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) \Big) \\ & + \sum_i \Big[\Big(\tilde{e}_i \Big(p^{a'}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a\prime)}, u_i^{a^*} \Big) - \tilde{e}_i \Big(p^{a^*}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) \Big) \\ & - \Big(p^{a'}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big) - p^{a^*}\big(\mathrm{g}^{a'}_{i(a\prime)}, \mathbf{x}^{a'}_{i(a')}\big) \Big) \Big]. \end{aligned} \tag{13}$$

Note that for each i, the term in the fourth line minus the term in the last line is equal to zero by the definition of $\tilde{e}$: the money necessary to maintain utility when $(g, \mathbf{x})$ is held fixed is equal to the change in the price of the bundle $(g, \mathbf{x})$. Thus, the expression simplifies to

$$\begin{aligned} dW = & \sum_i \Big[\tilde{e}_i \Big(p^{a^*}\big(\mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}\big), \mathrm{g}^{a'}_{i(a')}, \mathbf{x}^{a'}_{i(a')}, u_i^{a^*} \Big) - e_i \Big(p^{a^*}(), u_i^{a^*} \Big) \Big] \\ & + \sum_h \Big[\Big(p^{a^*}\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) - \Big(c\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) - c\big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a'}\big) \Big) \Big] \\ & + \sum_h \Big(p^{a^*}\Big(\mathrm{g}_h^{a^*}, \mathbf{x}_h^{a^*}\Big) - p^{a^*}\Big(\mathrm{g}_h^{a'}, \mathbf{x}_h^{a^*}\Big) \Big). \end{aligned} \tag{9}$$

But in the first line, the term in square brackets is nonnegative for each i: the value of a constrained expenditure minimization problem is no less than the value of an unconstrained expenditure minimization problem at the same prices and utility. Additionally, the second line is also nonnegative by assumption 3. Thus,

$$\sum_h \left(p^{a^*} \left(g_h^{a^*}, \mathbf{x}_h^{a^*} \right) - p^{a^*} \left(g_h^{a'}, \mathbf{x}_h^{a^*} \right) \right) \leq dW. \tag{14}$$

This completes the proof. The term on the left is the sum of price changes along the ex post hedonic holding $\mathbf{x}$ constant at its ex post level, which is the measurement of interest, and it is less than the welfare measure.

Note that assumptions 1 and 3 are necessary but not sufficient conditions for the bound, in the sense that the proposition is not an if-and-only-if statement.

References

Bajari, P., and L. Benkard. 2005. "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach." *J.P.E.* 113 (6): 1239–76.

Banzhaf, H. S. 2020. "Panel Data Hedonics: Rosen's First Stage as a 'Sufficient Statistic.'" *Internat. Econ. Rev.* 61:973–1000.

Banzhaf, H. S., and R. P. Walsh. 2008. "Do People Vote with Their Feet? An Empirical Test of Tiebout." *A.E.R.* 98 (3): 843–63.

Bartik, T. J. 1988. "Measuring the Benefits of Amenity Improvements in Hedonic Price Models." *Land Econ.* 64 (2): 172–83.

Bayer, P., F. Ferreira, and R. McMillan. 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." *J.P.E.* 115 (4): 588–638.

Bayer, P., R. McMillan, A. Murphy, and C. Timmins. 2016. "A Dynamic Model of Demand for Houses and Neighborhoods." *Econometrica* 84 (3): 893–942.

Bento, A., M. Freedman, and C. Lang. 2015. "Who Benefits from Environmental Regulation? Evidence from the Clean Air Act Amendments." *Rev. Econ. and Statis.* 97 (3): 610–22.

Bishop, K. C., and A. D. Murphy. 2019. "Valuing Time-Varying Attributes Using the Hedonic Model: When Is a Dynamic Approach Necessary?" *Rev. Econ. and Statis.* 101 (1): 134–45.

Bishop, K. C., and C. Timmins. 2019. "Estimating the Marginal Willingness to Pay Function without Instrumental Variables." *J. Urban Econ.* 109:66–83.

Cellini, S. R., F. Ferreira, and J. Rothstein. 2010. "The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design." *Q.J.E.* 125 (1): 215–61.

Chay, K. Y., and M. Greenstone. 2005. "Does Air Quality Matter? Evidence from the Housing Market." *J.P.E.* 113 (2): 376–424.

Crépon, B., E. Duflo, M. Gurgand, and P. Zamora. 2013. "Do Labor Market Policies Have Displacement Effects? Evidence from a Clustered Randomized Experiment." *Q.J.E.* 128 (2): 531–80.

Currie, J., L. Davis, M. Greenstone, and R. Walker. 2015. "Do Housing Prices Reflect Environmental Health Risks? Evidence from More than 1,600 Toxic Plant Openings and Closings." *A.E.R.* 105 (2): 678–709.

Davis, L. W. 2004. "The Effect of Health Risk on Housing Values: Evidence from a Cancer Cluster." *A.E.R.* 94 (5): 1693–704.

———. 2011. "The Effect of Power Plants on Local Housing Values and Rents." *Rev. Econ. and Statis.* 93 (4): 1391–402.

Ekeland, I., J. J. Heckman, and L. Nesheim. 2004. "Identification and Estimation of Hedonic Models." *J.P.E.* 112 (1): S60–S109.

Epple, Dennis, Louis Quintero, and Holger Sieg. 2020. "A New Approach to Estimating Hedonic Equilibrium Models for Metropolitan Housing Markets." *J.P.E.* 128 (3): 948–83.

Freeman, A. M., III, J. A. Herriges, and C. L. Kling. 2014. *The Measurement of Environmental and Resource Values.* Washington, DC: Resources Future.

Gamper-Rabindran, S., and C. Timmins. 2013. "Does Hazardous Waste Remediation Raise Housing Values?" *J. Environmental Econ. and Management* 65 (3): 345–60.

Greenstone, M. 2017. "The Continuing Impact of Sherwin Rosen's Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *J.P.E.* 125 (6): 1891–902.

Greenstone, M., and J. Gallagher. 2008. "Does Hazardous Waste Matter? Evidence from the Housing Market and the Superfund Program." *Q.J.E.* 123 (3): 951–1003.

Griffith, R., and L. Nesheim. 2013. "Hedonic Methods for Baskets of Goods." *Econ. Letters* 120:284–87.

Haninger, K., L. Ma, and C. Timmins. 2017. "The Value of Brownfield Remediation." *J. Assoc. Environmental and Resource Economists* 4 (1): 197–241.

Heckman, J. J., H. Ichimura, and P. E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Rev. Econ. Studies* 64:605–54.

Heckman, J. J., R. L. Matzkin, and L. Nesheim. 2010. "Nonparametric Estimation of Nonadditive Hedonic Models." *Econometrica* 78 (5): 1569–91.

Hicks, J. R. 1943. "The Four Consumer Surpluses." *Rev. Econ. Studies* 11 (1): 31–41.

Hirano, K., and G. W. Imbens. 2004. "The Propensity Score with Continuous Treatments." In *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*, edited by A. Gelman and X.-L. Meng, 73–84. Hoboken, NJ: Wiley.

Hudgens, M. G., and M. E. Halloran. 2008. "Toward Causal Inference with Interference." *J. American Statis. Assoc.* 103:832–42.

Imbens, G. W. 2000. "The Role of the Propensity Score in Estimating Dose-Response Functions." *Biometrika* 87 (3): 706–10.

Kanemoto, Y. 1988. "Hedonic Prices and the Benefits of Public Projects." *Econometrica* 56:981–89.

Kennan, J., and J. R. Walker. 2011. "The Effect of Expected Income on Individual Migration Decisions." *Econometrica* 79 (1): 211–51.

Klaiber, H. A., and V. K. Smith. 2013. "Quasi Experiments, Hedonic Models, and Estimating Trade-Offs for Local Amenities." *Land Econ.* 89 (3): 413–31.

Kuminoff, N. V., C. F. Parmeter, and J. C. Pope. 2010. "Which Hedonic Models Can We Trust to Recover the Marginal Willingness to Pay for Environmental Amenities?" *J. Environmental Econ. and Management* 60 (1): 145–60.

Kuminoff, N. V., and J. C. Pope. 2014. "Do 'Capitalization Effects' for Public Goods Reveal the Public's Willingness to Pay?" *Internat. Econ. Rev.* 55 (4): 1227–50.

Lang, C. 2018. "Assessing the Efficiency of Local Open Space Provision." *J. Public Econ.* 158:12–24.

Lee, D. S., and T. Lemieux. 2010. "Regression Discontinuity Designs in Economics." *J. Econ. Literature* 48 (2): 281–355.

Linden, L., and J. E. Rockoff. 2008. "Estimates of the Impact of Crime Risk on Property Values from Megan's Laws." *A.E.R.* 98:1103–27.

Manski, C. F. 2013. "Identification of Treatment Response with Social Interactions." *Econometrics J.* 16:S1–S23.

Mastromonaco, R. 2015. "Do Environmental Right-to-Know Laws Affect Markets? Capitalization of Information in the Toxic Release Inventory." *J. Environmental Econ. and Management* 71:54–70.

Muehlenbachs, L., E. Spiller, and C. Timmins. 2015. "The Housing Market Impacts of Shale Gas Development." *A.E.R.* 105 (12): 3633–59.

Ouazad, A., and R. Rancière. 2019. "Market Frictions, Arbitrage, and the Capitalization of Amenities." Working Paper no. 25701, NBER, Cambridge, MA.

Palmquist, R. B. 1992. "Valuing Localized Externalities." *J. Urban Econ.* 31 (1): 59–68.

Parmeter, C. F., and J. C. Pope. 2013. "Quasi-Experiments and Hedonic Property Value Methods." In *Handbook on Experimental Economics and the Environment*, edited by J. A. List and M. K. Price, 3–66. Cheltenham: Edward Elgar.

Pope, J. C. 2008. "Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries." *J. Urban Econ.* 64 (3): 601–14.

Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *J.P.E.* 82:34–55.

Sieg, H., V. K. Smith, H. S. Banzhaf, and R. Walsh. 2004. "Estimating the General Equilibrium Benefits of Large Changes in Spatially Delineated Public Goods." *Internat. Econ. Rev.* 45 (4): 1047–77.

VanderWeele, T. J., and E. J. Tchetgen Tchetgen. 2011. "Effect Partitioning under Interference in Two-Stage Randomized Vaccine Trials." *Statis. and Probability Letters* 81:861–69.