

Best Practices in Using Hedonic Property Value Models for Welfare Measurement

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Introduction

The hedonic property value model is among the most direct illustrations of how private markets can reveal consumers' willingness to pay for measures of environmental quality. There have been thousands of applications since the model was formalized in the 1970s and, if anything, the pace has accelerated due to advances in data accessibility, econometrics, and computing power. The hedonic model's enduring popularity is easy to understand. It seems like common sense by beginning with an intuitive premise that is both economically plausible and empirically tractable. The model envisions buyers choosing properties based on housing attributes (e.g., indoor space, bedrooms, bathrooms) and on location-specific amenities (e.g., air quality, park proximity, education, flood risk). In the absence of market frictions, spatial variation in amenities can be expected to be capitalized into housing prices. When buyers face the resulting menu of price-attribute-amenity pairings in the housing market, their purchase decisions can reveal their willingness to pay for marginal changes in each of the amenities.²

In recent years, the prevailing style of empirical hedonic research has evolved to incorporate insights from the "credibility revolution" in applied micro-econometrics. This revolution has raised expectations for data quality and econometric transparency. Recent research has refined our understanding of how parameters identified by quasi-experimental research designs map into welfare measures. This article distills the collective evidence from recent advances in the hedonic

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² Nearly 100 years ago, in some of the first work on hedonic modeling, Waugh (1929, p.100) proposed a remarkably similar "statistical analysis". He suggested that "...instead of compiling the reported likes and dislikes of individuals, this type of statistical analysis attempts to estimate these preferences for the whole group of dealers or consumers in the market area by measuring the market price differentials due to a number of quality factors."

property-value literature to summarize current “best practices” for credible research designs and valid welfare interpretations. While hedonic property-value models are used for many purposes, our focus is on welfare measures that can be used to inform public policy.

We outline best practices when the researcher’s goal is to measure households’ willingness to pay (WTP) for a change in a spatially-varying amenity. These best practices start with a research design that identifies a clear source of exogenous variation in an amenity that prospective buyers can be assumed to observe. Microdata on the observed sale prices and the physical attributes of individual houses, together with location-specific measures for amenities are then used to estimate a housing-price function. With a flexible specification for the price function and conditions that assure the model’s assumptions are satisfied, the derivative of the price function will also be a function that can be interpreted as a measure for the amenity’s implicit price. The first-order conditions for utility maximization provide the conceptual basis for linking these implicit-price estimates to measures of household marginal WTP (MWTP). In principle, this process is straightforward. In practice, there are several important modeling decisions that must be made in order to define measures for sale prices and amenities and to select an econometric specification. Data limitations can also complicate identification and welfare interpretation. While the number of issues that must be considered in developing a “best practices” study may seem daunting, the effort is justifiable. The modern hedonic property-value model has been refined through more than forty years of intense scrutiny to become one of the premier approaches to valuing changes in environmental amenities in academic research, litigation, and public policy (Palmquist and Smith 2002, US EPA 2010).

The next section reviews the hedonic property-value model’s foundations. We organize our remaining discussion around issues that need to be addressed in estimating MWTP and in using these estimates to inform policy. We discuss how MWTP measures can be used to assess small changes in amenities and to bound welfare effects of large changes. While we note that MWTP measures can also be combined with additional information to estimate amenity demand curves, we leave the task of defining best practices in “second stage” hedonic demand estimation to future research.³ We conclude with a summary of what we feel are high-priority opportunities to advance the literature.

³ Kuminoff, Smith and Timmins (2013) review methods for using housing data to estimate welfare effects of large changes.

Most of the studies that helped to establish modern best practices in hedonic modeling used rich data on metropolitan housing markets in advanced economies. Data describing housing transactions, characteristics, and amenities are becoming increasingly available around the world, creating new opportunities to use hedonic models for policy analysis. An online appendix to this article summarizes data availability, data sources, and sample applications for 24 countries, and discusses additional modeling issues that may arise in rural areas and less-than-ideal data settings.

Conceptual Background

The hedonic framework has a long history in economics (Waugh (1929), Court (1939), Griliches (1961), and Lancaster (1971)). Rosen's (1974) seminal paper established the hedonic framework as an equilibrium model for understanding what differentiated products' prices could reveal to market observers. It offered a direct analog to the Cowles Commission's logic for connecting structural and reduced-form models (Morgan (1990)).⁴ In the housing context, the primitives of the hedonic model consist of the supply for housing, including developers' decisions for new home construction and factors influencing re-sales of existing homes, and the joint distribution of household preferences and income. After buyers and sellers negotiate transactions, market equilibrium occurs when no agent can increase utility by moving. This equilibrium concept implies a relationship between house prices and characteristics that reveals each buyer's MWTP for each house characteristic under the assumptions that buyers are fully informed, freely mobile, and able to purchase continuous levels of each characteristic.⁵ We use four graphs in Figure 1 to explain key features of the model.⁶

Panel 1a plots housing price as a function of the measure for one of the local amenities, e.g., an environmental amenity, holding the physical characteristics and other location-specific features constant.⁷ Panel 1b illustrates the process through which the model will allow the price function to reveal buyers' MWTP. This panel adds two buyers' bid curves. These bid curves each trace out the maximum amount that each buyer is willing to pay as a function of the amenity level (holding

⁴ It is also closely connected to Tiebout's (1956) seminal analysis of local public goods provision.

⁵ These assumptions have subtle implications. For example, "free mobility" does not imply that it must be costless to move. Buyers' choices will still reveal their MWTP at the time of their purchase decisions if they were able to choose continuous levels of each characteristic facing a fixed cost of moving. Meanwhile, the assumptions may be violated if some prospective buyers are excluded from renting or buying properties because of discrimination.

⁶ Readers seeking a technical exposition should see Palmquist (2005), Kuminoff, Smith and Timmins (2013), Freeman, Herriges and Kling (2014), Phaneuf and Requate (2017) or Taylor (2017).

⁷ In Rosen's model, each point on the price function is the tangency between a particular seller's offer curve and a particular buyer's bid curve. These are the points at which market trades occur. We suppress sellers' offer curves in Figure 1b in order to focus on demand.

other influences on their choices constant). Purchases occur where bid curves are tangent to the price function. Buyer 2 purchases a house with amenity level A_2 at a price of P_2 and buyer 1 purchases a less expensive house in a lower-amenity area. These two coordinate sets, (P_1, A_1) and (P_2, A_2) , are the points at which each buyer's MWTP for a small change in the amenity (bid-curve slope) equals the amenity's implicit price (price-function slope). Panel 1c illustrates this same result in a different way: by explicitly distinguishing what is revealed by a hedonic equilibrium. First, notice that the algebraic form used for the hedonic price function implies an algebraic form for the implicit price function for the amenity, since this is implied by the derivative of the hedonic price function. The dashed demand curves are not observed by the analyst. With this in mind, Panel 1c illustrates that home purchases only reveal information about demand at the points of intersection where demand curves for the amenity intersect the implicit price function for the amenity A (P^A). Assuming this structure effectively describes the underlying market mechanics, one can recover each buyer's MWTP for the amenity in three steps: (1) use observed sales data to estimate the hedonic price function, (2) partially differentiate the price function with respect to the amenity of interest to recover the implicit price function, and then (3) evaluate the implicit price function for each buyer to recover their MWTP.

Panel 1c also illustrates another important point: the implicit price is just that – a price. Just as prices in a "regular market" are equal to MWTP at a point on the demand curve, so too the implicit price derived in step (2) reveals only a marginal value, not the entire demand function. Notice that any number of flatter or steeper demand specifications could be drawn through the point (P_1^A, A_1) . Following the logic of the Cowles' approach to demand estimation, applied by Rosen to the hedonic model, additional information would be needed to infer amenity demand from the implicit price function or, equivalently, to predict welfare effects of counterfactual, non-marginal changes in amenity levels. Researchers have developed several strategies for providing this additional information, which we will return to in a later section. For now, we focus on using the implicit price function to recover MWTP.

Finally, panel 1d illustrates another important point. It shows how demand curves and implicit price functions may change over time in response to changes in the distribution of amenity levels and market primitives. For example, at some point after the initial period S a new policy may lead to changes in the amenity levels throughout a market. Meanwhile, some households may experience wealth shocks. These types of changes can induce migration and alter the market-clearing

price function and its gradient (the implicit price function). The year-S implicit price function identifies MWTP for the distribution of buyers in year S and the same is true for buyers in year T, one year after the policy change. However, the year-S and year-T distributions of MWTP will generally differ. In this example, we assume that buyer 1 has left the market so we do not include a year-T demand function in the graph. Buyers who can be observed multiple times, such as buyer 2, may have experienced changes in their personal circumstances (demand shocks). Understanding temporal changes in the price function and the distribution of homebuyers' amenity demand curves can be important for econometric estimation of implicit amenity prices and for mapping implicit prices into measures of MWTP associated with changes in amenities.

Best Practices for Estimating Marginal Willingness to Pay

Market Definition

The model's conceptual logic implies that the market should be chosen to satisfy the "law of one price function". That is, when a house can be fully defined by a unique bundle of physical characteristics and location-specific amenities, then equivalent bundles sell for the same price throughout that market. The precise spatial and temporal boundaries that satisfy these conditions may vary across geography and over time as information, institutions, and moving costs change. A common approach is to define the market as a single metropolitan area over a few years (e.g. Pope 2008b, Abbott and Klaiber 2013). An alternative is to pool data over larger areas and longer periods, while modeling the parameters of the hedonic price function as evolving over space and time (e.g. Kuminoff and Pope 2014, Walls et al. 2017).

In principle, moving costs could lead to violations of the law of one price function. However, for households that move within metropolitan areas, moving costs are unlikely to vary substantially with the destination locations. This is due to the fact that the physical and financial moving costs (e.g., realtor fees and truck rentals) do not vary with within-metropolitan-area destination locations and the psychological moving costs are limited by the fact that within-metropolitan-area moves typically allow households to maintain ties to family, friends, and neighborhoods. Consequently, the "law of one price" can be maintained by arbitrage between locations within a metropolitan area. In contrast, moving between metropolitan areas may impose much larger moving costs. Equally important, workers who move between metropolitan areas may be forced to change jobs.

Potential variation across geographic areas in tax policy and the cost of living (aside from housing) adds further complications. Because the hedonic property-value model abstracts from labor-market considerations and heterogeneous moving costs, focusing on larger geographic areas which include multiple metropolitan areas can undermine the conceptual logic conventionally used for mapping a hedonic price function into MWTP measures. Researchers can avoid this problem by using data on commuting patterns to determine when moving to a different metropolitan area would likely imply moving to a new job.

Pooling data over a long period such as a decade or more introduces similar problems, as there is unlikely to be arbitrage over time. Housing-price functions can evolve during boom-bust cycles as macroeconomic factors change the amounts homebuyers are willing to pay for amenities. Homebuyers' MWTP may also evolve with changes in information and policy. For instance, a policy that improves air quality may reduce homebuyers' MWTP for further improvements (i.e., by moving them down their demand function for air quality) whereas a policy that improves homebuyers' knowledge about the negative health effects of pollution may increase their MWTP for clean air (i.e., by shifting out their demand function). Including time-specific dummy variables as "intercept shifters" in the hedonic price function may help to control for housing price inflation but will be insufficient to control for temporal changes that contribute to shifts in MWTP, as the hedonic equilibrium evolves.

In principle, some sources of spatio-temporal variation in the shape of hedonic price functions can be addressed through econometric flexibility (e.g., McMillen and Thorsnes (2003)). However, parametric assumptions used to model geographic and temporal changes dictate how the results should be interpreted. Researchers can relax parametric assumptions when pooling data over multiple metropolitan areas and years by using interactions between time dummies, geography dummies, and price function parameters to allow price functions to differ across space and time. We discuss some of the issues related to econometric specification in the following sections.

Overall, narrowing the assumed extent of the market will tend to improve internal validity by increasing the likelihood that the "law of one price function" holds, but it may reduce external validity and the ability to study geographically coarse amenities, such as climate features. If the goal is to understand how amenities affect residential sorting across metropolitan areas (where a different form of arbitrage, not the simplest version of the law of one price best describes the equilibrium process) then the class of Tiebout sorting models summarized by Kuminoff, Smith,

and Timmins (2013) provides one means for consistently incorporating job opportunities and moving costs.

Data Collection

The gold standard in data collection is to obtain a random sample (or the universe) of housing-transaction prices and characteristics for the relevant study area.⁸ Most studies focus exclusively on single-family houses. In most parts of the United States, for example, housing transactions are a matter of public record and are usually filed with county tax-assessment boards.⁹ This type of access enables researchers to work with data that approximate the universe of single-family housing sales in specific time periods.

Some studies use data on sales of undeveloped land or data on rental rates for houses and apartments. Estimating a hedonic model of vacant-land sales is consistent with the idea that the price function maps how prices vary with land characteristics. However, there are important institutional factors, such as zoning, prior easements, and access to public water supplies that affect how land may be used. Housing rents may be used in conjunction with sales prices by converting sales prices into annualized user-costs of housing using standard formulas in the literature (Poterba (1984) and Himmelberg, Mayer, and Sinai (2005)). However, rental rates can present added complications relative to data on single-family transactions in that there may be ambiguity about important rental-contract features, such as which party pays for utilities and maintenance. The short-term nature of rental contracts may also weaken the incentive for renters to become fully-informed about local amenities prior to entering the market. On the other hand, rentals may better reflect current amenity flows, allowing the analyst to avoid the dynamic problem that buyers face, as buyers are potentially forward-looking over future amenity flows. The use of rental-rate data may also be particularly important for recovering unbiased measures of average MWTP in neighborhoods where rates of owner occupation may be low.

In recent years, data on housing transaction prices, characteristics, and amenities have become increasingly available for large portions of other countries, including Australia, Japan, and South Korea. A few countries, such as Denmark and Sweden, have additionally granted researchers access to administrative records containing rich socioeconomic panel data on buyers and sellers. In

⁸ We note the potential selection bias that may occur when focusing only on houses that sell. Gatzlaff and Haurin (1998) propose a correction procedure that uses information on the non-price characteristics of houses that do not sell.

⁹ Cleaned data that had been previously filed with county boards can be purchased from CoreLogic, ATTOM Data Solutions, and other vendors.

other countries, such as Canada and Portugal, it is still difficult to obtain microdata on transactions. Appendix Table 1 (online supplementary material) provides a country-by-country summary of what we could determine about data availability, data sources, and sample applications for Australia, Austria, Belgium, Canada, Chile, China, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Japan, Netherlands, Norway, Poland, Portugal, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States. While this set of countries is far from comprehensive, it provides a starting point for researchers looking for housing data or sample applications. The appendix also discusses additional challenges that may arise in less than ideal data settings including regulation of prices, sparse transactions, and lack of transaction prices.

Data preparation

It is reasonable to expect that publicly-available data on housing sales, often collected for other reasons, will include some data-entry errors as well as some sales which do not arise in a competitive bidding process. Identifying these cases and dropping them reduces the scope for measurement error. For instance, it is common to exclude transactions in which the buyer and seller share the same last name and, therefore, have a higher probability of being related. It is also common to drop foreclosure sales and purchases by real-estate investment firms, as there is a higher probability that the property has characteristics or quality-issues not documented in transactions data. Finally, it is common to remove outliers that embed seemingly-conspicuous data entry mistakes (e.g., a house with 1,800 bedrooms or 3 square feet). Many researchers address these outliers by dropping a small fraction of sales with the highest and lowest values for each characteristic. Since there is no commonly-accepted threshold for what defines an outlier, it is important to document these types of decisions and assess the sensitivity of findings to them.

Predicted prices

Some studies rely upon prices that have been predicted in some form or another. One example is that Census data sets often include a self-reported “value”. These data are generated from survey questions that ask occupants how much they think their properties would sell for if they were to sell it. Another example is predicted prices from property assessors and other companies (e.g., Zillow). Transaction prices are always preferable to predicted prices. The problem with predicted

prices is that they embed measurement error which varies systematically over time, buyer demographics, housing characteristics, and neighborhood amenities (Banzhaf and Farooque 2013).¹⁰ This correlation may lead to bias in price-function-parameter estimates.

Spatially-aggregated data

Individual records of transaction prices are preferable to spatially-aggregated measures, such as mean or median prices within Census tracts, zip codes, or counties. A fundamental drawback of using such measures is that theory does not establish an equilibrium mapping from price aggregates to aggregate welfare measures. Regressing mean prices on mean amenity levels may yield an unbiased estimate of the hedonic price function, but not of the implicit price function (i.e., the derivative) which is necessary to recover MWTP.¹¹ Moreover, median prices are not necessarily equal to the price level at the median attributes, so hedonic price regressions using medians may be biased from the outset. Hence, using summary statistics as if they were transaction level prices can undermine welfare measurement.

Even apart from problems of interpretation, median prices have been found to introduce measurement error that can bias price-function parameters. For example, in an application to Superfund cleanups of hazardous-waste sites, Gamper-Rabindran and Timmins (2013) find that focusing on the median house within a neighborhood recovers lower estimates for MWTP than does using individual house records. This result occurs because hazardous-waste sites tend to be located near the lowest-price houses within a neighborhood and, as a result, the benefits of cleanups are mainly capitalized into housing prices at the lowest quantiles of the housing-price distribution. Problems with medians are not limited to studying hazardous-waste sites or other point-source amenities. Banzhaf and Farooque (2013) use data for Los Angeles to compare several commonly-used measures for house prices and find that among all the commonly-used measures, medians have the weakest correlation with local public goods, income, and other indices. While the reasons for this finding are not fully understood, it suggests that the results for hedonic models based on median prices should be interpreted with caution.

¹⁰ The problem may be especially pronounced when prices are predicted using an algorithm. In this case a hedonic regression may simply recover a re-construction of the algorithm.

¹¹ The derivative of the price function evaluated at the mean amenity level does not equal the mean of the derivatives, e.g., let $P_i^A = a + bA_i$ equal the implicit price function where $i = [1,2]$. In this case, $\bar{P}^A = \frac{P_1^A + P_2^A}{2}$ and $\bar{A} = \frac{A_1 + A_2}{2}$ and this result is easily verified.

Assigning amenity levels to houses

The model's revealed-preference logic requires the analyst to characterize how buyers perceive the amenity levels at each residential location. This task can present multiple challenges. One challenge is to develop an objective measure of spatial variation in the amenity that can be matched to individual houses. This process can be complicated by the often "patchy" nature of amenity data. For instance, air-quality monitoring networks generate data on pollution levels, measured as ambient concentrations defined as a statistic, e.g., the mean over a specific time period at a point in space. Since houses are naturally situated in gaps between monitoring stations, analysts must use spatial interpolation, air-dispersion models, or predictions from satellites to assign pollution levels to houses. Likewise, proximity to recreation sites such as beaches, lakes, and parks may be measured by geographical distance, by driving distance, by total travel time, or by the share of land devoted to that recreation use within some geographic area around a house. Analysts must decide which measure best reflects the landscape characteristics that matter to homebuyers.

Another challenge is to consider whether homebuyers' subjective beliefs about the amenity's dispersion coincide with objective measures and, if not, to consider alternative ways of modeling buyer beliefs. The broader, nonmarket-valuation literature suggests that subjective beliefs about environmental quality do not always coincide with objective measures (Boyd et al. (2015)). This concern also appears to hold for private attributes of many market goods outside of the environmental literature. Thus, it can be important to document the information channels that may influence buyers' beliefs and assess sensitivity to the choice among candidate measures of the amenity. For instance, Davis (2004) demonstrates that the measurement of cancer risk associated with a cluster of leukemia cases is robust to different assumptions about how homebuyers formed beliefs about the evolving level of risk, including basing it on the cumulative number of cancer cases, the cumulative number of newspaper articles about the cancer cluster, or a Bayesian rule for risk updating. In contrast, Pope (2008) found that a new law requiring real estate agents to disclose information about airport noise caused housing prices to adjust around an international airport. His findings suggest that the disclosure rule changed prospective buyers' beliefs about the spatial dispersion of noise. Under the hypothesis that the information disclosure improved buyers' knowledge of noise levels, sales after the post-disclosure period would be expected to provide more accurate estimates for MWTP.

The dynamic process that leads to changes in amenities presents another challenge. Because housing is a durable asset, households' purchase decisions may also reflect their expectations about the future evolution of local-amenity levels. When buying a house in the current period, for example, a forward-looking household would compare both the current and anticipated future flows of amenities to the current purchase price. In cases where amenity levels exhibit a mean-reversion (mean-diversion) in their trend and households are responding to it, the current implicit price of the amenity would underestimate (overestimate) households' MWTP. The conventional approach to this problem is to take a moving average of the amenity level through time. More recently, Bishop and Murphy (2018) show how to map hedonic-price-function estimates into households' MWTP when buyers are forward-looking over changing amenity levels. They clarify when a dynamic approach would be warranted.

Econometric Specification

Functional form

Theoretical and simulation evidence suggest that the hedonic price function should be assumed to be nonlinear. For example, Ekeland, Heckman, and Nesheim (2004) demonstrate that transactions between heterogeneous buyers and sellers in a differentiated-product market yield an equilibrium hedonic price-function gradient that is generically non-linear in characteristics.¹² Monte Carlo simulations by Cropper, Deck, and McConnell (1988) show that relatively-flexible specifications for the price function, such as Box-Cox transformations, provide more accurate estimates of average MWTP than simpler linear and log-linear specifications in realistic data environments when there are no omitted house characteristics. Moreover, Kuminoff, Parmeter, and Pope (2010) found that flexible Box-Cox models continue to outperform linear models in the presence of omitted variables when spatial dummies are used to mitigate omitted-variable bias. Semiparametric and nonparametric methods can provide additional flexibility in estimating hedonic price functions and their gradients though there is currently no simulation evidence on the implications of the bias-variance tradeoff implicit in such approaches (e.g., Bajari and Benkard (2005), Parmeter, Henderson, and Kumbhakar (2007), McMillen and Redfearn (2010), Bishop and Timmins (2018)).¹³ Yet another

¹² In other words, it would take extraordinarily strong assumptions about the shapes of utility functions and housing-production functions to generate linear hedonic price functions as equilibrium outcomes.

¹³ Simulation methods could be used to investigate bias-variance tradeoffs between parametric nonlinear models, semiparametric models, and nonparametric models to guide functional form decisions in future research.

reason for using nonlinear functional forms is to allow the description used for the market equilibrium to reflect complementarity between amenities. For example, the implicit price of proximity to a public park may vary with the levels of crime, noise, and air quality (Albouy, Christensen, and Sarmiento-Barbieri (2018)).

Econometric errors

As a rule, applications both rely on robust, “sandwich” variance-covariance estimators for the standard errors of the hedonic-price-function parameters and cluster at a spatiotemporal scale consistent with the variation in the amenity of interest. This practice is motivated by the common belief that it is prudent to assume the errors may exhibit heteroskedasticity and autocorrelation (spatial and temporal). Some applications have also experimented with spatial-weighting models that are analogous to feasible generalized least squares. While such models may enhance small-sample efficiency, provided the true parametric form of the error-correlation structure (e.g., nearest-neighbor weighting versus distance decay) is known, without this information, standard errors may be biased. As a rule, most applications avoid making such assumptions and rely on large sample sizes to justify invoking the asymptotic properties of robust, clustered, estimates for the standard errors.

Mitigating Omitted-Variable Bias and Related Threats to Identification

Theory and empirical evidence suggest that amenities will be spatially correlated due to natural features of geography, environmental feedback effects, and voting on local public goods. This potential for correlation fuels widespread concern about omitted-variable bias. There are two aspects of this concern: first, it seems reasonable to assume that analysts can never include every amenity that matters to buyers and, second, latent locational characteristics are likely to be correlated with the amenity of interest, causing bias. For instance, if wealthy and well-educated homebuyers move to areas with better air quality and then vote to increase public-school funding, estimates of MWTP for air quality will be biased upward if school quality is omitted from the model. Thus, a research design that isolates exogenous variation in the amenity of interest becomes necessary to ensure credibility of the resulting estimates. The literature has implemented many such approaches. We separately discuss many of the commonly-implemented research designs in this section.

These approaches amend the theoretical logic underlying the conventional hedonic framework in ways that introduce important tradeoffs in research designs. On the one hand, it is important to assure econometric credibility by mitigating threats due to omitted-variable problems. On the other hand, the economic foundations for the conventional hedonic framework provide a clear basis for recovering policy-relevant welfare measures. Sometimes efforts to enhance econometric credibility direct attention to quasi-experimental designs and/or data on predicted prices that compromise the ability to interpret the estimates as measures of MWTP. In these cases, the analyst has a defensible estimate of an effect but cannot link that estimate to a meaningful economic concept, limiting its policy relevance. We discuss this tradeoff with each research design.

Difference-in-Difference Research Designs

Numerous studies have leveraged environmental-policy changes and natural experiments as quasi-random shocks to amenities and used this interpretation to identify how the shocks lead to changes in housing prices. This process is colloquially described as “capitalization,” although the word’s precise meaning has evolved over time. Econometric models of the capitalization process generally fit within a difference-in-difference (DID) framework. This group includes fixed-effect and first-difference estimators that utilize repeated transactions for the same houses. It also includes estimators that pool repeated cross-sections of transactions from the same geographic market. Sometimes these models utilize instrumental variables and/or regression-discontinuity designs. Overall, the DID framework is distinguished by the way it analyzes transactions before, relative to after, a change to the spatial distribution of the amenity.

The DID framework’s main strength is to mitigate omitted-variable bias by isolating quasi-random variation in amenities over time. Chay and Greenstone’s seminal 2005 study demonstrates how non-attainment of the U.S. Environmental Protection Agency’s standards on maximum-allowable particulate-matter concentrations at the county level can be used as an instrument in analyzing how spatially-varying reductions in particulate matter between 1970 and 1980 influenced the median, self-reported, property value at the county level. Thus, their study is notable for the innovation in research design but is subject to concerns regarding the use of median prices, the use of predicted prices, and the assumption that the law of one price function holds across the United States from 1970 to 1980. In addition to mitigating concerns about omitted amenities, their instru-

mental-variables approach addresses potential bias from measurement errors in air-pollution levels. The quasi-experimental logic from this study has since been adapted to micro data and transaction prices to estimate capitalization effects of changes in a wide range of amenities including cancer risk (Davis 2004), fracking externalities (Muehlenbachs et al. (2015)), air pollution reductions (Bento, Freedman, and Lang (2015)), sand dune construction (Dundas (2017)) and open space (Lang (2018)) to name only a few.

The most common approach to DID is to assume a stationary price function. Figure 1d illustrates the main challenge in interpreting results from this approach: the price functions change over time. Indeed, theory suggests that environmental policies and other events that create quasi-experimental changes in amenity levels will also cause price functions to adjust. Thus, the prices of houses in the “control group” are affected by the policy, as well as prices of the “treated” houses. This result is distinct from any changes that may occur due to macroeconomic forces and other background events during the study period. The key issue is not whether price functions change, but rather whether the changes that occur are small enough to ignore. Large changes in price functions that are not specifically modeled can undermine welfare analysis.

Kuminoff and Pope (2014) show that when a price function shifts over time, the standard DID model ignoring the shift will yield biased estimates of the slopes of the price function and thus biased estimates of MWTP. The standard model mixes information from two equilibria into one estimate, but the economic logic of the hedonic model involves arbitrage at a point in time, not across time. Thus, the model conflates shifts in the price function with movements along the price function. Mixing these two effects becomes problematic if the change in amenities is correlated with the change in price from the shift. In an application to public school quality, Kuminoff and Pope show that price functions in five U.S. metropolitan areas changed during a 5-year boom period from 2003 to 2007. Importantly, this was the same time that the “No Child Left Behind Act,” a policy which targeted school quality and sought to improve information conveyed to parents, was implemented. Incorrectly assuming a time-constant price function would have produced a 75% downward bias in MWTP estimates, in part because school-quality changes were correlated with baseline school-quality levels. This outcome contrasts with a 94% upward bias in cross-section models that ignore the omitted variable problem. In a simulation-based study of housing market equilibria that compared capitalization to MWTP, Klaiber and Smith (2013) find that naïve

cross-section models may or may not outperform more sophisticated DID research designs if the latter are compromised by price-function changes.

One solution is to impose additional exclusion restrictions and to instrument for the change in the amenity of interest. As Kuminoff and Pope (2014) discuss, this strategy has the potential to identify MWTP in the post-shock period. However, it depends on strong orthogonality conditions: the instruments must be orthogonal to baseline conditions (amenities and structural characteristics), as well as to changes in unobservables. A second strategy is to model the change in the price function, generalizing the DID model by interacting price function parameters with time-period dummies. Kuminoff, Parmeter and Pope (2010) provide simulation evidence that this strategy improves the accuracy of estimates for MWTP in both the pre-shock and post-shock periods, and it has been implemented in recent empirical studies (e.g., von Gravenitz 2018). Banzhaf (2018) further shows that this approach can identify a lower bound on a general-equilibrium welfare measure under much weaker econometric assumptions. The results hold for open cities and in the presence of moving costs. A third approach is to assume a parametric form for the dynamic evolution of omitted variables and assume that buyers have rational expectations for that process (Bajari et al. 2011).

Matching Estimators

Matching estimators seek to mitigate omitted-variable bias by matching houses that received an amenity treatment with a set of untreated control houses. The goal is to find control houses that are as similar as possible to each treated house in terms of observed and unobserved physical and locational characteristics. This process essentially uses observed property characteristics to control for unobserved characteristics in a more flexible way than what would result from a simple linear OLS regression. The challenge is to determine the precise criteria for selecting matches. While the econometric properties of matching estimators have been thoroughly analyzed in the program-evaluation literature, the accuracy of their estimates for MWTP for amenities in housing market data has yet to be evaluated in the simulation frameworks that provide insights on other methods.

A notable feature of matching applications is that amenity treatment is typically discrete, such as whether a house provides lake access (Abbott and Klaiber (2013)) or whether it has received an Energy-Star certification (Walls et al. (2017)). Discrete treatment violates the hedonic model's assumption that buyers can choose continuous levels of each amenity, conditional on all other

variables. While this raises a concern that the tangency condition underlying welfare interpretation is violated, the simulation studies cited above generally find that such violations are not necessarily fatal in the sense that the margin of error in estimates for average MWTP for integer measures of housing attributes (e.g., number of bedrooms or bathrooms) is often similar to the margin of error for continuous attributes (e.g., square footage or proximity to parks).

Including spatial dummy variables

Transactions data often offer large sample sizes so it is possible to include a set of spatial dummy variables for local neighborhoods such as school districts, zip codes, or Census tracts in the U.S. Kuminoff, Parmeter, and Pope (2010) show that this strategy can mitigate omitted-variable bias and improve the accuracy of estimates for MWTP in both linear and non-linear specifications of the hedonic price function. Selecting the geographic scale for the dummies presents a tradeoff: shrinking neighborhood size strengthens the case for absorbing omitted variables (reducing bias) but reduces the identifying variation in the amenity (increasing variance). GIS maps showing how the amenity varies within and across candidate neighborhoods can help to diagnose this tradeoff (e.g., von Gravenitz (2018)). Abbott and Klaiber (2011) show how the Hausman-Taylor (1981) estimator may be used to judge the importance of this bias-variance tradeoff.

Boundary-Discontinuity Research Designs

Boundary-discontinuity designs seek to sharpen the spatial dummy-variable approach by leveraging variation in amenity levels within a neighborhood. The idea is to identify an amenity's marginal implicit price from sharp changes in amenity levels that occur at administrative or geographic boundaries. By limiting the estimation sample to houses located within close proximity to boundaries (e.g., within a quarter mile) and using dummy variables for neighborhoods around each boundary to absorb all of the omitted amenities common to both sides, this strategy assumes a sharp difference in the amenity of interest is most likely to lead to a price differential. Sample applications include school attendance zone boundaries (Black (1999)), flood zone boundaries (Pope (2008b)), and public water-service-area boundaries (Muehlenbachs, Spiller, and Timmins (2015)).

While the boundary-discontinuity design is consistent with the hedonic model's conceptual underpinnings, it presents at least two challenges. First, household sorting may confound the identification strategy by generating sharp differences across boundary zones in latent endogenous amenities. For instance, if wealthier households tend to locate on the "high quality" side of a school-zone boundary and also tend to divert more money to neighborhood parks, this would lead to a biased estimate of MWTP for school quality if parks are not included in the model. Bayer, Ferreira, and McMillan (2007) found that when they address this problem by controlling for differences in socioeconomic status of households on opposite sides of boundaries there is a first order change in their estimates of MWTP for school quality. The second challenge is that the resulting measures of MWTP may be limited in their ability to inform policies affecting the broader housing market; the analyst must be willing to assume that the identified part of the housing price surface is representative for the population of interest. While it is common to assume that the boundary neighborhoods are representative of the broader population, we are unaware of any evidence that evaluates these assumptions.

Assessing Robustness

Every study embeds modeling decisions that affect welfare conclusions. We have discussed the choice of the amenity variable, the source of variation in the amenity, the decisions made about sample composition (including observations removed as likely coding errors and outliers), and the parametric assumptions stemming from selecting a specification for the price function. Reporting the sensitivity of welfare conclusions to these and other modeling decisions can help to mitigate concerns that results are driven by arbitrary assumptions or by outlying observations. Dundas (2017, Figure 5) provides an informative graphical example of robustness within a targeted sensitivity analysis.

Best Practices for Using MWTP Estimates to Inform Policy

Incorporating Heterogeneity

Figures 1a and 1b illustrate how differentiating the hedonic price function with respect to the amenity of interest yields an implicit price function for the amenity that may be evaluated for each household's observed selection. These values provide point estimates for each household's MWTP. If it is possible to match housing-transaction records to administrative data on households,

then the heterogeneity in MWTP estimates may be linked to buyers' demographic characteristics (e.g., race, income, education, children). In the United States, this has been done by merging publicly-available, Home-Mortgage-Disclosure-Act data describing basic demographic characteristics of buyers who finance their purchases with federally-insured mortgages with data describing housing transactions (e.g., Bishop and Timmins (2017)). In some European countries, researchers can link property transactions with even richer government records on household demographics (von Graevenitz (2018)).

Demand Estimation for Non-Marginal Changes in the Amenity

As noted earlier, Figure 1c illustrates that a buyer's single observed consumption choice reveals only one point on the buyer's amenity-demand curve. Thus, the demand function, which would be required to measure welfare for non-marginal changes, cannot be recovered for each household. Rosen (1974) proposed estimating the demand function by regressing MWTP estimates on corresponding quantities consumed and demand shifters such as buyers' demographic characteristics. Unfortunately, this estimation strategy presents an endogeneity problem (see Bartik 1987 and Epple 1987), as unobserved tastes simultaneously determine both a buyer's MWTP (at the point of consumption) and their chosen quantity.

Thus, to recover the structure of demand, the literature has developed a variety of econometric strategies. These include imposing restrictions on: the parametric form of utility (e.g., Bajari and Benkard (2005)); the scope of preference heterogeneity (e.g., Ekeland, Heckman, and Nesheim (2004), Bishop and Timmins (2019)); the stability of preference heterogeneity across cities (Bartik (1987) and Zabel and Kiel (2000)); the stability of household preferences over time (Bishop and Timmins (2018) and Banzhaf (2017)); and the extent of spatial sorting (Bartik (1987) and Zhang, Boyle, and Kuminoff (2015)). These studies recover the demand function in a variety of ways. Several provide proof-of-concept applications. Yet, no individual approach has been clearly adopted by the empirical literature as a best-practices approach for amenity-demand estimation.

Non-Parametric Bounds and Approximations for Willingness to Pay

Some studies use hedonic price function estimates for back-of-the-envelope calculations that multiply MWTP by large changes in amenities. For these calculations to be exact, demand must be

perfectly elastic and invariant to the changes. The likelihood that such assumptions provide reasonable approximations decreases with the size of the change. When the change in the amenity is believed to be too large to assume a perfectly elastic demand curves, an alternative approach to estimation of the demand function is to obtain non-parametric bounds and approximations following the logic of Varian (1982). Consider Figure 1d. Suppose that a household's demand does not change between periods. In period T, household 2 is observed to pay an implicit price of P_3^A to consume A_3 units of the amenity. In Period S, this household pays an implicit price of P_4^A to consume A_4 units. If, for example, we had only observed the period-T choice, the rectangle defined by $P_3^A \times (A_4 - A_3)$ would provide an upper bound for the willingness to pay that would have been recovered by integrating under any downward sloping demand curve going through that point and over to A_4 . Naturally, the lower bound would be zero. If instead we had only observed the period-S choice, the rectangle defined by $P_4^A \times (A_4 - A_3)$ would provide a lower bound for the willingness to pay to avoid a policy that would decrease household 2's amenity level to A_3 from A_4 . Naturally, the upper bound would be infinity. Without additional functional-form restrictions, this is all that one can say about household-specific welfare from a single data point. Note that these bounds correspond to indifference curves that range between the cases where money and the amenity are perfect substitutes to perfect complements.

When the household is observed at two or more points, these bounds can be made tighter (Varian 1982). Moreover, with additional functional form restrictions, the demand curve can be calculated without any econometric estimation. As Bajari and Benkard (2005) and Bishop and Timmins (2018) point out, if we assume the demand curve is linear then two points are enough to identify it without any statistical estimation. One can simply connect the dots between (P_3^A, A_3) and (P_4^A, A_4) . By extension, three points are enough to identify a quadratic demand curve, and so forth. Furthermore, Banzhaf (2017) shows that, with two points, the connect-the-dots approach provides a second-order approximation to a true Hicksian welfare measure, regardless of the unknown Hicksian demand curve. Moreover, even if one cannot follow households over time, with a panel of houses one can either identify this second-order approximation with additional structure or alternatively bound it. Bishop and Timmins (2018) illustrate the connect-the-dots approach for air quality in the Bay Area of California, finding considerable heterogeneity in WTP that would be missed with the conventional approach.

Opportunities to Advance the Literature

Employing Administrative Records

Increased access to administrative records offers the potential to improve our understanding of buyers' revealed preferences for local amenities. First, enhanced information about buyers, including their demographic characteristics, working situation, income levels, and wealth, can enable researchers to analyze how hedonic estimates for MWTP vary with these factors (e.g., von Graevenitz 2018). Second, as some structural models of residential-sorting behavior rely on strong distributional assumptions (Kuminoff, Smith, and Timmins (2013)), greater access to administrative records would enhance our ability to recover the distributional implications of policies and would allow distributional assumptions to be evaluated. Finally, the information contained in administrative records may help in identifying demand curves for an amenity. For instance, consider household 2 in the lower right panel of Figure 1d that is observed in both period S and period T under different implicit price schedules; in principle, one should be able to literally "connect the dots" and recover this household's demand curve, as long as the household's income and preferences remain constant (Bishop and Timmins (2018)). Administrative records could assist in isolating the households who "fit" this assumption. Similarly, the data sets used by Voorheis (2017) and Bishop, Ketcham, and Kuminoff (2018) to track the long-term evolution of individuals' health and wealth could, in principle, be matched to housing transactions to yield new insights on how changes in health and wealth affect the demand for specific amenities.

Focusing on External Validation for MWTP Function Estimation

Another way to advance the empirical literature would be to determine which of the existing approaches to demand estimation is most suitable for policy analysis by testing the assumptions used to move from point estimates of MWTP to a demand function. For example, Galiani, Murphy, and Pantano (2015) illustrate how modeling assumptions may be tested in a discrete-choice model by developing testable, out-of-sample predictions about how changes in housing prices induce households to adjust their neighborhoods. In principle, this methodology could be adapted to propose testable predictions for how changes in local amenities would induce households to adjust their neighborhoods.

Adapting the Policy Elasticity to Hedonic Models

Recently, public economists have argued that Hendren's (2015) concept of a marginal value of public funds (MVPF) offers the means for economists "...to harness the fruits of the 'credibility revolution' for the public finance goal of welfare analysis" (Finkelstein (2018), p.1). While the MVPF concept is not new to the field of environmental economics, adapting it to the hedonic model has potential to enhance the relevance of MWTP estimates for assessing the efficacy of competing environmental policies. In the environmental context, the MVPF is defined as the willingness to pay for a marginal change in an amenity relative to the net incremental cost of providing that change through a policy. This metric differs from a simple benefit-cost ratio by incorporating the causal impact of behavioral responses to the policy on the government budget. For example, a policy that reduces air pollution may also reduce federal health-care expenditures or raise property tax revenues (by increasing property values). The challenge for future research would be to credibly estimate sufficient statistics for describing how these behavioral responses affect taxpayers (i.e., the policy elasticities) and then combine this information with hedonic estimates for MWTP and data on policy implementation costs.¹⁴ If this could be done for multiple policies, the resulting MVPF measures could be used to order policies according to their return on investment and determine the most efficient way to allocate a marginal increase in government expenditures on the environment. The hedonic equilibrium framework in Banzhaf (2017, 2018) could provide a starting point for further research on the relationship between MWTP and MVPF.

Investigating Heterogeneity in Beliefs

Finally, there is evidence that consumers often have heterogeneous beliefs about product attributes, with some consumers being misinformed at the time of purchase even when it comes to high-stakes financial decisions such as choosing a college major (Wiswall and Zafar (2015)), choosing a health insurance plan (Handel and Kolstad (2015)), or developing a strategy to save money for retirement (Bernheim, Fradkin, and Popov (2015)). The same is true for expensive durable goods such as cars (Busse et al. (2015)), refrigerators (Houde (2017)), and water heaters (Allcott and Sweeney (2017)). When consumers are not fully-informed about product characteristics, their choices can fail to reveal their preferences. Several of these studies overcome the problem by incorporating survey data on consumers' beliefs. Adapting such approaches to the hedonic property-

¹⁴ Chetty (2009) and Heckman (2010) discuss sufficient statistics in other contexts.

value context has potential to improve the accuracy of welfare measures for changes in amenities if buyers are not fully-informed.

Evidence on the degree to which buyers are informed about the characteristics of their houses and neighborhoods is mixed. Myers (2017) uses capitalization effects of fuel-price changes to conclude that homebuyers are well-informed about how future energy costs vary with a house's heating technology (gas versus oil). In contrast, Pope (2008a, 2008b) uses capitalization effects of real-estate information disclosures to conclude that some homebuyers did not pay attention to publicly-available information about flood risk and airport noise prior to mandatory disclosure laws that required them to sign forms stating their awareness of the amenities. Bakkensen and Barrage (2017) provide more direct evidence by surveying homebuyers about their beliefs of their flood risk. Their findings suggest residents of more flood-prone areas are more likely to underestimate flood risk. Since the current evidence suggests that the accuracy of buyers' beliefs varies from context to context, future research on housing purchases should consider adapting the methods that have been developed to incorporate heterogenous beliefs. The challenge is to improve our understanding of households' information sets and to use this information to refine welfare measures. A potential first step would be to combine transactions data with surveys that reveal buyers' beliefs about the spatial dispersion of amenities at a point in time. The next step would be to learn how households' beliefs evolve over time as they process new information. Ma (2018) demonstrates how one can model the learning process within a structural dynamic sorting model, finding that doing so has a large impact on estimates for the willingness to pay for brownfield remediation.

Conclusion

The choice of where to live is perhaps the single most important decision affecting a household's consumption of environmental amenities. It is natural to expect that housing markets would have the ability to reveal information about the welfare effects of changes in amenities. The hedonic property-value model provides an economically-plausible and empirically-tractable way to distil this information. The model's credibility and policy relevance have been improved in recent years by advances in applied theory and econometrics. While we noted many cautions regarding implementation, these cautions should not deter readers from using the model. The literature has simply generated more knowledge about the "do's" and "don'ts" of hedonic modeling than for most other microeconomic frameworks used to analyze policy. The model's success is underscored by the

fact that it is used in the real world to inform public and private decisions.¹⁵ The bottom line is that modern “best practices” property-value regressions can provide credible estimates for what households are willing to pay for environmental amenities.

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¹⁵ Triplett (1990) reported the first use of hedonic methods in a government price index in 1968 for new one-family houses sold. More recently (2007) he summarized the use of hedonic methods in developing prices indexes and other measures for the national accounts. In the private sector there are many areas where hedonic pricing is used in a proprietary fashion, most obviously in real estate by companies such as Zillow.

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Fig 1a: The hedonic price function in amenity space

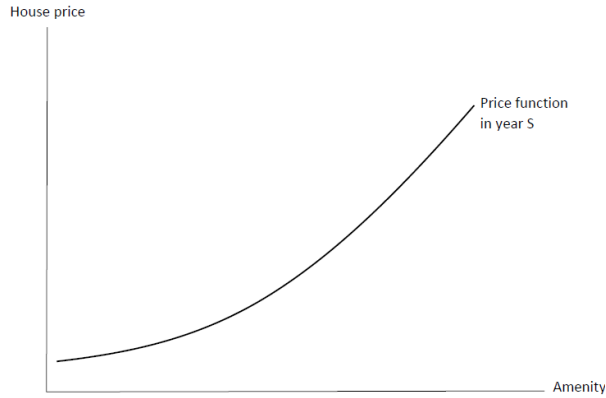


Fig 1b: The buyers' purchase decisions

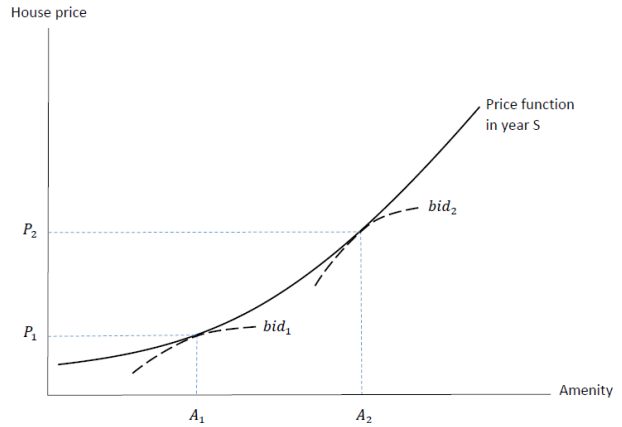


Fig 1c: The implicit price function reveals buyers' MWTP

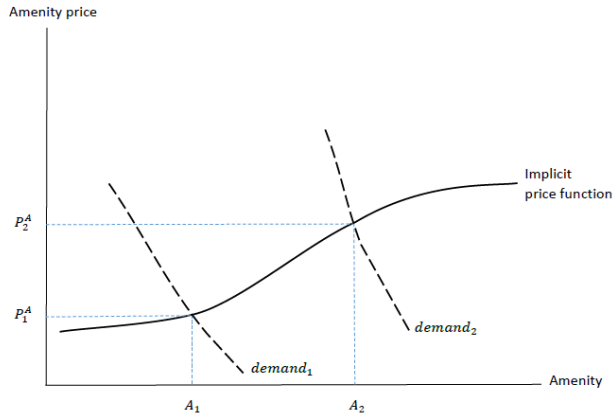


Fig 1d: The implicit price function and MWTP change over time

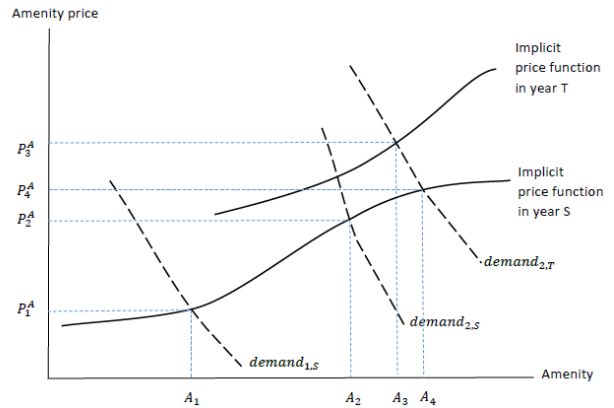


Figure 1: Using the Hedonic Price Function to Infer Buyers' MWTP for an Amenity

Note: Fig 1a shows the price of housing increasing in the level of an amenity. Fig 1b shows purchase decisions for two households. Household 2 purchases a house providing amenity A_2 at price P_2 . This is the point at which the household's demand curve intersects the amenity's implicit price function, as shown in Fig 1c. Fig 1d shows this relationship changing after a policy changes amenity levels. See the main text for additional detail.

SUPPLEMENTAL APPENDIX: FOR ONLINE PUBLICATION

The following table provides a country-by-country summary of data availability with references to sample applications. It is meant to provide a starting point for analysts preparing to estimate hedonic price functions. We are grateful to the following individuals for helping us to compile this information: Jens Abildtrup, Gabriel Ahlfeldt, Vilni Verner Bloch, Paula Dijkstra, Ricardo Flores, Stefan Hofbauer, Ingrid Kaminger, Hans R. A. Koster, Janet Lemoine, Jacob MacDonald, Marta Monteiro, Gerhard Muggenhuber, Orietta Patacchia, Gregg Patrick, Renata Rechnio, Judit Székely, Laetitia Tuffery and Isabella Wlosinska.

Country (Share of owner occupied housing ¹)	Type of data	Provider	Coverage	Examples applications
Australia (67 % in 2015/16 according to the Australian Bureau of Statistics, Survey of Income and Housing, “Housing Occupancy and Costs”.)	Australian Property Monitors have data on transactions, etc.	Australian Property Monitors have data on transactions and the rental market: http://www.apm.com.au/	Coverage on transactions is complete starting in the late 1980s.	Robert J. Hill, Iqbal A. Syed (2016): Hedonic price–rent ratios, user cost, and departures from equilibrium in the housing market, <i>Regional Science and Urban Economics</i> , 56: 60-72.
Austria (55 %)	Data on transactions is available at a price from private providers. For Vienna an open source data base exists.	Two data providers for transactions data are ZT datenforum and IMMOUnited. These providers can provide data on transactions and housing characteristics from actual sales contracts.	Information on the coverage of the transactions data available from datenforum and IMMOUnited was not	

¹ Source: If no source is indicated the information describes the year 2016 and comes from Eurostat, Distribution of population by tenure status - EU-SILC survey, Code: ilc_lvho02

	<p>Information on housing characteristics is very limited.</p> <p>Administrative data on housing characteristics is available from 2001 or 2011 (Gebäude- und Wohnungsregister, GWR), but not as micro data. The aggregated information is available in a 250 m raster format.</p>	<p>Open source data on transactions in Vienna is available here: https://www.data.gv.at/katalog/dataset/5fc523d5-c299-4d97-889f-01ed247b10fa.</p>	<p>available at the time of publishing.</p>	
Belgium (71 %)	<p>Data on sales prices are collected by the Belgian tax authorities. Information on the characteristics of housing are collected by the Land Registry authorities. This data has been used in the past, e.g. for noise valuation (see Franck et al. (2015)).</p>	<p>The Belgian Land Registry is found at www.kadaster.be.</p>	<p>Information on the coverage of the transactions data available was not available at the time of publishing.</p>	<p>Marieke Franck, Johan Eyckmans, Simon De Jaeger, Sandra Rousseau (2015): Comparing the impact of road noise on property prices in two separated markets, <i>Journal of Environmental Economics and Policy</i>, 4(1): 15-44.</p>
Canada (66 %, Statistics Canada. Table 203-0027 - Survey of household spending (SHS), dwelling characteristics	<p>Statistics Canada long form census collects information on self-assessed value of owner-occupied homes and on rental rates of rental homes.</p>		<p>Information from the census is available in 5-10 year intervals, however, from 2011 the long form census was replaced by a survey.</p>	

<p>and household equipment at time of interview, Canada, regions and provinces, annual (number unless otherwise noted), CANSIM (database). (accessed: 11 May 2018)</p>	<p>The Canadian Real Estate Association has some data aggregated to the level of the real estate board. Information on individual transactions may be available at a regional level from regional real estate associations or realtors.</p>			
<p>Chile (64 % in 2013 based on household survey “Encuesta de Caracterización Socioeconómica Nacional (CASEN)”)</p>	<p>Micro data on transactions exists at the Central Bank of Chile, but is not directly available for external researchers.</p>		<p>The micro data held by the Central Bank of Chile covers all transactions from 2002 onwards.</p>	
<p>China (approx.. 80 % in 2012 according to James R. Barth, Michael Lea and Tong Li (2012): China’s Housing Market: Is a Bubble About to Burst? Milken Institute.)</p>	<p>Fang.com has list prices for homes across 658 Chinese cities. Wen et al. (2018) use data provided by Hangzhou Real Estate Administration.</p>	<p>Fang.com (only available in Chinese)</p>		<p>Siqi Zheng, Matthew E. Kahn, Hongyu Liu (2010): Towards a system of open cities in China: Home prices, FDI flows and air quality in 35 major cities, Regional Science and Urban Economics, 40 (1): 1-10. Haizhen Wen, Zaiyuan Gui, Chuanhao Tian, Yue Xiao, Li Fang(2018): Subway Opening, Traffic Accessibility, and Housing Prices: A</p>

				Quantile Hedonic Analysis in Hangzhou, China. Sustainability, 10(7): 2254.
Denmark (62 %)	Administrative data on housing attributes and households composed from a number of different registries.	<p>All administrative data on households and transactions is available from Statistics Denmark. However, merging locational attributes (e.g. based on GIS calculations) requires access to location data outside the servers of Statistics Denmark.</p> <p>Geocoded data on housing and transactions is also available outside of Statistics Denmark: https://www.ois.dk/. A number of official data distributors (see website) have licenses to sell data for commercial and research use.</p> <p>External data (e.g. created using GIS) can be uploaded to a Statistics Denmark project with suitable precautions taken to preserve anonymity of the Statistics Denmark data with which it is merged.</p>	<p>Transactions data covering all transactions is available from 1992 onwards.</p> <p>Data on housing and households can be merged 1:1 via unique address codes.</p>	Kathrine von Graevenitz (2018): The Amenity Cost of Road Noise, Journal of Environmental Economics and Management, 90:1-22.
Finland (72 %)	Administrative data on housing attributes and transactions composed from a number of different registries	Statistics Finland and National Land Survey of Finland (https://www.maanmittauslaitos.fi/en).	<p>Transactions are covered 100 % from 1990 onwards.</p> <p>Data on housing and occupants can be merged through unique identifiers.</p>	
France (65 %)	Micro data on transactions available through the Notarial Base for the Ile de France region (<i>BIEN</i>) of the Chamber of Notaries of Paris. The notarial organization <i>Perval</i>	Notarial information is provided at a cost. Information about the data available and conditions including prices can be found on www.Immobilier.statistiques.notaires.fr .	Data for Ile de France is available from 1998 onwards (<i>BIEN</i>). For transactions outside the Ile de France data availability starts in 1994 (<i>Perval</i>). The coverage is 100 % -	Jean Cavailhès, Thierry Brossard, Jean-Christophe Foltête, Mohamed Hilal, Daniel Joly, François-Pierre Tourneux, Céline Tritz, Pierre Wavresky (2009) : GIS-Based Hedonic Pricing of

	<p>provides data for transactions outside Ile de France</p> <p>The data is not georeferenced and the smallest geographical unit is the IRIS level (comparable to a US census block group with approx. 2000 inhabitants).</p>		<p>however, as the data is provided voluntarily by notaries there can be many missing values for individual observations.</p>	<p>Landscape, Environmental and Resource Economics 44:571–590.</p> <p>Laetitia Tuffery (2017): The recreational services value of the nearby periurban forest versus the regional forest environment, Journal of Forestry Economics, 28: 33-41.</p>
Germany (52 %)	<p>Micro data availability varies across regions: For Berlin an excellent register of all transacted properties exists (<i>Kaufpreissammlung des Gutachterausschusses</i>) whereas in other regions such data is not available.</p> <p>For Germany-wide coverage only data on housing advertisements (list prices) is available starting from approximately 2007 onwards.</p>	<p>Depending on whether the data comes from a Gutachterausschuss (Appraisal committee) permission for data access must be granted by the committee. Actual transactions data covering a large share of transactions in a region are hard to come by, though vdpResearch (www.vdpresearch.de) maintains a transactions data set (starting 2007). To our knowledge, this data has not yet been used for scientific purposes.</p> <p>Data based on online ads (homes for rent and for sale) is provided by private companies such as Immobilienscout24 and Empirica AG. Prices and conditions vary.</p>	<p>For national coverage, only the list prices from online ads are available. The share of transacted objects included in these data sets is unknown and likely to vary across space and time.</p>	<p>Manuel Frondel, Andreas Gerster, Colin Vance (2017): The Power of Mandatory Quality Disclosure: Evidence from the German Housing Market. Ruhr Economic Papers #684.</p>
Hungary (86 %)	<p>Data on transactions is collected from the Hungarian tax authorities. About 80 % of the data is</p>	<p>Data can be accessed for research purposes in the research facilities of the Hungarian Central Statistics Office.</p>	<p>Coverage is 100 % from 2007 onwards, however the number of housing characteristics is limited.</p>	

	geocoded and can be merged with registries at the Hungarian Central Statistics Office.		Building type is always observed, but living area is only available for approx. 70 % of observations.	
Ireland (70 %)	<p>The Irish Central Statistics Office (CSO) has micro data on housing transactions based on administrative records. These data are the basis for the Residential Property Price Index.</p> <p>Transactions data from the Residential Property Price Registry (based on declarations for stamp duty purposes) is combined with data on Building Energy Ratings and location quality.</p>	<p>Micro data from the CSO can be made available to researchers under conditions of strict confidentiality. One condition is that the research is carried out in the Irish jurisdiction.</p> <p>Alternative providers include the online service www.daft.ie (list prices only).</p>	The CSO data covers 100 % of transactions since 2011.	
Italy (72 %)	Micro data on transactions is available at the Italian National Institute of Statistics (IStat). The data is not geocoded, but information on municipality and region is included. A limited set of housing characteristics is available. The source of the data is administrative (notarial deeds).	IStat holds micro data: https://www.istat.it/en/	Data coverage starts in 2007 (3 rd quarter). Coverage is complete for Italy except for the regions of Trento and Bolzano (2.3 % of the Italian population), which have a different cadastral system.	

Japan (62 % according to the 2013 Housing and Land Survey for Japan)	Data is made available from the Japanese Ministry of Land, Infrastructure, Transport and Tourism, Land General Information System.	More information in English about the data available can be found here: http://www.mlit.go.jp/en/totikensangyo/totikensangyo_fr5_000014.html	Almost full coverage from the fiscal year of 2007 onwards according to the Land General Information System.	Daiji Kawaguchi, Norifumi Yukutake (2017): Estimating the residential land damage of the Fukushima nuclear accident, Journal of Urban Economics, 99: 148-160.
Norway (83 %)	Administrative data on housing attributes and households composed from a number of different registries. Transactions information comes from a website used by a large share of Norwegian realtors: www.finn.no . This data forms the basis of the Norwegian residential property price index.	Statistics Norway has data on housing characteristics and data on housing transactions from finn.no.	The first registry on housing for Norway was published in 2006. Additional characteristics have been added over the years. Transaction prices are available from 2005. Coverage has been increasing over time. In 2010 it was approximately 70 % of transactions.	
Poland (83 %)	Micro data on transactions is collected by Statistics Poland. Information on characteristics is very limited and the data are not geocoded.	Access to the data held by Statistics Poland is restricted.	The data held by Statistics Poland covers the period from 2010 onwards.	
Portugal (75 %)	Micro data is not generally available. Aggregated data on list prices is available with the smallest unit being the level of civil parishes (freguesia).	Data at the freguesia level are supplied by Confidencial Imobiliário under certain conditions. The data is provided by real estate agencies.	The data coverage starts in 2007.	Sofia F. Franco, Jacob L. Macdonald (2018): The effects of cultural heritage on residential property values: Evidence from Lisbon, Portugal. Regional

				Science and Urban Economics, 70: 35-56.
South Korea (57 % in 2015 according to the South Korean National Statistical Office, "Population and Housing Census", Approval Statistics No. : 10101, 10102.	The Ministry of Land, Infrastructure, and Transport (MoLIT) holds transactions data.	MoLIT (in English): http://stat.molit.go.kr/portal/cate/engStatListPopup.do Another source is the Onnara Real Estate Information Portal, http://www.onnara.go.kr , (available in Korean).		Jeongseob Kim, Junsung Park, D.K. Yoon, Gi-Hyong Cho (2017): Amenity or hazard? The effects of landslide hazard on property value in Woomyeon Nature Park area, Korea. Landscape and Urban Planning, 157:523-531.
Spain (78 %)	Data on the Spanish housing market is not easily available for research purposes. Data on transactions may be available from Agencia Notarial de Certificación S.L. Unipersonal (Notary Certification Agency, ANCERT).	Individual agreements about access to data on mortgages have been made in the past with banks/mortgage providers (see example literature).	Maya (2018) raises the concern that cash side payments are common in Spain implying that prices from the official property register (Registro de la Propiedad) may not be accurate.	Josep M. Maya (2018): The determinants of foreclosures: Evidence from the Spanish case, Papers in Regional Science, 97(4):957-970.
Sweden (65 %)	Administrative data on housing attributes and households composed from a number of different registries.	The Swedish mapping, cadastral and land registration authority <i>Lantmäteriet</i> (www.lantmateriet.se) and official data distributors (see website) sell access to data on housing and transactions.	Transactions data covering the universe of transactions is available from 1996 onwards.	Henrik Andersson, Lina Jonsson, Mikael Ögren (2010): Property Prices and Exposure to Multiple Noise Sources: Hedonic Regression with Road and Railway Noise,

				Environmental and Resource Economics 45:73–89.
Switzerland (43 %)	<p>REIDA (Real Estate Investment Data Association) data on housing transactions etc. is provided for research purposes.</p> <p>Private providers from online real estate ads provide data on list prices and the rental market.</p>	<p>For more information on the REIDA data, please see http://www.reida.ch</p> <p>List prices only: Comparis.ch has data from apartments offered for sale or rent online from 2005 onwards. Homegate.ch has data on apartments for rent starting in 2002.</p>	<p>REIDA covers transactions, rentals, etc. from 2010/2011 onwards. Coverage is not complete.</p> <p>Coverage of the comparis.ch data is fairly good according to Basten et al. (2017), who compare administrative data on vacancy rates to the announcements listed on comparis.ch.</p>	<p>Christoph Basten, Maximilian Von Ehrlich, Andrea Lassmann (2017): Income Taxes, Sorting, and the Costs of Housing: Evidence from Municipal Boundaries in Switzerland, Economic Journal, 127(601): 653-687.</p> <p>Christian Almer, Stefan Boes, Stephan Nuesch (2017): Dynamics in the Housing Market after an Environmental Shock? Evidence from Online Advertisements. Oxford Economic Papers, 69(4):918-938.</p>
The Netherlands (69 %)	<p>Transactions data available from National Realtors' Association (NVM) for researchers based at a Dutch university.</p> <p>The Netherlands' Cadastre, Land Registry and Mapping Agency (Kadaster) collects and registers administrative and spatial data on property in the Netherlands.</p>	<p>National Association of Realtors (NVM) make data available for researchers in the Netherlands. www.nvm.nl</p> <p>Kadaster provides data access in secure facilities. www.kadaster.nl</p>	<p>The NVM data covers approximately 70 % of all transactions between 1985 and 2011 (Dröes & Koster, 2016) and 80 % of transactions between 2000 and 2014 (Koster and van Ommeren, 2017).</p> <p>The Kadaster data contains information on ownership and transactions for all parcels in the Netherlands.</p>	<p>Erdal Aydin, Dirk Brounen, Nils Kok (2017): Information Asymmetry and Energy Efficiency: Evidence from the Housing Market, Maastricht University Discussion Paper, September 2017.</p> <p>Martijn I. Dröes, Hans R.A. Koster (2016) Renewable Energy and Negative Externalities: The effect of</p>

			Information on housing characteristics is limited to a few characteristics (e.g year of construction and size).	Wind Turbines on House Prices, Journal of Urban Economics, 96:121-141. Hans R.A. Koster, Jos van Ommeren (forthcoming): Place-based policies and the housing market. Review of Economics and Statistics. https://doi.org/10.1162/rest_a_00779
United Kingdom (63 %)	Price paid data from HM Land Registry. Information on transaction, type of dwelling, location. Detailed information on housing characteristics is not contained. Data is not geocoded, but address information is available. Alternative sources: Data from the Nationwide Building Society on mortgages includes more detailed information on housing characteristics as well as minimal information on the type of mortgage and whether the buyer is a first-time buyer. It has been used in past	Price paid data is available for download at: https://www.gov.uk/government/collections/price-paid-data Koster and Zabihidan (2018) and Koster and Pinchbeck (2018) match the price paid data to a data set on Energy Performance Certificates to add information on characteristics. Data from the Nationwide Building Society have been used on a number of occasions through individually negotiated contracts.	Price paid data covers the population of free market transactions from 1995 onwards. Transactions may take up to 2 months to appear in the data. The data on Energy Performance Certificates covers properties sold after January 1, 2008. Nationwide Building Society data covers about 10 % of transactions according to Ahlfeldt et al. (2017). It covers a time span starting in 1995.	Gabriel Ahlfeldt, Pantelis Koutroumpis, Tommaso M. Valletti (2017): Speed 2.0: Evaluating Access to Universal Digital Highways. Journal of the European Economic Association, 15(3): 586-625. Steve Gibbons (2015): Gone with the wind: valuing the visual impacts of wind turbines through house prices. Journal of Environmental Economics and Management, 72: 177-196. Hans R. A. Koster, Mohammad S. Zabihidan (2018): The Welfare Effects of Greenbelt Policy: Evidence

	applications by e.g. Ahlfeldt et al. (2017)			from England, unpublished working paper, January 2018. Hans R. A. Koster, Edward W. Pinchbeck (2018): How do Households Value the Future? Evidence from Property Taxes, unpublished working paper, March 2018.
United States of America (64 % according to the US Census' Quarterly Residential Vacancies And Homeownership, Second Quarter 2018 (Release Number: CB18-107)	A number of different sources are available, e.g.: <ul style="list-style-type: none"> - Census data on owner estimates of home values - Transactions data from private providers such as CoreLogic or Zillow (only housing characteristics and prices) - Home Mortgage Disclosure Act data also contains limited information on the buyer 	County level data on property transaction sale prices and characteristics are available for purchase from CoreLogic: https://www.corelogic.com	Coverage varies across time and space, reflecting differences in record keeping at the county level. While data are available for most states since the mid 2000's, a few areas, notably Texas, have non-disclosure laws that prohibit release of complete information on transactions.	See papers referenced in the main article.

Hedonic Modeling with Less-Than-Ideal Data

The main article is based on knowledge that has been developed using housing-market data from advanced economies, especially metropolitan areas of the United States, where housing transaction prices and characteristics are widely available and institutions are well-established. Adapting any “best practices” to rural areas and/or developing economies may present additional challenges due to data limitations and institutional differences. This appendix discusses some of the challenges that may arise in these settings and outlines issues for researchers to consider.

Housing-Market Institutions

The first issue to consider is whether housing-market institutions will enable transaction prices to reflect households’ willingness to pay for amenities. Are property rights well-defined and secure? Are market prices decentralized? If the answer to either question is ‘no’ then it may be unrealistic to expect a housing-price function to fully reveal MWTP. This caveat also applies to advanced economies that use rent controls or other mechanisms to regulate prices in certain areas. For example, in Denmark rents for some segments of the rental market are restricted according to what is typical for existing contracts in an area (so-called “reasonable rents” as evaluated by a municipal rent committee). Such controls limit the speed with which markets can adjust when amenity levels change and limit researchers’ ability to infer MWTP, as the rents are not market-based prices.

Data Issues

Type of housing market data

The appendix table shows that the availability of housing market data varies substantially across countries. When the gold standard data (arms-length transactions) are not available, it does not necessarily mean that hedonic analysis cannot be performed. At a minimum, researchers should consider how accurately the alternative data sources are likely to reflect the MWTP for amenities in comparison to actual transactions prices. For example, Banzhaf and Farooque (2013) find that several different measures of housing prices in the Los Angeles metropolitan area generate highly correlated neighborhood-specific price indices (e.g., micro data on owner self-assessments, transaction prices for single-family houses, rental prices). Correlations between the measures range from 0.75 to 0.99. Median prices are the outlier, with

correlation coefficients to other price indices ranging from 0.34 to 0.61. It is an open question whether their findings generalize to other markets, either within the US or beyond.

List prices of housing are often available in Europe from online real-estate marketplaces. When transaction prices are not universally available throughout the study area, comparing list prices to transactions prices for regions where both are available can provide suggestive evidence on the degree to which the two data sources may differ systematically. For example, transaction data are not widely available in Germany. In a study of the capitalization of German energy performance certificates into housing prices, Frondel et al. (2017) use list prices from an online real estate marketplace covering most of the country and provide a sensitivity analysis comparing the list prices with transactions prices, which are available for the Berlin area. Frondel et al. find no evidence of systematic bias from using the list prices, although the transactions prices were generally 7% lower.

Data Density

The use of flexible functional forms and high-resolution spatial fixed effects is enabled by the availability of large, dense data sets. In rural locations it may not be possible to implement these best practices. An alternative approach would be to use matching as a pre-processing tool (Ho et al., 2007, von Graevenitz et al., 2018). Matching methods are often used in cases with few treated and many potential control observations to identify the most appropriate control group as discussed in the main text. However, Ho et al. (2007) suggests that matching can also be used to pre-process the data and reduce the importance of the choice of functional form by reducing the heterogeneity in the remaining data set. von Graevenitz et al. (2018) uses matching based on this argument in an analysis of capitalization of emissions information from the European Pollutant Release and Transfer Register into German housing prices.

An alternative way to address sparse data is to use the available observations to create synthetic controls (Abadie et al., 2010). As in the case of matching discussed in the main text, a synthetic-control approach seems most appropriate when the amenity of interest is discrete in nature. While the synthetic control approach has yet to be widely applied in hedonic modeling, Gautier et al. (2009) provides an example in which synthetic-control neighborhoods are constructed to compare the evolution of prices in various neighborhoods following the highly-publicized murder of a well-known Dutch celebrity.

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