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HEDONIC PRICE INDEXES FOR RESIDENTIAL HOUSING: A SURVEY, EVALUATION AND TAXONOMY*

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Abstract. Every house is different. It is important that house price indexes take account of these quality differences. Hedonic methods which express house prices as a function of a vector of characteristics (such as number of bedrooms and bathrooms, land area and location) are particularly useful for this purpose. I consider here some developments in the hedonic methodology, as it is applied in a housing context, that have occurred in the last three decades. A number of hedonic house price indexes are now available. However, it is often difficult to see how these indexes relate to each other. For this reason I attempt to impose some structure on the literature by developing a taxonomy of hedonic indexes, and then show how existing indexes fit into this taxonomy. Also discussed are some promising areas for future research in the hedonic field. In particular, greater use needs to be made of spatial econometric and nonparametric methods to exploit the increased availability of geospatial data. The main criticisms of the hedonic approach are evaluated and compared with those of the repeat-sales and stratified median methods. The overall conclusion is that the advantages of the hedonic approach outweigh its disadvantages.

Keywords. House price index; Hedonic regression; Repeat-sales index; Sample selection bias; Spatial econometrics; Geospatial data

1. Uses of House Price Indexes

The real estate sector can be divided into residential and commercial categories. My focus here is on residential housing. According to Syz (2008) about one-third of total wealth around the world (about $21.6 trillion) is tied up in residential housing. Case *et al*. (2005) find that changes in house prices have a larger impact than changes in stock-market prices on household consumption in the U.S. and other developed countries. In addition to the direct wealth effects, Case and Quigley (2008) predict that the main impact of a decline in US house prices will be felt through the income effect (i.e., due to falling employment in the construction and real estate industries) and the effect on financial markets. The importance of the housing market to the broader economy has been clearly demonstrated by the events that followed the collapse of the subprime mortgage market in the US. The subsequent fall in house prices, anticipated by Shiller (2007, 2008) and Case and Quigley (2008), triggered a global financial crisis.

This apparent propensity for boom and bust cycles in the housing market, and the way they impact on the rest of the economy, has acted to raise the profile of house price indexes and the level of scrutiny they receive. A housing boom can cause a significant redistribution of wealth from the younger to older

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generation, and increase inequality within each generation as renters (who are predominantly poorer) miss out on the capital gains received by home owners. Meanwhile, busts in the housing market can trigger a surge in defaults by households on their mortgages (particularly at the lower end of the income distribution), which can also destabilize the banking sector and cause credit markets to seize up.

More generally, house price indexes provide a barometer for the state of the economy that is useful for government fiscal policy, central bank monetary policy and financial markets. It is likely that central banks in particular may want to pay closer attention to asset prices (especially for housing) in future when setting monetary policy in the hope of avoiding the destabilizing effects of booms and busts. This can be done in a number of ways ranging from adopting asset price as well as consumer price inflation targets to modifying the way the cost of owner-occupied housing services are calculated in the consumer price index (CPI).

Most countries currently either exclude owner-occupied housing completely from the CPI (e.g., the European Union harmonized index or HICP) or include it using the rental equivalence approach (e.g., the US). Rental equivalence entails imputing rents for owner-occupied housing. In the period leading up to the financial crisis, house prices in most countries rose rather faster than rents (the US case is discussed in Poole *et al.*, 2005). As a result, the rise in house prices did not have much impact on the US CPI, thus perhaps explaining the failure of the Federal Reserve to raise interest rates more vigorously during the years preceding the financial crisis.

The main alternative to rental equivalence for including owner-occupied housing in the CPI, the user cost approach, also has its problems (see e.g., Diewert, 2007a). User cost is normally defined as the sum of foregone interest, depreciation and capital gains:

$$UC_t = r_t P_t + \text{dep}_t - (P_{t+1} - P_t).$$

There is some debate as to whether the last term should be expected or actual capital gains, and over the impact capital gains have on the volatility of the index (see Verbrugge, 2008; Diewert and Nakamura, 2009; Diewert *et al.*, 2009; Garner and Verbrugge, 2009; and Schreyer, 2009). What is clear, however, is that a house price index P_t is an important input into the user-cost formula.

Case *et al.* (1993) and Shiller (2008) meanwhile stress another important application of house price indexes. They argue that the development of derivative markets linked to house price indexes could improve the management of risk throughout the economy. Households may want to diversify their asset portfolios away from housing. According to Halifax Financial Services (2007), housing in 2007 accounted for 43% of household wealth in the UK, while according to Denk (2006) in 2004 it accounted for 39% of household wealth in the US. Owner-occupier households with most of their wealth invested in their house (and perhaps large mortgages) could reduce their exposure to housing by buying put options on a house price index. Pension funds and mutual funds, by contrast, hold very small amounts of their wealth portfolios in the form of residential housing, and hence could significantly diversify their portfolios by buying into the housing market through the purchase of call options on a house price index.

Until recently, however, the quality of house price indexes has been rather poor given their importance. This point was made forcefully, for example, by the Governor of the Reserve Bank of Australia in 2004.

> Housing is the biggest asset in the country. Certainly for the household sector it is about 60–70% of their total wealth. It is an extremely important asset class for most people, yet the information we have on prices is hopeless compared with the information we have on share prices, bond prices, and foreign exchange rates, and even the information we have on commodity prices, export prices, import prices and consumer prices. It really is probably the weakest link in all the price data in

the country so I think it is something that I would like to see resources put into. (Ian Macfarlane, Governor of the Reserve Bank of Australia, 4 June 2004).

The development of reliable house price indexes has been hampered by a combination of a lack of suitable data sets and the fact that every house is different both in terms of its physical characteristics and its location. The extreme heterogeneity of housing has required the development of new methods for quality-adjusting measured price changes.

The situation has improved in the last few years, although housing is still probably the weakest link in the list of macroeconomic price statistics. Hedonic methods which express house prices as a function of a vector of characteristics are starting to prove particularly useful for this purpose. I consider here some of the developments in the hedonic methodology, as it is applied in a housing context, that have occurred in the last three decades. One ongoing initiative, that covers some similar ground although with a somewhat different focus, is the Eurostat Handbook on Residential Property Price Indices (RPPI). A preliminary draft is available online.

More generally, quite a few quality-adjusted house price indexes are now available. In the US, the One-Family Houses Price Index of the Census Bureau, Multi-Family House Price Index of the Bureau of Economic Analysis (BEA) (see de Leeuw, 1993), and the FNC Residential Price Index all use the hedonic approach. Still in the US, the Standard and Poor's/Case-Shiller (SPCS) Home Price Indexes, CoreLogic National Home Price Indexes and Office of Federal Housing Oversight (OFHEO) indexes all use the repeat-sales method. Elsewhere, the hedonic approach dominates. Notable examples are the Halifax Home Price Index in the UK, the permanent tsb index in Ireland, the Conseil Supérieur du Notariat (CSN) and INSEE (the national statistical office of France) index in France, the Zürcher Wohneigentumsindex (ZWEX) in Switzerland, the indexes published by the statistical offices of Finland, Norway and Sweden, and the RPData-Rismark indexes in Australia. Other less transparent hedonic indexes include the Verbund Deutscher Pfandbriefbanken (VDP) and Hypoport AG indexes in Germany and the Recruit Residential Price, Residential Market and Tokyo Area Condominium Market Indexes in Japan. Some details of the Japanese indexes can be found in Chapter 10 of the draft Eurostat RPPI Manual, although no actual formulas are provided (see Eurostat 2011).

Derivatives markets are also gradually starting to appear for some of these indexes. The first foray into house price index derivatives happened in 1991, when the now defunct London Futures and Options Exchange (FOX) launched derivatives on the Nationwide Anglia Building Society House Price (NAHP) index in the UK. The product was withdrawn after 5 months, due to low trading volume and accusations of attempts to artificially inflate it (see Kawaguchi, 2007; and Shiller, 2008). This botched start probably held back the development of housing derivatives by many years. In 2003 Goldman Sachs started trading derivatives on the Halifax House Price Index (HPI) in the UK. The Chicago Mercantile Exchange in 2006 started trading futures and options contracts on the SPCS Home Price Indexes, the Zurich Cantonal Bank (ZKB) also in 2006 started trading derivatives on the ZWEX index. RPData-Rismark has recently developed a daily index for Australian cities (the RP Data-Rismark Daily Home Value Index) which should soon start being traded on the Australian Stock Exchange. In spite of these significant developments, the impact of house price index derivatives markets has thus far been disappointing. Most of the existing derivatives markets suffer from low trading volume and liquidity. It remains to be seen whether this situation will improve with time.

2. The Problem with Measuring Movements in House Prices using Median or Repeat-Sales Indexes

House price indexes can be based on actual market data or expert surveys or even a combination of the two (for an example of the latter see de Vries *et al*., 2009). Market prices for indexes using actual market data can take the form of asking prices, the price on which a mortgage backed offer is based, the price at which contracts are exchanged, or the actual price that is eventually officially recorded. Index providers tradeoff timeliness against accuracy depending on which market price they use. These tradeoffs are discussed further in Acadametrics (2009).

The simplest type of house price index is a median index that tracks the change in the price of the median dwelling from one period to the next. Examples include the National Association of Realtors (NAR) Metropolitan Median indexes in the US, and the Real Estate Institute of Australia (REIA) and LJ Hooker/BIS Shrapnel indexes in Australia. Derivatives on the NAR index have been traded on the Chicago Board Options Exchange since 2006.

The main attractions of median indexes are that they require less data, are easy to compute and easy to understand. Their main disadvantage is that they confound changes in prices with quality differences, and hence may provide very noisy estimates of the change in the cost of housing. This is because the quality of the median dwelling will tend to differ from one period to the next. For example, suppose there are two regions in a city denoted by A and B, and that region A is richer and hence has more expensive houses than region B. Suppose further that in 2006 and 2008 most of the houses sold (including the median) are from region A, while in 2007 most houses sold (including the median) are from region B. It is likely therefore that the median index will record a large fall from 2006 to 2007 and then a large rise from 2007 to 2008. Such an index could be a very poor indicator of what is actually happening in the housing market.

Some median index providers try to address this problem by computing stratified medians. Stratification (often alternatively referred to as mix-adjustment) in its simplest form divides a city into geographical regions and then computes a separate median for each region. The changes in the median indexes for each region are then averaged, usually by taking an arithmetic or geometric mean (where differing weights can be applied to each region if desired) to obtain the overall price index for that period. The REIDIN.com Turkey Residential Property Price Indices (TRPPI) is an example of such an index.

While stratification should reduce the amount of noise in the index, it will not eliminate it. Within each region, it will still be the case that the median dwelling sold in one period will tend to be of either superior or inferior quality to the median sold in the previous period. These differences will not necessarily offset each other from one region to the next. More sophisticated median indexes (see e.g., Prasad and Richards, 2006) stratify by structural attributes of dwellings within regions, the physical location of the dwelling, and neighborhood characteristics of regions. The Established Homes Price Index published by the Australian Bureau of Statistics (ABS) is an example of such an index (see Australian Bureau of Statistics, 2006). Stratified median indexes, such as those of Prasad and Richards and of ABS, can be viewed as an intermediate step between a simple median and a truly hedonic index.

As well as providing a noisy estimate of price changes, a median index may also be subject to systematic bias. Suppose, for example, that the average quality of houses sold improves over time. A median index will ignore this fact, and hence will be an upward-biased measure of the quality-adjusted price of housing. Stratification is of little use for dealing with this problem.

A repeat-sales index, as the name suggests, is computed only from repeat-sales data. Restricting the comparison to repeat sales ensures that each price relative compares like with like. One problem with this reasoning, however, is that the same dwelling at two different points in time is not necessarily the same. The repeat-sales methodology is used in the US by the Standard and Poor's/Case-Shiller (SPCS) Home Price Indexes (see Standard and Poor's, 2008), the CoreLogic National Home Price Index and the Office of Federal Housing Oversight (OFHEO) (see Calhoun, 1996). Residex and RPData-Rismark compute repeat-sales indexes for Australian cities, while the UK and Dutch Land Registries compute repeat-sales indexes for the UK and the Netherlands, respectively. Another repeat-sales index in the

Netherlands is the Woningwaarde Index Kadaster (House Price Index Kadaster), see Jansen *et al.* (2008).

The repeat-sales method is usually attributed to Bailey *et al.* (1963) , although Shiller (2008) traces back its origins to Wyngarden (1927) and Wenzlick (1952). The method was extended by Case and Shiller (1989) to better account for heteroscedasticity.

The repeat-sales method is actually a special case of a hedonic method. I return to this issue when I discuss the time-dummy hedonic method later in the paper.

The basic repeat-sales method estimates the following regression model by ordinary least squares (OLS):

$$\ln p_{th} - \ln p_{sh} = \sum_{\tau=0}^{T} \beta_\tau D_{\tau h} + \varepsilon_h, \tag{1}$$

where h indexes a particular dwelling, p_{sh} and p_{th} denote the prices at which dwelling h was sold in periods s and t, ε_h is an error term, and $D_{\tau h}$ is a dummy variable that takes the value 1 if the price of dwelling k is observed for the second time in period τ, -1 if the price of dwelling h is observed for the first time in period τ, and zero otherwise. The price indexes P_t are obtained by exponentiating the estimated parameters, denoted here by $\hat{\beta}_t$:

$$P_t = \exp(\hat{\beta}_t).$$

In fact, since this transformation is nonlinear, the resulting estimate is biased. A similar issue arises in the construction of hedonic indexes. Ways of correcting this type of bias are considered in Section 4.2.

The main advantages of the repeat-sales method are that it generates quality-adjusted indexes that are relatively easy to compute, and that only require transaction prices and unique dwelling identifiers.

It however also has a number of disadvantages. First, it throws away a lot of data (i.e., the prices of all dwellings that sell only once in the data set). Second, all the results change when a new period is added to the data set (see Clapp and Giacotto, 1999; Clapham *et al.* 2006). This could cause confusion for users, especially when the index forms the basis of derivatives contracts. Third, one cannot be sure that like is compared with like when comparing the price of the same dwelling at two different points in time. This is because the dwelling may have been renovated, extended, neglected, etc., between the two transaction dates. More specifically, it is assumed that all the characteristics of the dwelling remain constant over time. Providers of repeat-sales indexes try to correct for this problem. The S&P/Case-Shiller (SPCS) Home Price Indices, for example, exclude repeat sales that occur within 6 months on the grounds that such high frequency repeat sales suggest that the dwelling may have been renovated. Also, repeat sales with a relatively long time interval between sales are given less weight in the index because of the increased likelihood that they have experienced physical changes (see Standard and Poor's, 2008). The repeat-sales method is likely to work better in housing markets with higher turnover such as the US.

The introduction of weights, however, creates another problem. Repeat-sales indexes can be quite sensitive to the way repeat-sales at differing time intervals are weighted. Leventis (2008) in particular argues that the different weighting structures of the SPCS and OFHEO repeat-sales indexes in the US is largely responsible for the significant differences between these indexes.

Finally, the data set may suffer from sample selection bias which may in turn cause bias in the index. Clapp and Giaccotto (1992) argue that a repeat-sales sample has a "lemons" bias, since starter homes sell more frequently as a result of people upgrading as their wealth rises. This lemons bias has also been documented by Gatzlaff and Haurin (1997), Meese and Wallace (1997), and Steele and Goy (1997). Suppose further that better quality dwellings rise in price on average at a differing rate than worse quality dwellings. In this case, a repeat-sales index may be biased. This seems to be the situation observed by Hill *et al.* (2009) in their data set for Sydney, Australia over the period 2001–2006. Furthermore, Shimizu *et al.* (2010) find that, as a result of sample selection bias, repeat-sales indexes are up to 2 years late in identifying the low point in the Tokyo housing market in 2002.

Hedonic methods provide an alternative way of constructing quality-adjusted price indexes. It is to such methods that I now turn.

3. Origins of the Hedonic Approach and its Application to the Housing Market

The hedonic method dates back at least to Waugh (1928). Other early contributors include Court (1939) and Stone (1954). It was, however, only after Griliches (1961, 1971) that hedonic methods started to receive serious attention (see Schultze and Mackie, 2002 and Triplett, 2004). The conceptual basis of the approach was laid down by Lancaster (1966) and Rosen (1974).

A hedonic model regresses the price of a product on a vector of characteristics (whose prices are not independently observed). The hedonic equation is a reduced form equation that is determined by the interaction of supply and demand. One use of hedonic models is for constructing quality-adjusted price indexes. The majority of research in this field has focused on products subject to rapid technological change, such as computers (see e.g., Dulberger, 1989, and Berndt *et al*., 1995).

Hedonic methods can also be used to construct quality-adjusted price indexes for differentiated products. Housing is an extreme case of a differentiated product in the sense that every house is different. One can distinguish between a house's physical and locational attributes. Examples of the former include the number of bedrooms and land area, while examples of the latter include the exact longitude and latitude of a house, and the distance to local amenities such as a shopping center, park or school. Hedonic regressions for housing typically suffer from a severe omitted variables problem, both in terms of the physical and locational characteristics.

Hedonic methods are used in a number of ways in a housing context. First, as noted earlier, they are used to construct quality-adjusted house price indexes. Second, they can provide automated valuations (or general appraisals) of properties (see Mooya, 2011) . Third, they are used to explain variations in house prices and to determine the impact on house prices of certain characteristics. These include environmental bads such as pollution (see Kiel and Zabel, 2000; McMillen, 2004; and Anselin and Lozano-Garcia, 2008) or goods such as public parks (see Song and Knaap, 2004, and Rouwendal and van der Straaten, 2008), local taxes and public school provision (see Oates, 1969, and Gibbons and Machin, 2003) and crime (see Gibbons, 2004, and Naroff *et al*., 2006). Coulson (2008; chapter 3) provides a useful survey of this literature. Fourth, hedonic models are used in two-stage demand studies for non-market services (see Day *et al*., 2007, and Carruthers and Clark, 2010). Fifth, they are used to test for market segmentation (see Bourassa *et al*., 2003; Lipscomb and Farmer, 2005 and Tu *et al*., 2007). Sixth, hedonic methods are used to evaluate the effectiveness of government policy initiatives (see Seko and Sumita, 2007, and Burge, 2011).

The first applications of hedonic methods to the housing market tended to address the third of these objectives. Perhaps the first such study was Ridker and Henning (1967), which focused on air pollution. Research in the field began in earnest in the 1970s. Notable early contributions include Oates (1969), Kain and Quigley (1970), Berry and Bednarz (1975), Gillingham (1975), Chinloy (1977), Ferri (1977), Maclennan (1977), and Goodman (1978). These early contributions typically had access only to rather limited data sets and computing power. As a result of the combination of the development of new data sets, increased computing power, and the growing recognition of the economic importance of the housing sector, this field has since become a very active area of research.

Probably the first maintained hedonic house price index was the US Census Bureau's One-Family Houses index which was first disseminated in 1968 (see Triplett, 2004). The FNC Residential Price

Index in the US also uses the hedonic approach (see Dorsey *et al*., 2010). In the UK, the Halifax house price index and the Nationwide index both date back to the 1980s. More recently, a third UK hedonic index—the Communities and Local Government (CLG) index—was developed by the Office of National Statistics (ONS) (see Acadametrics, 2009 for a discussion of the various UK indexes). In Ireland, the permanent tsb index calculated using the same methodology as the UK's Halifax index dates back to 1996 (see Duffy, 2009). Conseil Supérieur du Notariat (CSN) and INSEE (the national statistical office of France) compute hedonic indexes for regions in France since 1998 (see Gouriéroux and Laferrère, 2009). Also, hedonic indexes are computed by Statistics Finland (see Saarnio, 2006), Statistics Norway (see Thomassen, 2007), Statistics Sweden (see Ribe, 2009), the Statistical Office of the Republic of Slovenia on an experimental basis (see Pavlin, 2006), RPData-Rismark for Australia, Informations und Ausbildungszentrum für Immobilien for Zurich, Switzerland (the Zürcher Wohneigentumsindex ZWEX index—see Syz *et al*., 2008), Verband Deutscher Pfandbriefbanken (VDP) and Hypoport AG for Germany (although these indexes lack transparency), and Recruit IPD Japan, the Japan Real Estate Institute and the Japan Research Institute (these indexes likewise lack transparency). According to Hoffman and Lorenz (2006), the German Federal Statistical Office is also in the process of developing hedonic indexes.

4. A Taxonomy of Hedonic Price Indexes for Housing

4.1 *The Need for a Taxonomy*

The hedonic approach can be implemented in a number of different ways. Given that index providers have their own perspectives and notations, it is not easy to see how the various hedonic indexes relate to each other. The underlying structures of these indexes and how they relate to each other can be more easily discerned if they are collected into taxonomic groups. This is what I attempt to do here. The taxonomy that follows where possible uses the terminology laid down by Triplett (2004).

4.2 *Time-Dummy Methods*

4.2.1 *Description of the Method*

The time-dummy method is the original hedonic method. It typically uses the semi-log functional form—see Diewert (2003) and Malpezzi (2003) for a discussion of some of the advantages of the semi-log model in this context. A standard semi-log formulation is as follows:

$$y = Z\beta + D\delta + \varepsilon, \tag{2}$$

where y is an $H \times 1$ vector with elements $y_h = \ln p_h$, Z is an $H \times C$ matrix of characteristics (some of which may be dummy variables), β is a $C \times 1$ vector of characteristic shadow prices, D is an $H \times T - 1$ matrix of period dummy variables, δ is a $T - 1 \times 1$ vector of period prices (with the base period price index is normalized to 1), and ε is an $H \times 1$ vector of random errors. Finally, H, C, and T denote, respectively the number of dwelling, characteristics, and time periods in the data set. The first column in Z consists of ones, and hence the first element of β is an intercept. Examples of characteristics include the number of bedrooms, number of bathrooms, land area, and dwelling type of a property (house or apartment). It is possible also to include functions of characteristics (such as land size squared), and interaction terms between characteristics. For example, one might want to interact bedrooms and land area, bathrooms and land area, and bedrooms and bathrooms. Focusing specifically on the last of these, the inclusion of bedroom–bathroom interaction terms could be justified by the fact that the value of an extra bathroom may depend on how many bedrooms are there.

It turns out that the repeat-sales method is a special case of the semi-log version of the time-dummy method obtained by including dummies for the unique address identifiers of each dwellings as the only characteristics in Z (see Shiller, 2008). As Shiller notes, houses that sell only once are "dummied out" of this regression.

Box-Cox tests (defined on characteristics other than unique address—i.e., not the repeat-sales case) almost invariably reject the semi-log model (see e.g., Halvorsen and Pollakowski, 1981). One problem with using the Box-Cox method to choose the functional form, however, is that the derivation of price indexes directly from the hedonic equation may become far from straightforward. One way round this problem is provided by Maurer *et al.* (2004). Their method is discussed in Section 4.4.

When the objective of the exercise is to construct a quality-adjusted price index, the primary interest lies in the δ parameters which measure the period-specific fixed effects on the logarithms of the price level after controlling for the effects of the differences in the attributes of the dwellings. One attraction of the semi-log time-dummy model is that the price index P_t for period t is derived by simply exponentiating the estimated coefficient $\hat{\delta}_t$ obtained from the hedonic model:

$$\hat{P}_t = \exp(\hat{\delta}_t). \tag{3}$$

Turning now to the issue of bias, the objective is to calculate the following:

$$E(P_t|Z, D_t = 1) = E[\exp(\hat{\delta}_t)].$$

Under the assumption of normally distributed errors, Goldberger (1968) shows that:

$$E[\exp(\hat{\delta}_t)] = \exp\left[\delta_t + \frac{1}{2}V(\hat{\delta}_t)\right],$$

where $V(\hat{\delta}_t)$ is the variance of $\hat{\delta}_t$. It follows that $\hat{P}_t$ in (3) is a biased estimator of P_t. Kennedy (1981) suggests the following estimator:

$$P_t^* = \exp\left[\hat{\delta}_t + \frac{1}{2}\hat{V}(\hat{\delta}_t)\right],$$

where $\hat{V}(\hat{\delta}_t)$ is the estimated variance of $\hat{\delta}_t$. Ways of estimating $\hat{V}(\hat{\delta})$ are discussed by van Garderen and Shah (2002). While P_t^* is in general still biased, Giles (1982) shows that except in very small samples P_t^* closely approximates the minimum variance unbiased estimator of P_t.

A small number of papers delve into this bias problem in greater detail (see in particular van Dalen and Bode, 2004 and Ramalho and Ramalho, 2011). The rest of the literature for the most part deals with the bias issue in one of three ways. The first group ignores it completely. The second group acknowledges that $\hat{P}_t$ is biased, refers the reader to Goldberger (1968) or Kennedy (1981), notes that the bias is typically small and then proceeds to ignore it (see e.g., Triplett, 2004; Hill *et al.*, 2009; de Haan, 2010; and Yu and Prud'homme, 2010). The third group actually uses the P_t^* formula, although then usually in the context of the hedonic imputation method discussed in Section 4.3 (see Malpezzi *et al.*, 1998; Coulson, 2008; and Dorsey *et al.*, 2010).[1]

Syed *et al.* (2008) investigate the magnitude of the difference between $\hat{P}_t$ and P_t^* for a single base period using data for Sydney, Australia over the period 2001–2006. They find that the difference manifests itself typically only in the third or fourth decimal place of the price indexes and hence the bias can indeed in most cases be ignored. The is not necessarily true though in a hedonic imputation context (again see Section 4.3).

One of the key determinants of house prices is location. The explanatory power of the hedonic model can therefore be significantly improved by exploiting information on the location of each property. Probably the simplest way to do this is to include postcode identifiers for each dwelling in the hedonic model. These postcode identifiers can take the form of dummy variables. In the case of the Sydney data set, the inclusion of postcode dummies acts to increase the R-squared coefficient from about 0.56 to 0.76 (see Hill *et al.*, 2009). The hedonic model now takes the following form:

$$y = Z\beta + B\gamma + D\delta + \varepsilon, \tag{4}$$

where the additional term B is an $H \times (M-1)$ matrix of postcode dummy variables, γ is an $(M-1) \times 1$ vector of postcode parameters, and M is the number of postcode identifiers.

When longitude and latitude data are available for each dwelling, spatial dependence can be modeled in a more rigorous way (see Section 5).

4.2.2 *Strengths and Weaknesses*

Perhaps the main strength of the semi-log time-dummy method is its simplicity. The price indexes are derived straight from the estimated hedonic equation along with standard errors. An additional advantage of the time-dummy method is that it can be combined with spatial econometric models such as SARAR(1,1) or STAR (see Section 5.3) thus allowing the inclusion of geospatial data.

The method has two main weaknesses. First, it is not clear how it can be extended to deal with the problem of missing characteristics for some dwellings in the data set (e.g., land area is available for some dwellings but not for others). The problem of missing characteristics is discussed in Section 6.

Second, it could be argued that the time-dummy method lacks flexibility. The period dummies and dwelling characteristics enter the hedonic function additively. In other words, the function exerts quite severe restrictions on the potential interactions between periods and characteristics. One way to increase the flexibility of the model is by allowing the periods to interact with the characteristics. This approach however requires the estimation of more parameters reducing the number of degrees of freedom. It also makes the derivation of the price indexes from the estimated hedonic model more complicated (see e.g., Syed *et al.*, 2008).

The time-dummy method is also inflexible in that it does not allow the characteristic shadow prices to change over time. To see more clearly some of the implications of fixing the reference characteristic shadow prices it is useful to write out the price index formula implied by the time-dummy model in (2). The estimated version of the time-dummy hedonic model can be written as follows:

$$\hat{y} = Z\hat{\beta} + D\hat{\delta}.$$

The estimated characteristic shadow price vector and price index vector are derived as follows:

$$\hat{\beta} = (Z^T Z)^{-1} Z^T (y - D\hat{\delta}), \tag{5}$$

$$\hat{\delta} = (D^T D)^{-1} D^T (y - Z\hat{\beta}). \tag{6}$$

It turns out that $D^T D$ in (6) is a diagonal matrix. As a result, the price index formula for a particular element $\hat{\delta}_t$ of $\hat{\delta}$ reduces to the following:

$$\hat{\delta}_t = \sum_{h=1}^{H_t} \left(\frac{\ln p_{th}}{H_t} \right) - \sum_{c=1}^{C} \left[\hat{\beta}_c \left(\frac{\sum_{h=1}^{H_t} z_{cth}}{H_t} \right) \right].$$

Taking exponents of both sides, we obtain the following price index in a comparison between periods s and t:

$$\frac{P_t}{P_s} = \frac{\left(\prod_{h=1}^{H_t} p_{th}\right)^{1/H_t}}{\left(\prod_{h=1}^{H_s} p_{sh}\right)^{1/H_s}} \Bigg/ \frac{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{ct}\right)}{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{cs}\right)}, \tag{7}$$

where

$$\bar{z}_{cs} = \sum_{h=1}^{H_s} z_{csh}/H_s, \quad \bar{z}_{ct} = \sum_{h=1}^{H_t} z_{cth}/H_t.$$

This formula can be found in Triplett (2004; p. 51), Diewert *et al*. (2007; p. 7), and Hill and Melser (2011).

The term $(\prod_{h=1}^{H_t} p_{th})^{1/H_t}/(\prod_{h=1}^{H_s} p_{sh})^{1/H_s}$ in the numerator of (7) compares the average price of a house in the two periods. The quality adjustment is provided by the term $\exp(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{ct})/\exp(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{cs})$ in the denominator of (7). This is a quantity index that compares the price of the average house in the two periods using the time-dummy average characteristic prices.

The denominator in (7) can now be rewritten as follows:

$$\frac{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{ct}\right)}{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{cs}\right)} = \left[\frac{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{ct}\right)}{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{c}\right)}\right] \Bigg/ \left[\frac{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{cs}\right)}{\exp\left(\sum_{c=1}^{C} \hat{\beta}_c \bar{z}_{c}\right)}\right] = \frac{\tilde{Q}_{X,t}^L}{\tilde{Q}_{X,s}^L}, \tag{8}$$

where $\tilde{Q}_{Xt}^L$ denotes a Laspeyres-type quantity index that compares the cost of the average house sold in period t to that sold in the average period X. Substituting (8) into (7), we obtain that

$$\frac{P_t}{P_s} = \frac{\left(\prod_{h=1}^{H_t} p_{th}\right)^{1/H_t}}{\left(\prod_{h=1}^{H_s} p_{sh}\right)^{1/H_s}} \Bigg/ \frac{\tilde{Q}_{X,t}^L}{\tilde{Q}_{X,s}^L}. \tag{9}$$

The fact that the time-dummy method uses a Laspeyres-type quantity index to make its quality adjustments raises the possibility of substitution bias. This issue is explored in Hill and Melser (2011).

A further concern with the time-dummy method is that when a new period is added to a data set, the price indexes for all periods change. Indeed this same criticism applies to the repeat-sales method.

The flexibility of the time-dummy method is improved if it is used to compare rolling pairs of adjacent periods. The overall index is then obtained by chaining these bilateral comparisons together. Triplett (2004) refers to this method as the adjacent period (AP) method. It has two advantages over the standard time-dummy method. First, it allows the shadow prices to change over time. Second, the results for earlier periods do not change when a new period is added to the data set.

4.2.3 *Usage*

Although it is the original hedonic method and is widely used in other contexts, such as for constructing quality-adjusted price indexes for computers and cars, the time-dummy method has received less attention in a housing context. A few applications of the method can be found in the academic literature. Examples include Follain and Malpezzi (1980), Palmquist (1980), Mark and Goldberg (1984), and Haughwout *et al*. (2008). The Statistical Office of the Republic of Slovenia has used it to construct an experimental house price index over the period 2003–2006. RPData-Rismark computes both time-dummy and AP variants on time-dummy indexes, although it prefers the latter to the former since the AP method allows the reference shadow prices to change over time. (RPData-Rismark also computes imputation indexes—see Section 4.3). The AP method is likewise used by Informations und Ausbildungszentrum für Immobilien to compute hedonic indexes for Zurich.

4.3 *Imputation Methods*

4.3.1 *Description of the Method*

Imputation methods make use of standard price index formulas. The two best known of these formulas are Laspeyres and Paasche. Laspeyres and Paasche price index formulas measure the change in the price of a given basket of goods (in our case dwellings) over time. This requires the price of each good in the basket to be available each period. In a housing context, therefore, it is not possible to compute Laspeyres and Paasche price indexes based on actual transaction prices, since each dwelling sells only at infrequent and irregular intervals. However, it may still be possible to compute such indexes if we are willing to replace actual transaction prices with imputed prices. This provides the underlying rationale of imputation methods. The estimated hedonic model is used to impute prices for dwellings. In this way it is possible to ensure that a price is available for both periods for each dwelling included in the price index formula. The price index can then be calculated in the standard way.

The price index formulas I focus on here are Paasche, Laspeyres, Fisher, Geometric-Paasche, Geometric-Laspeyres and Törnqvist. Let P_{st} denote a price index between periods s and t. The price of dwelling h in period t is denoted by p_{th}. In our context, each dwelling is unique and hence the quantity of each dwelling is 1. Hence the formulas look a bit different from their standard formulations in the price index literature.

$$\text{Paasche}: \; P_{st}^{P} = \left\{ \sum_{h=1}^{H_t} w_{th} \left[p_{th}/p_{sh} \right]^{-1} \right\}^{-1} = \sum_{h=1}^{H_t} p_{th} \bigg/ \sum_{h=1}^{H_t} p_{sh} \tag{10}$$

$$\text{Laspeyres}: \; P_{st}^{L} = \sum_{h=1}^{H_s} \left\{ w_{sh} \left[p_{th}/p_{sh} \right] \right\} = \sum_{h=1}^{H_s} p_{th} \bigg/ \sum_{h=1}^{H_s} p_{sh} \tag{11}$$

$$\text{Fisher}: \; P_{st}^{F} = \sqrt{P_{st}^{P} \times P_{st}^{L}} \tag{12}$$

$$\text{Geometric Paasche}: \; P_{st}^{GP} = \prod_{h=1}^{H_t} \left[(p_{th}/p_{sh})^{1/H_t} \right] \tag{13}$$

$$\text{Geometric Laspeyres}: \; P_{st}^{GL} = \prod_{h=1}^{H_s} \left[(p_{th}/p_{sh})^{1/H_s} \right] \tag{14}$$

$$\text{Törnqvist}: \; P_{st}^{T} = \sqrt{P_{st}^{GP} \times P_{st}^{GL}}. \tag{15}$$

A few issues in these equations need clarification. First, the terms w_{th} are expenditure weights defined as follows:

$$w_{th} = p_{th} \Bigg/ \sum_{m=1}^{H_t} p_{tm},$$

while H_s and H_t denote the total number of dwellings sold respectively in periods s and t. Second, the key difference between Paasche and Laspeyres is that Paasche focuses on the dwellings actually sold in time period t, while Laspeyres focuses on the dwellings sold in period s. Third, the exponents in Geometric-Paasche and Geometric-Laspeyres could alternatively be set to w_{th} and w_{sh}, respectively. As presented above these formulas give equal weight to all price relatives. If instead w_{th} and w_{sh} were used in the exponents, then these methods would give greater weight to the price relatives of more expensive dwellings.

These price index formulas, in general, all give different answers. This is what is meant by the price index problem. It is a problem that has attracted some of the greatest minds in the economics profession over the best part of two centuries, such as Marshall, Edgeworth, Keynes, Fisher, Hicks and Samuelson. The two main approaches for choosing between price index formulas—the economic and axiomatic approaches—generally end up favoring the Fisher and Törnqvist indexes (see Balk, 1995 and Diewert, 2007b).

This literature, however, typically assumes that there is no matching problem (i.e., that all products are available every period). Once this assumption is relaxed, the price index problem becomes more complex.

The use of the hedonic imputation method adds a new dimension to the price index problem. This is because we have some discretion as to which prices are imputed. If a product is unavailable in a particular period, we have no choice but to impute it. If the product is available, we may nevertheless still prefer to use an imputed price over the actual price. This might seem counterintuitive. However, it turns out that replacing real prices with imputations can sometimes reduce the omitted variables bias and help ensure that like is compared with like.

Focusing on the case of the semi-log model, to see why this is so let $\hat{p}_{th}(z_{sh})$ denote the estimated price in period t of a dwelling sold in period s. This price is imputed by substituting the characteristics of house h sold in period s into the estimated hedonic model of period t as follows:

$$\hat{p}_{th}(z_{sh}) = \exp\left(\sum_{c=1}^{C} \hat{\beta}_{ct} z_{csh}\right).$$

Again, a bias correction may be required since the focus of our attention is $p_{th}(z_{sh})$ and not $\ln p_{th}(z_{sh})$. The correction, again assuming normally distributed errors, now entails adding half the variance of the error term ϕ_t from the hedonic regression equation (see Malpezzi *et al.*, 1998; Coulson, 2008). The corrected imputed price index denoted here by $\hat{p}^*_{th}(z_{sh})$ is calculated as follows: $\hat{p}^*_{th}(z_{sh}) = \exp(\sum_{c=1}^{C} \hat{\beta}_{ct} z_{csh} + \phi_t^2/2)$. Malpezzi *et al.* (1998) provide comparisons of corrected and uncorrected imputed prices for average dwellings (see the characteristics approach below) and find that they differ between 5 and 10%. Given the earlier findings of Syed *et al.* (2008) this suggests that the correction may matter more in an imputation setting than in a time-dummy setting.

Two different varieties of the Laspeyres price index are obtained (denoted here by L1, L2) depending on how exactly the hedonic imputation method is implemented.

$$\begin{aligned}
\text{L1}: \; P_{st}^{L1} &= \sum_{h=1}^{H_s} \{w_{sh}\,[\hat{p}_{th}(z_{sh})/p_{sh}]\} = \sum_{h=1}^{H_s} \hat{p}_{th}(z_{sh}) \Big/ \sum_{h=1}^{H_s} p_{sh} \\
\text{L2}: \; P_{st}^{L2} &= \sum_{h=1}^{H_s} \{\hat{w}_{sh}\,[\hat{p}_{th}(z_{sh})/\hat{p}_{sh}(z_{sh})]\} = \sum_{h=1}^{H_s} \hat{p}_{th}(z_{sh}) \Big/ \sum_{h=1}^{H_s} \hat{p}_{sh}(z_{sh})
\end{aligned} \tag{16}$$

L1 only imputes prices in period t, while L2 imputes prices in both periods s and t. The imputed expenditure shares in L2 are calculated as follows:

$$\hat{w}_{sh} = \hat{p}_{sh}(z_{sh}) \Big/ \sum_{m=1}^{H_s} \hat{p}_{sm}(z_{sm}).$$

In the hedonic literature L1 is referred to as a single imputation index, and L2 as a double imputation index (see de Haan, 2004; Triplett, 2004; Hill and Melser, 2008). In the literature it is typically not made clear whether or not the double imputation method imputes expenditure shares as well. Hence one can distinguish between two double imputation methods, one that imputes expenditure shares and one that does not.

Varieties of Paasche, Fisher, geometric Paasche, geometric Laspeyres and Törnqvist can be derived in an analogous manner.

$$\begin{aligned}
\text{P1}: \; P_{st}^{P1} &= \left\{ \sum_{h=1}^{H_t} w_{th}\,[p_{th}/\hat{p}_{sh}(z_{th})]^{-1} \right\}^{-1} = \sum_{h=1}^{H_t} p_{th} \Big/ \sum_{h=1}^{H_t} \hat{p}_{sh}(z_{th}) \\
\text{F1}: \; P_{st}^{F1} &= \sqrt{P_{st}^{P1} \times P_{st}^{L1}} \\
\text{GP1}: \; P_{st}^{GP1} &= \prod_{h=1}^{H_t} \left[(p_{th}/\hat{p}_{sh}(z_{th}))^{1/H_t} \right] \\
\text{GL1}: \; P_{st}^{GL1} &= \prod_{h=1}^{H_s} \left[(\hat{p}_{th}(z_{sh})/p_{sh})^{1/H_s} \right] \\
\text{T1}: \; P_{st}^{T1} &= \sqrt{P_{st}^{GP1} \times P_{st}^{GL1}} \\
&= \sqrt{\prod_{h=1}^{H_t} \left[(p_{th}/\hat{p}_{sh}(z_{th}))^{1/H_t} \right] \times \prod_{h=1}^{H_s} \left[(\hat{p}_{th}(z_{sh})/p_{sh})^{1/H_s} \right]}
\end{aligned}$$

$$\text{P2}: \quad P_{st}^{P2} = \left\{ \sum_{h=1}^{H_t} \hat{w}_{th} \left[\hat{p}_{th}(z_{th}) / \hat{p}_{sh}(z_{th}) \right]^{-1} \right\}^{-1} = \sum_{h=1}^{H_t} \hat{p}_{th}(z_{th}) \Big/ \sum_{h=1}^{H_t} \hat{p}_{sh}(z_{th})$$

$$\text{F2}: \quad P_{st}^{F2} = \sqrt{P_{st}^{P2} \times P_{st}^{L2}}$$

$$\text{GP2}: \quad P_{st}^{GP2} = \prod_{h=1}^{H_t} \left[(\hat{p}_{th}(z_{th}) / \hat{p}_{sh}(z_{th}))^{1/H_t} \right]$$

$$\text{GL2}: \quad P_{st}^{GL2} = \prod_{h=1}^{H_s} \left[(\hat{p}_{th}(z_{sh}) / \hat{p}_{sh}(z_{sh}))^{1/H_s} \right]$$

$$\text{T2}: \quad P_{st}^{T2} = \sqrt{P_{st}^{GP2} \times P_{st}^{GL2}}$$

$$= \sqrt{\prod_{h=1}^{H_t} \left[(\hat{p}_{th}(z_{th}) / \hat{p}_{sh}(z_{th}))^{1/H_t} \right] \times \prod_{h=1}^{H_s} \left[(\hat{p}_{th}(z_{sh}) / \hat{p}_{sh}(z_{sh}))^{1/H_s} \right]}$$

Rounding errors can arise in the calculation of GP and GL type indexes for large data sets. This problem can be avoided by first taking logarithms, and then exponentiating at the end.

Which variety is best? To simplify matters this question will be addressed for the case of the Laspeyres index. The arguments carry forward equally well to other price index formulas. Our focus is on minimizing omitted variables bias and generating economically meaningful results.

The two varieties of Laspeyres indexes differ in their treatment of the price relatives and expenditure shares. A single imputation Laspeyres index uses the price relatives $\hat{p}_{th}(z_{sh})/p_{sh}$, while a double imputation index uses $\hat{p}_{th}(z_{sh})/\hat{p}_{sh}(z_{sh})$. There has been some debate in the literature on which approach is best. The discussion focuses primarily on the case of computers. Silver and Heravi (2001), de Haan (2004), and Hill and Melser (2008) all argue in favor of double imputation on the grounds that it can reduce omitted variables bias.

For example, consider the case of a dwelling for which $\hat{p}_{sh}(z_{sh}) > p_{sh}$. This means either that the buyer got a bargain or that the dwelling performs poorly on its omitted variables. Assuming that the latter is correct, it follows that $\hat{p}_{th}(z_{sh})$ will overstate the true price of a house with characteristics vector z_{sh} in period t. It follows that the price relative $\hat{p}_{th}(z_{sh})/p_{sh}$ will have an upward bias. In contrast, the biases in $\hat{p}_{sh}(z_{sh})$ and $\hat{p}_{th}(z_{sh})$ will partially offset each other in the price relative $\hat{p}_{th}(z_{sh})/\hat{p}_{sh}(z_{sh})$, thus tending to generate a more accurate overall estimate.

The use of double imputation is particularly beneficial in a housing context where there is likely to be a serious omitted variables problem. This leads me to prefer variety 2 over variety 1. Even using double imputation, omitted variables bias will still be a problem when either the average quantities of some of the omitted characteristics or their shadow prices change over time (see Benkard and Bajari, 2005). For example, if the overall quality of the omitted characteristics is improving over time, or their shadow prices are rising, the double imputed price relatives $\hat{p}_{th}(z_{sh})/\hat{p}_{sh}(z_{sh})$ will tend to be too large.

There remains the question of which price index formula should be used? The choice of formula should be between Fisher and Törnqvist since they have the best economic and axiomatic properties (see Diewert, 1976, 2007b; Balk, 1995).

When used in conjunction with the hedonic imputation method, we must also consider the functional form of the hedonic regression when choosing a price index formula. I recommend using T2 in conjunction with semi-log hedonic model. Following Hill and Melser, in this case, GL2 can be re-expressed as follows:

$$
\begin{aligned}
P_{st}^{GL2} &= \prod_{h=1}^{H_s} \left\{ [\hat{p}_{th}(z_{sh})/\hat{p}_{sh}(z_{sh})]^{1/H_s} \right\} \\
&= \prod_{h=1}^{H_s} \left\{ \exp\left[\frac{1}{H_s} \sum_{c=1}^{C} (\hat{\beta}_{ct} - \hat{\beta}_{cs}) z_{csh} \right] \right\} \\
&= \exp\left[\tfrac{1}{H_s} \sum_{h=1}^{H_s} \sum_{c=1}^{C} (\hat{\beta}_{ct} - \hat{\beta}_{cs}) z_{csh} \right] \\
&= \exp\left[\tfrac{1}{H_s} \sum_{c=1}^{C} (\hat{\beta}_{ct} - \hat{\beta}_{cs}) \sum_{h=1}^{H_s} z_{csh} \right] \\
&= \exp\left[\sum_{c=1}^{C} (\hat{\beta}_{ct} - \hat{\beta}_{cs}) \bar{z}_{cs} \right] \\
&= \prod_{c=1}^{C} \exp\left[(\hat{\beta}_{ct} - \hat{\beta}_{cs}) \bar{z}_{cs} \right],
\end{aligned}
$$

where we have defined

$$\bar{z}_{cs} = \frac{1}{H_s} \sum_{h=1}^{H_s} z_{csh}.$$

Rearranging GP2 in a similar manner we obtain that

$$P_{st}^{GP2} = \exp\left[\sum_{c=1}^{C} (\hat{\beta}_{ct} - \hat{\beta}_{cs}) \bar{z}_{ct} \right].$$

Taking the geometric mean of GP2 and GL2, we obtain the following expression for T2:

$$P_{st}^{T2} = \exp\left[\frac{1}{2} \sum_{c=1}^{C} (\hat{\beta}_{ct} - \hat{\beta}_{cs}) (\bar{z}_{cs} + \bar{z}_{ct}) \right].$$

The fact that T2 can be decomposed multiplicatively by its characteristics has advantages when interpreting the results. It means that the contribution of each characteristic to the overall price index can be easily discerned. That is, we can decompose the price index as follows:

$$P_{st}^{T2} = P_{st}^{1} \times P_{st}^{2} \times \cdots \times P_{st}^{C},$$

where P_{st}^{c} measures the multiplicative contribution of characteristic c to the differences in house prices between periods s and t. Of particular interest is the ratio P_{st}^{c}/P_{st}^{T2}. If this ratio exceeds 1, it implies that characteristic c is exerting upward pressure on the overall price index, while, when less than 1, c is exerting downward pressure on the index.

One of the key insights here is that the choice of price index formula and functional form for the hedonic regression model should not be decoupled. In particular, the semi-log model has a natural affinity with the Törnqvist price index. Hill and Melser (2008) likewise show that the linear model has a natural affinity with the Fisher index. Also, as is shown in the next section, in certain cases imputations methods are dual to characteristics methods. These duality results could also influence the choice of price index formula and functional form for the hedonic model.

So far I have focused exclusively on bilateral comparisons. Imputation methods generalize to three or more periods in the same way as the AP method. That is, a Fisher or Törnqvist index should be calculated between adjacent periods, and these bilateral indexes are then chained chronologically. For example, a comparison between periods 1 and 3 is made by multiplying a comparison between periods 1 and 2 by a comparison between periods 2 and 3.

4.3.2 *Strengths and Weaknesses*

Imputation methods are very flexible, in that they allow the characteristic shadow prices to evolve over time. The use of double imputation should also help to reduce omitted variables bias. The fact that the imputation method links in well with the much older price index literature and is dual to the characteristics method in some cases may be beneficial in certain contexts, such as the treatment of housing in the CPI, where it may be desirable to use a consistent approach across expenditure categories. Alternatively, the hedonic model can be estimated non/semiparametrically. It is also relatively straightforward to incorporate geospatial data either nonparametrically or using SARAR(1,1)-type models (see Section 5.3). Finally, as is discussed in Section 6, the imputations approach is well suited for handling the problem of missing characteristics for some of the dwellings in the data set.

Perhaps the biggest criticism of the imputations approach is that estimating a separate hedonic model for each period prevents the exploitation of interactions between the equations. From an econometric perspective it may be more efficient to estimate the equations as a system of seemingly unrelated regressions (SUR) (see Zellner, 1962). A SUR approach has the disadvantage though that it will cause all the results to change when a new period is added to the data set. A better alternative might be to estimate the model for a rolling sequence of multiple periods, as is done by the FNC Residential Price Index (see Dorsey *et al*., 2010).

One further disadvantage of the imputation method is that it does not immediately yield standard errors on the price indexes. Standard errors however can be computed indirectly (one such method is outlined in appendix 2 of Diewert *et al*. 2007).

4.3.3 *Usage*

The imputations method has not been used much. This is probably because it is conceptually more complicated that the time-dummy and characteristics methods. It should be remembered, however, that a number of characteristics methods (see below) can also be described as imputation methods. The only index providers to use an imputation method as far as I am aware are the FNC Residential Price Index in the US and RPData-Rismark in Australia. The FNC index described in Dorsey *et al*. (2010) uses the double imputation Laspeyres formula in the context of a SASAR(1,1) model (see Section 5.3). RPData-Rismark also uses double imputation in its Daily Home Value Index, although in its case given its high frequency the index covers a broader range of dwelling than those sold in either period (i.e., the formula is neither Paasche nor Laspeyres, nor an average of the two). The RPData-Rismark index imputes prices from a generalized additive model (see Hardman, 2011).

4.4 *Characteristics Methods*

4.4.1 *Description of the Method*

Characteristics methods, like imputation methods, generally estimate the hedonic model separately for each period. They also use standard price index formulas. The key difference is that a characteristics price index is defined in characteristics space. Characteristics methods typically construct an average dwelling for each period, and then impute the price of this hypothetical dwelling (which for example may have two and a half bedrooms) as a function of its characteristics using the shadow prices derived from the hedonic model. The average dwelling may be either the arithmetic mean or median. A price index is obtained by taking the ratio of the imputed price of the same average dwelling in two different periods. By construction the characteristics method uses double imputation since the average dwelling is hypothetical rather than an actual dwelling.

Taking the semi-log hedonic model as our point of reference, a price index between periods s and t can be calculated using the average dwelling from either period (see Dulberger, 1989 and Diewert, 2001). In this way we obtain Laspeyres and Paasche-type indexes, which we refer to here as L3 and P3.

$$\text{L3}: \; P_{st}^{L3} = \hat{p}_t(\bar{z}_s)/\hat{p}_s(\bar{z}_s) = \exp\left[\sum_{c=1}^{C}(\hat{\beta}_{ct} - \hat{\beta}_{cs})\bar{z}_{cs}\right], \quad \text{where } \bar{z}_{cs} = \frac{1}{H_s}\sum_{h=1}^{H_s} z_{csh}, \tag{17}$$

$$\text{P3}: \; P_{st}^{P3} = \tilde{P}_{st}^{P} = \hat{p}_t(\bar{z}_t)/\hat{p}_s(\bar{z}_t) = \exp\left[\sum_{c=1}^{C}(\hat{\beta}_{ct} - \hat{\beta}_{cs})\bar{z}_{ct}\right], \quad \text{where } \bar{z}_{ct} = \frac{1}{H_t}\sum_{h=1}^{H_t} z_{cth}. \tag{18}$$

Again a correction is required for bias when deriving the imputed prices. The correction is the same as for imputation methods as discussed in Malpezzi *et al*. (1998). Also, H_s and H_t are again the total number of dwellings sold respectively in periods s and t. Alternatively, $\bar{z}_{cs}$ and $\bar{z}_{ct}$ in (17) and (18) could be defined as the characteristic vectors of the median dwelling in each period.

The price index P_{st}^{L3} is analogous to a Laspeyres index in the sense that it uses the earlier period s as the reference, while P_{st}^{P3} is analogous to a Paasche index in that it uses the later period t as the reference. Taking the geometric mean we obtain a price index P_{st}^{F3} that is analogous to a Fisher index.

$$\text{F3}: \; P_{st}^{F3} = \sqrt{P_{st}^{L3} \times P_{st}^{P3}} = \exp\left[\frac{1}{2}\sum_{c=1}^{C}(\hat{\beta}_{ct} - \hat{\beta}_{cs})(\bar{z}_{cs} + \bar{z}_{ct})\right]. \tag{19}$$

What is particularly interesting here is that F3 on closer inspection can be seen to be identical to T2 from the previous section. In other words, an hedonic imputation index defined on the semi-log model and which uses the Törnqvist (or perhaps more precisely a Jevons type) price index formula is identical to a characteristics index defined on the average house of both periods and calculated using a Fisher-type formula.

Another approach to constructing characteristic price indexes is to first compute the quality adjustment factor and then use this to deflate a quality-unadjusted price index in a manner somewhat analogous to that used by the time-dummy method as outlined in (7). The quality-adjustment factor, with the characteristic shadow prices derived from the semi-log hedonic model, could take the form of Laspeyres, Paasche or Fisher-type quantity indexes, referred to here as QL, QP, QF.

$$\text{QL}: \; Q_{st}^{L} = \exp\left[\sum_{c=1}^{C}(\bar{z}_{ct} - \bar{z}_{cs})\hat{\beta}_{cs}\right], \quad \text{where } \bar{z}_{cs} = \frac{1}{H_s}\sum_{h=1}^{H_s} z_{csh}, \tag{20}$$

$$\text{QP}: \; Q_{st}^{P} = \exp\left[\sum_{c=1}^{C}(\bar{z}_{ct} - \bar{z}_{cs})\hat{\beta}_{ct}\right], \quad \text{where } \bar{z}_{ct} = \frac{1}{H_t}\sum_{h=1}^{H_t} z_{cth}. \tag{21}$$

$$\text{QF}: \; Q_{st}^{F} = \sqrt{Q_{st}^{L} \times Q_{st}^{P}} = \exp\left[\frac{1}{2}\sum_{c=1}^{C}(\bar{z}_{ct} - \bar{z}_{cs})(\hat{\beta}_{cs} + \hat{\beta}_{ct})\right]. \tag{22}$$

The quality-adjusted price indexes are now obtained implicitly as follows:

$$\tilde{P}_{st}^{L} = \frac{\prod_{h=1}^{H_t}(p_h)^{1/H_t}}{\prod_{h=1}^{H_s}(p_s)^{1/H_s}} \Big/ Q_{st}^{P} \;, \tag{23}$$

$$\tilde{P}_{st}^{P} = \frac{\prod_{h=1}^{H_t}(p_h)^{1/H_t}}{\prod_{h=1}^{H_s}(p_s)^{1/H_s}} \Big/ Q_{st}^{L} \;, \tag{24}$$

$$\tilde{P}_{st}^{F} = \frac{\prod_{h=1}^{H_t}(p_h)^{1/H_t}}{\prod_{h=1}^{H_s}(p_s)^{1/H_s}} \Big/ Q_{st}^{F} \;. \tag{25}$$

An intriguing feature of the implicit Paasche price index in (24) is that it only requires the hedonic model to be estimated in the base period. Presumably, the base would need updating every 5 years or so.

One other variant on the characteristics method is used by Maurer *et al*. (2004). They estimate a multi-period time-dummy model with the twist that they use Box-Cox rather that the semilog functional form. As was noted earlier, price indexes cannot easily be obtained directly from the Box-Cox model. Maurer *et al*. get round this problem by computing an average dwelling for their data set and then imputing prices for this hypothetical dwelling each period from the hedonic model.

4.4.2 *Strengths and Weaknesses*

The main strength of the characteristics method is its intuitive interpretation as measuring the change in the price of the average dwelling over time. The use of double imputation also reduces its sensitivity to omitted variables.

The characteristics method, however, has some weaknesses. First and foremost, it is not clear how it can be extended to incorporate geospatial data. Averaging longitudes and latitudes averages away the spatial dependence and the average geospatial location may anyway not make much sense. For example, in the case of a city like Sydney built round a natural harbor it may be underwater. Second, like the imputation method, in most cases it requires the hedonic model to be estimated separately for each period. Third, again like the imputations method it does not directly generate standard errors on the price indexes (although they can still be generated indirectly). Finally, like the time-dummy method, it is not clear how it can be extended to deal with the problem of missing characteristics for some dwellings in the data set.

4.4.3 *Usage*

The characteristics method in its various guises has proved to be by far the most popular for computing price indexes. The New House Price Index computed by the Census Bureau in the US, the Halifax and Nationwide indexes in the UK, and the permanent tsb index in Ireland are calculated using the

Laspeyres version L3 of the characteristics method in (17) with a semi-log functional form for the hedonic equation (see US Census Bureau undated, and Fleming and Nellis, 1985).

An alternative approach is used to construct the CLG index in the UK (see Communities and Local Government, 2003, 2004). The CLG index considers 100,000 different combinations of characteristics, which it refers to as cells. Using the characteristic shadow prices obtained from the hedonic model for that period, it imputes a price for each of these cells. The overall price index is obtained by taking a weighted average of these imputed cell prices. The derivation of these weights is an important feature of the method. Unfortunately, the available documentation does not explain how these weights are calculated. One interesting feature of the method that follows from its use of imputed characteristic prices is that it does not matter if some of the cells are empty in a particular period.

Statistics Finland uses a weighted variant on the implicit Paasche price index in (24) (see Saarnio, 2006) to compute house price indices for Finland. Statistics Norway uses the same method as Statistics Finland except that it calculates its hedonic model using the previous 5 years of data and chains the index on an annual basis (see Thomassen, 2007). Statistics Sweden also uses a variant on the implicit Laspeyres price index in (24) (see Ribe, 2009), although the exact details of the method are not provided. Closely related to these Nordic methods is the Conseil Supérieur du Notariat (CSN) and INSEE method used to compute hedonic indexes for regions in France (see Gouriéroux and Laferrère, 2009).

Characteristics methods have also proved useful for making comparisons of prices across regions (see Gillingham, 1975; Moulton, 1995; Wallace, 1996; Chowhan and Prud'homme, 2004).

4.5 *Repeat Sales and Hedonic Hybrid Methods*

Attempts have been made to combine the repeat-sales and hedonic approaches. Case and Quigley (1991) and Quigley (1995) use samples of single-sale and repeat-sale dwellings to jointly estimate price indexes using generalized least squares. Hill *et al.* (1997) undertake a similar although more general exercise using maximum likelihood. A rather different perspective is provided by Shiller (1993) who proposes a repeat-sales method that allows the price path for dwellings to depend on their quality measured using a hedonic method (see also Clapp and Giaccotto, 1998).

Ultimately, the rationale for hybrid methods is to try and combine the best features of each approach. Advocates of these hybrid methods presumably believe that repeat-sales price relatives (adjusted for estimated depreciation) are more reliable indicators of quality-adjusted price changes than are say double imputation hedonic price relatives. Conversely, repeat-sales methods throw away all the single sales data. By combining the two approaches, no data are discarded while repeat sales are still allowed to play a prominent role in the index construction methodology. My problem with this approach is that I have difficulty accepting the assumption that a repeat-sales price relative should be preferred to a double-imputation hedonic price relative. We must tradeoff the risk of omitted variables bias in the double imputation price relative against the risk that changes have been made to a repeat-sales dwelling. I am reminded of Heraclitus, who said that "you cannot step into the same river twice". I have similar concerns about repeat sales. If repeat-sales price relatives are not deemed more reliable than double-imputation price relatives, there is no reason to prefer hybrid methods to hedonic methods.

5. Geospatial Data and How to Use It in Hedonic Models

5.1 *Geospatial Data and Spatial Dependence*

As has been already noted, one of the most important determinants of house prices is location. The simplest way of accounting for location is through the inclusion of neighborhood dummy variables. However, when the exact addresses of individual dwellings are available, it is now relatively straightforward using geospatial software to calculate each dwelling's exact longitude and latitude. This increasing availability of geospatial data at the level of individual dwellings allows the impact of location to be modeled in much more sophisticated ways, and has indeed stimulated a burst of research activity.

Researchers using geospatial data tend to focus on modeling the housing market rather than the construction of house price indexes. In fact, as far as I know the only existing hedonic price indexes that use geospatial data are the FNC Residential Price Index and the RPData-Rismark Daily Home Value Index.

If location is an important determinant of price, then it follows that house prices are spatially dependent. Spatial dependence is likely to exist since many of the price determining factors are shared by neighborhoods but are difficult to document explicitly. Basu and Thibodeau (1998) note how neighborhoods tend to develop at the same time resulting in dwellings having similar structural characteristics, and dwellings in a neighborhood share the same locational amenities.

The presence of spatial dependence can be for tested for in a number of ways (see Anselin and Bera, 1998). One popular test uses Moran's I statistic, which is defined as follows:

$$I = \frac{\hat{\varepsilon}' S \hat{\varepsilon}/g}{\hat{\varepsilon}'\hat{\varepsilon}/n},$$

where $\hat{\varepsilon} = y - X\hat{\beta}$ is a vector of OLS residuals, S is a spatial weights matrix (see Section 5.3), and g and n are scaling factors. Under the null hypothesis of no spatial dependence, a normalized version of I (obtained by subtracting its expected value and then dividing by its standard deviation) has an asymptotic standard normal distribution (see Cliff and Ord, 1972). Moran tests in a housing context invariably reject the null hypothesis of no spatial dependence (see e.g., Can, 1990; Militino *et al.*, 2004; Cohen and Coughlin, 2008).

The implications of ignoring spatial dependence when it is present depend on the exact way the dependence manifests itself. For example, suppose the spatial dependence is captured by the spatial lag model (obtained by setting $\lambda = 0$ in the SARAR(1,1) model in Section 5.3 later). In this case, the estimated parameters in the hedonic model, when spatial dependence is ignored, may be biased and inconsistent (see Anselin, 2006). Alternatively, if the spatial dependence is described by the spatial error model (obtained by setting $\rho = 0$ in the SARAR(1,1) model in Section 5.3 later), then the estimated parameters may be inefficient and have biased standard errors (again see Anselin, 2006).

5.2 *Distance to Amenities as Additional Characteristics*

Perhaps the simplest approach to incorporating geospatial data into a hedonic model is by using it to measure the distance of individual dwellings to amenities such as the central business district, train station, airport, schools, shopping centers, parks, beaches, etc. These distances, or some function thereof, can then be included as additional characteristics in the hedonic model. Examples of this approach include Dubin and Sung (1987), Martins-Filho and Bin (2005), and Hill and Melser (2008). The former two papers include distance nonparametrically while the latter does it parametrically.

This approach, however, has its limitations. First, not all forms of spatial dependence can be quantified in terms of distance to an amenity. For parametric versions of this approach two additional criticisms arise. The impact of distance to an amenity on price may be nonmonotonic. For example, one may want to live not too close and yet not too far from say the local airport. Also, the impact of distance from an amenity on price may also depend on the direction. Focusing again on airports, a crucial consideration is the flight path. A dwelling nearer to the airport but not under the flight path may be less adversely affected than a dwelling further away but directly under the flight path.

Nonparametric treatment of distance from amenities is potentially more flexible and may be better able to deal with these latter two problems. For example, Dubin and Sung estimate separate splines for distance from the CBD in a number of different directions.

5.3 *Extending the Time-Dummy and Imputation Methods to Capture Spatial Dependence using Spatial Econometric Methods*

The main benefit of explicitly accounting for spatial dependence in a hedonic model is that it should help offset the locational omitted variables problem. This is because while many of the price determining factors shared by neighborhoods are difficult to document explicitly, their influence is contained in the prices of neighboring dwellings.

The (first-order) autoregressive spatial model with (first-order) autoregressive errors, referred to henceforth as the SARAR(1,1) model, has been widely used for this purpose (see e.g., Anselin, 1988; Corrado and Fingleton, 2012).

$$y = \rho S y + X\beta + u,$$

$$u = \lambda M u + \varepsilon,$$

where y is the vector of log prices, (i.e., each element $y_h = \ln p_h$), and S and M are spatial weights matrix that are calculated from the geospatial data. Often S and M are the same. I return shortly to a discussion of how S (and M) might be calculated.

A simplified version of the SARAR(1,1) model where λ is set to zero (typically referred to as the spatial lag model) is used in the construction of the FNC Residential Price Index (see Dorsey *et al.*, 2010), and by Ord (1975), Can and Megbolugbe (1997), and Kim *et al.* (2003), and others. It can be rationalized by buyers and sellers treating the price at which nearby dwellings sell as a signal of value. Alternatively, sometimes ρ is set to zero. LeSage and Pace (2009) provide an externality motivation for this version of the model (typically referred to as the spatial error model) where the quality of nearby dwellings directly influences the price of a particular dwelling. This version of the SAR model is used for example by Cliff and Ord (1973), Pace and Gilley (1997), Bell and Bockstael (2000), and Hill *et al.* (2009).

Methods used to estimate the β vector and ρ and λ scalars of the SARAR(1,1) model include maximum likelihood (see Anselin, 1988; Pace and Barry, 1997), two-stage-least squares (2SLS) (see Anselin, 1988; Kelejian and Prucha, 1998; Lee, 2003), and generalized method of moments (GMM) (see Lee, 2007; Kelejian and Prucha, 2010; Liu *et al.*, 2010). While generally less efficient than ML, 2SLS and GMM estimators have the advantage of relying on weaker assumptions and being computationally simpler (see Lee, 2007).

Turning now to the specification of the spatial weights matrix S, all terms on the lead diagonal S_{jj} are set to zero to prevent each dwelling from being spatially dependent on itself. A number of approaches have been used for calculating the off-diagonal terms. For example, the Delaunay triangulation algorithm—for which MatLab 6.5 has an inbuilt algorithm—reduces S to a matrix of zeros and ones (mostly the former). With longitude and latitude of each dwelling as inputs, the Delaunay algorithm creates a set of triangles in two-dimensional Cartesian space such that no points are contained in any triangle's circumcircle. The edges of each triangle satisfy the "empty circle" property. That is, the circumcircle of a triangle formed by three points is empty if it does not contain any other vertices apart from the three that define it. Two dwellings are categorized as neighbors if there exists a triangle on which they are both vertices. The main attraction of this approach is that a spatial matrix containing only binary numbers is computationally easier to work with. Alternatively, the spatial weight between a pair of dwelling could be calculated as some inverse function of the Euclidean distance d_{jk} between them, such as $s_{jk} = 1/d_{jk}$ or $s_{jk} = 1/d_{jk}^2$ for $j \neq k$. A common practice is to standardize the rows of S so that they sum to one, so as to ensure that the solution for ρ or λ is well defined.

Most of this literature, however, is concerned with the estimation of a hedonic model at a point in time rather than the construction of house price indexes. In principle, such indexes can be easily obtained by simply including quarter or year dummies in the X characteristics matrix, and then by exponentiating the estimated parameters on these dummy variables. The problem is that when the model is estimated over a number of years of data the spatial weights matrix S should be replaced by a spatiotemporal weights matrix W. That is, the magnitude of the dependence between observations depends inversely on both their spatial and temporal separation. One response to this problem is to use the AP version of the time-dummy method. In this case the temporal separation between observations never gets that large and hence it is more defensible to use a spatial weights matrix instead of the theoretically preferred spatiotemporal weights matrix. This is the approach followed by Hill *et al.* (2009).

The alternative is to actually compute a spatiotemporal weights matrix. The literature on this topic is thin. The main references are Pace *et al.* (1998), Tu *et al.* (2004), Sun *et al.* (2005), and Nappi-Choulet and Maury (2009). These papers use the the spatial-temporal autoregressive (STAR) model. This is obtained from the SARAR(1,1) model by setting $\rho = 0$, replacing the spatial weights matrix S with a spatiotemporal weights matrix W, and including time dummies in the X matrix. The STAR method can be written as follows:

$$(I - W)y = (I - W)X\beta + u,$$

where

$$W = \phi_S S + \phi_T T + \phi_{ST} ST + \phi_{TS} TS, \tag{26}$$

and S denotes a spatial weights matrix and T a temporal weights matrix. The parameters ϕ_S, ϕ_T, ϕ_{ST}, and ϕ_{TS} are all estimated endogenously (in place of λ). The last two terms in (26) allow for interactions between spatial and temporal effects.

Pace *et al.* (1998) recommend ordering the observations chronologically, with dependence only running from earlier to later observations. As a result, both S and T are lower triangular matrices. This reduces the computational complexity of the estimation process. While the existing STAR literature considers some ways of calculating S and T, there are clearly other ways in which these matrices could be constructed and then combined to form the spatiotemporal weights matrix W. Also, the restriction that $\rho = 0$ in the SARAR(1,1) model could be relaxed.

The SARAR(1,1) model has also been used in combination with the imputations method. The FNC Residential Price Index, which is computed on a monthly basis using a 12-month moving window, uses the spatial lag version of the SARAR(1,1) model (see Dorsey *et al.*, 2010), while Cominos *et al.* (2007) and Rambaldi and Rao (2011) use the spatial error version of the SARAR(1,1) model.

In conclusion, therefore, it is possible to incorporate a SARAR(1,1) structure into either the time-dummy or imputation methods. Spatial dependence can however also be modeled in an imputations setting using nonparametric methods. I turn now to this issue.

5.4 *Extending the Imputations Method to Capture Spatial Dependence using Nonparametric Methods*

Nonparametric methods provide an alternative to parametric modeling of spatial dependence. They can be used to construct a flexible topographical map describing how price varies by location (measured by longitude and latitude) holding the other characteristics fixed. Many of the articles that use nonparametric approaches to estimate the hedonic function, however, do not use geospatial data, and instead apply nonparametric methods to the physical or distance-to-amenity characteristics of dwellings. Examples not using geospatial data include Dubin and Sung (1987), Meese and Wallace (1991), Pace (1993), Wallace (1996), Kagie and van Wezel (2007), Bao and Wan (2004), and Martins-Filho and Bin (2005).

The main advantage of nonparametric methods is that they do not need to assume a functional form for the hedonic model, and hence avoid problems of misspecification. Comparisons of parametric and nonparametric models almost invariably find that the latter outperform the former in terms of mean-square error for out-of-sample predictions (see Pace, 1993; Bao and Wan, 2004; Martins-Filho and Bin, 2005).

There has been surprisingly little discussion of how to use nonparametric methods to construct price indexes. Probably the most natural way is by combining a nonparametric hedonic model with an imputation method. It makes no difference to the imputation method whether the hedonic model is parametric or nonparametric. All that is required is that it is possible to impute a price for any vector of characteristics, and that these imputed prices should be time dependent. I can find only three examples in the literature that combine a nonparametric or semiparametric hedonic model with the imputation method. Only two of these use geospatial data. Kagie and van Wezel (2007) estimate their hedonic model using a decision tree method called boosting, but without using geospatial data. Hill and Scholz (2011) estimate a semiparametric model in which the physical characteristics are modeled parametrically and the locational characteristics (i.e., longitude and latitude) are modeled nonparametrically. In both cases the price indexes are calculated using the Fisher formula, although Kagie and van Wezel use single imputation (i.e., F1) while Hill and Scholz use double imputation (i.e., F2). The third example is the aforementioned Daily Home Value Index of RPData-Rismark, described in Hardman (2011). As noted earlier, the RPData-Rismark Daily Home Value Index double imputes prices from a generalized additive model.

A nonparametric hedonic model can also be combined with the characteristics method. This is the approach followed by Meese and Wallace (1991), and Wallace (1996), who both use the Fisher price index formula F3 in (19). However, this first requires the derivation of characteristic shadow prices from the hedonic model, which is not necessarily straightforward. These authors derive the shadow prices from the slope of the estimated nonparametric surface. A more serious problem is that the use of the characteristics approach negates perhaps the main potential benefit of using nonparametric methods, namely the incorporation of geospatial data.

Nonparametric methods can be used to construct a flexible topographical map describing how price varies by location (measured by longitude and latitude) holding the other characteristics fixed. Such a map can then be added to a standard parametric hedonic model defined over the physical characteristics. This may be preferable to modeling all characteristics nonparametrically, since it limits the nonparametric estimation to three dimensions (i.e., price, longitude, and latitude). At the same time, the physical characteristics can be allowed to interact with location. Examples of this type of semiparametric approach include Colwell (1998), Pavlov (2000), Clapp *et al.* (2002), Fik *et al.* (2003), Clapp (2003, 2004), McMillen and Redfearn (2010), Hardman (2011), and Hill and Scholz (2011). What all these papers lack, with the exception of the last two, is a method for obtaining a house price index from the estimated hedonic model. The imputation method is the natural choice for this task.

5.5 *Conclusion on Geospatial Data*

It has been shown how the time-dummy and hedonic imputation methods can be extended to capture spatial dependence through the use of geospatial data. By contrast, it is not clear how the characteristics method can use geospatial data. This is a concern given that most existing hedonic house price indexes use the characteristics method.

6. Decisions To Be Made by Providers of Hedonic House Price Indexes

An index provider must make a number of decisions when computing a hedonic house price index. First, one must decide on the basic methodology. The index could be constructed using the time-dummy, imputation or characteristics methods. For the time-dummy method, the next tasks are to decide whether to use the AP variant on the basic method and then to choose a functional form for the hedonic model. For the imputation and characteristics methods, it is necessary to simultaneously choose both a price index formula and a functional form (which in the imputations case may be nonparametric).

One must also decide on the list of explanatory characteristics, and on whether to include interactions between particular combinations of characteristics (e.g., bedrooms and bathrooms) or transformations of particular characteristics, such as land area. Also, discrete variables such as bedrooms and bathrooms can be included either as standard variables or as dummy variables. For example, an explanatory variable could be the number of bedrooms or separate dummy variables can be included for two bedrooms, three bedrooms, four bedrooms, etc. The latter approach has the advantage of greater flexibility in that it allows the effect of an extra bedroom to differ depending on the initial number of bedrooms. However, this increased flexibility comes at the price of less degrees of freedom. For data sets with large numbers of observations, which is increasingly the norm, the dummy variable approach is probably preferable.

Similarly, estimating a separate hedonic model for each period, as the imputation and characteristics methods do, also acts to significantly reduce the degrees of freedom. While modern data sets are often large enough to allow separate estimation of the model for each period, from an econometric point of view this is clearly inefficient. Some variant on Zellner's (1962) seemingly unrelated regression (SUR) method would be a useful addition to the imputation and characteristics methods.

According to Sirmans *et al*. (2006), the nine characteristics that appear most often in hedonic regressions for housing (and all of which are of the physical variety) are floor area, land area, age, bedrooms, bathrooms, garage, swimming pool, fireplace, and air conditioning. To these presumably can be added postcodes and dwelling-type dummy variables (e.g., house, townhouse, apartment, etc). The choice of explanatory characteristics is often determined largely by data availability. For data sets with relatively few characteristics (see e.g., Hill *et al*., 2009) the omitted variables problem may be a particular concern. Such a situation strengthens the case for using double imputation to offset the omitted variables problem. Conversely, the case for using the time-dummy method is stronger when the number of dwellings in the data set is small. In such cases, estimating separate hedonic models for each period could generate erratic coefficients.

In most cases, the index provider has a prior expectation as to the expected sign on each coefficient in the hedonic model. At first glance, one might expect the estimated coefficients on all nine characteristics above to be positive, with the exception perhaps of age. The impact of age on house prices can be quite complex. Newer dwellings typically command a price premium. However, older dwellings may also command a premium in the same way as antique furniture. For example, in some cities in Europe, apartments built before 1914 are much sought after. In other words, the impact of age on house prices may be nonmonotonic. Imposing a monotonic relationship between house prices and age in the hedonic equation therefore may do more harm than excluding age completely from the model. A better approach in this case might be to assume a quadratic relationship between age and house prices or to specify dummy variables for dwellings in various age ranges (e.g., 0–10 years, 11–20 years, 21–40 years, etc).

The sign of the bedrooms coefficient may also be unclear when floor area is also included. This is because the inclusion of an extra bedroom while holding floor area fixed is not necessarily desirable, since it has an associated opportunity cost of less space for everything else in the dwelling. The same tradeoff may also exist to some extent between floor area and land area, since more floor area holding land area fixed implies a smaller garden.

An index provider with access to locational characteristics, such as postcodes or longitudes and latitudes for each dwelling faces further dilemmas. The latter can be used to construct numerous locational characteristics, such as the distance to the nearest school, train station, hospital, shopping center, airport, park, beach or to the city center. The relationship between distance to a particular amenity and house prices, like age, is sometimes nonmonotonic. For example, as has been discussed earlier, one might ideally want to live reasonably near but not too near a shopping center, train station or hospital. Hence as with age, a quadratic specification for the relationship between distance to an amenity and house prices (or the specification of dummy variables for various distance ranges) may in some cases be appropriate.

More generally, I am not convinced that there is much benefit to including locational characteristics. A better approach is to model spatial dependence directly via either a spatiotemporal weights matrix in a time-dummy setting or a semiparametric model in a hedonic-imputation setting.

Given that sufficient attention has been paid to the complexities that can arise from interactions between characteristics, how concerned should one be if some of the signs of the estimated coefficients do not accord with prior expectations? Pakes (2003) created some controversy by arguing that at least in monopolistically competitive markets subject to mark-ups one should not interpret the estimated coefficients as shadow prices, and hence that one should not have much in the way of prior expectations regarding the signs of these coefficients. In my opinion, Pakes's arguments do not carry through to the housing market, where the vast majority of buyers and sellers are private households, most dwellings on the market have not been produced in that particular period, and where the fundamental building block of value—namely the land itself—has not been produced at all. Hence I would argue that unexpected signs on some of the coefficients, at least in a housing context, are a cause for concern. Having said that, it is a fact of life in empirical research that the results do not work out exactly as one had hoped.

One particular data problem often encountered is missing observations for some characteristics. For example, the bedroom count may be missing for a certain percentage of the dwellings in the data set. This problem can be dealt with by deleting from the model any characteristics that are particularly prone to having missing observations, or alternatively by omitting all dwellings that have an incomplete list of characteristics. Neither of these solutions is particularly appealing. Both throw away potentially useful data. An alternative solution is to simply set all missing observations to zero or some other default value. This, however, may also create distortions and perhaps bias.

In my opinion, the problem of missing observations should be dealt with in one of two ways. The first approach can only be used in combination with the imputation method. This approach requires a number of hedonic models to be estimated for each period each with varying combinations of explanatory variables. The imputed price for each dwelling is then calculated from the hedonic model that includes exactly the same list of characteristics that are available for that particular dwelling. In this way, all the available and relevant information is used when imputing the price of each dwelling. While this method is computationally somewhat laborious, it is well within the capabilities of modern computers (see Hill and Syed, 2011).

The second approach is to impute values for the missing observations prior to estimating the hedonic model. That is, rather than imputing the price of a dwelling from its list of characteristics, one must first impute say the number of bathrooms in a dwelling from its price and its other characteristics. This approach risks introducing a circularity into the estimation method if prices are used to impute characteristic values which are then in turn used to impute prices. The multiple imputation (MI) method developed by Rubin (1976, 1987) and others is an example of such a method. MI imputes say 10 sets of values for the missing observations, then estimates the regression model for each set of imputations and only then averages the results across the 10 sets of results. The imputations exploits correlations between the variables to impute missing data points. The MI method is applied to housing data by Syed *et al.* (2008). It is important that the assumptions underlying the imputation methodology are appropriate to the particular context. Otherwise the process of imputation of missing observations may act merely to hide rather than reduce the problem of sample selection bias.

A further problem faced by an index provider prior to estimation of the hedonic model is the problem of outliers. For example, suppose a particular dwelling has 20 bedrooms. This may be because it is in fact a hotel, and hence should be excluded if the objective is to construct a price index for residential housing. Alternatively, the entry of 20 bedrooms may be a typo and should be 2 rather than 20. In housing data sets, the majority of outliers tend to be typos, and are probably best dealt with by simple deletion or replacement by imputed values. The problem here is deciding where to draw the line. For example, should the line be drawn at 6 bedrooms, 7 bedrooms, or 8 bedrooms or at some higher or lower level? Similar decisions need to be made for bathrooms, land area, floor area, and other characteristics.

7. Criticisms of Hedonic Price Indexes

7.1 *Omitted Variables Bias*

The omitted variables problem is likely to be much more severe for housing than say for computers. It is probably impossible to quantify all the factors that influence the price of a dwelling, while the list of relevant characteristics for a computer is presumably relatively short and more quantifiable (e.g., RAM, ROM, speed, screen type and size, manufacturer, weight).

In a housing context a distinction can be drawn between omitted variables that relate to the physical characteristics of a dwelling (such as land area) and those that relate to its location (such as distance to the city center). As noted above, according to Sirmans *et al.* (2006), the nine characteristics that appear most often in hedonic regressions for housing (and all of which are of the physical variety) are floor area, land area, age, bedrooms, bathrooms, garage, swimming pool, fireplace, and air conditioning.

Examples of likely omitted variables of the physical variety in hedonic models of the housing market include the following: state of maintenance of a dwelling, the amount of sunlight received, the functionality of the layout of the rooms, the presence or otherwise of damp or water damage, the quality of the building materials and workmanship, and the general ambience. One feature shared by these characteristics is that they are generally hard to quantify. Omitted variables related to location may include traffic noise, air quality, the quality of nearby dwellings, public service levels, public transport, nearby shops, the local crime rate, demographic characteristics of the neighborhood, the quality of local schools, and local taxes. Some of these locational characteristics are potentially quantifiable and hence sometimes are included in hedonic models (see e.g., Sedgeley *et al*., 2008).

The significance of the omitted variables problem depends on the objective of the exercise. For example, omitted variables are a much larger problem for automated valuation (appraisal) models or studies that focus specifically on the characteristic shadow prices (e.g., for clean air) than for price indexes. There is a reasonable expectation that the omitted variables bias will mostly offset itself across dwellings in a hedonic price index (see Malpezzi, 2008), particularly when double imputation is used. Furthermore, the extent of the locational omitted variables problem can be reduced by including postcode dummies or better still by modeling spatial dependence directly using geospatial data.

7.2 *Functional form Misspecification*

Given the hedonic model is a reduced form it is not possible to determine the appropriate functional form by theoretical reasoning alone (see Rosen, 1974). The most popular functional form is semi-log. Malpezzi (2008) lists five advantages of the semi-log model. These are that it allows the value added of an incremental increase in a particular characteristic to vary proportionally with the size and quality of a dwelling, the simple and appealing interpretation of the estimated coefficient parameters, computational simplicity, mitigation of heteroscedasticity, and the ease with which it can be extended to include nonparametric terms such as splines.

Interest in Box and Cox (1964) transformations, which nest semi-log as a special case, waxed and waned in the 1980s (see e.g., Halverson and Pollakowski, 1981). As Coulson (2008) points out, rather than turning to more flexible functional forms, researchers concerned about the restrictiveness of the semi-log model and the resulting risk of functional form misspecification have tended to turn instead to semiparametric or nonparametric models (an early notable example is Meese and Wallace, 1991). Nonparametric methods can approximate any relationship without prespecification of functional form. Given the availability now of various nonparametric approaches in the hedonic literature, functional form misspecification (beyond the omission of relevant explanatory variables) is no longer as big a concern as it used to be.

7.3 *Data Mining and Lack of Transparency and Reproducibility*

Shiller (2008) makes the following criticism of hedonic methods:

> The problem is that there are too many possible hedonic variables that might be included, and if there are *n* possible hedonic variables, then there are *n*-factorial possible lists of independent variables in a hedonic regression, often a very large number. One could strategically vary the list of included variables until one found the results one wanted. Looking at different hedonic indices for the same city, I remember seeing substantial differences, which must be due to choices the constructors made. Thus, the indices have the appearance of hypotheses rather than objective facts (Shiller, 2008; p. 10).

It is undoubtedly true that two researchers given the same data set will end up constructing different hedonic indexes. Shiller in fact understates the number of choices that must be made by an index provider (see Section 6).

The flexibility of the hedonic approach can be viewed both as an advantage and disadvantage. Shiller highlights the disadvantages of flexibility. One notable advantage is that the index provider can tailor the approach used to the data set and the needs of users. For example, the case for using double imputation rises when only a small list of characteristics are available, while the case for using the time-dummy method rises when the sample of dwellings is small.

There is also the matter of how sensitive the hedonic index is to all of these choices. Sirmans *et al.* (2006) find that the estimated shadow prices of characteristics are surprisingly stable across semi-log models estimated by different researchers using different data sets. It would be a useful exercise to see how sensitive hedonic house price indexes really are to the various choices faced by the provider.

Shiller also raises the specter of strategic manipulation. While it is true that academic researchers in the hedonic field seeking new results for publication in an academic journal have an incentive to use the choices available strategically, the same is unlikely to be true for index providers. An index provider typically chooses a methodology (hopefully makes it publicly available) and then sticks with it. Hence I feel that Shiller's concerns over strategic manipulation of hedonic indexes are overstated, at least for index providers.

Finally, it is worth remembering that the provider of a repeat-sales index (Shiller's preferred method) also has to make a number of choices (e.g., the treatment of outliers, of repeat sales at very short time intervals, and the relative weighting given to shorter and longer time interval repeat sales). Hence, two researchers given the same data set would probably likewise end up constructing different repeat-sales indexes as well. Leventis (2008), for example, documents how the differing treatment of repeat-sales with longer time intervals between sales generates significant differences between the SPCS and OFHEO repeat-sales indexes. This issue also warrants further investigation.

7.4 *Sample Selection Bias*

A hedonic sample may be subject to two types of sample selection bias. First the population of house sales may not be representative of the overall housing stock. This is a problem that applies to all index construction methods that rely on transaction as opposed to appraisal prices (particularly repeat-sales indexes). In fact, whether this is actually a problem may depend on how the index is used. For example, from the perspective of monetary policy, with its focus on actual market transactions, it is not clear whether it is desirable to try and adjust a hedonic index to make it more representative of the overall housing stock.

If characteristics information are available on all dwellings (not only those transacted) then it is possible if desired to correct for this type of sample selection bias. Gatzlaff and Haurin (1998) propose a censored regression method. The probability of a sale is estimated using property, owner, and macroeconomic factors. These probabilities are used to calculate a selection bias correction variable. Gatzlaff and Haurin find that their corrected price indexes are more volatile than the uncorrected indexes. LeSage and Pace (2004) and Reid (2007) follow a different approach and impute prices in each period for all properties for which characteristics data are available. LeSage and Pace impute prices using the multiple imputation approach of Rubin (1976, 1987). Reid, by contrast, imputes prices directly from the estimated hedonic model, and then constructs price indexes using the double imputation method applied to all dwellings in the data set irrespective of whether they were traded in either of the two periods being compared. He refers to this as the augmented double imputation method. These methods should all generate price indexes that are more representative of the overall housing stock.

The second type of sample selection bias arises when certain types of housing transactions are more likely to be recorded than others. Hill *et al.* (2009) find two such trends in their data set for Sydney, Australia (obtained from Australian Property Monitors). First, the coverage improves over time. For example, a transaction in 2006 is more likely to be included than a transaction in 2001. Second, the coverage seems to be better in richer suburbs of Sydney, both in terms of the percentage of total sales included and the list of characteristics provided. This latter type of sample selection bias in particular could translate into index bias if the price path across richer and poorer suburbs differs in a systematic way over time.

Incomplete lists of characteristics for some dwellings (e.g., the bathroom count is missing) can also cause problems, particularly if these dwellings are simply deleted. As well as wasting data, such wholesale deletion can cause sample selection bias. The relevance of this problem may differ considerably from one data set to the next. For an example where this problem is severe, see Hill *et al.* (2009). Ways of addressing this problem are discussed in Section 6 above.

8. Conclusion

Hedonic indexes seem to be gradually replacing repeat-sales indexes as the method of choice for constructing quality-adjusted house price indexes. This trend can be attributed to the inherent weaknesses of the repeat-sales method (especially its deletion of single-sales data and potential lemons bias) and a combination of the increasing availability of detailed data sets of house prices and characteristics including geospatial data, increases in computing power, and the development of more sophisticated hedonic models that in particular take account of spatial dependence in the data.

The hedonic approach provides a rich and flexible structure that allows index providers to tailor the method to the available data and the needs of users. As Hoffman and Lorenz (2006) say, "the future will belong to hedonic indices."

Note

1. One problem with P_t^* that has thus far been ignored in the literature is that, by construction, no correction is made to the price index of the base period which is still normalized to 1. The correction therefore acts to systematically increase the price index of every other period relative to that of the base period. Given that in the absence of this correction the time-dummy method is base-period invariant (subject to rescaling), the imposition of the correction therefore causes a violation of base-period invariance. The fact that the original time-dummy method is base-period invariant implies that the uncorrected indexes cannot be systematically biased relative to the base period. It follows that the corrected indexes, while correcting another source of bias, generate indexes that are systematically biased for each period relative to the base period. One resolution to this dilemma is to generate T sets of time-dummy results using each of the T periods in turn as the base period, then make the bias correction discussed earlier, and finally take a geometric average of the T sets of results. Such an approach, which as far as I know has never been tried, while more laborious will correct for both types of bias.

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