Occupant Well-Being and House Values

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Abstract

A difficulty in identifying the contribution of structure and neighborhood attributes to the market value of residential property is the lack of data on subjective characteristics of the neighborhood (friendliness of neighbors, proximity to friends and acquaintances) or difficult-to-observe subjective attributes of the structure itself (such as "curb appeal" or the presence of unpleasant odors).

Concern may also arise from the understanding that the observed market price of most residential property is the result of a process of bargaining. A buyer who is optimistic by nature may assume that the quality of the neighborhood will be wonderful, or that the unusual odor will eventually go away, and therefore be willing to bid a higher price for the structure than a prospective buyer who is more nervous about all the ways that a house purchase can generate disappointment. Estimates of the value of structure or neighborhood attributes may tell us as much about the emotional affect of the buyer as they do about the actual costs or benefits of the attributes (or of cleaning or mitigating them).

These observations suggest that incorporating data on the levels of subjective well being (SWB) and emotional affect of the buyers might be usefully applied to improve hedonic analysis of housing markets. The goal of this paper is to undertake such analysis and to explore the potential for improved analysis of the value of residential property. We make use of unique data collected as part of a multi-year analysis of health outcomes, matched with data on market transactions of residential property in three provinces of the Netherlands.

We employ the spatial model developed by Kelejian & Prucha (2010) which allows us to incorporate a spatial error specification, as well explicitly control for possible endogeneity between the measure of SWB and the transaction price. By examining aggregate measures of SWB at different spatial scales, we obtain insights into whether these measurements are capturing subjective characteristics of the community, the neighborhood or the structure and the buyer who negotiate over the eventual price.

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1 Introduction

The hedonic pricing idea put forward in the seminal paper by Rosen (1974) is fundamental to research in urban economics, community development and real estate valuation. In his paper, Rosen states that if "goods can be treated as tied packages of characteristics, observed market prices are also comparable on those terms" (Rosen 1974). In hedonic models of real estate valuation, these characteristics generally deal with characteristics of the property, and characteristics of the environment. Treating houses as a differentiated products, the transaction price paid is a function of an individual's (or household's) income and observed and unobserved preferences (Sheppard 1999).

These unobserved preferences conflict with an important assumption in estimating hedonic models, that of perfect observability of the characteristics of the product (Bajari & Benkard 2005). Obtaining accurate estimates of the value of individual characteristics of properties relies on the unlikely assumption that the model is estimated on a complete set of characteristics, or at least that the unobserved characteristics are orthogonal to the characteristics used in the model. So long as these assumptions hold, the estimates obtained through a hedonic price model remain unbiased. However, if these unobserved characteristics translate into a higher or lower expected utility by the prospective buyer, coefficients derived for the measurable characteristics might be biased. Moreover, if these unobserved characteristics contain regional attributes, the model's residuals will be spatially correlated, violating the model's assumed independence of observations.

Recent progress in the field of happiness studies offers suggestions on how to ameliorate these problems. Happiness as a measure of utility has been used in the field of economics since the seminal paper of Easterlin (1974), although until very recently the validity of measuring happiness was a hotly debated topic. Contributions by Diener & Suh (1997) and Veenhoven (2012) show that measures of self-reported happiness contain a lot of relevant variance and on the whole "measure what they set out to measure". This means that, following Frey & Stutzer (2002), rather than limiting studies to the observable choices made by individuals (e.g. moving, purchasing decisions), incorporating measures of happiness allows for the study of utility *in situ*. We argue that the interpretation of happiness as a measure of utility means it can be used to obtain an estimate of unobservable structure or neighbourhood attributes. Interpreting happiness as a measure of utility, a higher level of happiness implies that (*ceteris paribus*) a person is deriving a higher utility from living in a certain house or neighbourhood. Including SWB in the hedonic price function as a measure of unobserved attributes will then improving the estimation of the hedonic price function.

There have been a few prior applications of SWB in analysis of housing markets. Foye (2017) is concerned with the impact of the living space provided by a house on the SWB of the occupants. He finds that increased living space is associated with increased SWB, and intriguingly that this relationship is gender-dependent. Cattaneo, Galiani, Gertler, Martinez & Titiunik (2009) evaluate the power of a project to improve the quality of slum housing in Mexico. Again focusing on SWB as the outcome measure, they apply a careful experimental design and discover that the improvements in house quality increase maternal life satisfaction and decrease stress. Ferreira & Moro (2010) also consider measured SWB as the outcome, in this case of environmental attributes, while they control for house prices.

The approach we take is different, focusing on the ability of measures of SWB and emotional affect to provide information about the unobserved structure and neighborhood attributes. Our analysis contributes to the literature on hedonic price estimation in two ways. First, we aim to show that including a direct measure of happiness on the right hand side of the hedonic price function helps control for unobservable variables at the individual household level. A positive and significant coefficient for happiness, with transaction price as the dependent variable, shows that a higher expressed level of SWB corresponds to higher transaction price paid by the owner. These deviations would correlate with things such as curb appeal, odors, and proximity to friends and family. In addition to the individual unobservables related to solely the dwelling, the second contribution of this paper is to estimate the impact of unobserved neighbourhood effects, such as proximity of friends or quality of local public facilities. Using a spatial lag specification of the happiness variable, a positive and significant coefficient for lagged happiness would mean that higher utility in the neighbourhood, controlling for higher individual utility, corresponds to a higher transaction price. Together, these two specifications test for the effects on the transaction price of individual and local neighbourhood attributes that are approximately measured by expressed SWB.

To obtain our estimates, we employ the spatial model developed by Kelejian & Prucha (2010) which allows us to incorporate a spatial error specification, as well explicitly control for possible endogeneity between the measure of SWB and the transaction price. We adjust for the endogeneity of happiness and the (log of the) transaction price using an instrumental variables approach.

The data we use in this study consists of a large scale (95,413 respondents) multi-generation biobank survey called LifeLines, the data-collection run used in this study was collected between 2010 and 2012 and focuses on the North of the Netherlands. The survey contains individuals' place of residence (in xy-coordinates) and a large number of individual variables, including health, well-being, socio-economic status, and various psychometrics. From this study we obtain the locations of individuals and individual responses to questions relating to subjective well-being and positive and negative affect. These are then combined with data from the Dutch realtor association (NVM) which contains information on around 70% of real-estate transactions (Brounen & Kok (2011)). The NVM dataset provides real-estate characteristics, such as transaction price and date, numbers of rooms, bathrooms, and size of property and plot. Finally, we add neighbourhood data from Statistics Netherlands (CBS) and neighbourhood crime data from the National Police.

2 Theory

Real estate is by its very nature heterogeneous good, meaning that objects consist of a variety of attributes, which makes valuation at the level of the object (the explicit market) much more difficult (Sheppard 1999). Hedonic valuation allows the estimation of prices at the level of the underlying attributes (the implicit markets) by assuming that the characteristics of the heterogeneous good (e.g. floor space, number of bathrooms) are homogeneous goods. The theoretical foundation of hedonic housing models is that households derive utility from the consumption of the heterogeneous good, in this case the house. From there, estimating a regression model comprising the relevant characteristics of the real estate object as the explanatory variables, and the object's valuation as the dependent, and provided with sufficient numbers of observations, one can assess the value of each underlying characteristic separately.

The hedonic price that is arrived at for the house is a function of the household's preference, the characteristics of the house (including the structural characteristics, the immediate neighbourhood), and the household income (for the formal defintion see Sheppard (1999)). From this short summary of the determinants in the hedonic price function it is easy to see two main problems relating to unobservables when estimating a hedonic price function. First, not all attributes related to the house or immediate neighbourhood are directly measurable (Fomer, Suparman & Oud 2014) and second, individual household preferences are generally difficult to measure comprehensively (Niedomysl 2011).

The housing market is a particular example of heterogeneous goods (Bockstael & McConnell 2007) in that no two houses are exactly alike in both structural characteristics and location. This assertion exemplifies the two main sources of omitted variable bias, omitted variables related to the property or the buyers alone, and omitted variables related to the environment.

The first category of omitted variables contains those housing characteristics which are not usually measured but that do influence the price of the house. This category contains variables omitted as a result of varying levels of completeness of datasets between studies, and interactions between specific housing characteristics and combinations of characteristics, and their desirability. First, some characteristics are difficult to measure, even in more complete datasets, but are known to affect willingness to pay. Data on nuisance such as noise and smell, are available (perhaps through proxies) for larger disturbers, e.g. airports or recycling stations as discussed in van Praag & Baarsma (2005) and Anselin & Kelejian (1997). For domestic disturbances, data is rarely available, very time (and occupant) dependent, and very local in their area of effect. Second, where the size of the property and the indoor floorspace are known stable positive correlates with transaction price, specific layouts may also lead to higher desirability of the property. From Rosen (1974), the underlying characteristics of heterogeneous goods are considered homogeneous and traded in implicit markets. However, it is hard to argue against different combinations of attributes leading to different outcomes (cf. Helbich, Brunauer, Vaz & Nijkamp (2013)). These individual property level unobservable characteristics could significantly influence price, and, more importantly, they could coincide with other variables in the model: the popularity of certain features (e.g. a kitchen island, double garage) are not time-invariant, implying a correlation with building period, property age, and other features such as insulation, maintenance status, and so on. In short, these specific property features are unlikely to be orthogonal to the other determinants modeled.

The second category of omitted variables relates to the situation of the property, its place within a wider region. Similar to the unobservable structural characteristics of the house, the location of each house is an important determinant of the price of the property. Primarily, the location of the house with respect to accessing labor market opportunities is an import determinant of the price (Tomkins, Topham, Twomey & Ward 1998), while disamenities such as the previously mentioned pollution and crime can result in lower transaction prices (van Praag & Baarsma 2005), (Anselin & Kelejian 1997). Similar to the unobservable characteristics specific for the property mentioned previously, certain arrangements of the residential neighbourhood can provide a higher utility to households within that neighbourhood. However, even in instances where the underlying processes are relatively well known, data availability can be poor (Jim & Chen 2009). Local amenities such as parks and the quality of schools are known correlates with transaction prices (Cheshire & Sheppard 2004). However, not all parks are equal, nor is it easy to discern ex ante which specific amenities will affect transaction prices. The Lloyds Bank report coining the Waitrose effect (Lloyds Bank 2016), for example, showed that proximity to supermarket chains could lead to transaction price premiums ranging from 1,333 to 38,666, depending on which supermarket chain was located close to a property, while premiums also varied from one region to the next. In addition, the regional image or regional branding can influence how attractive a region is as a destination for a possible relocation (Rijnks & Strijker 2013), (Haartsen, Huigen & Groote 2013), while these perceptions of a region are related to a variety of factors varying from individual residential history, to life course stages, and sense of place (Thissen, Fortuijn, Strijker & Haartsen 2010).

A final complicating issue related to omitted variables is that, in addition to variations in the provision of local amenities or disamenities, recent developments in research on spatial heterogeneity suggest that both the correlation between local amenities and desirability of the location (Rijnks, Koster & McCann 2018) and the correlation between property characteristics and desirability of the property (Helbich et al. 2013) might be spatially non-stationary. This spatial non-stationarity of the coefficients most likely results from an omitted spatial variable interacting with the variables of interest (Billé, Benedetti & Postiglione 2017).

There are several ways in which these unobservables can be dealt with, depending on the specifications of the data available. When using longitudinal surveys, spatial fixed effect models can be used to control for (dummy out) spatial unobserved effects, although Abbott & Klaiber (2011) show that scaling issues mean this is only partially successful. In addition, these spatial fixed effects can not account for the specific interactions between residents' preferences and the spatial amenities, so are therefore subject to the effect being general to all residents in that location throughout the survey. For cross-sectional studies, the options for controlling for spatial unobservable variables are more limited still. There are two main ways of dealing with unobservables in the cross-section: first, there are regional proxies (e.g. presence of forests and lakes) and regional dummies, and second there is the use of spatial error models. Abbott & Klaiber (2011) are critical of the use of regional dummies at relatively small spatial disaggregation for two reasons. First, they inhibit the ability of finding spatial effects at spatial scales smaller than that of the dummies and, second, they capture some of the spatial effects of amenities at larger spatial scales meaning that the measured capitalization is lower than the real capitalization of these amenities. The second method used to control for regional unobservables is the use of spatial error models. Spatial error models introduce a spatial component in the error term of a general linear model, and estimate the coefficients through maximum likelihood (Vega & Elhorst 2015). The spatial component in the error term represents a spatial process which is otherwise unaccounted for in the model. The drawback of using this type of modeling is that, similar to the spatial fixed effects approach, is that the spatial error model provides no further information on this spatial process, other than its existence. In addition, because the spatial error model is estimated globally, it moves individual variations in, for instance, preferences for amenities, to the model's error term.

In short, the complications arising from unobservables range from data-unavailability at the individual (noise, smell, layout) property level, or at the regional level (curb appeal, amenities), as well as the interplay between individual preferences and property- and regional provisions (e.g. living close to family, kitchen islands). One solution to the problem of unobservables in cross-sectional studies is the inclusion of a proxy for these variables. Recent progress in research into happiness shows happiness could be a reasonable proxy for utility (Veenhoven 2012), (Diener & Suh 1997).

The use of self-reported measures of subjective well-being, or happiness, has long escaped the confines of the fields of sociology and psychology, with economists increasingly reaping the benefits of adding these softer, self-reported variables to their models (Frey and Stutzer, 2002). There are a number of benefits to using happiness as a complement to income in the economics literature, starting with Easterlin's 1974 study on the cross-sectional and longitudinal trends in the relationship between income and happiness. The analysis revealed that, although correlated cross-sectionally, income and happiness were not related in longitudinal studies where general increases income did not correspond with an increase in happiness. The interpretation of happiness in these studies is as a self-reported measure of overall utility (discussed by Frey & Stutzer (2002)), that is, the sum total of all uses a person obtains out of goods and processes. A higher utility represents a higher return of use from all goods and processes, and therefore a higher rating of happiness. The Easterlin paradox showed a conceptual separation between income and happiness, and demonstrated the use of happiness as a measure of utility. This links to the second benefit, which is that, in general, revealed preference approaches rely on the choices of individuals to determine whether one scenario provides more utility for those individuals than other scenarios (Frey & Stutzer 2002). Given an abundance of observed choices, this observability of preferences (one situation over another situation) is a powerful research tool. However, adding happiness to these equations means that constraining utility to choice is no longer necessary, and individual utility outcomes of both consequential utility (utility resulting from a decision) as well as procedural utility (utility derived from processes, irrespective of a change or choice) can be usefully employed (Sen, 1987).

Until now, a number of studies have combined happiness and home-ownership in their research, although researchers do not agree about the positions of happiness and home-ownership relative to each other. For instance, Ferreira & Moro (2010) estimate the impacts of environmental factors on well-being, while controlling for municipal real-estate valuation on the right hand side. This interpretation of housing prices implies that the environmental factors which contribute to the utility derived by the residents is not compensated through the hedonic valuation of the property, with the authors citing market imperfections and imperfect information as the reasons this discrepancy would occur. In their analysis, they find no effect of housing prices on well-being (it is only included as a control and not the main variables of interest). However, there are a number of limitations which could contribute to difficulties in estimating the relationship between the house prices and subjective well-being, varying from the use of average house prices per region (as opposed to individual income and subjective well-being data), and including both income and house price on the right hand side.

Although the reasoning for using the house price on the right hand side of the equation seems plausible, the implication that, *ceteris paribus*, higher average neighbourhood house prices will increase happiness does not (Luttmer 2005). Reversing this problem, Cattaneo et al. (2009) show that government schemes to improve the quality of the dwelling has a positive effect on life-satisfaction in Mexico. This is in line with the theoretical expectations outlined in this paper where an improvement in the dwelling increases the overall utility derived from housing characteristics by that individual, and as the transaction incurs no financial costs on the home owner, the overall result is positive.

In this paper we set out to generalise this finding to include unobservable housing characteristics and unobservable neighbourhood characteristics. The results presented in Cattaneo et al. (2009), reflect a special case where the government intervened to improve the quality of the housing, but in theory, the same principle applies to all housing characteristics.

From the discussion above we predict that happiness accounts for utility that individuals derive from living in a certain dwelling which is not otherwise accounted for in the explanatory variables; happiness captures the unobservable characteristics of the dwelling and is positively associated with transaction prices. However, the characteristics of the neighbourhood play an important role in the utility derived from living in a certain place. If certain neighbourhoods provide higher levels of utility (*ceteris paribus*) to their residents, this means that regional happiness would be positively associated with the transaction prices in an area. Using spatially lagged functions of happiness, this paper aims to disentangle individual unobservable characteristics, related to the dwelling itself, and regional unobservable characteristics.

3 Hedonic value of *emergent* attributes

In the preceding section we argue that structure and neighborhood characteristics that are not recorded in housing market data and hence are unobserved to the analyst might be reasonably be represented by expressions of subjective well-being (SWB) by the residents. As noted this is intuitively plausible and there is evidence in support of the idea.

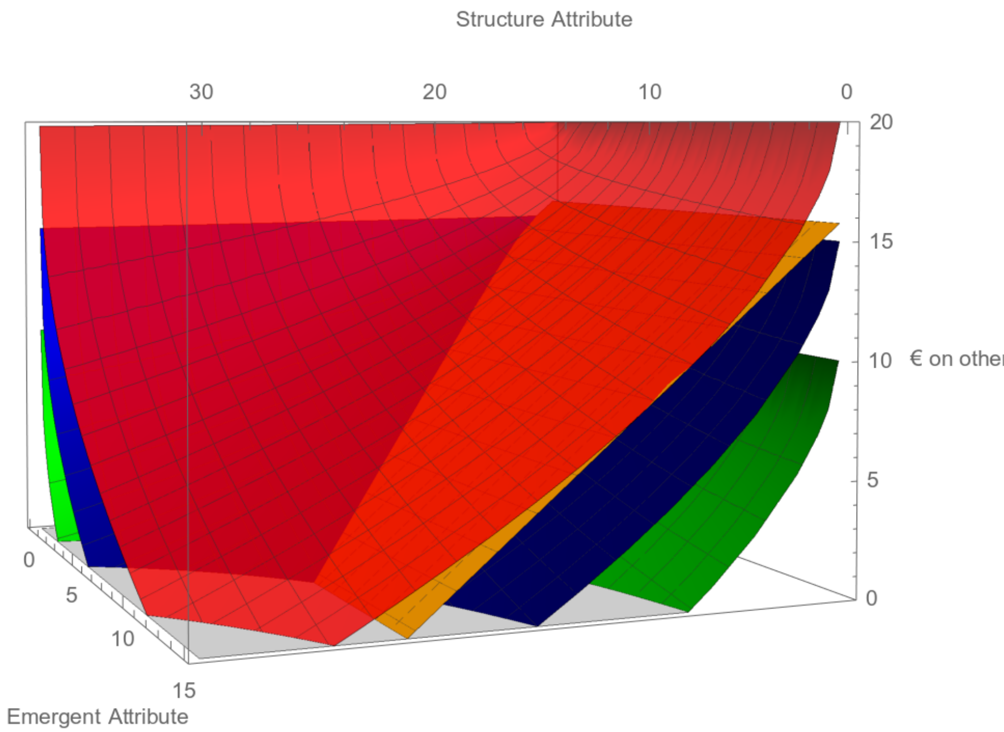
One might object, however, that the presence of desirable but unobserved attributes alone would be unlikely to increase final utility, and hence unlikely to increase SWB, if the price that must be paid for them is high. In this sense unobserved attributes may be no different than other structure or neighbourhood characteristics. Lot size, for example, is reasonably regarded as a desirable characteristic of residential property. Lot size also generally increases as we move from the urban center towards the urban periphery. This is a feature of equilibrium where the household consumes more land in locations where land is relatively less expensive. It does not imply that the household has achieved a higher level of utility, and indeed in an urban model we would expect the level of utility achieved to be invariant across locations for a given income class. If we think of SWB as a measurement of the achieved utility level and if we did not have observations on lot size, it might be argued to be a mistake to take expressed SWB as a "proxy" for lot size.

There are housing or neighbourhood attributes for which data are generally not observed, that could contribute to the overall value of a property but are not a produced addition to the structure or to the infrastructure of the community. We have in mind such attributes as the sense of community experienced by a resident in a neighbourhood where they have come to know several of the local residents with whom they might socialize, informally exchange favors, and rely upon in myriad ways when necessary. Such attributes are not produced in the normal way and they have no cost of production that can be expected to be reflected in the value of land or in some other component of the structure. Such attributes might be said to *emerge* or develop over time as a resident becomes acquainted and comfortable with others in the neighbourhood. As this process unfolds, the level of the emergent attribute increases and the well being of the resident increases without having to increase the amount paid for the house.

Consider a housing market in which the utility derived depends on a mixture of attributes that are available to the resident. The attributes are not priced separately. The attributes can be varied only by relocating to another house with a different combination of characteristics. These attributes can include produced characteristics that are features of the property itself (such as lot size or number of bathrooms), attributes that are "public" in the sense that they are available to any resident of the structure by virtue of the residential location (such as access to a particular school district or open space within a given distance). So far this is equivalent to a standard hedonic model such as that outlined in Sheppard (1999). Each characteristic has a marginal cost of production and the resident will have a marginal willingness to pay for the attribute. In equilibrium of a large, diverse housing market, the marginal cost of production and the marginal willingness to pay must be equal.

We extend this canonical hedonic model by considering attributes that are not produced in the normal sense. They are not observed by the housing market analyst and may not be observed by the household purchasing (or renting) the house until after they have taken up residence. There are several examples that can be raised of such attributes that are *emergent* in the sense that they are not produced but arise from bringing together residents and/or neighbourhood features that become valuable when they are accessible to one another. Figure 1 illustrates indifference manifolds with a *numeraire* composite good on the vertical axis, structure and emergent attributes on the x and y axes, respectively.

Figure 1: Indifference Surfaces

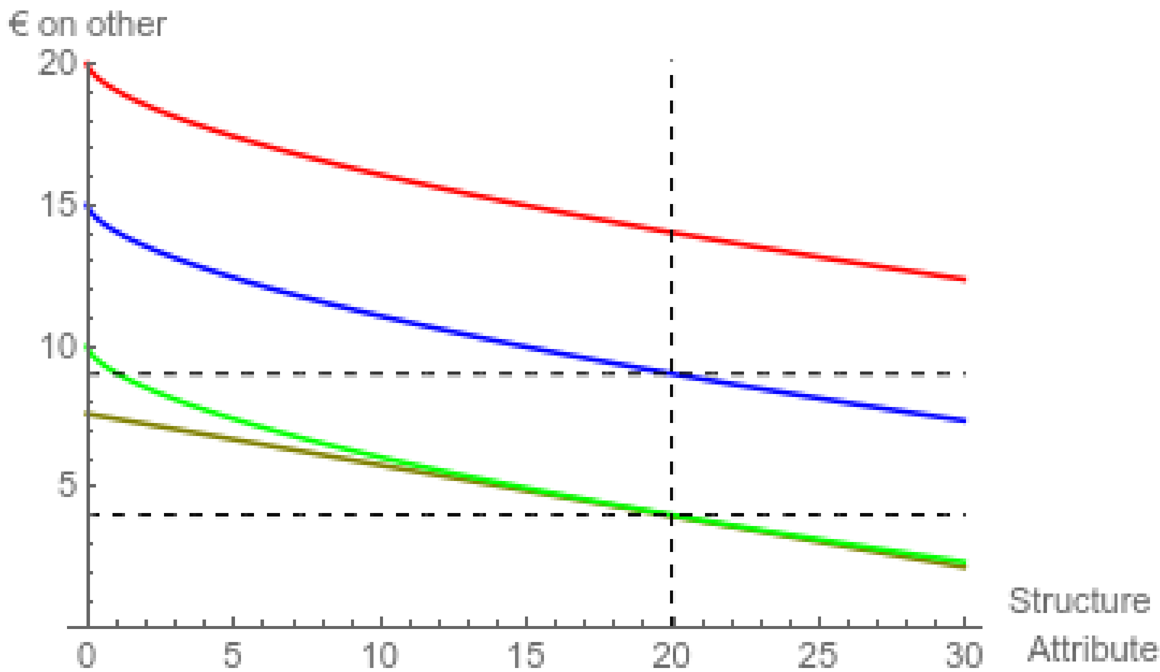


A budget plane extends through these indifference surfaces, and the household considers the trade-off imposed by the budget between expenditure on other goods and the hedonic price of the attribute. No reduction in consumption is imposed as a result of consumption of the emergent attribute, nor is choice really possible. The household would prefer a "more friendly" community but is assumed to make a choice of house and see what emerges in terms of social interaction. The choice of structure attribute is illustrated in Figure 2, where their budget and the hedonic price leads them to choose a house with 20 units of the attribute and permits them to achieve the level of utility associated with the lowest indifference curve.

Taking this structure choice, consider the "slice" through the indifference manifolds illustrated in Figure 3. When the household first arrives in the neighbourhood, they will be at a point like A on indifference curve U_{10}. Over time, they will get to know others in the community and the level of this emergent attribute will increase to a point like B, on indifference curve U_{15}. This illustrates the positive relationship between the level of achieved utility and the quantity of the unobserved emergent attribute, a quantity that can be plausibly approximated by the expressed level of SWB.

If the emergent attribute approximated by expressed SWB cannot be produced, is it reasonable to expect it to have

Figure 2: Indifference and choice of priced attribute

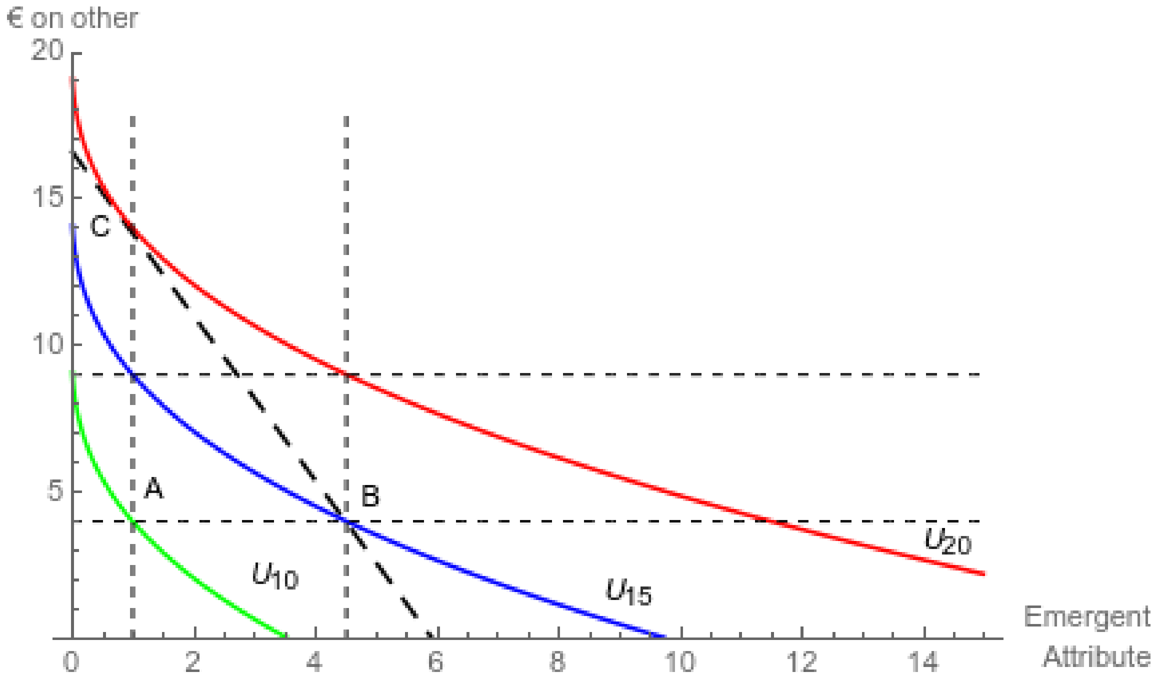


an observable hedonic price? The marginal valuation of the emergent attribute to the household is indicated by marginal rate of substitution at point B. The attribute of a sociable community cannot be produced in the usual way so the normal equilibrium in the hedonic market in which the marginal cost of increasing the attribute is equal to the household's marginal valuation will not hold. In this case the equilibrium hedonic price is the increase in consumption that must be offered to induce the household to vacate the property and move to another house. The equilibrium magnitude of this required incentive will depend on the nature of the discrete adjustment to the new neighbourhood. In Figure 3 the household can change residential location to consume attribute combination C, and the required inducement is indicated by the slope of the dashed line through point B and tangent to indifference curve U_{20} at C. This suggests a positive relationship between the required compensation for moving and the increase in utility.

The nature of this relationship may depend on how the desired consumption of the emergent attribute changes with income (and utility). Research by Bianchi & Vohs (2016) indicates that social contact with neighbours is inversely correlated with income, as is all social contact. They find, based on analysis from the *General Social Survey*, that a doubling of income is associated with a reduction in the total number of days and individual engaged in social contact by about 6. The total number of days during which the individual had social contact with neighbours fell by about 7. This analysis includes controls for a variety of demographic, gender and community factors, and supports the assumption that socializing with neighbours is an inferior good.

Inferiority of the emergent attribute (and convexity of preferences) would further reinforce the expectation of a positive hedonic price for increasing SWB. It implies that the marginal valuation at point C will exceed the original (and lower utility) valuation at point A.

Figure 3: Indifference and choice of emergent attribute



4 Data and empirical strategy

Our goal, then, is to explore whether the inclusion of SWB improves the estimation of hedonic models. To this end, we estimate a threesome of ordinary least squares models using property characteristics, property and neighbourhood characteristics, and property and neighbourhood characteristics and SWB. These three models are then assessed using the Akaike Information Criterion (a Log-Likelihood, penalised for addition degrees of freedom), with lower AIC's reflecting a better fit.

Second, we address the suspected endogeneity between SWB and transaction price, using instrumental variable regression, with SWB as the endogenous variable, and instrumenting with self-reported health. Self-reported health is known to be positively correlated with SWB (Diener, Suh, Lucas & Smith 1999), satisfying the condition that the instrument is correlated with the endogenous variable. The second condition that needs to be satisfied is that there is no direct effect of health on transaction price, and as far as we can ascertain, there is no plausible evidence that health directly affects house prices. Some recent research shows that changes in house prices correspond to health (Atalay, Edwards & Liu 2017), (Fichera & Gathergood n.d.). However, the causal mechanism links a post-transaction increase in median neighbourhood house-price as a proxy for wealth to increases in health. Since the possible changes in median neighbourhood income and subsequent health would occur after this transaction price, they are temporally exogenous to the transaction price paid, satisfying this second condition. We assess the instrumental variables regression with the usual diagnostics, testing for endogeneity in the OLS (Durbin-Wu-Hausman), we test for weak instruments, and we add self-reported pain as a second instrument to test for the overidentifying-restrictions.

Having established the appropriate a-spatial model, we proceed with the estimation of the generalized methods of moments spatial models. As Vega & Elhorst (2015) note, there are a number of ways in which spatial relationships can be modeled. Although a full overview of spatial econometrics is beyond the scope of this paper, we discuss a few key principles to aid legibility. A key principle of spatial econometric models is that there is a spatial component to the data generating process. There are three dominant positions where spatial structures may enter into the data generation process, a spatially autocorrelated dependent term (lag Y), spatial autocorrelation in one or more of the independent terms (lag X), and a spatial disturbance term (spatial error), and all combinations of these three spatial terms. The lag Y term is used when a higher value for the dependent term in one region directly influences the value for the dependent term in the neighboring region. For example, an increase in office floor rents in one region of a cities central business district might directly impact rents in neighboring areas as demand for office space spills over administrative boundaries. The lag X term is used for data where the determinants have a spatial effect on the dependent. For instance, the rate of property crime in one neighborhood might affect house prices in that neighborhood, but this negative effect might also spillover into contiguous neighborhoods. Finally, the spatial disturbance term accounts for spatial autocorrelation in the error term, meaning that spatial clustering in unobservable variables (orthogonal to the model determinants) is accounted for. We use robust Lagrange Multiplier tests for the spatial error specification, and the spatial autoregressive dependent variable (lag Y) specification (Anselin & Kelejian 1997). Based on these test we either choose the GMM spatial error model, or a GMM spatial autoregressive model.

We expect the spatially lagged variable of SWB to act as a measure of neighborhood unobservable variables. Following Anselin & Kelejian (1997), we select the model with the highest robust Lagrange Multiplier test score, we add the spatially lagged SWB variable (as a lag X), and assess the change to coefficients in this spatial durbin error model. Finally, we test the robustness of the results using a series of spatial bandwidths, see Abbott & Klaiber (2011), who state that different amenities interact with capitalization on different scales.

The two main datasets used in this study are from the LifeLines Biobank study and the NVM dataset on real-estate transactions. The LifeLines Biobank is a multi-generational cohort study used to assess multi-morbidity and multi-generational health in the North of the Netherlands (Scholtens, Smidt, Swertz, Bakker, Dotinga, Vonk, van Dijk, van Zon, Wijmenga, Wolffenbuttel & Stolk 2015). Data collection of the initial survey started in 2006, with data included in this survey up to and including 2012. There were three ways participants could join the study. First, respondents aged 25 to 50 were approached through their general practitioner, resulting in a 24.5 per cent response rate (Scholtens et al. 2015). Those who participated were then requested to list their immediate family, who were subsequently invited. This second set yielded a response rate of 70.2 per cent. Finally, people who were not personally approached could enlist through a general website. The data we use in this study is the initial data release of 2013 with data from the baseline questionnaire which was administered to all respondents when they joined the study, comprising a total of 95,413 individuals. Klijs, Scholtens, Mandemakers, Snieder, Stolk & Smidt (2015) report that the study is broadly representative of the population in the North of the Netherlands, with minor differences in gender composition (slightly higher percentage of female participants) and middle-aged individuals (as per the original survey characteristics).

The data from the LifeLines questionnaire is matched with real-estate transaction data from the Dutch Association of Realtors (NVM). The NVM dataset comprises data on the most recent transactions for 153.030 cases in the years 2000-2012 in the North of the Netherlands. As Brounen & Kok (2011) note, the NVM dataset covers about 70 per cent of the Dutch private real estate market with Debrezion, Pels & Rietveld (2011) stating that the scope of the dataset provides enough randomness to alleviate concerns regarding selection bias. The datasets were cross-matched based on addresses using the Municipal Administration (BAG), leaving a total of 18.184 cases for which both real-estate transaction data and LifeLines questionnaire data was available. Tidying the data down to those cases for which SWB data was available, leaves a total of 16.645 cases in the dataset.

This study combines data from two different sources, and as such, selection into either one of these datasets could pose problems. First, the NVM dataset contains around 70% of private property transactions. However, other than the statement by Debrezion et al. (2011) there is little empirical data available to assess the representativeness of the dataset. According to the Dutch National Statistics (CBS) (2018*b*) the total number of properties sold was 232.637, which would have the NVM dataset at 65.8% for the north of the Netherlands, meaning this subset contains broadly the same level of representativeness as used by Brounen & Kok (2011) and Debrezion et al. (2011).

The NVM dataset is matched to the LifeLines dataset, which means we both exclude those property transactions not linked to the LifeLines dataset, and those LifeLines participants not linked to the NVM dataset. From the LifeLines survey design, we know that a relatively large proportion will be between 25 to 50 years old, which might have some bearing on the types of homes in the dataset. To check for undue influences, we compare average price, floor space, and plot size between the matched datasets and the NVM total dataset. We find few discrepancies between the matched dataset and the NVM dataset as whole. Borrowing from the representativeness claims mentioned previously we find the LifeLines dataset broadly representative for the home-owning population in the North of the Netherlands. In addition, for SWB we find there is very little difference between the LifeLines dataset as a whole and the matched dataset. From this, we conclude that our data are broadly representative for the North of the Netherlands.

Operationalization

The use of subjective measures of happiness has seen tremendous progress over recent decades, although the field has yet to reach consensus on which measures are preferable (Frey & Stutzer 2002). Generally, three distinct constructs of happiness are evaluated which capture separate but complementary information on overall subjective well-being. The first component of overall subjective well-being is the general happiness or general life satisfaction component. Generally this is measure either through a single survey item (e.g. all things considered, how satisfied are you with your life these days?) or preferably (Kahneman & Krueger 2006) a compound measure using a set of questions. The general happiness or general life satisfaction component is used to measure a cognitive evaluation of the quality of life by the respondent.

The measurement used for this study is drawn from the SF-36 item short form survey. The SF-36 survey is one of the most widely used health related quality of life studies (Hays & Morales 2001), and groups the 36 items into eight separate constructs. Seven of these deal with a variety of issues relating physical health, subjective health, social functioning, and experienced limitations and pain. The construct from SF-36 we use in this study is Emotional well-being. Emotional well-being is measured on a 0 to 100 scale by weighting and adding together the underlying items, which are to what extent an individual felt happy, nervous, depressed, calm, and downhearted over the past four weeks. The measure is tested for internal reliability (Cronbach's Alpha = 0.83), showing that the underlying items are indeed reliably correlated.

The general SWB scores could be, however, confounded with more short term mood and whether or not the participant was subjected to positive or negative events recently. Several studies show significant deviations for life-satisfaction based on mood (*c.f.* Yap, Wortman, Anusic, Baker, Scherer, Donnellan & Lucas (2017)), although these results were less or not significant on replication.

In our study, we control for these positive events, or temporal mood, through the positive affect score in the PANAS measurement tool (Watson 1988). In addition, correlations between happiness and transaction price could be the function of buyer optimism: Optimistic individuals, indicated by positive affect, are more likely to overestimate the positive outcomes of their decision (Nygren *et al.*, 1996) (although Nygren *et al.* (1988) and Nygren *et al.* (1996) also find that the same individuals are more loss-averse). The estimated consequential utility by optimistic individuals leads to higher transaction prices, as a function of the overestimation of positive outcomes. To avoid confounding optimism related to consequential utility with SWB as a measure of procedural utility, this optimism needs to be controlled for through a measure of positive affect.

There are several important concerns relating to the measurement of positive affect in the LifeLines dataset. The PANAS scales have been extensively validated using relatively short time spans (Crawford & Henry 2004), generally the questions pertain to the most recent week. In the LifeLines survey, the questions are framed for the past four weeks. The validation of such longer time frames is more sparse, but notably (Watson 1988) finds that PA and NA reliability remain high, even with time frames of up to a year.

Table 1 provides an overview of all variables, source, and measurement levels. Some notes on these variables: distance to urban center in the North of the Netherlands is a compound measure, combining population density and population size. Using only size would lead to some large but rural municipalities to be included as urban center. Súdwest Fryslân is the largest municipality by land area and has a higher population than Drenthe's provincial capital Assen, although it is mostly a rural municipality (approximately 85,000 versus 68,000). Similarly, Harlingen is one of the most densely populated municipalities in the North of the Netherlands, but that is mainly the result of the municipal boundary following the urban boundary precisely, with the total population of Harlingen numbering just over 15,000). The compound measure resulted in four central places, Groningen, Leeuwarden, Assen, and Zwolle. Zwolle is located just to the south of the study area, but given the size of the city it seemed appropriate to include the distance to this city. The distance used in the models is the (Euclidean) distance to the nearest major urban center.

Non-western foreigners in the Netherlands are people who have a migration history (their own or at least one of their parents) from Africa, Latin-America, Asia, or Turkey, excluding Indonesia and Japan (Dutch National Statistics (CBS) 2018*a*).

5 Results

We initially estimate an OLS regression with on the left hand side the log of the transaction price, and on the right hand side property characteristics (table 5). This model shows that most of the variable behave as expected, a per cent change in floorspace increases the transaction price with 0.66 per cent, and a per cent change in plot size increases the transaction price with 0.05 per cent. The number of rooms, and availability of bathrooms, balconies, and parking are all associated with an increase in the transaction price. The presence of an attic, basement, and under-roof storage are associated with lower transaction prices. However, per the measurement instruction for usable surface area (NVM and VBO and VastgoedPRO and Vereniging Nederlandse Gemeenten and Waarderingskamer 2018), the quoted floorspace (floorm2) includes all usable surface area, which includes basements, attics, and under-roof storage area. The negative coefficients in the OLS are then the result of some of that usable surface area not being part of the living area. Listed buildings (monuments) are more valuable than those that are not listed, and for non-monuments, a monumental appearance leads to a smaller increase in price. Higher levels of interior and exterior maintenance are associated with higher transaction prices, and similarly higher levels of insulation are associated with higher transaction prices, although buildings with only one layer of insulation appear to sell for less than those with no insulation (reference group). This is probably a spurious result. Structures from the 1980's attract the lowest transaction prices. Finally, the year of transaction dummies show that, with the reference year at 2012, house prices rose from 2000 on to 2007 to 2008, with the sharpest increase between 2000 and 2001. They have since decreased, following the global financial crisis. Between 2011 and 2012 the decrease is the sharpest in the North of the Netherlands, which is consistent with the national statistics (Dutch National Statistics (CBS) 2018*b*).

In the second OLS models we add the neighborhood characteristics. Adding the neighborhood characteristics leaves the coefficient estimates for the property characteristics largely the same, with no changes in sign or significance and only very small (<0.02, <0.03 including maintenance dummies) numerical changes in the coefficients. Increases in density are associated with increases in transaction price, which is consistent with the standard urban land use model (Alonso 1964). Controlling for that, larger distances to an urban center (as a proxy for labor market access) are associated with lower transaction prices, burglaries are associated with lower transaction prices, as is ethnic diversity.

The final OLS model includes subjective well-being and positive affect. Both coefficients are significant and positively related to transaction price. This lends credence to the hypothesis that higher transaction prices are associated with higher derived utility from living in a house and location, which can be measured using subjective well-being. In addition, this model shows that positive affect is associated with a higher transaction price, which would be consistent with the optimistic buyer hypothesis. The AIC's for these three models suggest that the fully specified model is the preferred one, decreasing from -2,153 for the property characteristics model, to -3,112 for the model including neighborhood characteristics, and finally -3,174 for the model including subjective well-being. Similar to (Anselin & Kelejian 1997) we test for spatial dependence in our data, and find robust Lagrange Multipliers of >3,513 for spatial dependence in the error term, and >267 for spatial dependence in the dependent term. These indicate that we need to control for spatial dependence in the data, and that the preferred model is the spatial error model.

Instrumental variables Using the fully specified model, we test for endogeneity between subjective well-being and the transaction price using an instrumental variables regression using self-reported health as the instrument and subjective well-being as the endogenous variable (table 5). The diagnostics show that subjective well-being is significantly endogenous with the transaction price (Wu-Hausman $p < 0.001$). Instrumenting for subjective well-being leaves the sign and significance of most of the coefficients intact, with the exception of positive affect. Although tempting, the mis-specification of the OLS means that we cannot trust the coefficients as reported in the OLS. In our IV, the results indicate that self-reported health is a strong instrument for subjective well-being (weak instruments $p < 0.001$). In order to test for overidentifying restrictions we add a second instrumental variable, self reported pain, and rerun the regression. The resulting Sargan test score has a p-value of 0.33, which means we accept that the instruments self-reported health and self-reported pain are not correlated with the error term. The estimated r-squared results for the IV regressions are lower than those for the OLS, a common feature of using instrumental variables, although the change is only very modest.

The coefficients for the IV regression with instruments self-reported health and pain show that subjective well-being is significantly positively related to transaction price. The coefficient is around 0.18 for both IV specifications, meaning that an increase in subjective well-being of 1 is associated with a 0.18 per cent increase in transaction price. Without previous results to go on, the size of this coefficient seems reasonably plausible.

Spatial models The robust Lagrange multiplier tests suggest that the main dependence problem is associated with the error term rather than spatial auto-regression in the dependent variable. However, as previously specified, we suspect that we might find a spatial lag in the independent variables as well (see Vega & Elhorst (2015)), serving as a proxy for unobservable neighborhood effects. We first calculate a spatially lagged variable of subjective well-being (inverse euclidean distance, 1 kilometer bandwidth) and add this tot the spatial models. The first model we estimate is, therefore, a generalized methods of moments instrumental variables version of the Spatial Durbin Error model, which can be reduced to a spatial error model provided the coefficient for the lagged variable is not significant (see table 5).

The Spatial Durbin Error model specification shows that the lagged subjective well-being variable is significantly and positively related to the transaction price, with a coefficient of 0.20. This is in line with the expectation stated earlier, that areas in which individuals derive a higher utility would be associated with higher transaction prices. The size of the coefficient for subjective well-being has decreased somewhat, relative to the specification without the lagged subjective well-being variable. For completeness the spatial error specification is also reported in table 5. In the spatial error specification we observe a smaller coefficient for the direct effect of subjective well-being on the transaction price as well, indicating that a specification without allowing for spatial structure in the error terms leads to an overestimation of the effect of subjective well-being. In both the Spatial Error model and the Spatial Durbin Error model we find similarly sized significant contributions of subjective well-being, and the precision with which the effect of subjective well-being on the transaction price is measured stays relatively constant for all the instrumental variables regressions (between 0.020 and 0.023). We calculate an approximation of model r-squared by correlating the predicted and observed transaction prices. For the Spatial Durbin Error specification this gives 0.7030, for the spatial error specification 0.7027, and for the GNS 0.7475, indicating reasonably high explained variances, considering no property or regional level fixed effects could be added.

Comparing the coefficients for the controls across the two instrumental models and the two spatial and instrumental models, most of the coefficients stay within the same order of magnitude meaning the results are relatively stable. However, we do see some differences larger differences among the variables that are based on distance functions. This is to be expected, as these are by definition spatially autocorrelated. The only other notable change is the log of the burglary rate, which is significantly negatively correlated in the instrumental variable models but it is not in the spatial models.

Figure 6 shows the results from the first stage estimation of the Spatial Durbin Error model. Compared to the outcome variable, we that there is a good fit for the first stage estimation at the higher levels of subjective well-being. As is common in subjective well-being, fewer people give lower scores for their well-being, meaning the first stage regression can not be estimated with the same level of precision. At the higher end of the scale, we see that the first stage estimates exceed the maximum theoretical value of the subjective well-being scale. This is likely the result of a ceiling effect quite commonly found in self-report well-being and health scales, where beyond a certain level of happiness marginal gains can no longer be registered in the survey. Given the lower numbers of respondents involved in the problems at the lower end of the distribution and at the higher end of the distribution, we believe these deviations are unlikely to have much leverage for shifting the coefficients for subjective well-being.

Finally, we check for spatial autocorrelation in the residuals using Moran's I, and find that this remains an issue. All three model specifications report significant residual spatial autocorrelation, with the statistic relatively similar for the Spatial Durbin Error and Spatial Error models, and lower (but still significant) for the GNS model. The residual maps are displayed in 4 and give an indication of the location of the spatial autocorrelation. Given the cross-sectional nature of our data, the usual approach of region fixed effects is not an option. The locations of the high and low residuals do make a lot of intuitive sense, considering some background characteristics of the North of the Netherlands. The main low cluster towards the east of the North of the Netherlands corresponds with the Veenkoloniën and Oldambt areas, which have a history of difficult economic development, and relatively low levels of in-migration (Rijnks & Strijker 2013), (Thissen et al. 2010). Similarly, the region to the north of the mainland was, at the time of measurement starting a shift towards population decline and demographic aging (Haartsen & Venhorst 2010). The finding that house values are depressed somewhat in these regions is not surprising, and would be remedied by a regional fixed effects specification. The smaller clusters of positive residuals appear to correspond with smaller urban regions, indicating that there is perhaps a non-linearity to the effect of population density or labor market opportunity. Up to a five degree polynomial for population density was added to the model to correct for this. This did not resolve the issue, in part because the effect does not appear to be general across all smaller urban areas. This indicating that some unobserved regional effect or interaction, specific to some but not all smaller urban areas, remains.

6 Conclusion and Discussion

This paper aims to establish a connection between transaction prices and subjective well-being measures as a proxy for both unobservable house characteristics and unobservable neighborhood characteristics. The unobservability of housing characteristics is one of the main problems facing housing market researchers. The extent of these problems ranges from not being able to identify property level characteristics (e.g. interior arrangement, curb appeal), as well as regional characteristics (e.g. subtle differences between amenities such as expensive versus low-cost supermarkets). This unobservability can stem from a lack of data, or from the unobersvable characteristics emerging after the sale, such as friendliness of the neighbors. Recent progress in happiness research (Diener & Suh 1997), (Veenhoven 2012) shows that a measure of happiness might be usefully employed to estimate utility. This paper aims to combine progress in the literature surrounding happiness with hedonic modeling, using subjective well-being as a proxy measure for utility derived from unobservables at the house or regional levels.

We find that subjective well-being is significantly and positively correlated with transaction prices, after correcting for a large number of know correlates. Using instrumental variables regressions we show that the subjective well-being of the owner/occupier is endogenous with the transaction price paid for the property. Instrumenting for self-reported health and pain allows us to get a consistent estimate of a one *per cent* increase in subjective well-being corresponds to an approximately 0.18 *per cent* increase in transaction price. This effect is consistent with what would be expected from the literature linking subjective well-being with utility, and in size is within a plausible range. The relationship between subjective well-being and transaction price remains positive and significant when estimated using the explicit spatial two stage least squares regression detailed in Kelejian & Prucha (2010). The relation shows that measured utility is positively associated with transaction price at the individual house or household level, and at the regional level.

The outcomes from this study reveal that subjective well-being indicators can be usefully employed to estimate the impact on price of unobserved characteristics using hedonic pricing models. Model estimation improved with the inclusion of the direct effect of subjective well-being, and similarly for the regional effect of subjective well-being.

The models estimated here add to the plausibility of subjective well-being as a measure of *in situ* utility. The coefficients estimated in the models are positive and significant, both for the direct effect as well as the spatially lagged effect of subjective well-being. The results are consistent with the hypothesis that motivates this paper and that almost every house buyer or estate agent understands: there are unobserved and difficult-to-measure attributes of structure, neighborhood, and community that affect the utility of a house or residential location. While these factors do not show up in usual property data, they affect the willingness-to-pay of a buyer after inspection of the house, or the price that must be paid to induce a resident to sell the house and relocate. Our study provides the first estimates of the importance of these effects.

Table 1: Variables used in analysis

Variable	Source	Measurement level	Description
Ln(floor area)	NVM	Property	Natural log of floorspace in the house, natural numbers, missings deleted. The floorspace reported is the residential floorspace, as used by the NVM measurement instructions. This is the net square meterage of the house, excluding area <1.5 meters high, and rooms which are lower than 2 meters, or otherwise suitable for storage only. Lofts, attics, and basements are included in this measurement provided they have more than 4 square meters floorspace with standing hight of over 2 meters tall, and a window.
Ln(plotsize)	NVM	Property	Natural log of square meters plot size, natural numbers, missings deleted. Square meters measured taken from national registry, 0 for apartments
Ln(rooms)	NVM	Property	Natural log of the number of rooms
Ln(bathrooms)	NVM	Property	Natural log of the number of bathrooms
Balcony	NVM	Property	Dummy indicating presence of one or more balconies
Parking	NVM	Property	Dummy for private parking 1=yes
Basement	NVM	Property	Dummy for basement 1=yes
Attic	NVM	Property	Dummy for attic 1=yes (possibly more accurately this could be termed the LOFT)
Under roof	NVM	Property	Dummy for under roof storage area 1=yes (possibly more accurately this could be termed the ATTIC)
Monument	NVM	Property	Dummy for listed building 1=yes
Monumental	NVM	Property	Dummy for monumental appearance (assessed by realtor) 1=yes
Maintin	NVM	Property	Quality of maintenance indoors (assessed by realtor) 1=poor through 9=excellent
Maintout	NVM	Property	Quality of maintenance outdoors (assessed by realtor) 1=poor through 9=excellent
Insulation	NVM	Property	Measurement of level of insulation (assessed by realtor), 0= no insulation, 1= one type of insulation, 5= fully insulated

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Variable	Source	Measurement level	Description
Ln(urban distance)	CBS	Property to municipal centroid	Natural log of distance to nearest major urban center. Due to municipal arrangement in the North of the Netherlands, population size alone is not a sufficient proxy, as some municipalities are large in population, but also large in area. Similarly, population density is not a great proxy alone, as some municipalities are more narrowly defined (spatially), leading to higher densities. To counter both, we have defined major urban areas as those that are both in the 90th percentile regarding population size and population density. This leaves Groningen, Leeuwarden, and Assen. As Zwolle is a sizeable city, but just outside the study area, we have included the distance to Zwolle as well.
upto1905	NVM	Property	Building period for the property (dummies), reference category is built between 2000 and 2012.
upto1930	NVM	Property	
upto1944	NVM	Property	
upto1959	NVM	Property	
upto1970	NVM	Property	
upto1980	NVM	Property	
upto1990	NVM	Property	
upto2000	NVM	Property	
Ln(density)	CBS	Municipality	Natural log of population per square kilometer, at the municipal level. Controls for effects of smaller population centers (rural towns and large villages)
Ln(foreign)	CBS	Municipality	Natural log of 1 + percentage of population with a non-western background. Measured at the municipal level, included as a proxy for ethnic diversity in the neighbourhood. Non-western foreigners are individuals who were born (or who have one parent born) in Africa, Latin-America, or Asia (excluding Japan and Indonesia).
Ln(burglary)	Politie	Municipality	Natural log of 1 + number of burglaries per 10.000 inhabitants in a municipality (2012), published by Dutch Police.
Ln(well-being)	LifeLines	Individual	Natural log of 1 + RAND-36 survey tool, component: Emotional well-being. Measured as: Over the past 4 weeks, how often were you: depressed, nervous, calm, downhearted, happy. The questions are scored to correspond to a 0-100 scale, where higher is better, and averaged per individual.

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Variable	Source	Measurement level	Description
Ln(positive affect)	LifeLines	Individual	Natural log of 1 + PANAS Positive affect negative affect scales, with PANAS PA as the positive affect component, and PANAS NA as the negative affect component.
Ln(negative affect)	LifeLines	Individual	
Lag Ln(well-being)	LifeLines	Individual	Spatial lagged value of natural log of 1 + emotional well-being. Lagged by up to 1, 2.5, 5 and 10 kilometers, using an inverse euclidean distance weighting.
y2000	NVM	Property	Transaction year indicators, reference category is 2012.
y2001	NVM	Property	
y2002	NVM	Property	
y2003	NVM	Property	
y2004	NVM	Property	
y2005	NVM	Property	
y2006	NVM	Property	
y2007	NVM	Property	
y2008	NVM	Property	
y2009	NVM	Property	
y2010	NVM	Property	
y2011	NVM	Property	

Table 2: Descriptive statistics for model variables

Variable name	Mean	Std Dev	Min	Max
Property sales price	199,116	96,523	18501	2450000
Ln(sales price)	12.110	0.418	9.826	14.712
Ln(positive affect)	3.552	0.419	1	5
Ln(well-being)	79.134	13.524	0	100
Lag well-being	79.078	4.394	24	100
Ln(urban distance)	9.366	1.149	2.692	10.769
Ln(density)	5.874	0.943	4.007	7.797
Ln(foreign)	1.362	0.605	0	2.398
Ln(burglary)	29.021	14.170	5.700	56.700
Ln(floor area)	4.808	0.294	3.401	6.223
Ln(plotsize)[1]	5.419	1.764	0	11.206
Ln(rooms)	4.796	1.287	0	34
Ln(bathrooms)[2]	0.948	0.393	0	3
Balcony	0.124	0.337	0	2
Dichotomous Variables				
Parking	0.600	0.490	0	1
Basement	0.932	0.252	0	1
Attic	0.336	0.473	0	1
Under Roof Area	0.140	0.347	0	1
Listed	0.004	0.067	0	1
Monument	0.007	0.083	0	1

[1]Flats have no recorded plotsize so that Ln(plotsize+1)=0. Other properties have minimum values for this variable greater than 0.

[2]To count as a bathroom the property must have both a toilet and bathing/washing facilities. One property in the sample had only toilets, hence the minimum value of 0.

Table 3: Data observations available and excluded

		Source	
	Lifelines	**Merged**	**NVM**
Observations available	95,413		191,804
With location information	75,292		$\downarrow$
In North of Netherlands	74,074		$\downarrow$
With data on plotsize and parking	$\downarrow$		190,411
Keep only most recent sale	$\downarrow$		153,030
	$\searrow$		$\swarrow$
Observations successfully merged		18,184	
With socio-economic data		18,010	
With subjective well being and affect		17,439	
Plotsize $<$ 100,000 m^2		17,428	
Floor area $>$ 0		17,231	
Price $<$ €100 million		17,229	
Price $\geq$ €1000		17,218	
With reliable geocode		16,957	
With some obs in neighbor cells		16,645	

Table 4: Descriptive statistics for indicator variables

Variable	**Mean**	**Variable**	**Mean**
Interior maintenance		*Exterior maintenance*	
Interior 1 (Poor)	0.002	Exterior 1 (Poor)	0.003
Interior 2	0.001	Exterior 2	0.000
Interior 3	0.009	Exterior 3	0.007
Interior 4	0.003	Exterior 4	0.003
Interior 5	0.059	Exterior 5	0.056
Interior 6	0.030	Exterior 6	0.033
Interior 7	0.764	Exterior 7	0.775
Interior 8	0.015	Exterior 8	0.014
Interior 9 (Excellent)	0.117	Exterior 9 (Excellent)	0.110
Construction period		*Year property sold*	
Up to 1905	0.047	Y_{2000}	0.054
1906-1930	0.104	Y_{2001}	0.067
1931-1944	0.078	Y_{2002}	0.077
1945-1959	0.056	Y_{2003}	0.078
1960-1970	0.134	Y_{2004}	0.084
1971-1980	0.218	Y_{2005}	0.100
1981-1990	0.133	Y_{2006}	0.109
1991-2000	0.179	Y_{2007}	0.111
2000 and later	0.052	Y_{2008}	0.092
		Y_{2009}	0.069
Insulation		Y_{2010}	0.063
No insulation	0.115	Y_{2011}	0.054
1 type of insulation	0.331	Y_{2012}	0.043
2 types of insulation	0.133		
3 types of insulation	0.121		
4 types of insulation	0.104		
Fully insulated	0.196		

Table 5: Hedonic model estimates

Variable	OLS Model 1	OLS Model 2	OLS Model 3	IV Health	IV Health/Pain	Spatial Durbin	Spatial Error
Behavioural and Subjective Characteristics							
Ln(well-being)			0.0385***	0.1810***	0.1745***	0.1361***	0.1239***
σ			*0.009*	*0.029*	*0.026*	*0.020*	*0.023*
Lag Ln(well-being)						0.1984***	
σ						*0.040*	
Ln(positive affect)			0.1019***	-0.0077	-0.0027	-0.0060	-0.0071
σ			*0.020*	*0.029*	*0.028*	*0.021*	*0.024*
ρ						0.6046***	0.6048***
σ						*0.007*	*0.007*
Environmental characteristics							
Ln(urban distance)		-0.0053*	-0.0055*	-0.0058*	-0.0058*	-0.0153**	-0.0143**
σ		*0.002*	*0.002*	*0.002*	*0.002*	*0.005*	*0.005*
Ln(density)		0.1008***	0.1006***	0.1003***	0.1003***	0.0945***	0.0953***
σ		*0.005*	*0.005*	*0.005*	*0.005*	*0.010*	*0.010*
Ln(foreign)		-0.1536***	-0.1535***	-0.1531***	-0.1531***	-0.1579***	-0.1582***
σ		*0.009*	*0.009*	*0.009*	*0.009*	*0.018*	*0.018*
Ln(burglary)		-0.0185***	-0.0181***	-0.0171**	-0.0171**	-0.0099	-0.0109
σ		*0.005*	*0.005*	*0.005*	*0.005*	*0.012*	*0.012*
Ln(water distance)		-0.0087***	-0.0087***	-0.0088***	-0.0088***	-0.0170***	-0.0171***
σ		*0.002*	*0.002*	*0.002*	*0.002*	*0.002*	*0.002*
Ln(forest distance)		-0.0045*	-0.0043*	-0.0038*	-0.0038*	-0.0114***	-0.0117***
σ		*0.002*	*0.002*	*0.002*	*0.002*	*0.003*	*0.003*
Ln(nature distance)		-0.0553***	-0.0549***	-0.0546***	-0.0546***	-0.0405***	-0.0413***
σ		*0.003*	*0.003*	*0.003*	*0.003*	*0.005*	*0.005*
Structure characteristics							
Ln(floor area)	0.6617 ***	0.6509***	0.6487***	0.6473***	0.6473***	0.5791***	0.5798***
σ	*0.009*	*0.009*	*0.009*	*0.009*	*0.009*	*0.008*	*0.008*
Ln(plotsize)	0.0461 ***	0.0514***	0.0514***	0.0514***	0.0514***	0.0627***	0.0627***
σ	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*
Ln(rooms)	0.0309 ***	0.0327***	0.0326***	0.0323***	0.0323***	0.0515***	0.0520***
σ	*0.009*	*0.009*	*0.009*	*0.009*	*0.009*	*0.008*	*0.008*

*** - $p < 0.001$, ** - $p<0.01$, * - $p<0.05$

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Variable	OLS Model 1	OLS Model 2	OLS Model 3	IV Health	IV Health/Pain	Spatial Durbin	Spatial Error
Ln(bathrooms)	0.2079 ***	0.2022***	0.2010***	0.1995***	0.1995***	0.1524***	0.1522***
σ	*0.012*	*0.011*	*0.011*	*0.012*	*0.012*	*0.010*	*0.010*
Balcony	0.1195 ***	0.1158***	0.1153***	0.1153***	0.1153***	0.0755***	0.0757***
σ	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.005*	*0.005*
Parking	0.1244 ***	0.1342***	0.1338***	0.1327***	0.1327***	0.1224***	0.1232***
σ	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
Basement	-0.0191 *	-0.0228**	-0.0226**	-0.0222**	-0.0222**	-0.0345***	-0.0344***
σ	*0.008*	*0.008*	*0.008*	*0.008*	*0.008*	*0.007*	*0.007*
Attic	-0.0392 ***	-0.0371***	-0.0373***	-0.0389***	-0.0389***	-0.0289***	-0.0292***
σ	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
Under roof	-0.0064	-0.0051	-0.0054	-0.0074	-0.0073	-0.0111*	-0.0117*
σ	*0.006*	*0.006*	*0.005*	*0.006*	*0.006*	*0.005*	*0.005*
Listed	0.2466 ***	0.2316***	0.2290***	0.2261***	0.2262***	0.1792***	0.1790***
σ	*0.029*	*0.028*	*0.028*	*0.028*	*0.028*	*0.024*	*0.024*
Monument	0.1416 ***	0.1425***	0.1400***	0.1418***	0.1418***	0.1577***	0.1563***
σ	*0.024*	*0.023*	*0.023*	*0.023*	*0.023*	*0.020*	*0.020*
Constant	8.3236 ***	8.6177***	8.3084***	7.8719***	7.8917***	7.5047***	8.4224***
σ	*0.072*	*0.085*	*0.094*	*0.126*	*0.121*	*0.248*	*0.134*
Int/Exterior maintenance	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Insulation level	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Construction Period	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year of sale	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Residual σ	0.225	0.218	0.217	0.219	0.219		
R^2	0.704	0.722	0.724	0.719	0.720		
$\bar{R}^2$	0.702	0.721	0.722	0.718	0.718		
F	675.50 ***	652.30***	634.80***				
LM Error	4877.90 ***	3563.30***	3513.40***				
LM Lag	177.79 ***	259.86***	266.69***				

*** - p < 0.001, ** - p<0.01, * - p<0.05

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Variable	OLS Model 1	OLS Model 2	OLS Model 3	IV Health	IV Health/Pain	Spatial Durbin	Spatial Error
Wald test				625.10***	626.00***		
Weak instruments				1744.49***	57.11***		
Wu-Hausman				28.08***	31.01***		
Sargan					0.33		

*** - $p < 0.001$, ** - $p<0.01$, * - $p<0.05$

Figure 4: Residual maps for selected models

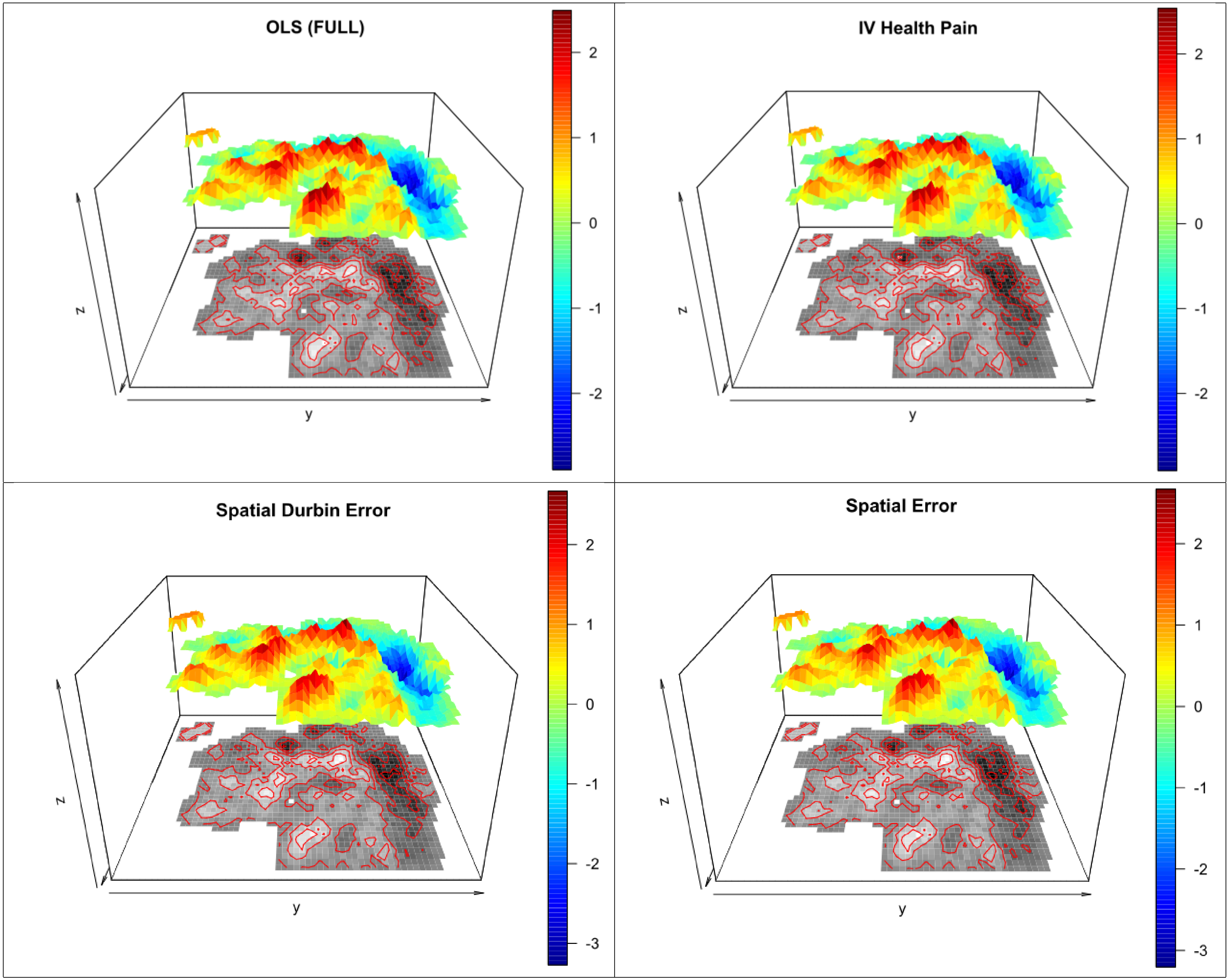


Figure 5: North Holland Region

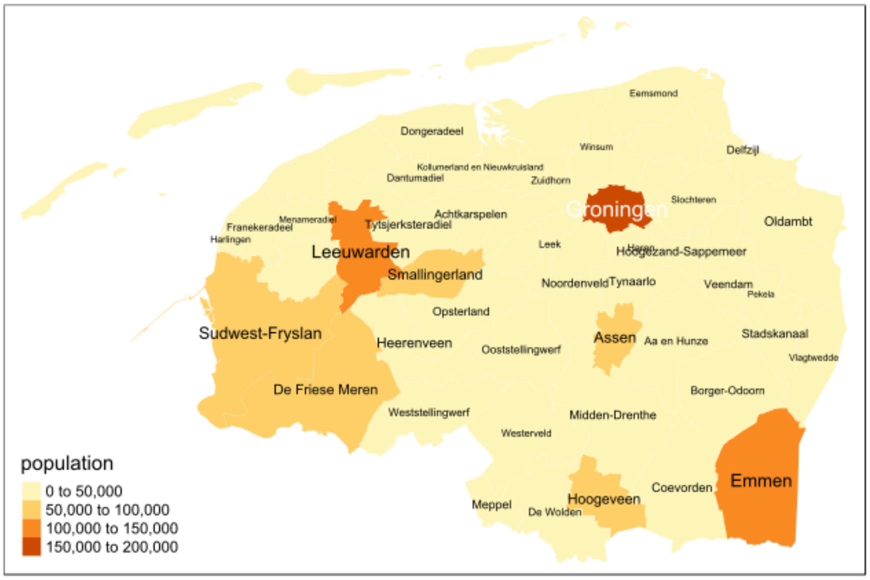


Figure 6: Residuals from instrument estimate of SWB

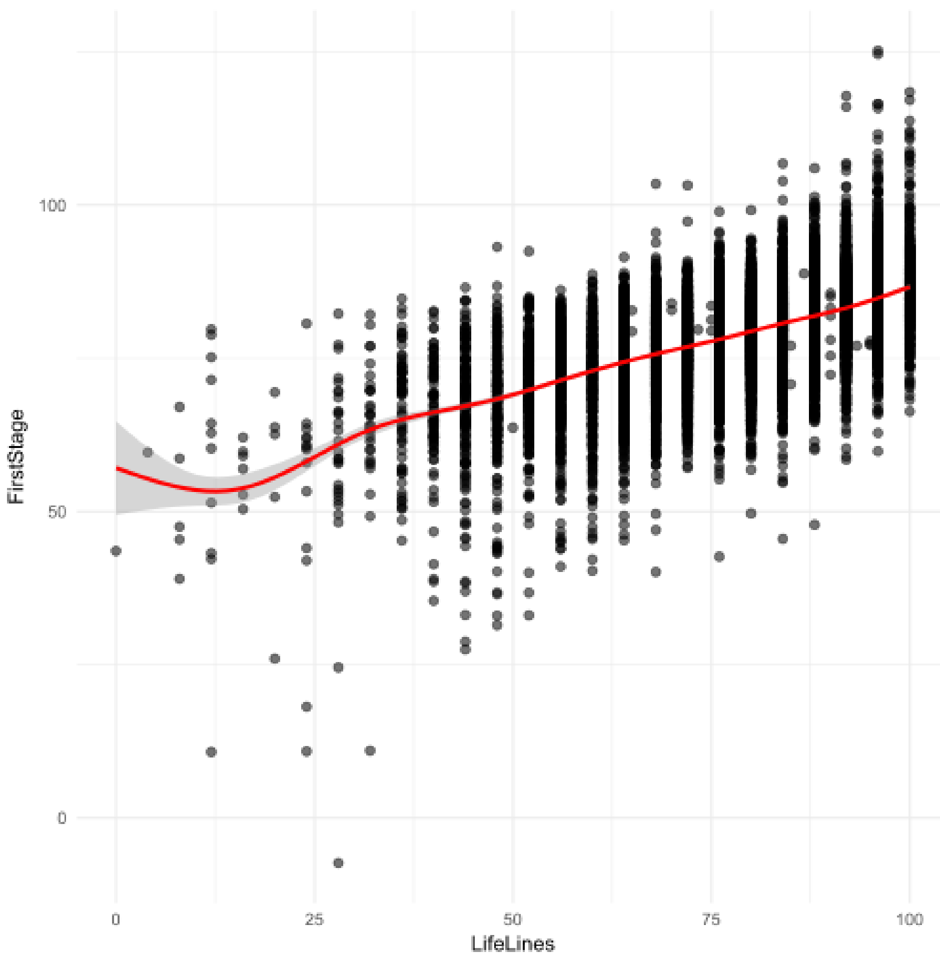
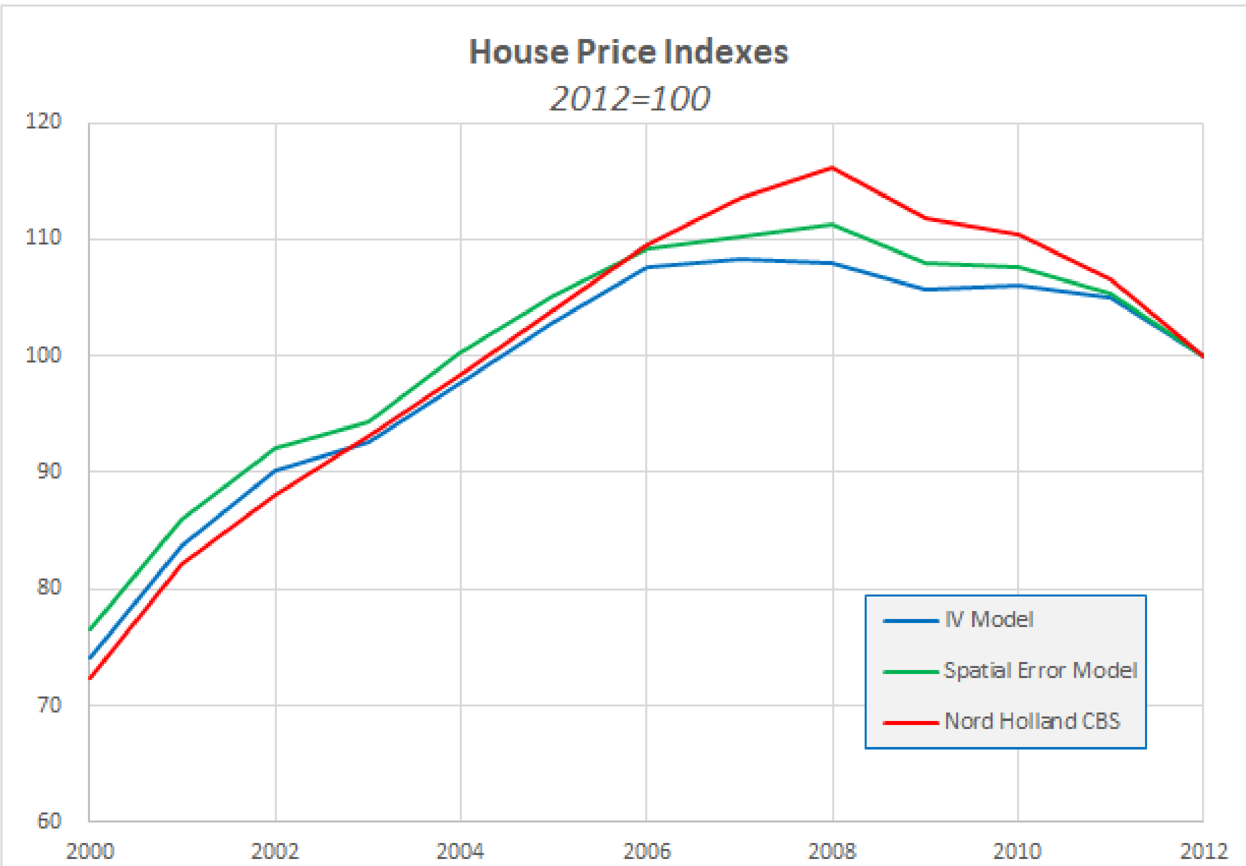


Figure 7: Indices implied by model estimates compared with CBS repeat sales index for north NL



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