Occupant Well-Being and House Values[†]

Richard H. Rijnks[‡] Stephen Sheppard [§]

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Abstract

Recent research indicates that the subjective evaluation of well-being increases when conditions of housing are improved. This suggests that subjective well-being might serve as a useful proxy for characteristics of a home or neighbourhood that are relevant to an occupant, but unobserved by the analyst. In this paper, we assess this idea through analysis of residential property valuation, using a sample of 95,413 respondents matched to house sales for 2000 to 2012 in the North of the Netherlands. Using a spatial econometric approach, we find a significant and positive association between individual and regional subjective well-being and house prices. This suggests that house buyers are willing to pay more for, or that house sellers require greater compensation to sell and move from, properties and areas in which the resident experiences greater happiness. Our study provides the first estimates of the importance of these effects.

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[‡]Department of Economic Geography, University of Groningen, Groningen, Netherlands

[§]Department of Economics, Williams College, Williamstown, Massachusetts

1 Introduction

Hedonic models popularised by Rosen (1974) and others are fundamental to analysis of prices in markets for differentiated commodities. 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." In hedonic models of house prices, these characteristics generally deal with characteristics of the property, and characteristics of the environment. Treating houses as differentiated products, the transaction price paid for the house is a function of observed and unobserved characteristics of the house.

Unobserved characteristics pose difficulties in estimation of the parameters of hedonic models, which requires data on all relevant characteristics of the product as noted in Bajari and Benkard (2005). Obtaining accurate estimates of the contribution to value of individual characteristics of properties relies on the assumption that the model is estimated using data on all 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 amounts of unobserved characteristics are correlated with the observed characteristics, then the estimates of the contribution to value of the observed 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 suggests an approach that might address some of 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 and Suh (1997) and Veenhoven (2012) show that measures of self-reported happiness on the whole "measure what they set out to measure". This means that, following Frey and 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 estimate the value of unobservable structure or neighbourhood attributes. Interpreting happiness as a measure of well-being, a higher level of happiness implies that (*ceteris paribus*) a person is deriving greater benefit from their life-situation, including living in a certain house or neighbourhood. Including subjective well-being (SWB) in the hedonic price function as a measure of unobserved attributes will then improve the estimation of the hedonic price function.

This paper is not the first to use SWB as a measure of unobserved utility. Previously, Goetzke and Islam (2017) used measures of SWB to identify deviations from a spatial equilibrium of utility. The basis of their analysis is that in equilibrium SWB would be equal across space. They show, controlling for individual level variables, that there is evidence of a spatial disequilibrium with marginal rates of substitution of around $16,000 to move from regions with the lowest values to the mean. In addition, Goetzke and Islam (2017) find that positive deviations from spatial equilibrium in SWB are associated with higher subsequent in-migration.

The link between neighbourhood location or housing characteristics and SWB has motivated several applications of SWB in analysis of residential location or housing markets. For example, Stutzer and Frey (2008) examine the association between SWB and time spent commuting, and find a consistently negative relationship. Standard urban economic theory would suggest that increased commuting time is the implicit price paid for access to better labor markets or housing, and that in equilibrium the utility (and possibly the SWB) would be equal at all locations. They label the negative association as the "paradox of commuting" and offer some possible explanations including intra-household bargaining and frictions that keep households from reaching equilibrium location patterns. Dickerson et al. (2014) tackle this paradox econometrically, suggesting that while the association is negative and precisely estimated in pooled ordered logit models of SWB, the situation is less clear using fixed-effects or more exotic estimation techniques. Using these alternative estimation methods does not reverse the sign of the estimated relationship, but the magnitude is reduced and the variance of the estimator increased sufficiently that we cannot say that the association is not zero, as theory might predict.

Other studies examine a more direct association between SWB and housing or neighbourhood characteristics. 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 et al. (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 and 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 or idiosyncratically-valued structure and neighbourhood 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 unobserved 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 could correlate with things such as curb appeal, odours, and proximity to friends and family.

In addition to the individual unobserved attributes of 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 and Prucha (2010) which allows us to incorporate a Spatial Error specification, as well explicitly control for possible endogeneity between the measure of occupant SWB and the transaction price. We adjust for the endogeneity of happiness and the (log of the) transaction price using an instrumental variables approach. We use the package 'sphet' in R to estimate the spatial models, discussed in Piras (2010).

The data we use in this study consists of a large scale (95,413 individuals) multi-generation biobank survey called LifeLines, the data-collection run used in this study was collected between 2006 and 2012 and focuses on the North of the Netherlands. The survey contains individuals' place of residence (addresses) 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 as described in Brounen and 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 Hedonic analysis with unmeasured attributes

Housing is a heterogeneous good consisting of varying quantities of attributes, which makes measurement of value and analysis of demand more difficult, as discussed in Sheppard (1999). Hedonic models allow the estimation of prices at the level of the relatively homogeneous component attributes (the implicit markets), facilitating valuation and analysis of the heterogeneous individual properties. The hedonic prices of these characteristics depend upon the household's willingness-to-pay (determined by the household's preferences and income) and the costs of bringing to market structures for sale, whether through new production or resale of existing structures.

There are two problems that arise from unobserved factors when estimating a hedonic price function. First, not all attributes related to the house or immediate neighbourhood are directly measurable, as discussed in Folmer et al. (2014). Second, as discussed in Niedomysl (2011), individual household preferences are difficult to measure or control for, which may be required if we are using data that arise from diverse households in many communities.

The nature of these markets, as discussed by Bockstael and McConnell (2007), with properties that are structurally different and in different locations results in (at least) two sources of omitted variable bias: omitted variables related to the property or the buyers alone, and omitted variables related to the neighbourhood or environment. The first category of omitted variables contains those housing characteristics that are not usually measured but that do influence the price of the house. Data on some attributes such as noise and smell, might be available (perhaps through proxies) for larger sources of nuisance, e.g. airports or recycling stations as discussed in van Praag and Baarsma (2005) and Anselin and Lozano-Gracia (2008). For more modest sources, data are rarely available, or are time (and occupant) dependent, and very local in the extent of impact.

Beyond these localised external effects, structure design and layout may enhance the well-being of occupants but be difficult to measure or quantify even though they are readily observed by a prospective buyer. For such subjective considerations it might be expected that different combinations of attributes lead to different outcomes as discussed in Helbich et al. (2013). These property-level unobserved characteristics could significantly influence price, and, more importantly, they could be related to other measured attributes: 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 or maintenance status. In short, these specific and frequently unrecorded property features are unlikely to be orthogonal to the other factors included in the model.

A second category of unobserved attributes relates to the situation of the property 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. While the location of the house with respect to labour market opportunities is the central determinant of property values as noted by Tomkins et al. (1998), disamenities such as pollution and crime can result in lower transaction prices as found by van Praag and Baarsma (2005) and Anselin and Lozano-Gracia (2008). Analogous to the unrecorded characteristics of properties mentioned above, unrecorded or difficult-to-observe features of the residential neighbourhood can alter household well-being within that neighbourhood. Indeed Tivadar and Jayet (2019) argue that differentiation in willingness to pay for (local) amenities between more and less affluent buyers affects property values at the neighbourhood level. In their model of urban house price patterns, local amenities have a long term effect on house prices which in turn contributes to the generation of new amenities valued more specifically by wealthier individuals.

Even when local neighbourhood attributes are relatively well known, data availability can be poor as noted by Jim and Chen (2009). Cheshire and Sheppard (2004) and Panduro et al. (2018) found that local amenities such as parks and the quality of schools affect observed transaction prices. Not all parks and open spaces are equivalent, nor is it easy to discern *ex ante* which specific amenities will affect transaction prices. For example, the report presented in Lloyds Bank (2016) introduced the "Waitrose effect" and found that proximity to supermarket chains could lead to price premia ranging from about one to nearly 39 thousand pounds, depending on which supermarket chain was located nearest a property. Price premia also varied from one region to the next. Grislain-Lerémy and Katossky (2014) find a similar variation regarding proximity to hazardous industrial facilities between three French cities, concluding that dissimilarities in neighbourhoods and perceived risk likely explain the variation.

The heterogeneity of these impacts suggests that the value of some amenities will be highly location-specific, while others may affect much larger regions. At the very local scale, Fleming et al. (2018) show that reducing daily sunlight hours as a result of neighbourhood development in Wellington, New Zealand, is associated with a non-trivial decline in property values. Taking a more regional focus, regional image or regional branding can influence how attractive a region is as a destination for a household as noted by Rijnks and Strijker (2013) and Haartsen et al. (2013). These perceptions of an area interact with a variety of factors varying from individual residential history, to life course stages, and sense of place as discussed in Thissen et al. (2010).

Recent developments in research on spatial heterogeneity suggest that both the correlation between local amenities and desirability of the location (noted in Rijnks et al. (2018)) and the correlation between property characteristics and desirability of the property (discussed in 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, as discussed in Billé et al. (2017).

For cross-sectional studies, the most common approach is the use of regional proxies (e.g. presence of forests and lakes) and regional dummies. Abbott and Klaiber (2011) are critical of the use of regional indicators at relatively small levels of spatial disaggregation for two reasons. First, they inhibit the ability to find spatial effects at scales smaller than that of the variables and, second, they capture some of the spatial effects of amenities at larger spatial scales meaning that the measured capitalisation is lower than the real capitalisation of these amenities.

A second method used to control for unobserved spatially autocorrelated effects 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 as discussed in Vega and Elhorst (2015). The spatial component in the error term represents a spatial process that is otherwise unaccounted for in the model. Although OLS estimates remain unbiased even when a spatial error model would be appropriate, the standard errors obtained are inefficient. This is corrected by using a spatial error model. The drawback of using this type of modelling is that the Spatial Error model provides no further information on the unaccounted for spatial process, other than its existence. In addition, because the Spatial Error model is estimated globally, it accounts for spatially autocorrelated individual variations in, for instance, preferences for amenities, through the model's error term.

3 Subjective well-being and unobserved amenities

One solution to the problem of unobserved or unmeasured amenities and spatial effects in cross-sectional studies is the inclusion of a proxy for these variables. Recent progress in research into happiness by *inter alia* Veenhoven (2012) and Diener and Suh (1997) suggests that SWB could be a reasonable proxy for the utility impacts of these unobserved factors.

The use of self-reported measures of happiness and SWB has been widely used in psychology and seen increasing use in economics. Frey and Stutzer (2002) identify a number of benefits to using happiness as a complement to income in the economics literature, starting with Easterlin (1974) who examined the cross-sectional and longitudinal association between income and happiness. The analysis revealed that, although correlated cross-sectionally, income and happiness were not closely related in longitudinal studies. This "Easterlin paradox" suggested a conceptual separation between income and happiness, and required a nuanced use of SWB as a measure of utility. As suggested by Sen (1987) and Frey and Stutzer (2005), individual utility may be best thought of as being determined by *consequential* utility (resulting from conventional choice among alternatives) and *procedural* utility that is derived or emerges from a process, irrespective of the choice made. Some important attributes of housing consumption such as social capital and the external amenity derived from friendships and familiarity with the neighbourhood may emerge from such processes.

As noted above, while studies have examined the relationship between happiness and housing consumption, researchers do not agree about the positions of happiness and home-ownership relative to each other. Ferreira and 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 fully reflected in the hedonic valuation of the property. The authors argue that market imperfections and imperfect information explain this discrepancy. 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 that could contribute to difficulties in estimating the relationship between the house prices and subjective well-being, varying from the use of average house prices for the region (as opposed to individual structure price) and collinearity arising from inclusion of both income and house price on the right hand side.

The implied assumption that higher average neighbourhood house prices will, *ceteris paribus*, increase happiness seems questionable as suggested in 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 to improve SWB.

In this paper we set out to generalize this approach to include unobservable housing characteristics and unobserved 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.

We expect that happiness accounts for utility that individuals derive from living in a certain dwelling which is not otherwise accounted for in the explanatory variables; occupant SWB captures the beneficial impact of unobserved 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.

There are three potential pathways that, in theory, provide a link between measured levels of subjective well-being and the market value of residential property. These are not necessarily mutually exclusive but do involve differences in interpretation of the responses to surveys of subjective well-being as well as understanding of the mechanisms through which the value of structure and neighbourhood attributes are capitalised into house prices.

The pathways are that first, measured levels of subjective well-being (SWB) may directly proxy for desirable amenities of a structure or neighbourhood. If these attributes are observable to potential buyers when directly viewing the property, then buyers can condition their willingness to pay on the levels of such attributes present.

This is similar to the relationship identified in Oswald and Wu (2010). Working with health survey data from US states, they show that state-specific differentials in measured SWB correlates very well with quality-of-life rankings of US states presented in Gabriel et al. (2003). These rankings, in turn, are based on identification of compensating variation in housing costs and incomes. The essential idea is that higher quality of life is associated with those states having high house prices relative to prevailing income levels. The higher quality of life attracts migration into the area resulting in higher house prices, and the differential in house prices is a compensating variation for the attractive features of life in that location. Oswald and Wu (2010) find that state-specific differences in subjective well being are significantly correlated with these objectively measured compensating variations, interpreted as the "non-income elements of human well-being". This relationship, applied to the level of the individual property, would allow for interpreting occupant subjective well-being as a proxy for important attributes available at that location.

One might object 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 centre 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 as discussed in Ballas and Tranmer (2012) and Goetzke and Islam (2017). 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.

A second pathway is that a household may purchase a property with an *ex ante* expectation about the level of some amenities that might be experienced upon occupation, and the price they pay reflects this expectation. When the *ex post* outcome is known, those households whose expectations are exceeded may experience an increase in SWB due to this fortunate outcome. As a result, the price required to induce them to sell the property would increase and the increased SWB would provide a proxy for this unexpectedly high level of amenity.

Finally, a third pathway is that there may be some levels of amenity that emerge during the course of living in the property. An example of such *emergent attributes* would be the social capital that a household accumulates while living in a community. They learn whom to trust, who can be relied upon to get advice about activities in the community, and identify persons with whom they can enjoy these activities.

One of the first papers to illustrate the existence of this effect was the interesting paper of DiPasquale and Glaeser (1999). The focus of their analysis is to identify the extent to which owner-occupants of residential property tend to devote more resources towards investing in social capital than renters. Mindful of the fact that home ownership itself can increase moving costs and lead households to remain longer in the community, they analyse the separate contribution of duration of residence on social capital formation. They find that the effect of increased duration of residence, separate from owner-occupation itself, contributes as much as 60% to 90% of the increased social capital formation among owner-occupants.

As noted by Glaeser et al. (2002), this social capital is valuable and can be expected to rise and fall over the course of the life cycle. In the specific context of housing markets, Hilber (2010) finds that direct measures of social capital are greater in communities and neighbourhoods with an inelastic supply of housing, suggesting that stability of residence in the community encourages social capital accumulation. His analysis shows that increases in social capital are associated with increases in house prices and this, in turn, affects who will choose to live in the community. Fu (2005) also finds evidence that social and cultural capital is reflected in house prices, although the data used are less detailed and the analysis somewhat less robust.

Combined, these studies suggest that accumulation of social capital is an important contributor to household well-being and an ongoing component of life in communities. As this process proceeds, the aggregate level of social capital in the neighbourhood emerges and is capitalised into house prices. This increased availability of social capital may be measured indirectly by the increased subjective well-being of households in the area.

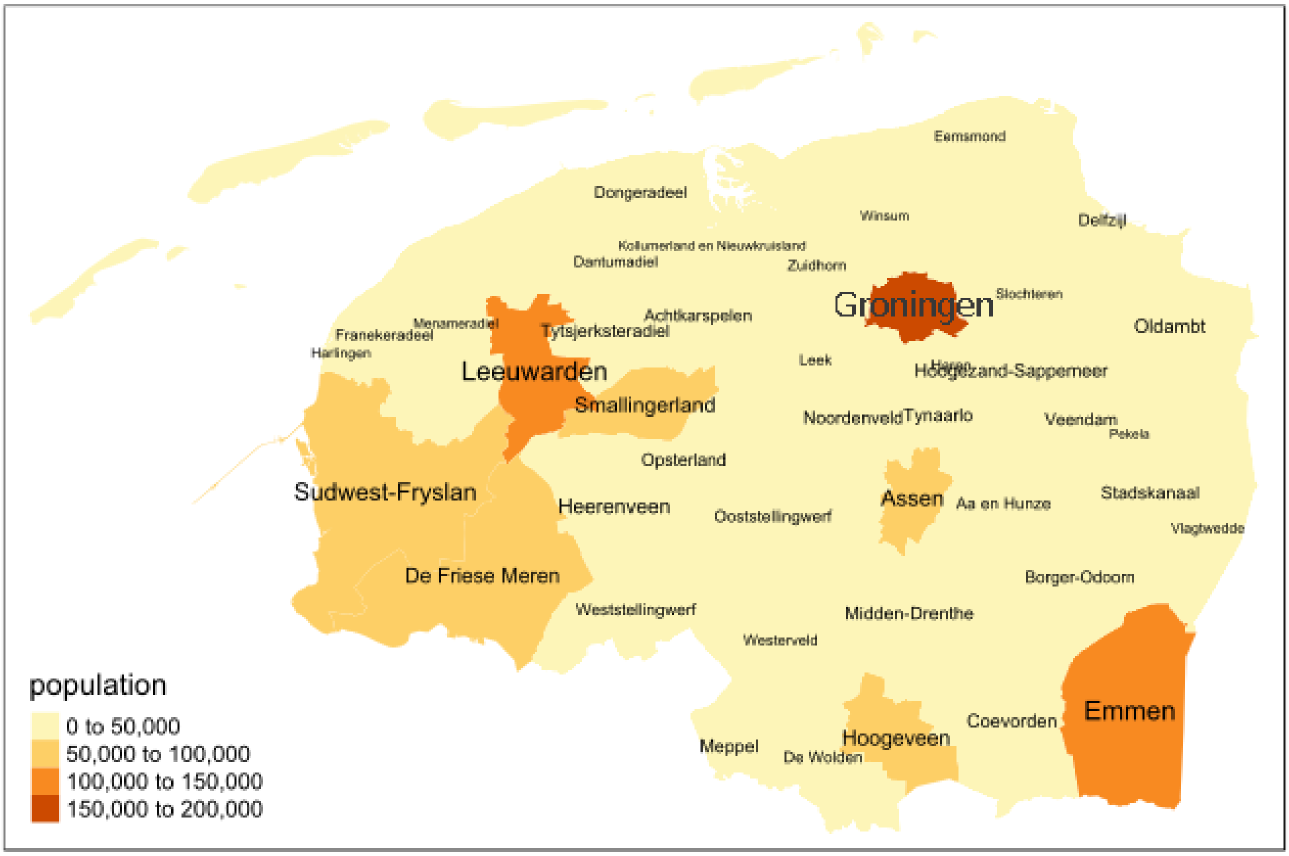
While the first pathway discussed above is more or less static, the other two pathways imply that SWB should be increasing over time as a household continues to reside in the community.

4 Data and empirical strategy

Data

The two main datasets used in this study are from the LifeLines Biobank study and the Dutch Association of Realtors and Appraisers (NVM) data 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 (discussed in more detail in Scholtens et al. (2015)). Figure 1 illustrates the region from which the data were collected.

Figure 1: North Holland Region



In addition to the LifeLines and NVM data, we make use of data from Dutch National Statistics to obtain population density and the share of population with a non-western heritage. Table 1 lists and describes the variables used in the analysis, along with the source of the data and the measurement level of the variables.

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.
Ln(plotsize)	NVM	Property	Natural log of one plus square meters plot size, natural numbers, missings deleted.
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 (in other markets called a "Loft" space)
Under roof	NVM	Property	Dummy for under roof storage area 1=yes (in other markets called an "Attic" space)
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
Ln(urban distance)	CBS	Property	Natural log of distance from property to centroid of nearest major municipal area.
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.
Ln(foreign)	CBS	Municipality	Natural log of 1 + percentage of population with a non-western background.
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.

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Variable	Source	Measurement level	Description
Ln(positive affect)	LifeLines	Individual	Natural log of 1 + PANAS Positive affect scale.
Lag Ln(well-being)	LifeLines	Individual	Spatial lagged value of natural log of 1 + emotional well-being.
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	

Data collection of the initial survey started in 2006, with data included in this survey up to and including 2012. There were three ways individuals could join the study. First, individuals aged 25 to 50 were approached through their general practitioner, resulting in a 24.5 per cent response rate. 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, individuals who were not personally approached could enlist through a general website.

The data we use in this study are from the initial data release of 2013 with data from the baseline questionnaire which was administered to all individuals when they joined the study, comprising a total of 95,413 individuals. Klijs et al. (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 are matched with real-estate transaction data from the NVM. The NVM data provide information on the most recent transactions for 153,030 properties in the years 2000-2012 in the North of the Netherlands. As Brounen and Kok (2011) note, the NVM dataset covers about 70 per cent of the Dutch private real estate market with Debrezion et al. (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 leaving a total of 18,184 properties for which both real-estate transaction data and LifeLines questionnaire data were available. Selecting those properties for which occupant SWB data were available, leaves a total of 16,645 property-occupant matches in the dataset. The nature of the dataset means we obtain measures of occupants after the transaction of the property occurred.

Selection into either one of our two main 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) (2018b) 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 and Kok (2011) and Debrezion et al. (2011).

When we match the two main data sources, we exclude both those property transactions without a corresponding observation in the LifeLines dataset, and those LifeLines participants in a residence without a recorded sale in the NVM dataset. From the LifeLines survey design, we know that a relatively large proportion of respondents 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 overall. Table 2 provides a schematic description of the number of observations from each source used, and indicates the number of observations remaining after each refinement of the data.

Table 2: Data observations available and excluded

		Source	
	Lifelines	**Merged**	**NVM**
Observations available	95,413		191,804
With location information	75,292		↓
In North of Netherlands	74,074		↓
With data on plotsize and parking	↓		190,411
Keep only most recent sale	↓		153,030
	↘		↙
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	
With (bath-)room data		15,409	
Price < €100 million		15,407	
Price ≥ €1000		15,397	
With reliable geocode		15,171	
With some obs in neighbor cells		14,857	

Tables 3 and 4 provide descriptive statistics for variables used in the analysis.

The NVM are the source of most data on structure characteristics. NVM instructions for measuring floor area provide the net square meters within the house, excluding areas within a room that are less than 1.5 meters high, and excluding 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 height of over 2 meters tall, and a window.

Plot size is measured in square meters of land area taken from the national land registry, although apartments are recorded as having zero land area. Therefore 1 is added to all plot size measures to enable use of natural logs in measuring area.

Urban centres in the North of the Netherlands have been defined using a compound measure that combines population density and population size. Using only size would lead to some large but essentially rural municipalities being included as urban centers. 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.

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 closely, and the total population of Harlingen is just over 15,000). The compound measure resulted in four urban centers: Groningen, Leeuwarden, Assen, and Zwolle. Zwolle is located just to the south of the study area, but given the size of the city it is appropriate to include the distance to

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

Table 3: Descriptive statistics for model variables

Variable name	Mean	Std Dev	Min	Max
Property sales price	200,311	96,523	18501	2450000
Ln(sales price)	12.118	0.412	9.826	14.712
Ln(positive affect)	1.511	0.095	0.693	1.792
Ln(well-being+1)	4.366	0.207	0	4.615
Ln(lag well-being+1)	4.381	0.057	3.219	4.615
Ln(urban distance)	2.443	1.154	-4.216	3.862
Ln(density)	5.904	0.942	4.007	7.797
Ln(foreign+1)	1.633	0.469	0.693	2.485
Ln(burglary+1)	3.294	0.508	1.902	4.055
Ln(floor area+1)	4.813	0.290	3.555	6.223
Ln(plotsize+1)[†]	5.399	1.742	0	11.195
Ln(rooms)	1.541	0.260	0	3.526
	Dichotomous Variables			
Two Bathrooms	0.056	0.0019	0	1
Three Bathrooms	0.001	0.0002	0	1
Balcony	0.126	0.332	0	1
Parking	0.605	0.489	0	1
Basement	0.936	0.245	0	1
Attic	0.344	0.475	0	1
Under Roof Area	0.143	0.350	0	1
Listed	0.004	0.065	0	1
Monument	0.007	0.082	0	1

this city. The distance used in the models is the (Euclidean) distance to the nearest major urban center for each observation. The population density of the municipality containing the house is included as an additional control for effects of smaller population centers (rural towns and large villages).

The official classification of "Non-western foreigners" in Dutch statistics is 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, as described in Dutch National Statistics (CBS) (2018a). We include 1 plus the percentage of population with a non-western background in the municipality containing the house as a proxy for ethnic diversity in the neighbourhood.

From Table 4 we see that just over 60% of the sample was properties were constructed in the 1970's or later. The median sales date of properties in the sample is mid-2006.

Operationalisation of main variables

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, as noted by Frey and 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. This is measured

Table 4: Descriptive statistics for indicator variables

Variable	Mean	Variable	Mean
Interior maintenance		*Exterior maintenance*	
Interior 1 (Poor)	0.10	Exterior 1 (Poor)	0.11
Interior 2	0.07	Exterior 2	0.02
Interior 3	0.66	Exterior 3	0.48
Interior 4	0.24	Exterior 4	0.26
Interior 5	5.18	Exterior 5	4.84
Interior 6	2.79	Exterior 6	3.06
Interior 7	77.24	Exterior 7	78.33
Interior 8	1.47	Exterior 8	1.41
Interior 9 (Excellent)	12.25	Exterior 9 (Excellent)	11.50
Construction period		*Year property sold*	
Up to 1905	4.35	Y_{2000}	5.47
1906-1930	9.65	Y_{2001}	6.91
1931-1944	7.39	Y_{2002}	7.98
1945-1959	5.18	Y_{2003}	8.05
1960-1970	12.98	Y_{2004}	8.79
1971-1980	22.51	Y_{2005}	10.24
1981-1990	13.81	Y_{2006}	11.05
1991-2000	18.82	Y_{2007}	9.51
2000 and later	5.31	Y_{2008}	8.64
		Y_{2009}	6.95
Insulation		Y_{2010}	6.43
No insulation	9.99	Y_{2011}	5.53
1 type of insulation	32.52	Y_{2012}	4.45
2 types of insulation	13.58		
3 types of insulation	12.48		
4 types of insulation	10.94		
Fully insulated	20.50		

either through a single survey item (e.g. all things considered, how satisfied are you with your life these days?) or preferably a compound measure using a set of questions as suggested in Kahneman and Krueger (2006). 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 approaches to measuring health related quality of life, and is surveyed in Hays and Morales (2001). The survey groups 36 items into eight separate constructs. Seven of these deal with a variety of issues relating to 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 the extent an individual felt happy, nervous, depressed, calm, and downhearted over the past four weeks. The responses then averaged for each individual. The measure is tested for internal reliability (Cronbach's Alpha = 0.83), showing that the underlying items are reliably correlated. Spatial lags of this variable were considered at 1, 2.5, 5 and 10 kilometers, using an inverse euclidean distance weighting.

The general SWB scores could be confounded with 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 (for example, Yap et al. (2017)) although these results were less or not significant on replication. In our analysis, we control for these positive transitory events, or temporal mood, by including the *positive affect score* obtained through the PANAS measurement tool discussed more fully in Watson (1988).

Correlations between happiness and transaction price could be the function of buyer optimism: optimistic individuals, indicated by positive affect, may be more likely to overestimate the positive outcomes of their decision as suggested in Nygren et al. (1996), although Isen 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 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 (see for example Crawford and 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 less frequently undertaken, but Watson (1988) finds that positive affect (and negative affect) reliability remain high, even with time frames of up to a year.

Based on the evaluation of correspondence between the population and samples mentioned above we find the LifeLines data are 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 data as a whole and the matched data subset used on our estimation. From this, we conclude that our data are broadly representative for the North of the Netherlands.

Econometric specification

Our goal 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 Informetion Criterion (a Log-Likelihood, penalised for addition degrees of freedom), with lower AIC's reflecting a better fit.

Second, we suspect there are various ways in which unobserved variables associated with SWB might be associated with transaction price paid, e.g. a recent financial windfall may result in a higher than expected willingness to pay as well as a higher (short term) SWB. 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. Diener et al. (1999) found that self-reported health is positively associated with SWB, which implies 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, such as Atalay et al. (2017) and Fichera and Gathergood (2016), suggests that changes in house prices correspond to health outcomes. The proposed 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 and Elhorst (2015) note, there are a number of ways in which spatial relationships can be modeled. 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 (see Anselin and Lozano-Gracia (2008) for further discussion). 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 and Lozano-Gracia (2008), 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 and Klaiber (2011), who state that different amenities interact with capitalization on different scales.

The spatial lag was constructed using the 'spdep' package in R (see Bivand and Wong (2018) and Bivand et al. (2013)for details). Related observations were weighted inversely to the Euclidean distance between the properties $1/d$, with a maximum distance of 1 kilometre emphasising neighbours in close proximity. We used a row-standardized spatial weights matrix to account for heterogeneity in the number of neighbours. As a robustness check results were run with a bandwidth of 2.5 kilometres, which returned similar results.

5 Results

Subjective well-being and time in residence

Since a focus of our analysis is to evaluate the use of SWB in analysis of house prices, we first consider how measured SWB evolves over the course of residence. As shown in Figure 2, our data include households who have been in residence for as little as 100 days to as many as 4500 days. As we noted above for at least two of our three pathways that might link SWB to structure and neighborhood attributes, we would expect SWB to rise over time.

Figure 2: Distribution of observations of time in residence (days)

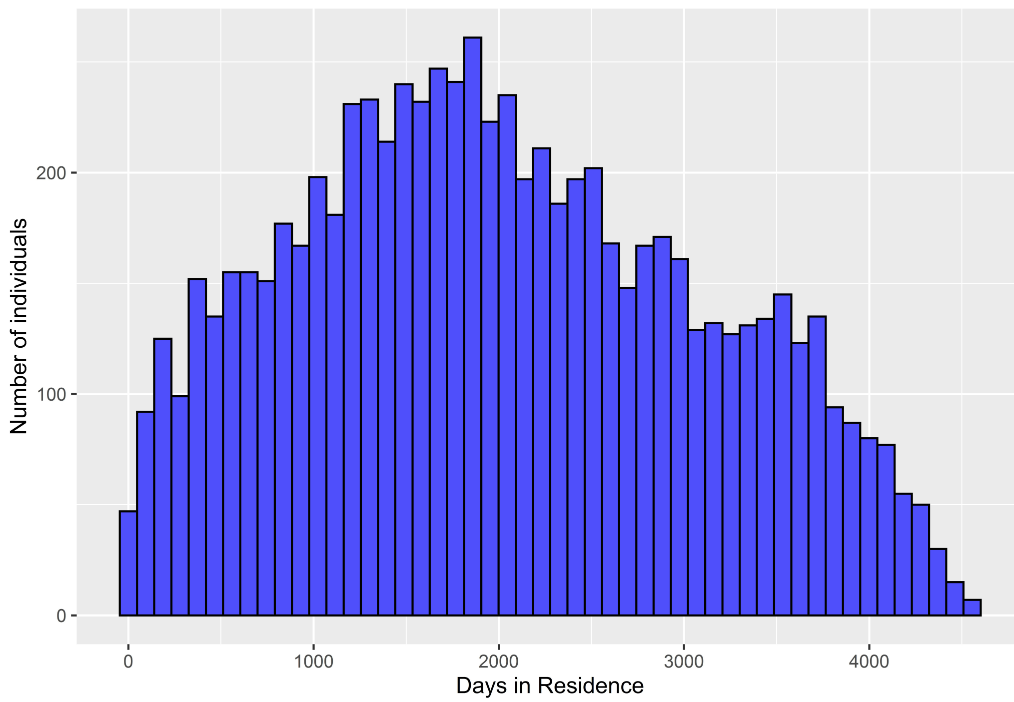

Table 5 presents the results of two very simple models that summarise the relationship between time in residence and subjective well-being. Models are presented for time in residence measured in years and in days, with controls for positive affect and structure price included. The estimated parameters imply that the evolution of SWB over time declines slightly for the first 2-3 years of residence, rising sharply after 929 days in residence. This seems in line with other known processes of social capital accumulation and is at least consistent with the pathways we suggest through which SWB might play an important role in analysis of house prices.

Ordinary least squares

Table 6 presents the results of our model estimates. We combine all estimation approaches in a single table to facilitate comparison between estimation approaches and model specifications. Nested model specifications estimated using OLS are presented in columns 2 through 4. These are followed in columns 5 and 6 by models estimated using an instrumental variables approach to account for potential endogeneity of measured SWB. Finally in columns 7 and 8 we present alternative

Table 5: Subjective well-being and time in residence

Coefficients:	**Years**	**Days**
Constant	2.8497***	2.8530***
σ	0.0522	0.0547
Ln(Affect + 1)	0.7642***	0.7710***
σ	0.0167	0.0173
Ln(Price)	0.0294***	0.0284***
σ	0.0039	0.0041
TiR	-1.4867×10^{-3}	-5.5870×10^{-6}
σ	1.5609×10^{-3}	5.7080×10^{-6}
TiR^2	3.5530×10^{-4}**	3.0070×10^{-9}**
σ	1.4390×10^{-4}	1.3180×10^{-9}
$F(4, 14852)$	562.7***	527.6***
RSE	0.1931	0.1943
R^2	0.1316	0.1943
$\bar{R}^2$	0.1314	0.1324

*** - p < 0.001, ** - p<0.01, * - p<0.05, † - p<0.10

spatial econometric approaches to account for spatially correlated errors and spatial autoregressive structures. The dependent variable in all models is the log of the transaction price.

Table 6: 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				
Well-being			0.0385***	0.181***	0.1744***	0.0893***	0.1149***
σ			*0.009*	*0.029*	*0.026*	*0.018*	*0.023*
Lag well-being						0.1007**	
σ						*0.035*	
Positive affect			0.1018***	-0.0077	-0.0027	0.0321	0.0094
σ			*0.02*	*0.029*	*0.028*	*0.021*	*0.024*
ρ (spatial error)						0.4282***	0.4238***
σ						*0.012*	*0.012*
λ (spatial autocorrelation)						0.2409***	0.2445***
σ						*0.012*	*0.012*
			Neighborhood and Environmental Characteristics				
Ln(Urban distance)		-0.0053*	-0.0055*	-0.0058*	-0.0058*	-0.0119***	-0.0116***
σ		*0.002*	*0.002*	*0.002*	*0.002*	*0.003*	*0.003*
Ln(Density)		0.1008***	0.1006***	0.1003***	0.1003***	0.0859***	0.0859***
σ		*0.005*	*0.005*	*0.005*	*0.005*	*0.007*	*0.007*
Ln(Foreign)		-0.1536***	-0.1535***	-0.1531***	-0.1531***	-0.1164***	-0.1159***
σ		*0.009*	*0.009*	*0.009*	*0.009*	*0.013*	*0.013*
Burglary		-0.0185***	-0.0182***	-0.0171**	-0.0172**	-0.0118	-0.012
σ		*0.005*	*0.005*	*0.005*	*0.005*	*0.008*	*0.008*
Ln(Water distance)		-0.0087***	-0.0087***	-0.0088***	-0.0088***	-0.0116***	-0.0115***
σ		*0.002*	*0.002*	*0.002*	*0.002*	*0.002*	*0.002*
Ln(Forest distance)		-0.0045*	-0.0043*	-0.0038*	-0.0039*	-0.0039	-0.004†
σ		*0.002*	*0.002*	*0.002*	*0.002*	*0.002*	*0.002*
Ln(Nature distance)		-0.0553***	-0.0549***	-0.0546***	-0.0547***	-0.0357***	-0.0359***
σ		*0.003*	*0.003*	*0.003*	*0.003*	*0.004*	*0.004*
				Structure Characteristics			
Ln(Floor Area)	0.6616***	0.6508***	0.6485***	0.6471***	0.6471***	0.5932***	0.5931***
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***	0.0553***	0.0552***
σ	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*

*** - p < 0.001, ** - p<0.01, * - p<0.05, † - p<0.10

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Variable	OLS Model 1	OLS Model 2	OLS Model 3	IV Health	IV Health/Pain	Spatial Durbin	Spatial Error
Rooms	0.0309***	0.0327***	0.0326***	0.0323***	0.0323***	0.0498***	0.05***
σ	*0.009*	*0.009*	*0.009*	*0.009*	*0.009*	*0.008*	*0.008*
Two Bathrooms	0.1438***	0.1395***	0.1386***	0.1374***	0.1375***	0.1164***	0.116***
σ	*0.008*	*0.008*	*0.008*	*0.008*	*0.008*	*0.007*	*0.007*
Three Bathrooms	0.2432***	0.2489***	0.2487***	0.2542***	0.254***	0.1801***	0.1806***
σ	*0.063*	*0.061*	*0.061*	*0.061*	*0.061*	*0.053*	*0.053*
Balcony	0.1196***	0.1158***	0.1153***	0.1153***	0.1153***	0.087***	0.0871***
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***	0.1203***	0.1205***
σ	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
Basement	-0.0192*	-0.0228**	-0.0227**	-0.0223**	-0.0223**	-0.032***	-0.0319***
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***	-0.0316***	-0.032***
σ	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
Under roof	-0.0064	-0.0051	-0.0054	-0.0073	-0.0073	-0.0106*	-0.0112*
σ	*0.006*	*0.006*	*0.005*	*0.006*	*0.006*	*0.005*	*0.005*
Listed	0.2465***	0.2313***	0.2287***	0.2257***	0.2258***	0.1899***	0.1895***
σ	*0.029*	*0.028*	*0.028*	*0.028*	*0.028*	*0.025*	*0.025*
Monument	0.1416***	0.1425***	0.14***	0.1418***	0.1418***	0.1648***	0.1648***
σ	*0.024*	*0.023*	*0.023*	*0.023*	*0.023*	*0.02*	*0.02*
Constant	8.3239***	8.5819***	8.271***	7.8333***	7.8533***	4.8285***	5.1519***
σ	*0.072*	*0.079*	*0.088*	*0.122*	*0.117*	*0.242*	*0.185*
				Other variables in models			
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

*** - p < 0.001, ** - p<0.01, * - p<0.05, † - p<0.10

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Variable	OLS Model 1	OLS Model 2	OLS Model 3	IV Health	IV Health/Pain	Spatial Durbin	Spatial Error
				Measures of model fit to data			
Residual σ	0.2247	0.2175	0.217	0.2187	0.2186		
R^2	0.7035	0.7223	0.7235	0.7191	0.7195	0.7574	0.7568
$\bar{R}^2$	0.7024	0.7212	0.7224	0.7179	0.7183		
AIC	-2150.58	-3109.98	-3172.68				
				Tests of performance of variables in model			
F	662.7***	641.4***	624.5***				
Wald test				615***	615.9***		
Weak instruments				1744.71***	1057.375***		
Wu-Hausman				28.05***	30.969***		
Sargan					0.332		
				Tests for spatial dependence and autocorrelation			
LM spatial error	4877***	3561.8***	3511.8***				
LM spatial lag	177.84***	259.98***	266.8***				
Moran's I						55.294***	54.548***
				Partial first stage results for well-being instruments			
Ln(Health+1)				0.1723***	0.1723***	0.1723***	
σ				0.006	0.006	0.006	
Ln(Pain+1)					0.0807***	0.0807***	
σ					0.005	0.005	

*** - p $<$ 0.001, ** - p<0.01, * - p<0.05, † - p<0.10

OLS Model 1 presents estimates that include only structure characteristics. The estimated parameters are largely as would be expected. A one per cent change in floorspace is associated with a 0.65 to 0.66 percent increase in the transaction price. A one percent change in plot size increases the transaction price by 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 area are associated with lower transaction prices. The data for usable interior surface area as described in NVM and VBO and VastgoedPRO and Vereniging Nederlandse Gemeenten and Waarderingskamer (2018) specify that floorspace (floorm2) includes all usable area, which includes basements, attics, and under-roof storage. The negative coefficients estimates arise from a portion of the interior 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). Structures from the 1980's attract the lowest transaction prices.

OLS Model 2 adds the neighbourhood characteristics. Increases in density are associated with increases in transaction price, which is consistent with the standard urban land use model presented in Alonso (1964). Controlling for that, larger distances to an urban center (as a proxy for labour market access) are associated with lower transaction prices, burglaries are associated with lower transaction prices, as is ethnic diversity.

OLS Model 3 includes subjective well-being and positive affect. Both coefficients are significant and positively related to transaction price. This supports our 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 supports the optimistic buyer hypothesis. The AIC's for these three models suggest that the fully specified model is the preferred one, decreasing from -2,151 for the property characteristics model, to -3,110 for the model including neighbourhood characteristics, and finally -3,173 for the model including subjective well-being.

Across the three OLS model specifications we observe only very small changes in the parameter estimates. From the variables included in the baseline, the changes for all variables except two are smaller than 0.01 with the addition of more parameters to the model. The exceptions are the log of floor space (change of 0.0130), and if a building was a listed property (change of 0.0176). This suggests that estimates obtained at just the property level are largely unaffected by the addition of environmental or individual parameters.

Similar to Anselin and Lozano-Gracia (2008) we test for spatial dependence in our data, and find robust Lagrange Multipliers in excess of 3,511 for spatial dependence in the error term, and greater than 177 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.

Endogeneity and IV estimation

Columns 5 and 6 of Table 6 present estimates of the fully specified model using an instrumental variables approach with self-reported health as an instrument for the potentially endogenous subjective well-being variable. Diagnostic statistics indicate that SWB is significantly endogenous with the transaction price, with the Wu-Hausman being highly significant at $p < 0.001$. Instrumenting for subjective well-being leaves the sign and significance of most of the coefficients intact, with the exception of positive affect whose presence as a control for temporal mood is not of central interest to our analysis. The results indicate that self-reported health is a strong instrument for subjective well-being (weak instruments $p < 0.001$). The suggests that the differences in parameter estimates relative to the OLS models (particularly noticeable for SWB and positive affect) may be due to endogeneity bias in the OLS estimates. Partial results from first stage regressions for both self-reported health status and self-reported experience of pain as instruments are provided in the final four lines of the table.

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 familiar feature of using instrumental variables, although the change is modest.

The coefficients for the IV regression with self-reported health and pain instruments show that SWB is significantly positively related to transaction price. The coefficient is similar for both IV specifications, indicating that an increase in subjective well-being of 1 percent is associated with a 0.18 – 0.174 per cent increase in transaction price. Although the novelty of our estimates means any comparison must be tentative, the size of this coefficient seems plausible given that subjective well-being is capturing a range of structure and neighbourhood amenities that are unobserved.

Spatial models

The robust Lagrange multiplier tests presented in columns 2 through 4 for the OLS models suggest that the primary 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 suggested in Vega and Elhorst (2015), serving as a proxy for unobservable neighbourhood effects. To address this, we first calculate a spatially lagged variable of subjective well-being (inverse euclidean distance, 1 kilometer bandwidth) and add this to the spatial models. The first model we estimate is, therefore, a generalised methods of moments instrumental variables version of the Spatial Durbin Error model, which can be reduced to a Spatial Error model if the coefficient for the lagged variable is not significant (see table 6).

The Spatial Durbin Error model presented in the penultimate column of table 6 indicates that the lagged SWB variable is positively related to the transaction price, with a coefficient of just over 0.10. This is consistent with the expectation that neighbourhoods where individuals derive a higher utility would be associated with higher transaction prices. The size of the coefficient for subjective well-being has decreased relative to the specification without the lagged subjective well-being variable. For completeness the Spatial Error specification is also reported in the final column of table 6.

In the Spatial Error specification we observe a smaller coefficient for the direct effect of subjective well-being on the transaction price (0.1149) than reported in the non-spatial IV estimates, 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 SWB on the transaction price is measured (standard error) 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 0.7574 and for the Spatial Error specification 0.7568, 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 larger differences among the variables that are based on distance functions (e.g. distance to water or forests, distance to urban centres). This is to be expected, as these are by definition spatially autocorrelated. The only other notable change is the burglary rate, which is significant and negative in the instrumental variable models. In the spatial models it remains negative but the estimate is so imprecise that we cannot be confident that the true effect is other than zero.

Figure 3: Residuals from instrument estimate of Ln(well-being)

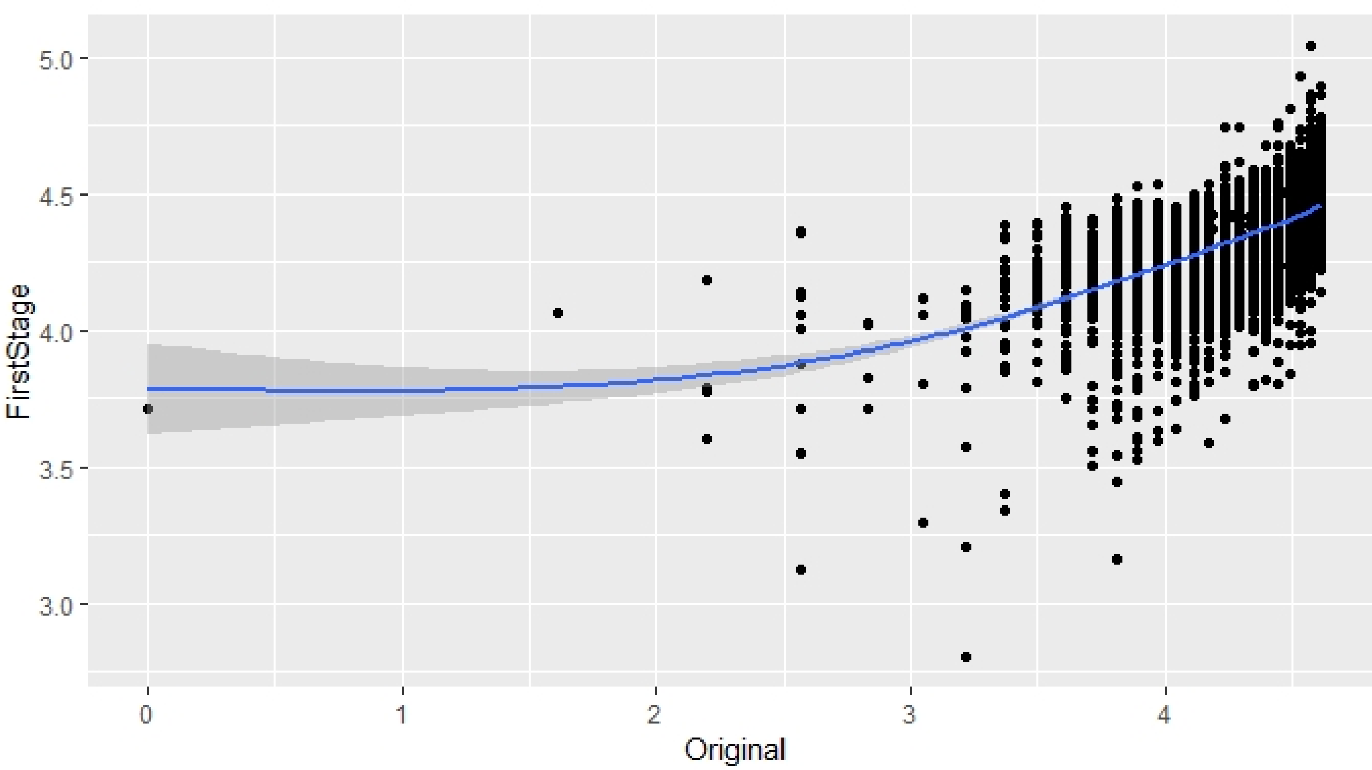
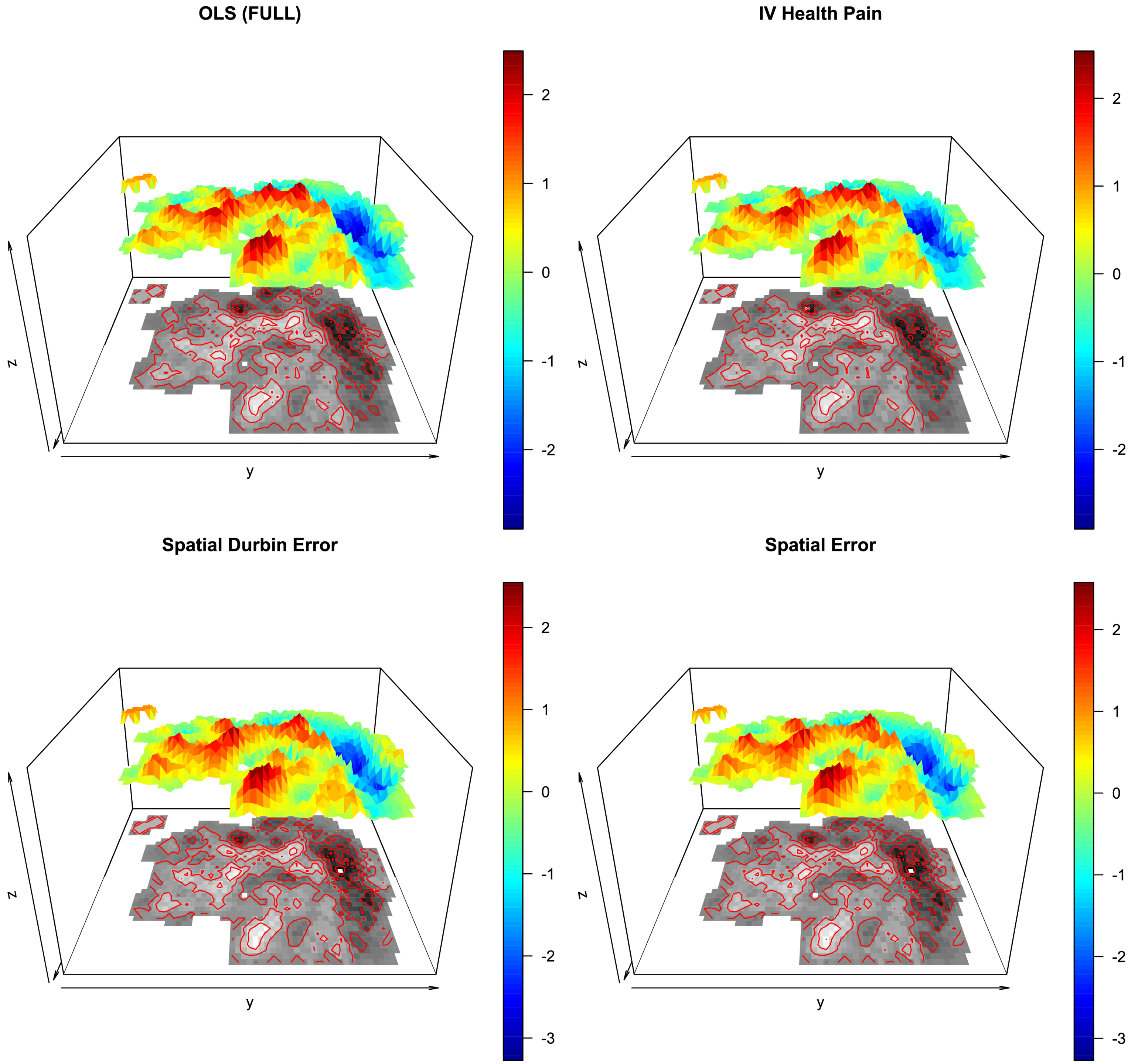


Figure 3 shows the residuals from the first stage estimation of the Spatial Durbin Error model. Compared to the outcome variable, we see that there is a good fit for the first stage estimation at the higher levels of subjective well-being. As is common in SWB measurement, fewer people give lower scores 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 observed in other 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.

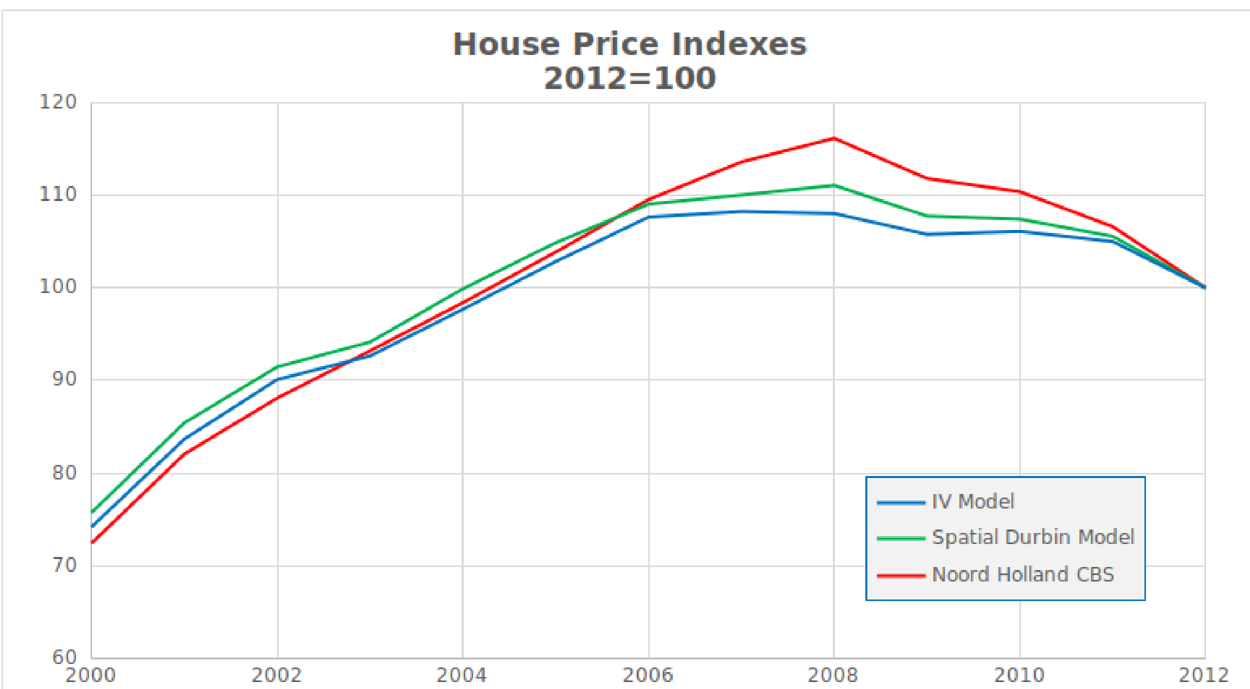
Figure 4: Residual maps for selected models



We check for spatial autocorrelation in the residuals using Moran's I, and find that this remains an issue. Both model specifications report significant residual spatial autocorrelation, with the statistic relatively similar for the Spatial Durbin Error and Spatial Error models. The residual maps are displayed in Figure 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 some intuitive sense, considering some background characteristics of the North of the Netherlands. The main low cluster towards the east of North Holland corresponds with the Veenkoloniën and Oldambt areas, which have a history of difficult economic development, and relatively low levels of in-migration, as discussed in Rijnks and Strijker (2013) and 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 ageing as noted in Haartsen and Venhorst (2010). The finding that house values are depressed somewhat in these regions is not surprising, and might be remedied by a regional fixed effects specification if dynamic data were available. The smaller clusters of positive residuals correspond with smaller urban regions, indicating that there is perhaps a non-linearity to the effect of population density or labour 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, perhaps because the effect does not appear to be general across all smaller urban areas. This indicates that some unobserved regional effect or interaction, specific to some but not all smaller urban areas, remains.

Over the sample period of 2000 to 2012, the pattern of house prices estimated by the Spatial Durbin or IV hedonic models produces a price index that closely matches the CBS house price index for Noord Holland. Figure 5 presents three house price indices together.

Figure 5: Indices implied by model estimates compared with CBS repeat sales index for north NL



The Spatial Durbin model hits a peak in 2008, similar to (but slightly lower than) the CBS model. The IV model generates a price index that peaks in 2007. Overall, this confirms both the representativeness of our sample and the performance of our estimates noted above.

6 Conclusion and Discussion

This paper aims to establish a connection between house transaction prices and subjective well-being measures, used as a proxy for both unobserved house characteristics and unobserved neighbourhood characteristics. The unobservability of 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 neighbours. Recent progress in happiness research, for example Diener and Suh (1997) or 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 modelling, 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 using self-reported health and pain allows us to get a consistent estimate. 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 and Prucha (2010). The relation shows that measured utility is positively associated with transaction price both at the individual house or household level, and at the regional level.

Linking back to the literature on a spatial equilibrium of utility, we find that higher SWB both individually and in the neighbourhood are indeed related to higher transaction values. Regional variations in utility are translated into higher rents, and in turn a move towards spatial equilibrium (see Goetzke and Islam (2017) and Ballas and Tranmer (2012)). Additionally, 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, neighbourhood, 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.

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