

Wirth, Benjamin; Mense, Andreas

Conference Paper

Flat Prices, Cell Phone Base Stations, and Network Structure

54th Congress of the European Regional Science Association: "Regional development & globalisation: Best practices", 26-29 August 2014, St. Petersburg, Russia

Provided in Cooperation with:

European Regional Science Association (ERSA)

Suggested Citation: Wirth, Benjamin; Mense, Andreas (2014) : Flat Prices, Cell Phone Base Stations, and Network Structure, 54th Congress of the European Regional Science Association: "Regional development & globalisation: Best practices", 26-29 August 2014, St. Petersburg, Russia, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/124511>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Flat Prices, Cell Phone Base Stations, and Network Structure

An instrumental variable approach to endogenous locations

Andreas Mense*

Benjamin Wirth†

August 11, 2014

Abstract

Following the critique of [Pinkse & Slade \(2010\)](#) and [Gibbons & Overman \(2012\)](#), we develop an instrument for the estimation of local price effects of cell phone base stations (CPBS) in an urban area. The instrument is derived from the spatial structure of the network and technical requirements. Such a strategy could be useful in other contexts in which location choice is endogenous but depends on an existing network structure. We find a significantly negative impact of nearby CPBS on flat prices. The discount amounts to 4.2% of a property's value when two similar flats at distances of 50 and 100 m to the nearest CPBS are compared. The relatively small difference between OLS and IV results suggests that the location of a CPBS may not be endogenous in general, in opposition to [Brandt & Maennig \(2012\)](#).

Keywords: cell phone base stations, property prices, instrumental variable, endogenous locations

JEL classification: R39, Q51, Q53

*Institute of Economics, FAU Erlangen-Nuremberg; **address:** Kochstr. 4 (17), 91054 Erlangen; **e-mail:** Andreas.Mense@fau.de
†School of Business and Economics at the FAU Erlangen-Nuremberg; **address:** Chair of Social Policy, Findelgasse 7/9, 90402 Nuremberg, Germany; **phone:** +49-911-5302-955; **fax:** ++49-911-5302-953; **e-mail:** Benjamin.Wirth@fau.de

1 Introduction

Health effects of mobile phone radiation have been discussed vividly in the German public in the last years (Reitzner, 2012; Altunordu, 2013) and there is still ongoing opposition against sites in residential areas (Ziob, 2013; Reinthaler, 2013; Blumberg, 2012). This is confirmed by a survey on perceived risks of electromagnetic fields across countries (Burgess, 2002). Scientific evidence on negative health effects shows that this discussion is not completely irrational. Khurana et al. (2009) find that cell phone radiation doubles the odds for some types of brain tumours within ten years, but this effect is confined to cell phone usage rather than proximity to a cell phone base station (CPBS). Hutter et al. (2006) document that people living less than 250 m (600 m) from a CPBS in urban locations (rural locations) more often showed symptoms such as headaches and difficulties to concentrate than people from a control group. Their regression uses exposure to electromagnetic fields as the explanatory variable and controls for fear of adverse effects from electromagnetic fields.

A reason behind the public interest in CPBS sites and protests against such sites in the own neighbourhood could be the fact that a CPBS lies outside the reach of the residents. Whereas protesters interviewed by Drake (2006) acknowledged that the use of a personal cell phone was much more dangerous than living close to a CPBS, they argued that their phone was a tool that could increase the odds of survival in an emergency situation and that they had complete control over the way they used their phone. Conversely, the benefits of the CPBS did not outweigh the (small) health risks associated with it, since network coverage could potentially be achieved by a CPBS some hundred metres further away. Similarly, Lin & Lin (2011) note that the willingness to pay for a removal of a CPBS was highest among women with a high level of risk perception and high expenditure on mobile phones. As argued by Fischel (2001) the insecurity about adverse health effects and a potential reduction of property values may lead to a “not in my backyard” problem that in turn increases awareness towards CPBS sites.¹

Scientific evidence on the effect of CPBS on property prices is still scarce. Moreover, some authors find a negative effect of proximity to a CPBS (Bond & Beamish, 2005; Bond & Wang, 2005; Bond, 2007) while others argue that omitted variables are responsible for the observed price differences (Brandt & Maennig,

¹“Not in my backyard” problems are a concern in other areas as well. In Germany, it is feared that it will become increasingly difficult to realise large infrastructure projects such as the construction of high voltage transmission lines, airports or power plants, which often encounter the opposition of the local residents.

2012). The present study examines flat prices in the city of Nuremberg and adds to these results. A discount of approximately 4.2% of the property value is found when comparing a house located 50 m from a CPBS with a house at 100 m.

In order to deal with the problem of endogenous locations an instrument is developed. Pinkse & Slade (2010) and Gibbons & Overman (2012) have raised concerns about the prevalent use of spatial econometric techniques for the identification of causal relationships. Pinkse & Slade (2010) criticise the reliance on “guessed” functional forms of spatial dependence and the resulting problems of identification. This raises the question whether other empirical strategies might be superior when the main goal of a study is to document a causal relationship. Gibbons & Overman (2012) argue that the “experimentalist paradigm” is a more fruitful approach, since it focuses on exogenous variation required to identify parameters and is less prone to spurious identification that comes from wrong assumptions about the spatial structure and the data generating process. Therefore, we construct an instrument by making use of the network structure. Importantly, this approach could be used in other contexts where location choices are endogenous.

In the next section, the literature on price effects of CPBS is discussed. We also present an overview of the use of instrumental variables (IV) in the hedonic pricing literature and other branches of spatial economics. In section 3, the empirical strategy is presented and the instrument is discussed. The data are described in section 4. Results are presented and discussed in section 5. These are followed by some conclusions (section 6).

2 Literature review

There are a number of papers that deal with the effects of CPBS on property prices. Bond & Beamish (2005) and Bond & Wang (2005) examine neighbourhoods exposed to a CPBS in Christchurch, New Zealand. Both opinion surveys and analysis of transaction data reveal that closeness to a CPBS is viewed as a threat to property value. The authors conjecture that the bad reputation of CPBS is closely related to the attention the topic cell phone radiation receives in the media. Similarly to the effects of CPBS high voltage overhead transmission lines have been found to reduce property prices although adverse health effects are debatable. The literature also points to the importance of media attention (Des Rosiers, 2002) and the visibility of the structures (Sims & Dent, 2005).

Using data from Florida, [Bond \(2007\)](#) compares transaction prices before a new CPBS was constructed to prices obtained in the time after. She finds a positive distance gradient of approximately 0.2% per metre. [Locke \(2013\)](#) examines house prices around cell phone towers in central Kentucky. In a regression with repeated sales data he finds a significant effect of the distance to an antenna. Depending on the specification, house prices increase by 0.4% to 0.8% per 300 m. In a difference-in-difference regression, he finds a discount of 3.3% when comparing houses less than 600 m from an antenna at the time of the sale to other houses.

For Germany, [Brandt & Maennig \(2012\)](#) estimated the price discounts of CPBS in the city of Hamburg. Their findings call into question the negative effects found by the studies mentioned above: Only groups of antennas reduced prices while single CPBS did not. The estimation relies on observables in a spatial lag model. The main result is obtained by introducing an interaction effect in the regression that indicates whether an antenna is located on a “visually disruptive building”. However, there are no data available on this variable for control observations. If the effect of a “visually disruptive building” is negative, the prices of the control observations are biased downwards, and the estimated discount due to proximity to a CPBS will be too small. Additionally, [Brandt & Maennig](#) show that flats closer than 100 m to a group of CPBS sold for 5.4% less than comparable flats outside of this range.

The results of [Filippova & Rehm \(2011\)](#) are similar to those of [Brandt & Maennig \(2012\)](#) in that only the proximity to antenna batteries was found to reduce prices significantly. To obtain this result, only observations closer than 500 m to the nearest antenna were considered. However, when using the whole sample, the authors find a significant effect for all types of towers when comparing observations closer than 100 m to observations farther away. Altogether, the findings in the literature suggest that in urban areas ([Brandt & Maennig, 2012](#)) a possible effect is limited to very close CPBS (100 m or less) compared to larger distances in rural areas ([Bond, 2007](#); [Locke, 2013](#)).

In the literature on local price effects, the endogeneity problem has been approached in various ways. Papers in the spirit of [Brandt & Maennig \(2012\)](#) use spatial models to account for unobserved spatial factors. Other authors use repeated sales data that can be analysed with panel techniques. [Locke \(2013\)](#) is an example for this type. In this paper, we construct an instrument and use the IV estimator. IV has been used by a number of papers, e.g. [Irwin & Bockstael \(2001\)](#), [Cho et al. \(2008\)](#), and [Cavailhès et al. \(2009\)](#) in the context of open

space, and [Hanna \(2007\)](#) and [Bayer et al. \(2009\)](#) in the context of aerial pollution.

[Irwin & Bockstael \(2001\)](#) present a theoretical formulation of the endogeneity problem. In their empirical application, the goal is to estimate the value of open space. They use the soil's drainage ability, the soil quality and the parcel's slope to instrument for the amount of privately owned open space that is developable and show that the insignificant OLS coefficient becomes significantly positive in the IV regression. [Cavailhès et al. \(2009\)](#) do not find evidence for the endogeneity of open space with regard to property prices. They attribute this to more stringent regulation of buildable land in France. The instruments are based on geographical patterns. [Cho et al. \(2008\)](#) also use instruments for the distance to open space, but their choices are not discussed or defended. Among others, their instruments include the distance to the city centre, to the nearest water body, to the nearest golf course, and to the nearest rail road. Thus, it is not clear whether the exclusion restriction is valid for these instruments.

[Hanna \(2007\)](#) estimates the impact of industrial pollution on property prices in a system of simultaneous equations. As an instrument, she uses the number of persons employed in the mining and agriculture industries. Instrumenting the pollution variable produces a significantly negative coefficient whereas the coefficient is positive when OLS is used instead. [Bayer et al. \(2009\)](#) instrument local pollution by the share of pollution from sources more than 80 km away, observing a similar bias in the OLS regression. However, in contrast to [Irwin & Bockstael \(2001\)](#) and [Cavailhès et al. \(2009\)](#) as well as the present study, the latter two studies consider aggregated property prices. Another example is due to [Luechinger \(2009\)](#) who uses mandated scrubber installation at power plants and wind directions to instrument for the impact of pollution levels on life satisfaction and housing rents.

[Gibbons & Overman \(2012\)](#) list a number of studies that rely on the IV approach to deal with spatial endogeneity. Here, we sketch the instruments used in these papers. [Michaels \(2008\)](#) examines the effect of interstate highways on trade within the US. He treats highway location as endogenous due to the possibility that local pressure groups influence the path of the highway to gain access to the transportation network. His instruments are based on the original plans for the highway network and on the fact that highways usually run through counties south, east, west, or north of major cities. This approach is similar to the approach taken in this paper, since the spatial structure of the highway network is used to predict the probability of highway

access.

Similarly to a network of CPBS, school locations are distributed across space in a specific structure. [Hoxby \(2000\)](#) and [Gibbons et al. \(2008\)](#) make use of this fact in the construction of instruments for the level of school competition. [Hoxby \(2000\)](#) argues that the number of streams in a city is a proxy for the number of *natural* school district boundaries which in turn affect competition. The idea behind this argument is that in the 18th and 19th century, travel time was a primary justification for district boundaries, and travel time of students was affected greatly by natural boundaries such as rivers. This allows to deal with the problem of endogenous school district delineations. The instrument in [Gibbons et al. \(2008\)](#) predicts school competition by using the distance to the school district boundary. The rationale is that the average distance to schools other than the nearest school is greater close to the district boundary than in the centre of the district. Therefore, the schools at the boundaries face less competition.

[Lyytikäinen \(2012\)](#) studies the dependencies of local property tax rates between neighbouring counties and uses time and spatial lags of predicted tax rate increases for the construction of the instrument. The instrumentation is necessary since the tax rates are chosen simultaneously, and a spatial lag approach is discarded on the grounds discussed extensively in [Gibbons & Overman \(2012\)](#). Instruments are also used in two studies on ethnic segregation by [Cutler & Glaeser \(1997\)](#) and [Cutler et al. \(2008\)](#). [Cutler & Glaeser \(1997\)](#) use topographical features and political factors as an instrument for location choices of minorities in US cities. Similarly, [Cutler et al. \(2008\)](#) use the group composition of census tracts and metropolitan areas.

The present study provides a new approach to the construction of instruments for problems that involve a network structure and endogenous locations. Moreover, it adds to the results on the effect of CPBS on property prices found in the literature. Since most modern communication relies on radio transmission, and since data volumes are likely to increase in the future, it will be necessary to set up new CPBS and to expand existing sites. Therefore, it is important to have more reliable evidence on externalities that are related to these transmitters.

3 Empirical strategy

3.1 Basic framework

The theoretical framework is the hedonic approach due to [Rosen \(1974\)](#) that establishes a functional relationship between the observed price and the characteristics of the flats (housing characteristics) and its location or neighbourhood (neighbourhood characteristics). The model can be written in compact form as

$$\ln p = X\beta + \gamma \ln \text{DIST_CPBS} + u \tag{1}$$

where p is the $N \times 1$ vector of property prices, X is the $N \times k$ matrix of exogenous regressors, β is a $k \times 1$ coefficient vector, γ is the coefficient of main interest, and u is a composite error term that is neither independently nor identically distributed. \ln denotes the natural logarithm. The logarithmic model is selected here because of its better fit than a linear model and it is often used in housing price studies ([Can, 1992](#); [Irwin, 2002](#); [Brandt & Maennig, 2012](#)). The matrix X incorporates housing and neighbourhood characteristics. DIST_CPBS is the distance to the nearest CPBS.

A common approach to the identification of β is to introduce a spatial weight matrix W to take into account spatial spill-over effects across neighbourhoods that cause spatial dependency. The matrix W is assumed to be known and can be used to estimate spatial dependencies between neighbouring observations in three ways: via an autoregressive term, Wy , via the regressors WX , or via the error term Wu ([Can, 1992](#)). If the true model includes Wy or WX , it should be included in a regression in order to prevent an inconsistent estimate. Furthermore, it is argued that the inclusion of WX may guard against omitted variable bias (cf. [LeSage & Pace, 2009](#), pp. 155-158). On the downside, this requires a correct guess for W . Additionally, other sources of endogeneity are neglected. Lately, these shortcomings have been criticised heavily by [Pinkse & Slade \(2010\)](#) and [Gibbons & Overman \(2012\)](#). As an alternative, [Gibbons & Overman \(2012\)](#) advocate the use of quasi-experimental approaches.

Here, we attempt to estimate eq. (1) by the instrumental variables approach. Letting Z denote the matrix of instruments, this yields a consistent estimate if $E[Z'u] = 0$. We assume the error structure be $u = \Lambda u + e$, where Λ captures the unknown spatial structure of the error term. Making explicit the spatial dependence of

the error term, the exclusion restriction translates into $E[Z'(I - \Lambda)^{-1}e] = 0$, i.e. the instrument needs to be independent of the spatial structure of the error term.

3.2 Instrument construction

Estimation of eq. (1) is straightforward if an instrument is available. Obviously, the main task here is to find a suitable instrument that provides the necessary exogenous variation in \mathbf{X} .

Assume the network company has to decide on the location of new base stations. Several technical aspects will be important for this decision. First of all, the station will improve coverage the most if it is built at a location where the distance to the nearest station is largest. Secondly, the heights of the surrounding buildings will be important (Bond & Wang, 2005). An exposed location allows the station to cover a greater range in all directions. A roof top that is lower than the adjacent buildings does not allow this because the signal would be shielded. Thirdly, the density of the population at a given location plays a role if the capacity of the existing stations is limited. Moreover, if two locations are equally far from the nearest base station, the place with the higher population density will be preferred because a greater number of (potential) customers will benefit from the improved coverage. Fourth, some places might be avoided in general, such as schools or kindergartens.

The idea behind the instrument is that the existing CPBS sites are only one possible outcome. In an alternative world, the stations could also be located at other locations that meet the requirements. Most likely, however, not all of the aspects just mentioned are exogenous to property prices. Indeed, we concentrate on the first aspect. We argue that spacing between CPBS locations is exogenous to the price of housing.

Consider a CPBS location $l_i = (x_i, y_i)$ of CPBS i somewhere in the city's network and assume that the network consists of hexagonal elements.² In this case, six "nearest" CPBS locations around i can be identified, each in a different direction. In Figure 1, these are the dark triangles around the white triangle that represents CPBS location i . If i were not installed yet, the network company's problem would be to choose a location c_i for i inside the hexagon spanned by the six corner CPBS. Under the assumption that spacing of the network is important, a naive guess for c_i would be the centroid, $c_i = \sum_{j=1}^6 l_j / 6$. In Figure 1, the light grey triangle is the centroid of the dark triangles that constitute the hexagon around CPBS location i . Following this procedure for every CPBS location inside such a hexagon produces a simulated network of counter-factual locations. The

²Ideally, UMTS and GMS networks have a hexagonal structure (Niemelä & Lempiäinen, 2003).

log distance of an observation to the nearest counter-factual location can then be used in the estimation as an instrument for *log distance nearest CPBS*.³

Two problems arise at this point: Some locations are at the edge of the network and have only $n < 6$ directions in which a neighbour can be found. In this case, the centroid between the two neighbours left and right to the missing neighbour(s) was used (see Figure 2). The second problem is related to the exogeneity of the simulated network: When the network was built in the first place, spacing considerations with respect to other CPBS locations did not play the same role as in a network as dense as in 2014. On the other hand, the absolute position of the network depends on these first choices.

The validity of the instrument stems from the fact that extensions of the network depend heavily on the existing structure which has developed over time. To improve network coverage in an area, a base station must be erected somewhere in that area. The possibilities to locate the new CPBS in a neighbourhood where prices are low in the first place are much more limited due to the spatial and technical constraints than they were when the network used to be less dense. This argument applies to the centre of the city whereas in the suburbs network density is much lower. Even if the original positions of CPBS were not exogenous to the price structure, this dependence is likely to be reduced over time for the initial group of antennas. Moreover, note that network coverage in a typical European city is very high nowadays. Within cities, cell phone users will hardly recognise when coverage needs improvement in a certain area, and house prices should thus be uncorrelated to the quality of network coverage. As a robustness check we estimated the model for a sub-sample: All observations nearest to a CPBS location with allowance date before 2004 were removed.⁴

One potential source of endogeneity that might contaminate the instrument is network density. Network density increases with proximity to the city centre. It is widely acknowledged that housing prices are likely to increase as well as distance to the central business district decreases. We therefore include distance variables as controls. Additionally, results are presented for a standardised instrument. The original instrument was divided by the perimeter of the hexagon, since the perimeter of the hexagon is a good proxy for network density.⁵

³Technical details on the selection of the hexagon's corners can be found in the appendix.

⁴The year 2004 is a reasonable choice since UMTS licences were auctioned in 2000 (Van Damme, 2002). A basic UMTS network was constructed in 2001 - 2003. The commercial launch took place in 2004 (Telekom, 2005).

⁵The instrument, the log distance to the counter-factual CPBS location, is divided by the perimeter of the hexagon of the counter-factual CPBS location. This removes a large part of the correlation between the instrument and the distance to the city centre.

4 Data

The property prices we use are listing prices of flats for sale in Nuremberg. Being smaller than Berlin, Hamburg or Munich, the city of Nuremberg has 498 000 inhabitants (2014). The data on prices come from the online real estate market place ImmobilienScout24 and were provided free of charge thanks to a cooperation agreement concluded between ImmobilienScout24 and the authors in the context of the "TransparenzOffensive Immobilienwirtschaft"⁶. Recent studies on the German housing market that use listing prices are [Brandt & Maennig \(2012\)](#) and [Mense & Kholodilin \(2012\)](#).

The ImmobilienScout24 data were filtered for duplicates. We only considered flats with an exact street address and house number that are larger than 15 square metres, sold for at least 25 000 Euro and had a price per square metre below 10 000 Euro.⁷ Furthermore, we excluded all flats that had not been constructed yet or were built before the year 1000.⁸

The resulting data set contained 1709 observations. Further 15 observations were excluded because their distance to the nearest CPBS was below 10 metres. Results that include these 15 observations indicate a positive effect for these locations. Possible explanations are the lease income from a CPBS if it is located on the same building and the unawareness of the residents if it is not visible from the apartment (e.g. located on the next or opposite building). Additionally, radiation is lower below an antenna due to the sharp angle. Since we use log distances instead of dummies for distance bands, keeping these observations would reduce the efficiency of our model. Therefore, these 15 observations were excluded. The final data set contains 1694 flats offered for sale between the 1st of April 2011 and the 31st of March 2014.

Next to the size and the offer price, the property data contain a list of quality characteristics. These are dummies for the presence of a built-in kitchen, an elevator, a balcony or terrace, number of bathrooms, a sauna, parquet flooring, floor heating and stove heating. There are dummies for access to the garden and for the quality of the flat as well as for its state (in need of renovation, first-use etc.), and a variable that indicates whether the property is located in a historic building (monument). The year of construction is reported in the offers. It is used to calculate the building's age. An overview of the large set of housing characteristics including summary

⁶For further details see <http://www.transparenzoffensive.net>

⁷The restrictions on the price and size of the flat were relevant only for a couple of offers. In most cases, these offers had other defects that also required to exclude them.

⁸Note, the first documentary evidence on Nuremberg refers to the year 1050 ([Stadt Nürnberg, 2014](#)). The oldest building in the final sample has an age of 394 years.

statistics is given in Table 1 in the appendix.

A general problem of real estate offers is that sellers or estate agent can decide freely about how much information about a flat to provide with the offer. Thus, there is a potential for measurement error in the control variables that cannot be resolved. If we compare our data set with the data set of [Brandt & Maennig \(2012\)](#) the distribution of housing characteristics like dwelling size, number of rooms, age of the building, availability of a balcony and parking space are comparable in both cities. However, built-in kitchens are less common in Nuremberg than in Hamburg (30 versus 61 percent). In the further analysis, part of the mentioned variables will be excluded due to missing relevance in the empirical model.

As already noted, the data we use are listing prices. Listing prices differ from transaction prices in important ways. From theoretical bargaining models it follows that the offered price serves as an upper bound at which a transaction can be made at any time. Hence, under regular conditions there is no incentive for the buyer to ever pay more than the listing price (see for example [Yavas & Yang, 1995](#)). By and large, this has been validated by empirical studies. For a sample of housing sales from Stockton, California, [Knight \(2002\)](#) reports that 376 of 2,759 objects sold above their listing price, but the author attributes these cases to special financial arrangements between the sellers and buyers. 684 houses sold below their listing price, while the rest (1,669) did not experience a price change. Moreover, [Knight](#) finds that the difference between listing and offered price becomes larger with the time an offer remains on the market. These results have been confirmed by [Merlo & Ortalo-Magné \(2004\)](#) for data from England. The sales price to listing price ratios were between 93.4% and 97.3%, depending on the region, while the sales price exceeded the listing price in only 30 of 780 cases. [Fillipova & Fu \(2011\)](#) find similar relationships. They note that in booming markets the time on the market is shorter and has a higher explanatory power for the price difference.

[Faller et al. \(2009\)](#) regress the difference between offer and sales prices for owner-occupied property on the time on the market and on dummies for the year of construction and the size (m²) of the flat. The time on the market turns out to be the most important variable in that regression. The data used in the present study contain one variable that indicates the time an observation remained online in months.⁹ However, this information is truncated at both ends of the sample since we do not know when an observation from April 2011 came online and we also do not know how long observations from March 2014 stayed online. We therefore

⁹For technical reasons we have this information only for 1574 observations and not for the full-sample.

construct a dummy that is equal to 1 if an observation remained online for more than one month. To assess the potential bias in the present data set, the pairwise correlation between this dummy and *log distance CPBS* was checked. It is -0.02 and not significant. The coefficient of the time on market dummy is significant and has the expected positive sign in the OLS or IV regressions but is insignificant in the first stage. Since its inclusion has no effect on the effect of the next CPBS, this variable was omitted from the analysis.

A set of neighbourhood characteristics obtained from various sources was added to the data set. The variable of main interest, the distance to the nearest CPBS, was calculated using a geographical information system. The respective summary statistics are reported in Table 2 in the appendix. The address of each observation was matched with the official house coordinates directory of [Bayerische Vermessungsverwaltung \(2013\)](#) to obtain coordinates. Furthermore, addresses were matched with Nuremberg’s ten townships (Stadtteile), 83 districts (Bezirke) and 316 zones (Distrikte) to incorporate administrative data at the district level like unemployment rates and to calculate clustered standard errors at the district and zone level. We included the following variables provided by the urban statistical office ([Amt für Stadtforschung und Statistik, 2010](#)): *average living space per person*, *unemployment rate* and the *percentage of houses with more than 7 apartments*. These variables are available for 2010.¹⁰ We further added a dummy variable *noisy night* that indicates whether the street noise level at the locations is above 55 db on average at night.¹¹

The log of the straight line distance to the most important landmark in Nuremberg, the Kaiserburg, (*log distance castle*) was also included for observations in the centre and northern part of Nuremberg. Likewise, the log distance to Nuremberg Central Station (*log distance central station*) was used for the southern part.¹² The location and allowance dates of 362 CPBS in Nuremberg were taken from the [Amt für Stadtforschung und Statistik \(2013\)](#) and matched with the official house coordinate directory. Figure 3 illustrates the spatial distribution of the CPBS locations across the city and the development of the network over time. The average distance of a flat to its nearest CPBS is about 216 m. 55.7% of the flats are closer than 200 m to the nearest

¹⁰We also considered the share of foreign population, share of population above 60 years, and the number of cars per 1000 inhabitants and a gravity variable based on firm sizes at the district level to measure the proximity to employment. These variables were insignificant.

¹¹The data are provided by the environmental office of Nuremberg. The data encompass for every address in Nuremberg an estimate of the noise level at the facade of the building. 55 db was chosen as the threshold since this number is used in many studies on the effect of noise on property values and the federal benchmark of the maximum allowed noise varies between 49-59 db with respect to different area types ([16. BImSchV, 2006](#)). [Andersson et al. \(2010\)](#) find the same noise level to have an effect on property prices.

¹²The commercial and administrative centre of Nuremberg is nearby. Thus, the variables can also be interpreted as the log distance to the central business district. We chose to estimate the slopes separately for the southern (*log distance central station*) and the northern townships (*log distance castle*) of Nuremberg.

CPBS. In the case of Hamburg only 38% of all flats were located within 200 m of a CPBS (Brandt & Maennig, 2012). Table 3 contains further information on the spatial relationship of flats and CPBSs. All distance variables were used in natural logs in order to account for non-linear effects and to improve the goodness of fit.

5 Results

5.1 Housing characteristics

The OLS results for the housing characteristics can be found in Table 4. As the modelling strategy, we started from a large model that includes a variety of housing characteristics and quarterly time dummies, see OLS (1). The large model was reduced to a more parsimonious model by the `stepwise` command¹³ in `Stata` with a threshold p-value of 0.2, see OLS (2). The application of the *general-to-specific* approach¹⁴ seems justified due to little theoretical guidance on the model specification (Irwin, 2002). Furthermore, a model specification driven by a priori beliefs or the literature provides no general advice with respect to the exclusion of variables. The latter model was used as the basis in the further analysis, but including the full set of housing characteristics does not change the results for *log distance nearest CPBS* in the OLS and IV models. All significant variables have the expected sign and the model fit is very high in OLS (2). While the adjusted R² of OLS (1) and (2) hardly differ, the AIC (457.2 vs. 500.1) favours the full set of variables. Conversely, the BIC (767 vs. 690.3) supports the specification in OLS (2). We consider the latter criterion to be more relevant, since AIC penalises less for additional variables (Kuha, 2004). Besides, variance inflation factors of all variables are all below 10 in OLS (2) but not in OLS (1). The model OLS (3) shows that the inclusion of neighbourhood characteristics and *log distance nearest CPBS* adds explanatory power. Across all specifications the results for housing characteristics change little. Therefore, we will not report them in the following.

¹³The `stepwise` command in `Stata` implements a model selection using the *general-to-specific* or the *specific-to-general* approach given an a priori defined set of potential variables. We did not allow the quarterly time dummies to be dropped.

¹⁴This approach and its advantages are discussed in Hoover & Perez (1999). However, it must be noted that it does not ensure a correct post-model selection inference (Demetrescu et al., 2011). Bohl et al. (2012) take a similar approach in their housing price study.

5.2 Main results

Table 5 contains the main results for the OLS and IV regressions of *log distance nearest CPBS* on property prices. All standard errors are clustered on the district level to guard against spatial correlation in the residuals. The estimated coefficient of *log distance nearest CPBS* in the OLS model is significant at the 10% level and positive. Translated into price discounts, the model predicts that the price of a flat located 100 m from a CPBS is 2% higher than the price of a similar flat at 50 m distance from a CPBS. Moving another 100 m away from the CPBS, the price difference would be 4.1%.¹⁵ These results are similar to those of other studies. Brandt & Maennig (2012) find a discount of 2.2% in a comparable model when the distance is below 100 m.¹⁶ Bond (2007) reports a discount of 0.2% per metre. Between 10 and 50 m, the discount per metre implied by the OLS model would be 0.12%. Between 50 and 100 m, it reduces to 0.04%.

Several neighbourhood characteristics were added as controls. All of them have the expected sign. Prices decline with increasing log distance to the Nuremberg Castle (Kaiserburg) and to Central Station for observations in the northern and respectively in the southern part of Nuremberg. The land price gradient for *log distance central station* is slightly steeper. This might reflect the lower attractiveness of southern townships like Langwasser or the “Südstadt” (“Southern City”). A high level of night noise decreases prices. Areas with a higher average living space per inhabitant exhibit slightly higher prices, while a high unemployment rate reduces prices substantially. The percentage of houses with seven or more apartments (multi-storey buildings) is higher in areas where land is scarce and valuable. This holds for the city centre but also for sub-centres. This variable is included as a proxy for high accessibility with respect to jobs, shopping opportunities and other local amenities that are capitalised in land values and thus in prices. The positive coefficients in the OLS and the IV models confirm this reasoning.

In columns 2 and 3 of Table 5, *log distance nearest CPBS* is instrumented using the log distance to the nearest counter-factual CPBS. The coefficient doubles in size and it is highly significant with a p-value of 0.007. The respective discount amounts to 4.2% when two similar flats at distances of 50 and 100 m to a CPBS are compared. All other coefficients are very similar compared to the OLS estimation.¹⁷ Compared to Brandt &

¹⁵This result conforms to an evaluation of the price effect using sample mean distance to nearest CPBS (216m) and its standard deviation (151m). The difference would be 3.5%.

¹⁶We replicated the regression in Brandt & Maennig (2012) and obtained a significant effect of -5.1% below 100 m. Beyond 100 m the effect is insignificant.

¹⁷We also clustered standard errors at the level of urban zones to account for a spatial autocorrelation of the residuals within

Maennig (2012) we have only a small set of neighbourhood variables at our disposal. Since the omission of locational variables can cause imprecise or biased estimates, we included postal zone fixed effects in column 3. A similar approach is used by Locke (2013) who showed that the identification of an effect may depend on the inclusion of spatial fixed effects. We find that the coefficient of *log distance nearest CPBS* is unchanged compared to IV (1) and it is significant at the 5% level. Other neighbourhood variables vary within 95% confidence intervals here.

Columns 4 and 5 of Table 5 report the first-stage regressions for IV (1) in column 2 and IV(2) in column 3. The instrument is highly significant and has the expected sign. There is no weak instrument problem given F-values larger than 10.

In summary, the results suggest that the OLS estimate might be *downward* biased rather than the other way around. This is in contrast to the results presented by Brandt & Maennig (2012) who find an upward bias due to local disamenities. One explanation for this disparity could be that Brandt & Maennig (2012) control for some local disamenities exclusively around CPBS sites, but not in the control group. Secondly, the spatial lag term in their model implies the existence of feedback loops. If it is positive, this would mean that total marginal effects are larger than the direct effects reported in their paper. Thirdly, the downward bias of OLS might stem from the fact that the endogeneity of location choice varies between the centre and the suburbs of a city. In the following section, this issue is explored further.

5.3 Robustness checks for the basic model

Table 6 reports some robustness checks of the basic model IV (1) in Table 5. The instrument used in column 1 is standardised by the perimeter of the hexagon around the respective CPBS location, as described in section 3.2. This reduces the correlation between the distance to the centre of the city and the instrument. The coefficient remains significant, but it is slightly larger than in the basic model. The first stage results in Table 7 show that the adjusted instrument performs weaker in terms of the F-statistic and lower adj. R^2 , which might explain the change. If instead the sample is restricted to observations for which the nearest CPBS has an allowance date greater than 2003 (column 2), the results hardly differ from the basic model. In sum, these results do not

smaller geographical areas. The average area of the 316 urban zones in Nuremberg is 0.59 km² and the median is 0.33 km², whereas the 86 urban districts have average area of 2.14 km² and a median of 1.5km²). Consequently, a zone correspond to a neighbourhood rather than a district. The respective coefficient is not significant in OLS (p-value=0.111) but still significant for IV (p-value=0.04).

corroborate the criticisms regarding the exogeneity of the instrument, as discussed in section 3.2.

For the models reported in columns 3 to 6 of Table 6, the sample was divided into two approximately equally large parts. In columns 3 and 4, the sample consists of observations for which the distance to the castle exceeds 3000 m. In the OLS model (column 3), the coefficient is marginally significant and has the same size as in the baseline OLS model from Table 5. In contrast to this, the IV estimator suggests that the effect is zero (column 4). The situation is reversed for the sub-sample of observations located closer than 3000 m from the castle. While the OLS estimate is insignificant but of the same size as in the baseline model, the IV estimate suggests a strong positive price-distance gradient. This is in line with the argument that it is much more difficult for the network company to find a “bad” (i.e. low-price) location in the central city than it is in the suburbs. Therefore, the argument put forward by Brandt & Maennig (2012) seems to apply only for CPBS locations in the suburbs.

6 Conclusion

The paper re-examines the effect of CPBS on property values in a German city using the example of Nuremberg. We found a positive and significant coefficient of 0.062 for *log distance to nearest CPBS* in the IV regression (Table 5, column 2). For example, the model predicts that a flat located 50 m from the nearest CPBS would be offered at a discount of 4.2% compared to similar flats at a distance of 100 m. A similar effect was found for “bad view” locations that host a CPBS in Hamburg (Brandt & Maennig, 2012).

Whereas the study area of Brandt & Maennig (2012) is urban, most other studies (cf. Bond, 2007; Locke, 2013) consider rural areas. Therefore, the present results are closely related to Brandt & Maennig (2012). At a basic level both studies can be compared directly and find similar results. However, we propose an alternative approach to the identification of the relevant coefficient which leads to a different interpretation. The structure of the network was used to simulate counter-factual locations of CPBS from which a counter-factual distance was calculated. The log of this counter-factual distance was then used as an instrument. We argue that network structure depends on technical requirements that are not related to property prices. Therefore, the instrument should also be unrelated to property prices.

Since network density is higher in the city centre, the instrument might be correlated with distance to the

city centre. As is widely known, the Alonso model predicts a negative correlation between distance to the city centre and land values (Alonso, 1964). Consequently, the exclusion restriction might be violated if the land price gradient is not controlled for in the model. However, even after purging the instrument of this correlation, the results remained almost unchanged.

The IV results suggest that OLS estimates are not biased upwards in central locations where the observed negative effect of a CPBS does not seem to depend on the unobserved characteristics of the CPBS location. Brandt & Maennig (2012) argue that CPBS are likely to be located on “visually disruptive” structures such as industrial facilities or office buildings. Therefore, it is not possible to distinguish between the effect of a CPBS and its location. However, industrial facilities or unsightly office buildings are rare in city centres where the network is dense and distances to CPBS are smaller. This reduces the potential for an endogeneity bias. In contrast to this, the endogeneity problem might be much more prevalent in less densely populated areas.

While recognized widely, endogenous location choices are a challenge for many applications in regional economic research (Pinkse & Slade, 2010). The approach taken in this paper is related to the instrumental variable strategies in Hoxby (2000) or Michaels (2008). It might be useful for problems where location choices are endogenous but at the same time depend on an existing network structure.

7 Acknowledgements

We would like to thank the City of Nuremberg, especially Thomas Nirschl of Amt für Stadtforschung und Statistik für Nürnberg und Fürth and Uwe Reiter of the Umweltamt. Furthermore, we thank Erich Eisenschmid of the Bayerische Vermessungsverwaltung and Jan Hebecker of ImmobilienScout24. The paper has benefited from the comments in the doctoral seminars in Nuremberg and Erlangen.

8 Appendix

8.1 Technical details on the instrument construction

In section 3.2 the construction of the instrument is described. The simulation of the counter-factual network requires to select the corners of a hexagon around each CPBS location. All of the corners should be nearest neighbour CPBS locations, each in a different direction. As can be seen in Figure 1, we divided the space around a CPBS location into six wedges and selected the nearest CPBS location in each wedge as a hexagon corner. The centroid from these six location was then used as the position of the counter-factual CPBS.

One potential problem arises when CPBS locations are very close to one of the lines that divide two adjacent wedges. Assume that a CPBS is located inside wedge A and very close to wedge B. Furthermore, let this CPBS be the second nearest CPBS in wedge A. Hence, it is not considered in the calculation of the centroid. This is troublesome if the nearest CPBS in wedge B is very far away. We therefore repeated the procedure twice and rotated the wedges by an angle of $(2\pi/6)/3 = \pi/9$ each time. The centroid was then calculated as the centroid of all 3×6 hexagon corners.

8.2 Tables

Table 1: Summary statistics: housing characteristics

Variable	Mean	Std. Dev.	Min.	Max.
total sale price	171911.385	126938.549	15400	753900
net dwelling area	77.656	34.991	17	291.7
age of property in years	39.445	35.907	0	394
landmarked building	0.058	0.234	0	1
n. of rooms	2.724	1.095	1	10
several bathrooms yes/no	0.053	0.223	0	1
built-in kitchen	0.302	0.459	0	1
cellar space	0.737	0.44	0	1
hobby room	0.019	0.136	0	1
some type of balcony	0.754	0.431	0	1
garden	0.181	0.385	0	1
guest toilet	0.256	0.436	0	1
elevator	0.478	0.5	0	1
handicapped accessible	0.131	0.338	0	1
designated for seniors	0.09	0.286	0	1
object is rented	0.228	0.42	0	1
provision yes/no	0.247	0.431	0	1
first time use	0.279	0.449	0	1
mint condition	0.047	0.211	0	1
modernized	0.038	0.192	0	1
new renovated	0.083	0.275	0	1

Continued on next page...

... table 1 continued

Variable	Mean	Std. Dev.	Min.	Max.
new decorated	0.086	0.28	0	1
well-kept	0.215	0.411	0	1
need renovation	0.037	0.188	0	1
luxury interior of housing	0.032	0.177	0	1
upmarket interior of housing	0.258	0.438	0	1
normal interior of housing	0.191	0.393	0	1
simple interior of housing	0.019	0.138	0	1
floor heating	0.152	0.359	0	1
sauna	0.01	0.1	0	1
fireplace	0.016	0.125	0	1
stove heating	0.024	0.154	0	1
distance heating	0.144	0.351	0	1
heating type NA	0.191	0.393	0	1
parquet floor	0.078	0.268	0	1
timber floor	0.005	0.073	0	1
laminated floor	0.091	0.288	0	1
carpet floor	0.028	0.164	0	1
some Wooden floor	0.081	0.274	0	1
ground flat	0.143	0.35	0	1
penthouse	0.078	0.268	0	1
loft	0.01	0.1	0	1
maisonette	0.049	0.216	0	1
parking space yes/no	0.496	0.5	0	1
nr. of observations		1694		

Table 2: Summary statistics: neighbourhood characteristics

Variable	Mean	Std. Dev.	Min.	Max.	N
average living space per person	39.999	5.609	25.2	60.5	1694
unemployment rate	0.048	0.02	0.009	0.099	1694
% of houses with 7 or more apartments	71.124	21.303	1.2	95.3	1694
noisy night	0.25	0.433	0	1	1694
distance to castle Nuremberg	3103.627	2127.26	112.93	12229.78	1694
distance to central station Nuremberg	2888.149	1861.653	345.833	11077.475	1694

Table 3: Summary statistics: distance to CPBS

Variable	Mean	Std. Dev.	Min.	Max.	N
distance nearest CPBS	216.079	151.305	12.396	1176.492	1694
distance second nearest CPBS	341.573	213.964	25.512	2220.286	1694
distance third nearest CPBS	451.773	272.934	82.074	2662.548	1694
Share of observations:					
nearest CPBS within a radius of 50 m*	0.062	.	0	1	1694
nearest CPBS within a radius of 50 - 100 m	0.153	.	0	1	1694
nearest CPBS within a radius of 100 - 150 m	0.158	.	0	1	1694
nearest CPBS within a radius of 150 - 200 m	0.184	.	0	1	1694

* Observations below 10 metres are excluded.

Table 4: OLS Regressions for Housing Characteristics

	OLS (1) coef./SE	OLS (2) coef./SE	OLS (3) coef./SE
Housing Characteristics excluded from the final model:			
landmarked building	0.008 (0.059)		
several bathrooms yes/no	-0.036 (0.043)		
hobby room	0.068 (0.060)		
garden	0.053** (0.020)		
elevator	0.059** (0.029)		
handicapped accessible	0.041 (0.042)		
designated for seniors	-0.057 (0.043)		
provision yes/no	-0.025 (0.024)		
luxury interior of housing	0.155** (0.072)		
upmarket interior of housing	0.084** (0.037)		
normal interior of housing	-0.042 (0.030)		
simple interior of housing	-0.111* (0.062)		
sauna	-0.026 (0.075)		
fireplace	-0.018 (0.105)		
heating type NA	0.038 (0.025)		
parquet floor	0.175 (0.130)		
timber floor	0.003 (0.093)		
carpet floor	-0.047 (0.034)		
some wooden floor	-0.106 (0.138)		
penthouse	0.006 (0.032)		
loft	-0.132 (0.117)		
maisonette	0.050 (0.048)		
Housing Characteristics included in the final model:			
net dwelling area	0.025*** (0.002)	0.026*** (0.002)	0.025*** (0.002)
net dwelling area squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
age of property in years	-0.004*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
age of property squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)

Continued on next page...

... table 4 continued

	OLS (1)	OLS (2)	OLS (3)
	coef./se	coef./se	coef./se
n. of rooms	0.009 (0.022)	0.002 (0.021)	0.013 (0.019)
built-in kitchen	0.030 (0.020)	0.048** (0.019)	0.044** (0.018)
cellar space	0.065** (0.030)	0.066** (0.032)	0.051** (0.023)
some type of balcony	0.090*** (0.032)	0.095*** (0.034)	0.111*** (0.024)
guest toilet	-0.038 (0.028)	-0.029 (0.030)	-0.014 (0.023)
object is rented	-0.114*** (0.028)	-0.119*** (0.026)	-0.105*** (0.023)
first time use	0.311*** (0.042)	0.347*** (0.044)	0.315*** (0.034)
mint condition	0.113* (0.057)	0.150** (0.060)	0.107* (0.059)
modernized	0.097** (0.038)	0.083** (0.037)	0.094*** (0.031)
new renovated	0.079* (0.042)	0.099** (0.048)	0.088** (0.038)
new decorated	0.051 (0.036)	0.071* (0.042)	0.050 (0.036)
well-kept	0.005 (0.027)	-0.007 (0.025)	-0.028 (0.022)
need renovation	-0.282*** (0.059)	-0.309*** (0.062)	-0.324*** (0.055)
floor heating	0.099** (0.043)	0.126*** (0.042)	0.113*** (0.032)
stove heating	-0.135*** (0.050)	-0.156*** (0.051)	-0.124*** (0.042)
distance heating	0.040 (0.032)	0.039 (0.036)	0.022 (0.033)
laminated floor	-0.048 (0.029)	-0.062* (0.032)	-0.049* (0.026)
ground flat	-0.016 (0.021)	-0.011 (0.022)	-0.011 (0.016)
parking space yes/no	0.063** (0.026)	0.071** (0.029)	0.078*** (0.019)
Quarters:			
3/2011	-0.021 (0.027)	-0.025 (0.032)	-0.023 (0.025)
4/2011	0.006 (0.031)	0.005 (0.034)	0.002 (0.027)
1/2012	-0.003 (0.029)	-0.018 (0.030)	-0.002 (0.024)
2/2012	0.064* (0.035)	0.044 (0.036)	0.072** (0.031)
3/2012	0.141*** (0.035)	0.122*** (0.039)	0.142*** (0.035)
4/2012	0.135*** (0.045)	0.111** (0.042)	0.140*** (0.032)
1/2013	0.171*** (0.037)	0.151*** (0.037)	0.171*** (0.031)
2/2013	0.191*** (0.043)	0.195*** (0.044)	0.195*** (0.032)

Continued on next page...

... table 4 continued

	OLS (1)	OLS (2)	OLS (3)
	coef./se	coef./se	coef./se
3/2013	0.174*** (0.034)	0.148*** (0.035)	0.148*** (0.030)
4/2013	0.291*** (0.048)	0.299*** (0.047)	0.297*** (0.044)
1/2014	0.217*** (0.047)	0.203*** (0.043)	0.221*** (0.042)
Neighbourhood Characteristics:			
log distance central station			-0.098*** (0.017)
log distance castle			-0.094*** (0.018)
log distance nearest CPBS			0.029* (0.015)
average living space per person			0.009*** (0.003)
unemployment rate			-3.200** (1.359)
% of houses with 7 or more apartments			0.001* (0.001)
noisy night			-0.061** (0.023)
Obs.	1694	1694	1694
Rank	57	35	42
R2	0.868	0.861	0.887
adj. R2	0.863	0.858	0.884
AIC	457.247	500.116	161.785
BIC	767.033	690.335	390.049

Standard errors are clustered at the district level. Signif. codes: *** 0.01 **0.05
* 0.1. All models include a constant term.

Table 5: Main Regression Results

	OLS (3) coef/se	IV (1) coef/se	IV (2) coef/se	1st stage IV (1) coef/se	1st stage IV (2) coef/se
log distance nearest CPBS	0.029* (0.015)	0.061*** (0.023)	0.058** (0.025)		
log distance counterfactual CPBS				0.621*** (0.075)	0.613*** (0.063)
log distance central station	-0.098*** (0.017)	-0.108*** (0.019)	-0.146*** (0.027)	0.052 (0.128)	0.167 (0.149)
log distance castle	-0.094*** (0.018)	-0.103*** (0.020)	-0.117*** (0.028)	0.038 (0.127)	0.136 (0.145)
average living space per person	0.009*** (0.003)	0.009*** (0.003)	0.006* (0.004)	-0.005 (0.011)	0.003 (0.012)
unemployment rate	-3.200** (1.359)	-3.156** (1.331)	-4.529*** (1.410)	-3.158 (3.630)	-5.190 (4.157)
% of houses with 7 or more apartments	0.001* (0.001)	0.002* (0.001)	0.003*** (0.001)	-0.003 (0.003)	-0.003 (0.004)
noisy night	-0.061** (0.023)	-0.059** (0.023)	-0.056*** (0.022)	-0.064 (0.060)	-0.102* (0.055)
housing characteristics	yes	yes	yes	yes	yes
postal zones	no	no	yes	no	yes
Obs.	1694	1694	1694	1694	1694
Rank	42	42	69	42	69
adj. R2	0.884	0.883	0.887	0.445	0.496

Standard errors are clustered at the district level. Included constant term, quarterly time dummies and housing characteristics are not reported. Signif. codes: *** 0.01 **0.05 * 0.1.

Table 6: Robustness Checks

	IV Cell Size (1) coef/se	IV Time (2) coef/se	OLS Sub (3) coef/se	IV Sub (4) coef/se	OLS City (5) coef/se	IV City (6) coef/se
log distance nearest CPBS	0.081** (0.031)	0.065** (0.027)	0.038* (0.021)	-0.006 (0.050)	0.025 (0.028)	0.091** (0.039)
log distance central station	-0.114*** (0.022)	-0.126*** (0.022)	-0.109** (0.044)	-0.127*** (0.046)	-0.128*** (0.037)	-0.160*** (0.043)
log distance castle	-0.109*** (0.022)	-0.121*** (0.023)	-0.110** (0.044)	-0.127*** (0.045)	-0.120*** (0.035)	-0.150*** (0.041)
noisy night	-0.058** (0.023)	-0.095*** (0.029)	-0.048* (0.027)	-0.055** (0.028)	-0.068** (0.030)	-0.072** (0.030)
average living space per person	0.009*** (0.004)	0.003 (0.003)	0.009*** (0.003)	0.009*** (0.003)	0.006 (0.006)	0.005 (0.006)
unemployment rate	-3.129** (1.334)	-3.885*** (1.454)	-4.184*** (1.198)	-4.632*** (1.249)	-3.525** (1.738)	-3.535** (1.737)
% of houses with 7 or more apartments	0.002** (0.001)	0.001 (0.001)	0.002** (0.001)	0.002** (0.001)	0.002 (0.001)	0.001 (0.001)
Obs.	1694	1148	653	653	1041	1041
Rank	42	42	42	42	42	42
adj. R2	0.882	0.884	0.923	0.921	0.870	0.868

Standard errors are clustered at the district level in 1 and 2 but at the zone level in 3-6. All Models include quarterly time dummies, a constant term and housing characteristics. Results of first stages are reported in table 7. Signif. codes: *** 0.01 **0.05 * 0.1.

(1) uses the normalised instrument as described in the text. The sample used in (2) is restricted to observations for which the nearest CPBS has an allowance date from 2004 or later. The sample for (3) and (4) is restricted to observations for which the distance to the castle exceeds 3000 m. For (5) and (6) the distance is below 3000 m.

Table 7: IV First Stage Results of Robustness Checks

	Cell Size (1) Coef./SE	Time (2) Coef./SE	Sub (3) Coef./SE	City (4) Coef./SE
cell size corrected instruments	0.339*** (0.123)			
log distance counterfactual CPBS		0.691*** (0.094)	0.477*** (0.118)	0.707*** (0.063)
log distance central station	0.111 (0.143)	-0.089 (0.121)	-0.528* (0.280)	0.221 (0.133)
log distance castle	0.097 (0.139)	-0.107 (0.122)	-0.551* (0.282)	0.198 (0.127)
noisy night	-0.084 (0.062)	-0.014 (0.065)	-0.151 (0.106)	0.004 (0.057)
average living space per person	-0.005 (0.015)	-0.001 (0.012)	-0.010 (0.010)	-0.007 (0.021)
unemployment rate	-4.586 (4.098)	-5.151 (3.960)	-12.855** (5.439)	-3.986 (5.029)
% of houses with 7 or more apartments	-0.000 (0.004)	-0.002 (0.003)	-0.005 (0.004)	-0.003 (0.004)
Constant	9.246*** (2.729)	2.719** (1.278)	8.768*** (2.610)	0.789 (1.896)
Obs.	1694	1148	653	1041
Rank	42	42	42	42
ad. R2	0.321	0.441	0.364	0.495
F-Test	0.000	0.000	0.000	0.000
F-Value	14.91	19.81	11.00	13.54

*Standard errors are clustered at the district level in 1 and 2 and zone level in 3 and 4. Further tests of IV-specification can be reported on request. Signif. codes: *** 0.01 **0.05 * 0.1.*

8.3 Figures

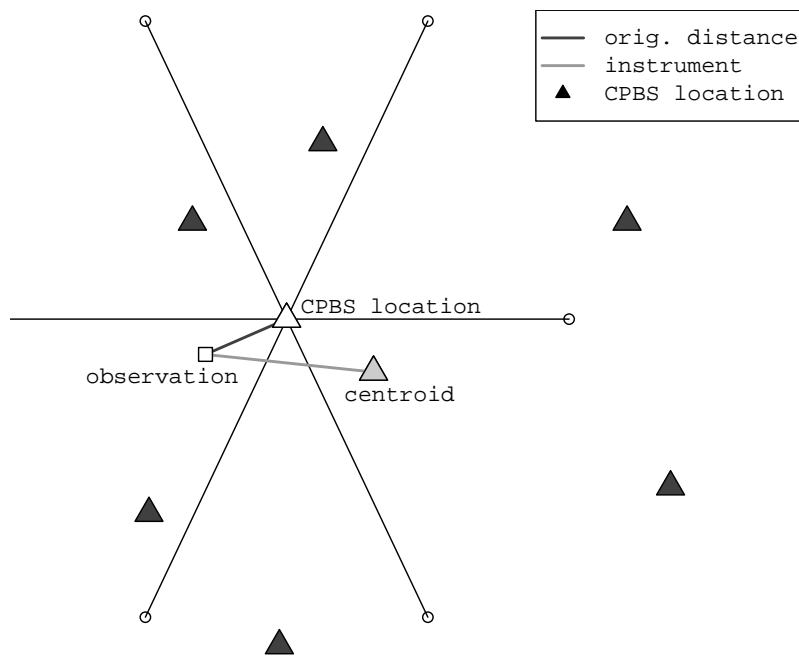


Figure 1: Construction of the instrument - hexagon centroids as counterfactual CPBS locations

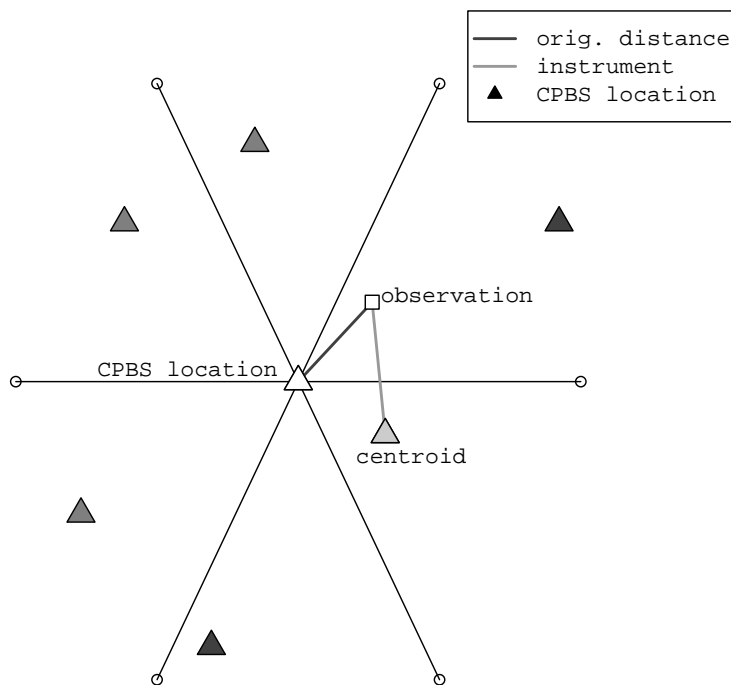


Figure 2: Construction of the instrument - CPBS missing in one direction

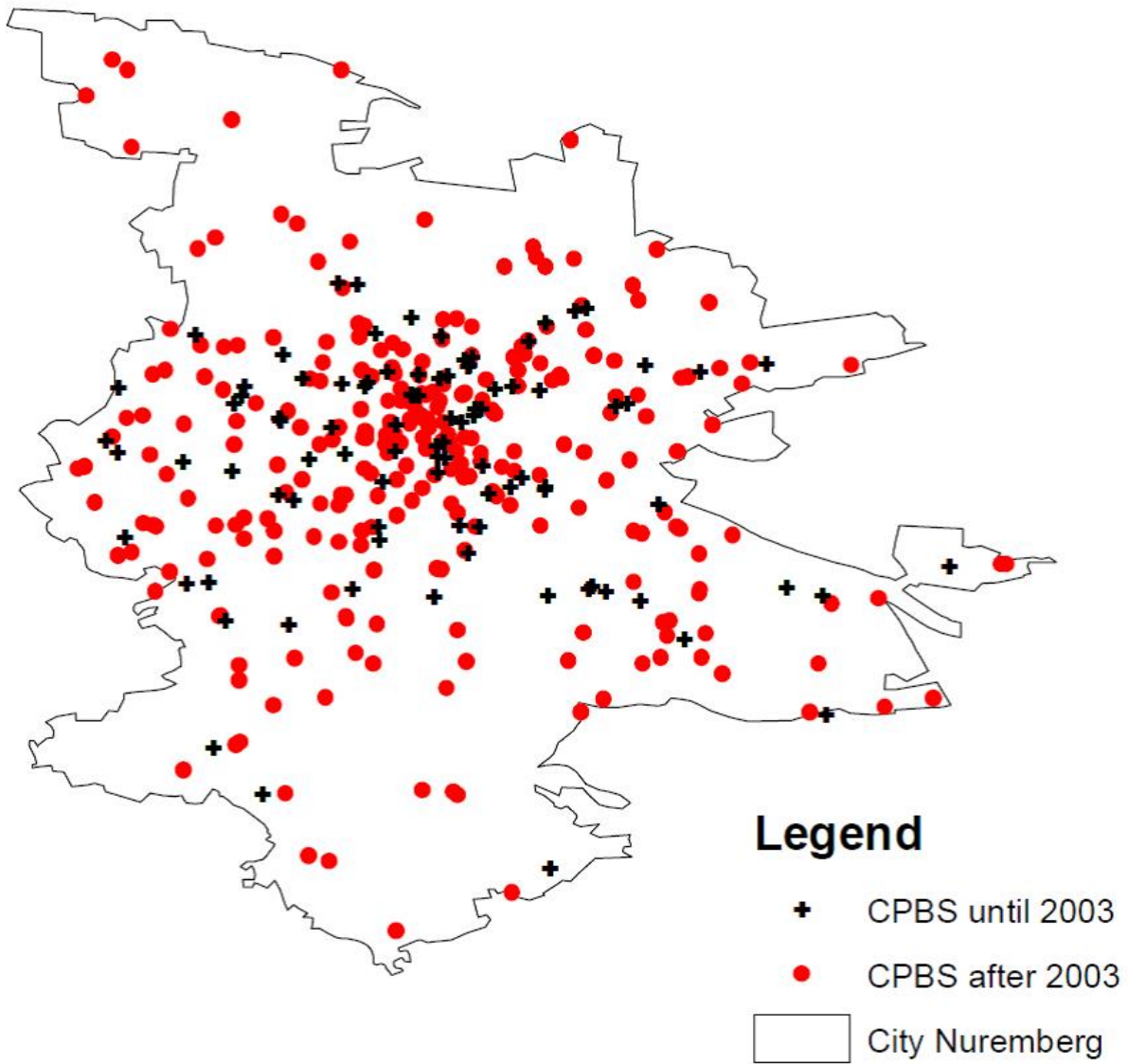


Figure 3: Spatial distribution of cell phone base stations (CPBS)

9 References

References

16. BImSchV (2006). Verkehrslärmschutzverordnung vom 12. Juni 1990 die durch Artikel 3 des Gesetzes vom 19. September 2006 geändert worden ist (16. BImSchV). *Bundesgesetzesblatt*, 1, 2146.
- Alonso, W. (1964). *Location and land use. Toward a general theory of land rent*. Cambridge, Mass.: Harvard Univ. Pr.
- Altunordu, V. (2013). Naturschützer warnen vor der Gefahr des Mobilfunks. Available at: <http://www.nordbayern.de/naturschuetzer-warnen-vor-der-gefahr-des-mobilfunks-1.3188970?searched=true>, accessed February 26th, 2014.
- Amt für Stadtforschung und Statistik (2010). *Innergebietliche Strukturdaten Nürnberg 2010*. Nuremberg: Stadt Nürnberg.
- Amt für Stadtforschung und Statistik (2013). Stadtplandienst Nürnberg. Available at: http://www.archiv.statistik.nuernberg.de/geoinf/spn//mittel_gross2.gif, accessed Februar 26th, 2014.
- Andersson, H., Jonsson, L., & Ögren, M. (2010). Property prices and exposure to multiple noise sources: Hedonic regression with road and railway noise. *Environmental and resource economics*, 45(1), 73–89.
- Bayer, P., Keohane, N., & Timmins, C. (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management*, 58(1), 1–14.
- Bayerische Vermessungsverwaltung (2013). Hauskoordinaten. Available at: http://vermessung.bayern.de/geobasis_lvg/hauskoordinaten.html, accessed February 26th, 2014.
- Blumberg, L. (2012). Mobilfunkbetreiber verspricht Verzicht. Available at: <http://www.rundschau-online.de/wipperfuertth-und-lindlar/getarnter-handymast-mobilfunkbetreiber-verspricht-verzicht,19081524,20988334.html>, accessed February 26th, 2014.
- Bohl, M., Michels, W., & Oelgemöller, J. (2012). Determinanten von wohnimmobilienpreisen: Das beispiel der stadt münster. *Jahrbuch für Regionalwissenschaft*, 32, 193–208.

- Bond, S. (2007). The effect of distance to cell phone towers on house prices in florida. *Appraisal Journal*, 75(4), 362–370.
- Bond, S. & Beamish, K. (2005). Cellular phone towers: perceived impact on residents and property values. *Pacific Rim Property Research Journal*, 11(2), 158–177.
- Bond, S. & Wang, K. (2005). The impact of cell phone towers on house prices in residential neighborhoods. *Appraisal Journal*, 73(3), 256.
- Brandt, S. & Maennig, W. (2012). Perceived externalities of cell phone base stations: housing prices in hamburg, germany. *Environment and Planning A*, 44(2), 396–410.
- Burgess, A. (2002). Comparing national responses to perceived health risks from mobile phone masts. *Health, risk & society*, 4(2), 175–188.
- Can, A. (1992). Specification and estimation of hedonic housing price models. *Regional science and urban economics*, 22(3), 453–474.
- Cavaillès, J., Brossard, T., Foltête, J.-C., Hilal, M., Joly, D., Tourneux, F.-P., Tritz, C., & Wavresky, P. (2009). Gis-based hedonic pricing of landscape. *Environmental and Resource Economics*, 44(4), 571–590.
- Cho, S.-H., Poudyal, N. C., & Roberts, R. K. (2008). Spatial analysis of the amenity value of green open space. *Ecological Economics*, 66(2), 403–416.
- Cutler, D. M. & Glaeser, E. L. (1997). Are ghettos good or bad? *The Quarterly Journal of Economics*, 112(3), 827–872.
- Cutler, D. M., Glaeser, E. L., & Vigdor, J. L. (2008). When are ghettos bad? Lessons from immigrant segregation in the United States. *Journal of Urban Economics*, 63(3), 759–774.
- Demetrescu, M., Hassler, U., & Kuzin, V. (2011). Pitfalls of post-model-selection testing: experimental quantification. *Empirical Economics*, 40(2), 359–372.
- Des Rosiers, F. (2002). Power Lines, Visual Encumbrance and House Values: A Microspatial Approach to Impact Measurement. *Journal of Real Estate Research*, 23(3), 275–302.

- Drake, F. (2006). Mobile phone masts: protesting the scientific evidence. *Public Understanding of Science*, 15(4), 387–410.
- Faller, B., Helbach, C., Vater, A., & Braun, R. (2009). Möglichkeiten zur bildung eines regionalindex wohnkosten unter verwendung von angebotsdaten. Research Notes 34, RatSWD.
- Filippova, O. & Rehm, M. (2011). The impact of proximity to cell phone towers on residential property values. *International Journal of Housing Markets and Analysis*, 4(3), 244–267.
- Filippova, O. & Fu, S. (2011). Time-on-market and house prices in Auckland, New Zealand. *Pacific Rim Property Research Journal*, 17(1), 70–91.
- Fischel, W. A. (2001). Why are there nimbys? *Land economics*, 77(1), 144–152.
- Gibbons, S., Machin, S., & Silva, O. (2008). Choice, competition, and pupil achievement. *Journal of the European Economic Association*, 6(4), 912–947.
- Gibbons, S. & Overman, H. G. (2012). Mostly Pointless Spatial Econometrics? *Journal of Regional Science*, 52(2), 172–191.
- Hanna, B. G. (2007). House values, incomes, and industrial pollution. *Journal of Environmental Economics and Management*, 54(1), 100–112.
- Hoover, K. D. & Perez, S. J. (1999). Data mining reconsidered: encompassing and the general-to-specific approach to specification search. *The Econometrics Journal*, 2(2), 167–191.
- Hoxby, C. M. (2000). Does Competition among Public Schools Benefit Students and Taxpayers? *The American Economic Review*, 90(5), pp. 1209–1238.
- Hutter, H. P., Moshhammer, H., Wallner, P., & Kundi, M. (2006). Subjective symptoms, sleeping problems, and cognitive performance in subjects living near mobile phone base stations. *Occupational and Environmental Medicine*, 63(5), 307–313.
- Irwin, E. G. (2002). The effects of open space on residential property values. *Land economics*, 78(4), 465–480.

- Irwin, E. G. & Bockstael, N. E. (2001). The problem of identifying land use spillovers: Measuring the effects of open space on residential property values. *American Journal of Agricultural Economics*, 83(3), 698–704.
- Khurana, V. G., Teo, C., Kundi, M., Hardell, L., & Carlberg, M. (2009). Cell phones and brain tumors: a review including the long-term epidemiologic data. *Surgical neurology*, 72(3), 205–214.
- Knight, J. R. (2002). Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes. *Real estate economics*, 30(2), 213–237.
- Kuha, J. (2004). Aic and bic comparisons of assumptions and performance. *Sociological Methods & Research*, 33(2), 188–229.
- LeSage, J. & Pace, R. K. (2009). *Introduction to spatial econometrics*. CRC press.
- Lin, H.-C. & Lin, Y.-M. (2011). Willingness to Pay for Relocating Mobile Phone Base Stations. Technical report, Working Paper.
- Locke, S. L. (2013). Two essays on housing: Using hedonic and quasi-experimental methods in (dis-) amenity valuation with housing data: The case of communication antennas, and the value of brand name franchises compared to local real estate brokerage firms. Doctoral dissertation, University of Kentucky.
- Luechinger, S. (2009). Valuing Air Quality Using the Life Satisfaction Approach. *The Economic Journal*, 119(536), 482–515.
- Lyytikäinen, T. (2012). Tax competition among local governments: Evidence from a property tax reform in Finland. *Journal of Public Economics*, 96(7), 584–595.
- Mense, A. & Kholodilin, K. A. (2012). Noise expectation and house prices. DIW Discussion Papers 1244, DIW Berlin, German Institute for Economic Research.
- Merlo, A. & Ortalo-Magné, F. (2004). Bargaining over residential real estate: evidence from england. *Journal of Urban Economics*, 56(2), 192–216.
- Michaels, G. (2008). The effect of trade on the demand for skill: evidence from the interstate highway system. *The Review of Economics and Statistics*, 90(4), 683–701.

- Niemelä, J. & Lempiäinen, J. (2003). Impact of base station locations and antenna orientations on umts radio network capacity and coverage evolution. In *IEEE 6th Wireless Personal Multimedia Communications Conference, WPMC*, volume 2, (pp. 82–86).
- Pinkse, J. & Slade, M. E. (2010). The Future Of Spatial Econometrics. *Journal of Regional Science*, 50(1), 103–117.
- Reinthal, G. (2013). Sendestation kommt an den Wertstoffhof . Available at: <http://sz.de/1.1824644>, accessed at February 26th, 2014.
- Reitzner, H. (2012). Hausbesitzer schirmt seine Mieter gegen Strahlen ab. Available at: <http://www.nordbayern.de/region/erlangen/hausbesitzer-schirmt-seine-mieter-gegen-strahlen-ab-1.1770483>, accessed February 26th, 2014.
- Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *The journal of political economy*, 82(1), 34–55.
- Sims, S. & Dent, P. (2005). High-voltage overhead power lines and property values: a residential study in the UK. *Urban Studies*, 42(4), 665–694.
- Stadt Nürnberg (2014). Stadtarchiv. Available at: <http://www.stadtarchiv.nuernberg.de/stadtgeschichte/daten.html>, accessed February 26th, 2014.
- Telekom, D. (2005). Geschäftsbericht 2004.
- Van Damme, E. (2002). The european umts-auctions. *European Economic Review*, 46(4), 846–858.
- Yavas, A. & Yang, S. (1995). The strategic role of listing price in marketing real estate: theory and evidence. *Real Estate Economics*, 23(3), 347–368.
- Ziob, C. (2013). Funkmast-Pläne in Fürth entsetzen Anwohner. Available at: <http://www.nordbayern.de/region/fuerth/funkmast-plane-in-fuerth-entsetzen-anwohner-1.3055871?searched=true>, accessed February 26th, 2014.