RENT ANALYSIS BEYOND CONDITIONAL EXPECTATION - HOW TO ESTIMATE THE SPATIAL DISTRIBUTION OF QUOTED RENTS BY USING GEOGRAPHICALLY WEIGHTED REGRESSION

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- 1. Motivation
- 2. Alternative Data Sources
- 3. Methodology
- 4. Empirical Application
- 5. Conclusion

MOTIVATION

- 57 percent of all households in Germany are living in a rented accommodation (Statistisches Bundesamt, Wiesbaden 2015, effective 2013).
- Most areas with a high population density are embossed by tight and dynamically developing rental markets.
- It is expected that the increasing number of households caused by the demographic transition and urbanization leads to increasing rents also in cities like Magdeburg, which right now are characterized by quite a relaxed rental market.
- Monitoring of the developments at the rental markets are relevant for urban planning and social welfare.

ALTERNATIVE DATA SOURCES

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- $\cdot\,$ Traditional data collection to rental analysis focus asset rents:
 - \rightarrow information of the common (average) level of residental cost over a longer time-period
 - \rightarrow insufficient conclusions for the market price by re-letting in very dynamic markets
- · Alternative data sources make it possible to focus actual rent prices by re-letting: \rightarrow information about the current market situation and development

Advantages

- · In-time-data-collection of actual offers
- Easy availability of a high number of rental property offers, e.g. via online platforms or the advertisement section in local newspapers
- $\cdot\,$ Easy and cheap data-collection by the dint of
 - · Web-crawling-algorithms
 - · Web-APIs
 - · Database of commercial service providers

Disadvantages

- Rental offers prices may differ from the real price by re-letting.
- $\cdot\,$ Data are biased by the interest of supplier.
- The researcher has no bearing on the characteristics covered in the rental property offer.
- Very good housing supplies are likely to be re-hired without a publication on an online platform.

METHODOLOGY

- Background: The rental price of a property is determined by the individual characteristics of the flat and the characteristics of the surrounding neighborhood.
- Method of hedonic modeling: Estimation of the prices of the individual characteristic by multiple regression-models
- Enables the estimation of the conditional expectation by a special constellation of characteristics.
- It will be possible to estimate the expected price of a hypothetical average flat and to compare this price depending on the location of the flat or the date of the offer.



Department of Statistics, Landeshauptstadt Magdebur Data: Empirica-Systeme

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• The quantile regression enables the analysis of the conditional quantile to the quantile value $\tau \in (0, 1)$ of a dependent variable in conjunction with a set of explanatory variables (Koenker and Basset (1978)).

Quantile Regression Model for $\tau \in (0, 1)$

$$Y_{i} = \beta_{0}(\tau) + \beta_{1}(\tau)X_{1i} + \ldots + \beta_{(p-1)}(\tau)X_{(p-1)i} + U_{i}(\tau)$$
$$= X_{i}^{T}\beta(\tau) + U_{i}(\tau) \qquad i = 1, \ldots, n$$

Assumption: $F_{U_i(\tau)}(0) = \tau \Rightarrow Q_Y(\tau | X_i = x_i) = x_i^T \beta(\tau),$ $U_i(\tau)$ for i = 1, ..., n are independent.





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- Toblers first law of geographic: "Everything is related to everything else, but near things are more related than distant things." (Tobler (1970))
- The principal of the geographically weighted regression (GWR) is based on the ideas of Fotheringham et al. (2002). The geografical weighted extension of QR-Modell is based on the description from Chen et al. (2014) and McMillen (2013).
- The basic idea of the geographical weighting is a local estimation of the model at special target-points which are denoted by their geographical position $s_i = (lat_i, lon_i)$.

Model of the Geografically Weighted Quantile Regression (GWQR)

$$Y_i = \mathbf{X}_i^{t} \boldsymbol{\beta}(\tau; \mathbf{s}_i) + U_i(\tau; \mathbf{s}_i), \quad i = 1, ..., n$$

Assumption: $F_{U_i(\tau; \mathbf{s}_i)}(0) = \tau \Rightarrow Q_Y(\tau; \mathbf{s}_i | \mathbf{X}_i = \mathbf{x}_i) = \mathbf{x}_i^T \boldsymbol{\beta}(\tau; \mathbf{s}_i), U_i(\tau; \mathbf{s}_i)$ is independent.

Υ _i	dependent variable	X _i	$= (1, X_{1i}, \ldots, X_{(p-1)i})$	independent variables
$U_i(\tau, \mathbf{s}_i)$	perturbation depending on $ au$	$\boldsymbol{\beta}(\tau; \mathbf{s}_j)$	$= (\beta_0(\tau, \mathbf{s}_i), \ldots, \beta_{(p-1)}(\tau; \mathbf{s}_i))$	parameters depending on $ au$
	at location s _j			at location s _j

Basic Principle

- · Nearby observations will be integrated with a higher weight.
- The weights are denoted by a kernel function $K(\frac{d_{i0}}{h})_{i=1,...,n}$ of the scaled distance d_{i0} of the observation *i* to the target-point by the bandwidth *h*.
- · Fixed kernel weighting routine
- · Adaptive kernel weighting routine



EMPIRICAL APPLICATION

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Data

- $\cdot\,$ Rental offers from the empirica systema AG database
- $\cdot\,$ Published between January 1, 2012 and the March 31, 2016
- $\cdot \,$ Subset of the row data by
 - $\cdot\,$ geocoded offers with a location precision fewer than 10 meters
 - $\cdot\,$ accommodations with a living area of 30 to 250 squares meters
- \cdot 18442 offers are included into the research

Methodical Specification

- \cdot Semi-log model; dependent variable: log of price per square meter
- · First step: Estimation a global global OLS-model and global QR-models by the quantile values $\tau \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$
- · Seccond step: Estimation the local GWR-models and GWQR-models by the quantile values $\tau \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$
 - $\cdot\,$ Spatial weighting by a gaussian kernel-function and an adaptive bandwith
 - target-points: location of each observation
 - mapping: target points are the center points of a grid over the town area which covered with buildings (adaptive bandwidth have to be under 1 km)

Semi-log Qr/gwqr-model for au=0.5

	GWQR	$\tau = 0.5$					QR	
	mean	min	1st quantile	median	3rd quantile	max	Std.	Sign.
Intercept	1.69	1.55	1.66	1.68	1.72	1.91	1.658	***
log(living area)	-0.03	-0.07	-0.03	-0.02	-0.02	0.004	-0.02	***
elevator	0.02	-0.05	-0.00	0.01	0.04	0.11	0.01	*
balcony/terrace	0.03	-0.02	0.02	0.03	0.04	0.05	0.02	***
parking	0.06	0.02	0.05	0.06	0.08	0.11	0.07	***
kitchen	0.04	-0.01	0.03	0.04	0.05	0.07	0.05	***
social housing	-0.04	-0.10	-0.04	-0.04	-0.03	-0.00	-0.03	***
good condition	-0.00	-0.03	-0.00	0.00	0.01	0.01	0.00	
bad condition	-0.08	-0.17	-0.11	-0.08	-0.05	0.02	-0.10	***
time	0.02	0.01	0.02	0.02	0.02	0.03	0.02	***
-	GWR						OLS	
Intercept	1.63	1.49	1.58	1.61	1.65	1.90	1.67	***
log(living area)	-0.01	-0.07	-0.02	-0.01	-0.00	0.02	-0.00	
elevator	0.04	-0.01	0.02	0.03	0.06	0.11	0.03	***
balcony/terrace	0.03	-0.01	0.01	0.03	0.04	0.06	0.02	***
parking	0.06	0.03	0.05	0.06	0.07	0.11	0.06	***
kitchen	0.05	0.01	0.04	0.05	0.06	0.08	0.06	***
social housing	-0.06	-0.11	-0.07	-0.06	-0.05	-0.01	-0.05	***
good condition	0.01	-0.02	0.01	0.01	0.01	0.02	0.01	***
bad condition	-0.07	-0.14	-0.1	-0.07	-0.05	0.03	-0.08	***
time	0.02	0.02	0.02	0.02	0.02	0.03	-0.02	***

Significance levels [0,001]'***';(0.001,0.01]'**';(0.01;0.05]'*';(0.5,0.1]'°',(0.1,1]' '

SPATIAL HETEROGENEITY OF THE TIME EFFECT (MAGDEBURG)







Flat characteristics: 61.8 square meters, balcony, good condition effective July 1,2012



Flat characteristics: 61.8 square meters, balcony, good condition effective July 1,2015



Flat characteristics: 61.8 square meters, balcony, good condition effective July 1,2012



Flat characteristics: 61.8 square meters, balcony, good condition effective July 1,2015



CONCLUSION

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- Geocoded online-data are a substantial data-source for the analysis of rental data.
 - Enables a lot of analysis in detail; high potential for geostatistical analysis
 - $\cdot\,$ Data-restriction has to be kept in mind.
- $\cdot\,$ Quantile regression allows a detailled view at the conditional distribution of the variable of interest.
 - $\cdot\,$ Main advantages: rubustness aigainst outlier
 - $\cdot\,$ Disadvantages: local estimation could lead to quantile-crossing
- The extension of the geographical weighting allows to consider the location of interest.
- $\cdot\,$ Time trends could be analyzed considering the geographical position.
 - Indicator for the development in special districts (social segmentation or heterogenity).
- $\cdot\,$ GWQR-Model based on local estimation.
 - $\cdot \,$ computationally intensive
 - $\cdot\,$ difficults in modell-selection

THANK YOU FOR YOUR ATTENTION!

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- · In case of empirical analysis, the unknown parameter $\beta(\tau)$ has to be estimated.
- · Solution of the minimization problem:

$$\hat{\boldsymbol{\beta}}(\tau) = \arg\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \mathsf{R}_{\tau}(\boldsymbol{\beta}) = \arg\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \sum_{i=1}^n \rho_{\tau}(\boldsymbol{y}_i - \boldsymbol{x}_i^{^{\mathrm{T}}}\boldsymbol{\beta})$$

· The loos-function $ho_{ au}$ is defined by:

$$\rho_{\tau}(u) = (u)(\tau - l(u < 0)) = \begin{cases} \tau \cdot u & , & \text{for } u \le 0 \\ u \cdot u & , & \text{for } u < 0 \end{cases}$$

 $R_{\tau}(\beta)$ is not differentiable. \rightarrow The minimization-problem has to be solved by methods of linear programming.



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Minimization Problem

$$\hat{\boldsymbol{\beta}}(\tau; \mathbf{s}_0) = \arg\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \sum_{i=1}^n (\rho_{\tau}(y_i - \mathbf{x}_i^{\mathsf{T}} \boldsymbol{\beta}(\mathbf{s}_0)) \cdot \mathsf{K}(\frac{d_{i0}}{h}))$$