

# Ergebnisbericht der Plagiatsprüfung

## Untersuchter Text

Eingangsdatei	Thesis (1).pdf
Autor	n/v
Prüfdatum	17.10.2024
Projekt	n/v
Bemerkungen	n/v

## Prüfergebnis

Kopierte / gesamte Wörter: 357 / 11471

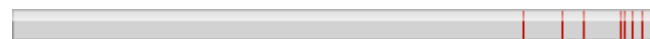
Verdächtige Quellen: 13

Akzeptierte Quellen: 0

Ausgeschlossene Quellen: 1



Prozentsatz kopierte Wörter / gesamte Wörter



Anordnung kopierter Abschnitte

## Legende und Erklärungen

**Originaler Text** Text ohne identifizierte relevante Online- oder Bibliotheksquellen.

**Verdächtige Quelle** Text mit identifizierten Übereinstimmungen in Online- oder Bibliotheksquellen. Der Text wurde möglicherweise umgeschrieben.

**Akzeptierte Quelle** Text mit korrekt zitierten Übereinstimmungen in Online- oder Bibliotheksquellen. Der Text wurde möglicherweise umgeschrieben.

## Durchsuchte Quellen und Einstellungen

Minimale Zeichen in einer Phrase	125	Suche in Online Quellen	Ja
Minimale Zeichen in einer Phrase	50	Suche in Bibliotheksquellen	Ja
Minimale Wortzahl pro Quelle	10	Minimale Ähnlichkeit	100%

## Annotierter Prüftext

Regional Growth Determinants Across the European Union and its Candidates

Wirtschaftsuniversität Wien Department of Economics Elia Di Gregorio October 17, 2024

Regional Growth Determinants Across the European Union and its Candidates Abstract This study investigates regional economic growth determinants in 301 European NUTS-2 regions, encompassing EU Member States and Candidate countries from 2009 to 2019. Using

Bayesian Model Averaging and spatial econometric techniques on 35 variables, we acco... [

14927 Zeichen übersprungen] ...tly, a Spatial Autoregressive (SAR) structure is incorporated, adding a spatial lag term to capture spillover effects between neighboring regions. This

progression allows for a comprehensive analysis of regional growth by accounting for both cross-regional differences and the spatial correlation inherent in economic growth processes.

Building on Cuaresma et al. (2014), these models can be expressed within the general SAR

framework:  $y = \alpha \mathbf{1}_N + X_k \beta_k + \rho W y + \epsilon$ , (2.1) where  $y$  is the  $N \times 1$  vector of the growth rates of income per capita for  $N$  regions,  $\alpha$  is the intercept term,  $\mathbf{1}_N$  is an  $N \times 1$  vector of ones,  $X_k$  is the  $N \times K$  matrix of explanatory variables,  $\beta_k$  represents the corresponding coefficients,  $W$  is the  $N \times N$  spatial weight matrix capturing spatial dependence,  $\rho$  is the spatial autoregressive

parameter, and  $\epsilon$  is the error term. In specifications including fixed effects, region-specific effects are included in the deterministic part of the model, not in the error term. The residuals  $\epsilon$

are assumed to be independently and identically distributed with zero mean and variance  $\sigma^2$ , such that the covariance matrix is  $\Sigma = \sigma^2 \mathbf{I}_N$  (Cuaresma et al., 2014). Elia Di Gregorio (WU)

Page 7 Regional Growth Determinants Across the European Union and its Candidates BMA tackles model uncertainty by estimating all possible combinations of explanatory variables in  $X_k$ , constructing a weighted average of these models. With  $K$  potential variables, this results

in  $2^K$  model combinations, indexed by  $M_j$  for  $j = 1, \dots, 2^K$ . We can write the posterior distribution of the coefficient  $\beta_k$  as:  $p(\beta_k | D) = \sum_{j=1}^{2^K} p(\beta_k | M_j, D) p(M_j | D)$ , where  $D$  represents

the data. The posterior distribution of  $\beta_k$ , given the data  $D$ , is the average of its posterior distributions under each model, weighted by the posterior model probabilities. The posterior

model probabilities (PMPs) are derived using Bayes' theorem:  $p(M_j | D) = \frac{p(D | M_j) p(M_j)}{p(D)}$   $p(D) = \sum_{j=1}^{2^K} p(D | M_j) p(M_j)$ , where  $p(D)$  is the integrated likelihood, serving as a

constant scaling factor across models and ensuring that the posterior probabilities sum to one. The PMP  $p(M_j | D)$  is proportional to the marginal likelihood of model  $M_j$ ,  $p(D | M_j)$ ,

multiplied by the prior model probability  $p(M_j)$ . In this study, a Bayesian linear regression

model with Zellner's g-prior is us... [ 1214 Zeichen übersprungen ] ... The prior on the model

space  $p(M_j)$  also plays a crucial role in BMA, reflecting beliefs about the likelihood of different models being true before observing the data. A random Elia Di Gregorio (WU) Chapter 2.

Methodology Page 8 Regional Growth Determinants Across the European Union and its

Candidates theta prior inclusion probability for each regressor is used, following Ley and Steel

(2009), who suggest a beta-binomial prior distribution, where a beta distribution is employed as a hyper-prior [on the inclusion probability](#). This beta-binomial specification allows for more flexibility by allowing the prior to adapt to [the expected model size](#), making it a better choice when prior information on the model size is limited. The beta-binomial prior mitigates the risk of overfitting by spreading the prior probability across a wider range of possible model sizes, reducing the risk of concentrating too much prior mass on models of a specific size (Feldkircher and Zeugner, 2015). In this application, the expected model size is fixed at  $K/2$ . Given the large number of models under consideration ( $2^K$ ), implementing BMA can be computationally challenging. [ 1996 Zeichen übersprungen ] ... main effects are not accounted for.

Elia Di Gregorio (WU) Chapter 2. Methodology Page 9 Regional Growth Determinants Across the European Union and its Candidates Finally, to ensure robust results, the MC3 sampler was calibrated with 10 million draws and a burn-in period of 3 million iterations. This extensive sampling period was chosen to ensure that the algorithm converged to an accurate estimate of the posterior model probabilities. From the BMA analysis, we obtain the following results: the [Posterior Inclusion Probability](#) (PIP), the Posterior Mean (PM), and the [Posterior Standard Deviation](#) (and thus the Variance) for each variable. The PIP of each variable  $x_k$  is the sum of the probabilities of all models that include  $x_k$ :  $p(\beta_k \neq 0|D) = \sum_j \beta_k M_j p(M_j|D)$ . It represents the probability that a given variable is included in the “true” model, considering all possible models. Variables with PIP values greater than 0.5 are considered significant. Based on Kass and Raftery (1995), PIP values can be classified as weak (50–75%), substantial (75–95%), strong (95–99%), and decisive (99% or higher). [The posterior mean of  \$\beta\_k\$](#)  is the [model-weighted mean of the model-specific](#) posterior means:  $E(\beta_k|D) = 2^K \sum_{j=1}^K p(M_j|D) E(\beta_k|D, M_j)$ . It is the average effect of a given variable on the dependent variable, calculated across all possible models, weighted by their posterior probabilities. Finally, the posterior variance accounts for both within-model variance and variance across models:  $Var(\beta_k|D) = 2^K \sum_{j=1}^K p(M_j|D) [Var(\beta_k|D, M_j) + (E(\beta_k|D, M_j) - E(\beta_k|D))^2]$ . This expression combines the variance of  $\beta_k$  within each model and the variance of the estimates across different models. [ 1790 Zeichen übersprungen ] ... onships, multiple spatial weight matrices are considered in the analysis. This approach ensures that the model does not depend on a single, potentially incorrect assumption about spatial interactions, enhancing the reliability of the estimates through BMA. The spatial weight matrices included in the analysis are the inverse distance matrices, first-order and second-order queen-contiguity matrices, and k-nearest neighbors (k-NN) matrices. The inverse distance matrix is defined as:  $W_{ij} = d^{-\alpha} ij$ , [where  \$d\_{ij}\$  is the distance between regions  \$i\$  and  \$j\$ , and  \$\alpha\$  controls the decay of spatial influence](#). Both  $\alpha = 1$  and  $\alpha = 2$  are used to model varying strengths of spatial interaction. The first-order queen-contiguity matrix assigns equal weights to regions that share a boundary, while the second-order queen-contiguity matrix extends this relationship to include neighbors of neighbors, thereby capturing more distant spatial dependencies. The k-nearest neighbors

(k-NN) matrix defines spatial relationships by selecting the closest k neighbors for each regi... [ 3038 Zeichen übersprungen ] ...status as a capital city or Objective 1 region1, and Eurozone membership. • Interaction terms: The CEE and Candidate dummies were combined with GDP per capita, sectoral components of GVA, and share of population with tertiary education. Additionally, CEE dummies were interacted with the capital specification, but not Candidate dummies, since the majority of these countries were treated as single regions. Primary data sources include Eurostat, ARDECO, and for Candidate countries, the World Bank, [Wiener Institut für Internationale Wirtschaftsvergleiche \(WiiW\)](#), and national statistical offices. Supplementary data were incorporated where necessary, especially from the ESPON database for EU countries. Table A.2 in the Appendix lists all variables, definitions, descriptive statistics, and sources. All explanatory variables capture the initial values of regions at the start of the sample period, allowing them to be treated as predetermined in the least squares estimation and helping to mitigate potential endogeneity concerns. This is particularly import... [ 548 Zeichen übersprungen ] ...2.1. Each model analysis was conducted in three stages, with different sets of regressors. First, only the "core" variables were included. In the second stage, the CEE and Candidate dummy variables were added. Finally, in the third stage, interaction terms were introduced. This incremental approach allows for a systematic assessment of the robustness of the results, enabling a comparison of how the significance and magnitude of the estimates change as the model becomes more specific. The tables [report the posterior inclusion probabilities](#) (PIP) [of each regressor, together with the](#) posterior mean (PM) and posterior standard deviation (PSD) [of the posterior distribution for the associated parameter. The results](#) are obtained from 10 million draws of the MC3 sampler, after a burn-in phase of 3 million [iterations. In all cases](#), a binomialbeta prior is used, where the expected model size equals K/2 regressors. For easier readability, the variables shown in the tables are restricted to those that have PIP > 0.5, which is labeled robust in at least one of the specifications used. Results are obtained with R packages BMS and spat.BMS developed by Feldkircher and Zeugner (2015). The corresponding code for the whole research is available at my public repository on GitHub.

3.1 Regional Growth Determinants between European R... [ 1528 Zeichen übersprungen ] ... - - - 0.980 -0.000 0.000 CEE/Candidates - Dummy interactions Candidates 1.000 0.039 0.004 1.000 0.107 0.011 CEE 1.000 0.023 0.003 1.000 -0.009 0.010 Candidates × GVA Industry 1.000 -0.153 0.020 CEE × Pop. Tertiary Edu 1.000 0.142 0.023 Candidates × Pop. with Tertiary Edu. 1.000 -0.194 0.031 Candidates × Capital 0.983 -0.025 0.007 CEE × Capital 0.999 -0.026 0.005 Share of posterior probabilities - Best model 0.25 0.14 0.11 Share of posterior probabilities - Top 25 models 0.80 0.71 0.45 Share of [posterior probabilities](#) - Top 50 models 0.87 0.78 0.53 Corr PMP 1.0000 1.0000 0.9999 Adjusted R2 0.37 0.39 0.42 Notes: PIP, [posterior inclusion probability](#); PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC3) sampling with 3 million burn-ins and 10 million posterior

draws. Time fixed effects were included across all model specifications. Model 1: Cross-section of regions (baseline). Model 2: Cross-section of regions including the Central and Eastern Europe (CEE) and Candidates dummy variable. Model 3: Cross-section of regions further including interaction terms. Unde... [\[ 20212 Zeichen übersprungen \]](#) ...patial interactions across multiple years can dilute or obscure the actual spatial relationships between regions, as temporal dynamics may complicate the spatial structure. When examining the cross-sectional dataset, which aggregates GDP growth over the entire decade from 2009 to 2019 (301 observations), spatial autocorrelation characteristics similar to those found in Cuaresma et al. (2014) were observed. In contrast, the panel dataset with annual GDP growth (3,311 observations) exhibited weak [spatial autocorrelation](#). Several factors may contribute to this weak [spatial autocorrelation](#). First, Moran's I, commonly used to detect [spatial autocorrelation](#), is primarily designed for purely spatial data, and its effectiveness diminishes when applied to panel data where temporal dependencies interact with spatial relationships. Second, annual GDP growth rates capture short-term fluctuations, and key spatial dependencies may not be reflected in the residuals, especially if significant regional factors are accounted for in the model. Finally, the inclusion of key explanatory variables may explain much of the spatial variation, leaving little residual... [\[ 4058 Zeichen übersprungen \]](#) ...PMs across the different models. This consistency indicates that the spatial weighting method does not substantially affect the core relationships in Elia Di Gregorio (WU) Chapter 4. Robustness Check Page 24 Regional Growth Determinants Across the European Union and its Candidates the model, confirming the robustness of the results. Fourth, to further investigate the transmission channels of growth spillovers, an unrestricted Spatial Durbin Model (SDM) was estimated. This involved expanding the [set of potential growth determinants by introducing](#) spatial lags of the explanatory variables. The spatially lagged variables in the models capture the extent to which economic outcomes in neighboring regions influence the growth of a focal region. The presence of such spillover effects is indicative of regional interdependencies within the European Union and its Candidate countries. The results remained largely consistent with those from the benchmark model, reinforcing the robustness of the findings. In some cases, the spatially lagged covaria... [\[ 10294 Zeichen übersprungen \]](#) ...and inclusive growth across European regions. Elia Di Gregorio (WU) Chapter 5. Conclusion Page 29 Regional Growth Determinants Across the European Union and its Candidates Appendix A Additional Material A.1 NUTS-2 Nomenclature des Unités Territoriales Statistiques (NUTS)-2 Regions Albania [S] Austria [9] Burgenland Niederösterreich Wien Kärnten Steiermark Oberösterreich Salzburg Tirol Vorarlberg Bosnia and Herzegovina [S] Belgium [11] Région de Bruxelles-Capitale/ Brussels Hoofdstedelijk Gewest [Prov. Antwerpen Prov.](#) Limburg [Prov. Oost-Vlaanderen Prov.](#) Vlaams-Brabant [Prov. West-Vlaanderen](#) Prov. Brabant wallon Prov. Hainaut Prov. Liège Prov. Luxembourg Prov. Namur Bulgaria [6] Severozapaden Severen tsentralen Severoiztochen Yugoiztochen

Yugozapaden Yuzhen tsentralen Cyprus [S] Kypros Czech Republic [8] Praha Strední Cechy Jihozápad Severozápad Severovýchod Jihovýchod Strední Morava Moravskoslezsko Germany [38] [Stuttgart Karlsruhe Freiburg Tübingen Oberbayern Niederbayern Oberpfalz Oberfranken Mittelfranken Unterfranken Schwaben Berlin](#) Brandenburg Bremen Hamburg Darmstadt Gießen Kassel Mecklenburg-Vorpommern Braunschweig Hannover Lüneburg Weser-Ems Düsseldorf Köln Münster Detmold Arnsberg Koblenz Trier (Continued) Elia Di Gregorio (WU) Page 30 Regional Growth Determinants Across the European Union and its Candidates NUTS-2 Regions. Continued Rheinhessen-Pfalz Saarland Dresden Chemnitz Leipzig Sachsen-Anhalt Schleswig-Holstein Thüringen Denmark [5] Hovedstaden Sjælland Syddanmark Midtjylland Nordjylland Estonia [S] Eesti Greece [13] Attiki Voreio Aigaio Notio Aigaio Kriti Anatoliki Makedonia, Thraki Kentriki Makedonia Dytiki Makedonia Ipeiros Thessalia Ionia Nisia Dytiki Ellada Sterea Ellada Peloponnisos Spain [16] Galicia [Principado de Asturias](#) Cantabria País Vasco [Comunidad Foral de Navarra](#) La Rioja Aragón Comunidad de Madrid Castilla y León Castilla-la Mancha Extremadura Cataluña [Comunidad Valenciana](#) Illes Balears Andalucía Región de Murcia Finland [4] Länsi-Suomi Helsinki-Uusimaa Etelä-Suomi Pohjois- ja Itä-Suomi France [22] Île de France Centre - Val de Loire Bourgogne Franche-Comté Basse-Normandie Haute-Normandie Nord-Pas-de-Calais Picardie Alsace Champagne-Ardenne Lorraine Pays-de-la-Loire Bretagne Aquitaine Limousin Poitou-Charentes Languedoc-Roussillon Midi-Pyrénées Auvergne Rhône-Alpes Provence-Alpes-Côte d'Azur Corse Croatia [2] Jadranska Hrvatska (NUTS 2016) Kontinentalna Hrvatska ... [ [3473 Zeichen übersprungen](#) ] ...[S] Notes: Contained in squared brackets is the number of region making up the country. [S] flags all countries made up by single regions. If NUTS-2 display corresponding classification year, it is because they differ from the 2021 version currently adopted (more information here). Elia Di Gregorio (WU) Appendix A. Additional Material Page 33 <https://ec.europa.eu/eurostat/web/nuts> Regional Growth Determinants Across the European Union and its Candidates A.2 Variables Summary Statistics Variable [Description Source Min Mean Max Dependent Variable](#) Economic Growth Growth rate of real GDP per capita: [deflated by national prices, price base year is 2009](#) ARDECO/ WiiW -0.160 0.679 0.011 1. Factor accumulation and convergence Initial income Initial real GDP per capita (in logs): price base year is 2009 ARDECO/ WiiW 6.945 11.436 9.810 Investment Rate Gross Fixed Capital Formation by GVA ARDECO/ WiiW/ WDI 0.079 0.748 0.237 2. Demography Migration Rate Migration Rate total ARDECO/ WDI -0.042 0.067 0.002 Life Expectancy Life Expectancy total Eurostat\*/ Nat/ WDI 69.030 85.500 79.950 Fertility Rate Fertility Rate total Eurostat/ Nat/ WDI 0.960 3.910 1.... [ [1631 Zeichen übersprungen](#) ] ... of Monthly Gross Wage in EUR (current prices) ARDECO/ WiiW 5.109 8.708 7.637 Continued on next page Elia Di Gregorio (WU) Appendix A. Additional Material Page 34 Regional Growth Determinants Across the European Union and its Candidates Table B - Summary Statistics (continued) Variable Description Source Min Mean Max 5.



Socio-geographical Output Density Initial output density; GDP (millions)/area (km<sup>2</sup>); initial year; price base for GDP is 2009 ARDECO/ WiiW 0.09 12.43 1,004.21 Employment Density [Initial employment density](#): employed persons (thousands)/area (km<sup>2</sup>); initial year ARDECO/ WiiW -0.03 0.18 10.78 Population Density [Initial population density](#): population (thousands)/area (km<sup>2</sup>); initial year ARDECO/ WiiW 0.003 0.34 10.84 Distance to Brussels Distance to Brussels (km) Eurostat/ GADM 0 952.78 3,142.71 6. Binary Variables CEE Regions of Cyprus, Croatia, [Czech Republic, Estonia, Hungary, Latvia, Lithuania](#), Poland, Slovakia, Slovenia, Romania, Bulgaria "1" : 58 "0" : 243 Candidates Regions of Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, Serbia, Turkey, and Moldova. "1" : 36 "0" : 265 Capital Capital city: 0 = region without capital cities; 1 = capital cities "1" : 37 "0" : 160 Objective 1 EU Regions eligible for structural funds in areas where GDP per capita is less than 75% of the EU average "1" : 65 "0" : 236 Island Island: 0 = region is not an island; 1 = region is an ... [ 4228 Zeichen übersprungen ] ...nzi-Weiss, E. Merkus, R.-J. Molemaker, and R. Stehrer (2017): "The European Construction Value Chain: Performance, Challenges and Role in the GVC," wiiw Research Report. Bartlett, W. and I. Prca (2016): "Interdependence between core and peripheries of the European economy: secular stagnation and growth in the Western Balkans," LEQS Paper. Błażejowski, M., J. Kwiatkowski, and J. Gazda (2019): "Sources of economic growth: A global perspective," Sustainability, 11, 275. Boldrin, M. and F. Canova (2001): ["Inequality and convergence in Europe's regions: reconsidering European regional policies," Economic policy, 16, 206–253.](#) Brock, W., S. N. Durlauf, and K. D. West (2003): "Policy evaluation in uncertain economic environments," . Brock, W. A. and S. N. Durlauf (2001): "What [have we learned from a decade of empirical research on growth? Growth empirics and reality](#)," the world bank economic review, 15, 229–272. Brunet, R., J.-C. Boyer, et al. (1989): [Les Villes européennes, Rapport pour la DATAR, Délégation à l'Aménagement du Territoire et à l'Action Régionale](#), Paris: La Documentation Française, [under the supervision of Roger Brunet, with the collaboration of Jean-Claude Boyer et al., Groupement d'Intérêt Public RECLUS.](#) Chipman, H. (1996): ["Bayesian variable selection with related predictors,"](#) Canadian Journal of Statistics, 24, 17–36. Cuaresma, J. C., G. Doppelhofer, and M. Feldkircher (2014): "The [determinants of economic growth in European regions](#)," Regional Studies, 48, 44–67. D'Andrea, S. (2022): "Are there any robust determinants of growth in Europe? A Bayesian Model Averaging approach," International Economics, 171, 143–173. Egri, Z. and I. Lengyel (2024): ["Convergence and Catch-Up of the Region Types in the Central and Eastern European Countries,"](#) Applied Spatial Analysis and Policy, 17, 393–415. Feldkircher, M. and S. Zeugner (2015): ["Bayesian Model Averaging Employing Fixed and Flexible Priors: The BMS Package for R," Journal of Statistical Software, 68.](#) Fernandez, C., E. Ley, and M. F. Steel (2001): ["Benchmark priors for Bayesian model averaging," Journal of Econometrics, 100, 381–427.](#) Ferry, M. and I. McMaster (2013): "Cohesion policy and the evolution of regional policy in Central and Eastern Europe," Europe-asia studies, 65, 1502–1528. George, E. (2007):

"Discussion of "Model averaging and model search strategies"," Bayesian Statistics, 6, 175–177. Gereben, Á. and P. Wruuck (2021): ["Towards a new growth model in CESEE: convergence and competitiveness through smart, green and inclusive investment,"](#) Tech. rep., EIB Working Papers. Hinne, M., Q. F. Gronau, D. van den Bergh, and E.-J. Wagenmakers (2020): "A conceptual introduction to Bayesian model averaging," Advances in Methods and Practices in Psychological Science, 3, 200–215. Kass, R. E. and A. E. Raftery (1995): "Bayes factors," Journal of the american statistical association, 90, 773–795. 39 Regional Growth Determinants Across the European Union and its Candidates Ley, E. and M. F. Steel (2009): "On [the effect of prior assumptions in Bayesian model averaging with applications to growth regression](#)," Journal of applied econometrics, 24, 651–674. Man, G. (2015): "Competition and the growth of nations: International evidence from Bayesian model averaging," Economic Modelling, 51, 491–501. Maras, M. (2022): "The spillover effect of European [Union funds between the regions of the new European Union members](#)," [Croatian Review of Economic, Business and Social Statistics](#), 8, 58–72. Monastiriotis, V. (2011): "Regional growth dynamics in Central and Eastern Europe," LEQS Paper. [Moral-Benito, E. \(2012\): "Determinants of economic growth: A Bayesian panel data approach,"](#) Review of Economics and Statistics, 94, 566–579. Özyurt, S. and S. Dees (2015): [Regional dynamics of economic performance in the EU: To what extent spatial spillovers matter?](#), 1870, ECB working paper. Shimbov, B., M. Alguacil, and C. Suárez (2019): "Export structure upgrading and economic growth in the Western Balkan countries," Emerging Markets Finance and Trade, 55, 2185–2210. Stanišić, N., N. Makojević, and T. ČURČIĆ (2018): "The EU enlargement and income convergence: Central and Eastern European countries vs. Western Balkan countries," Entrepreneurial Business and Economics Review, 6, 29–41. Zugravu, B.-G. and A. Ștefania Sava (2014): "Patterns in the Composition of Public Expenditures in CEE Countries," Procedia Economics and Finance, 15, 1047–1054, emerging Markets Queries in Finance and Business (EMQ 2013). Elia Di Gregorio (WU) Page 40 Introduction Opening Remarks Literature Review Paper Contribution Methodology Econometric Model Spatial Weight Matrix W Dataset Results Between Countries Model Within Countries Model Spatial Model Robustness Check Conclusion Additional Material NUTS-2 Variables Top Models References

## Plagiatsverdächtige Quellen

- 1 [www.econstor.eu/bitstream/10419/203922/1/wiiw-wp-057.pdf](http://www.econstor.eu/bitstream/10419/203922/1/wiiw-wp-057.pdf)  
Verdächtige Online-Quelle - 168 Worte in 30 Phrasen (1.46%)
- 2 [bms.zeugner.eu/addon-code/web\\_tutorial\\_spatfilt\\_102010.pdf](http://bms.zeugner.eu/addon-code/web_tutorial_spatfilt_102010.pdf)  
Verdächtige Online-Quelle - 12 Worte in 4 Phrasen (0.10%)
- 3 [www.stata.com/manuals/bma.pdf](http://www.stata.com/manuals/bma.pdf)  
Verdächtige Online-Quelle - 23 Worte in 3 Phrasen (0.20%)



- 4 [Master\\_thesis\\_NEW-Dominik Lud...](#)  
Verdächtige Bibliotheks-Quelle - 48 Worte in 8 Phrasen (0.42%)
- 5 [germany.representation.ec.europa.e...ze-bei-investitionen-2016-07-14\\_de](#)  
Verdächtige Online-Quelle - 12 Worte in 2 Phrasen (0.10%)
- 6 [journals.open.tudelft.nl/iphs/article/view/1315](#)  
Verdächtige Online-Quelle - 35 Worte in 2 Phrasen (0.31%)
- 7 [www.econstor.eu/bitstream/10419/71913/1/742552845.pdf](#)  
Verdächtige Online-Quelle - 121 Worte in 24 Phrasen (1.05%)
- 8 [link.springer.com/article/10.1007/s12061-023-09551-w](#)  
Verdächtige Online-Quelle - 15 Worte in 1 Phrasen (0.13%)
- 9 [www.jstatsoft.org/v68/i04](#)  
Verdächtige Online-Quelle - 13 Worte in 1 Phrasen (0.11%)
- 10 [www.econstor.eu/handle/10419/231396](#)  
Verdächtige Online-Quelle - 16 Worte in 1 Phrasen (0.14%)
- 11 [ideas.repec.org/a/vrs/crebss/v8y2022i1p58-72n2.html](#)  
Verdächtige Online-Quelle - 19 Worte in 2 Phrasen (0.17%)
- 12 [www.econstor.eu/bitstream/10419/203214/1/1043486534.pdf](#)  
Verdächtige Online-Quelle - 13 Worte in 1 Phrasen (0.11%)
- 13 [www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1870.en.pdf](#)  
Verdächtige Online-Quelle - 14 Worte in 1 Phrasen (0.12%)

## Ausgeschlossene Quellen

- 1 [Thesis.pdf](#)  
Ausgeschlossene Bibliotheks-Quelle - 10578 Worte in 250 Phrasen (79.6%)