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PhD Thesis Summary

ECONOMETRIC TOOLS FOR SPACE-TIME PREDICTIVE ANALYSIS

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Cluj-Napoca
2025

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INTRODUCTION

Throughout this thesis, I offer an overview of the cutting-edge spatial and space-time econometrical modelling techniques and applications to respond to the main research problems discussed within the scientific community during the last years. The aim is to define, explore, apply, and extend these methods, to ultimately design the most fitted ones that address both the spatial and the temporal dependence of data in the context of understanding economical phenomena. At different stages I stress on the importance of space in modelling the contemporary socio-economic landscape (Fratesi et al 2024).

The case studies chosen to put the theory into practice are represented by: the assessment of the space-time effects of the Covid-19 pandemic over Romania's banking sector (sub-chapter 2.4), the assessment of the spatial effects of Romania's behavioural and socio-economic factors on the pandemic (sub-chapters 2.1, 2.2 and 2.3), and the space-time static and dynamic effects of the economic wealth upon health expenditures in EU countries (sub-chapter 2.5).

The **research questions** addressed in this PhD thesis, are the following:

- How do advanced spatial and space-time econometric models address the limitations of traditional approaches when analysing rapidly evolving socio-economic phenomena?
- In what ways does accounting for spatial autocorrelation, heterogeneity, and dynamic temporal relationships enhance the predictive accuracy and policy relevance of econometric models in the context of public health and economic crises?
- Which methodological considerations are most critical for specifying and estimating spatial interaction effects to capture both local and global spatial effects across diverse socio-economic settings?
- To what extent can spatial panel approaches improve our understanding of the interactions of economic factors in geographically interconnected regions?
- How do different spatial and temporal data structures—ranging from aggregated to disaggregated units—impact model selection, estimation, and the interpretation of space-time effects on economic outcomes?
- What are the methodological challenges and potential innovations involved in extending classical econometric techniques to incorporate complex space-time dependencies for more informed and effective policymaking?

Data is intrinsically linked through its geospatial context, necessitating models and specialized methodologies that can capture these interactions. Overall, this work focuses on the construction of a body of knowledge on different aspects of space-time statistical approaches from two main perspectives: methodological and empirical. Therefore, the main objectives of the thesis can be stated as follows:

- To offer a review and extension of various aspects of space-time methodologies, highlighting the evolution of modelling approaches from classical cross-sectional approaches to dynamic spatial panel methodologies
- To demonstrate the empirical applicability of space-time methods through in-depth analyses of spatially and temporally evolving socio-economic phenomena such as pandemic spread, vaccination behaviours, and economic impacts.
- To evaluate how incorporating spatial autocorrelation and heterogeneity, cross sectional and temporal effects, and temporal dynamics can improve the performance, accuracy, and interpretability of econometric models, ultimately informing more effective public health and economic policymaking.

This thesis has the following structure:

Chapter 1 covers a comprehensive review of the state-of-the-art methodologies for space-time predictive analysis touching on different aspects related to: exploratory spatial data analysis, spatial models with and without the time component, optimal inference, model diagnostics and evaluation.

Chapter 2 addresses the diagnosis, analysis and incorporation of different spatial interaction effects into diverse realistic data settings guided by different strands of methodological literature..

1. STATE-OF-THE-ART SPATIAL AND SPACE-TIME ECONOMETRICAL METHODOLOGIES

Spatial and space-time econometrical models are extensions of the classical linear regression model – the Ordinary Least Square (OLS) model in which different spatial and space-time effects are included. All spatial interaction effects that are normally accounted for when extending the classical OLS to spatially dependent data, gravitate around spatial dependency itself. In this section I highlight the importance of taking space into consideration by introducing the notion of spatial autocorrelation, which sits at the core of modelling spatially dependent phenomena. The discussion evolves towards spatial interaction effects and modelling the neighbourhood.

1.1.TAKING SPACE INTO CONSIDERATION

The most challenging aspects in the literature of spatiotemporal modelling seem to converge on the issues of space-time autocorrelation and heterogeneity, often complicating model design. Autocorrelation, in its temporal, spatial, and especially space-time form, is indispensable for robust and reliable spatiotemporal analysis, and its omission can lead to poor or unrealistic predictions. While some studies suggest simpler models may sometimes outperform complex space-time models, the role of exploratory diagnostics remains critical. Techniques such as Moran's I and LM (Lagrange Multiplier) tests help identify and address spatial dependencies, while heterogeneity, if unaddressed, might lead to insignificant or biased predictions. Robust approaches, like adjusting for heteroskedasticity through GMM or Bayesian methods, ensure accurate inferences regarding spatial spillovers. Integrating spatial autocorrelation and heterogeneity is vital for reliable spatial panel data analyses, hence the need for comprehensive model specifications and diligent diagnostics to avoid misinterpretations and maintain predictive performance.

Controlling for different spatial effects in econometric modelling is the way to account for the spatial dependencies of the data under investigation. This involves incorporating spatial interaction effects as spatial lags into model terms: dependent, independent, and/or error terms. The exclusion of all three terms lead to a simple OLS model while the introduction of all three estimate a General Nesting Spatial (GNS) model. Once restrictions are imposed on the GNS model, one or two spatial interaction effects are excluded and the model can be simplified to: the Spatial Autoregressive (SAR) model, the Spatial Lag of X (SLX) model, the Spatial Error (SEM) model, the Spatial Autoregressive Combined (SAC or SARAR) model, the Spatial Durbin (SDM) model or the Spatial Durbin Error (SDEM) model. Basically, the model can be simplified from the most complex one, the GNS, to the simplest one, the OLS. The complexity of a GNS model offers comprehensive spatial process adaptability but risks overspecification; thus, simpler models like SAR or SLX may be preferred. The challenge lies in selecting appropriate effects, as models differ in estimating direct and spillover effects, crucial in empirical research. Decisions on spatial interaction modelling, including whether effects should be global or local, depend heavily on the empirical research's objectives and the spatial data structures. Ultimately, achieving unbiased parameter estimates necessitates thorough diagnostics and a balance between complexity and simplicity, avoiding overfitting while ensuring robustness in capturing true spatial relationships.

Spatial lags are introduced in the model via the specification of the neighbourhood as given by the spatial weights matrix. This is a non-negative matrix that determines the spatial resolution at which observations are analysed and affects the estimation of model parameters, which may lead to distortions in the predictive model. Various configurations of , such as p-order binary contiguity, geographical distance (a comparison between different orders of the contiguity against distance-based is revealed in sub-chapter 2.3), k-nearest neighbours (sub-chapter 2.5 presents an example of this specification type), and economic-distance matrices, allow for different representations of spatial dependencies, each with varying levels of density. A sparse matrix reflects fewer connections, whereas a dense matrix indicates more interactions between spatial units. The choice of specification significantly impacts model estimation and interpretation and should be done upon prior empirical knowledge and careful consideration of the spatial structures at hand. Researchers often test multiple configurations to ensure robustness, employing criteria like likelihood-ratio tests or AIC for performance evaluation[1].

1.2. SPATIAL AND SPACE-TIME METHODOLOGIES

This sub-chapter covers the main spatial econometrical models as per the estimated effects followed by the introduction of temporal dependencies outlining their progression from simple cross-sectional to complex space-time and spatial panel data models. Spatial econometrics categorizes models into static and dynamic, with dynamic models incorporating temporal lags in the dependent variable and in the lagged dependent variable, enhancing their complexity and ability to capture intricate data patterns. While the basic OLS can be extended to capture spatial dependencies in models like SAR, the SLX or SEM, each offers distinct approaches to estimating spatial spillovers, albeit with varying degrees of flexibility and reliability. More complex models like the Combined Spatial Autoregressive Model with Spatial Autoregressive disturbance[2]

[1] In sub-chapters 2.3 and 2.4 distinct sparse and dense spatial weights matrices are computed and attached to different models to allow choosing the best fitted model

2 The SARAR model is applied on a use-case of Covid-19 infections' clustering effects in sub-chapter 2.1

(SARAR or SAC), the SARAR Durbin[3], the SDM, SDEM[4] and GNS address spatial dependencies with different focuses.

All the above-mentioned models can be respecified in the case of multivariate cross-section, space-time, spatial-panel and dynamic spatial panel analysis. To respecify them for space-time data, the models can incorporate an explicit time component that allows the analysis of the evolution or difference of the spatial relationships from one period to another in the form of single-period spatial models. They can allow analysis of the immediate spatial spillovers and short-term variations but lack the ability to examine persistent spatial specific effects or unobserved heterogeneity over the entire study period.

Single-period spatial models cannot match the depth of analysis provided by spatial panel models[5] as these introduce the time-specific and space-specific effects. The use of such effects depends on the explicit model specification choices and objectives. Spatial panel models are argued to control for individual, time-invariant heterogeneity with the addition of the cross-sectional effects and/or for the omitted spatial-invariant variables with the addition of the time effects, hence they bring more information that could be valuable to different stakeholders as they are intended for capturing more complex dependencies in space-time: spatial spillovers and cross-sectional dependence over time (Baltagi, 2008).

Adding complexity on top of the previous spatial data models, the dynamic spatial panel models introduce the temporal and spatiotemporal lags to assess how past observations and spillovers influence current outcomes. Even though the specification of the model in a dynamic form offers deeper insights into the spillover processes, they also impose challenges to the parameter estimation, computational demand, and model interpretation. It is recommended to take multiple factors into consideration when choosing between a static spatial model and its' dynamic counterpart. In advanced models, common factors represent another layer of complexity, offering a generalized approach to time-fixed effects by accounting for cross-sectional dependencies.

3 The SARAR-het Durbin model is applied on a use-case of Covid-19 vaccinations data in sub-chapter 2.2 where selected independent variables are spatially lagged

4 The SDEM is applied on a use-case of Covid-19 vaccinations data in sub-chapter 2.3. The study also provides arguments against using SDM for this case and against simplifying the model to SEM or SLX

5 Different spatial panel models in the static and dynamic form are assessed in sub-chapters 2.4 and 2.5

The choice between these models hinges on the specificities of the dataset and research objectives, with guides suggesting detailed comparisons using criteria like AIC or BIC to determine the best fit.

2. EMPIRICAL APPLICATIONS OF SPATIAL AND SPACE-TIME METHODOLOGIES

This chapter is dedicated to the empirical applications of the state-of-the-art spatial and space-time econometrical methodologies described in the previous chapter. Building on the foundational methodologies, the intention is to transition from theory to applying the right modelling approaches for temporally evolving and spatially dependent data and to present their application in a manner that would follow the increase in complexity imposed when shifting from classical cross-sectional data, to spatial panel data.

The analysis outlined in this chapter progresses logically, both in terms of complexity in the data and in the relationships between different socio-economic factors and the pandemic indicators as we elaborate a more comprehensive picture of a global crisis. The complexity of the applied econometric models also increases from one use case to another to address the need to estimate different spatial interaction effects, to accommodate spatial heterogeneity and spatial autocorrelation, when focusing on distinct research questions.

The empirical applications in this chapter are aimed at both validating the state-of-the-art econometrical methods discussed in chapter 1 and investigating their applicability when addressing public health and economic challenges. Moreover, another objective is to sequentially address the research challenges of spatially dependent and temporally evolving data depending on different scenarios and the research questions addressed. On a case-to-case basis, there is an increasing or decreasing spatial granularity depending on the data availability, which imposes an adaptation in the interpretation of the spatial dependence and effects, in the assessment of the model estimates as well as in the consequent formation of the policy implications.

In the first four use cases, I have chosen the pandemic as an essential example to showcase the applicability of space-time econometrics, and the importance of assessing and controlling for the spatial interaction effects. It goes without saying that the spread of a virus, in this case, Covid-19, is conditioned by special spatial processes (Vandelli et al., 2024) which require special attention to efficiently model the direct and indirect effects and to avoid unbiased parameter estimates. There is also an interchange between the pandemic indicators as either dependent or independent variables, when addressing different research questions, hence assessing either the spatial effects *of* or *upon* the pandemic in relation to the economic landscape. What is more, beyond the implied spatial processes, the pandemic has come with high resolution microeconomic spatial panel data (big data), which allows for a low-level assessment of these effects.

The last use case shifts the focus toward the analysis of health expenditures driven by key economic factors, a topic where EU member states' data provides a different lens than micro-level pandemic data. Working with aggregated country-level data enables the exploration of spatial panel econometrics which are not fully applicable in highly granular pandemic analyses. This transition showcases how varying data resolutions can reshape both methodological choices and the scope of policy-relevant insights.

2.1.USE CASE 1. ANALYSIS OF THE SPATIAL AUTOCORRELATION AND APPLICATION OF A CROSS-SECTION SARAR-HET MODEL - SPATIAL CLUSTERING BEHAVIOUR OF COVID-19 CONDITIONED BY THE DEVELOPMENT LEVEL

The study represents the first attempt to spatially and temporally model the Covid-19 infection explained by economic variables to proxy the development in Romania. This empirical application is based on Cioban and Mare (2022) and addresses spatial autocorrelation and heterogeneity issues imposed by the spread of the Covid-19 virus, at a high spatial resolution: municipalities. Transitioning from theory to practice, the study analyses the temporal evolution of the global and local Moran's I coefficients to detect spatial and space-time autocorrelation across local administrative units, followed by spatial diagnosis phase in which a simple OLS model of the level of development against the infection rates is computed (Elhorst, 2014). Here a spatial weights matrix is attached, to allow testing for spatial dependencies that could be due to the strong clustering patterns. After confirming the autoregressive and moving average spatial processes, a spatial modelling phase is exemplified, using Anselin's (2011) GMM method for spatial lag and error model -with heteroskedasticity to account for the high spatial heterogeneity- to statistically test the development as a conditioning factor and spatial transmission channel of the pandemic.

Overall, this study illustrates the importance of the exploratory spatial data analysis, when important spatial patterns become visible even from computing basic quantile maps: the clustering patterns of the pandemic and the spatial arrangement consistency with the unemployment and LHDI. Temporal evolutions are slowly being introduced, to allow for a multi-dimensional perspective upon the association between the development and the pandemic. The methods are employed in a progressive manner, from the simple quantile maps to spatially smoothed rates, to spatial diagnosis and ultimately to more nuanced spatial models as outlined in the previous chapter.

The methods and the resulting findings related to the clustering processes underscore the theoretical principles of spatial econometrics and the importance of taking space into consideration in understanding the complex dynamics of pandemic-related phenomena. Through this lens, a critical research gap is addressed, contributing valuable perspectives on localized pandemic impacts. Nonetheless, the study opens the discussion for more in-depth investigations, to analyse the space-time effects on and of the pandemic related to more socio-economic characteristics.

2.2. USE CASE 2. APPLICATION OF A CROSS-SECTION SARAR-HET DURBIN MODEL - HYBRID HEALTH REGIMES: ACCESS TO PRIMARY CARE PHYSICIANS AND COVID-19 VACCINE UPTAKE ACROSS MUNICIPALITIES IN ROMANIA

The second use case is based on Petrovici et al. (2023) and is intended to build on top of the clustering patterns identified in the previous sub-chapter and to offer a more nuanced analysis of the pandemic. The focus is, therefore, shifting from simpler spatial econometrics of a more exploratory nature to complex modelling approaches given by multilinear spatial regression analytics. Moreover, the exploration of the spatial effects of the pandemic also shifts to an exploration of the local vaccination attitudes.

This sub-chapter is dedicated to the exploration of the complex forms of spatial dependence by extending the previously mentioned cross-sectional SARAR model with a selection of Heteroskedastic Durbin factors (Kelejian and Prucha 2010, Anselin 2011). Here, multiple spatial autoregressive processes are accounted: the ones given by the vaccination uptake (dependent), and the ones imposed by unobserved factors (error term), along with the effects of municipal-level indicators: the pandemic -as given by the incidence rate studied previously-, health regime, socialist investments, labour, education, and poverty. The modelling approach showcases flexibility in capturing spatial spillover effects only on a selection of factors, specified via simulation of combinations of spatially lagged independent variables. Moreover, in alignment with the state-of-the-art econometrics for spatially dependent data, the proposed methodology addresses heteroskedasticity, and the spatial autoregressive processes imposed by the multitude of factors analysed and by the high spatial granularity.

In the context of global health regimes and Covid-19 vaccine hesitancy, both endogenous and exogeneous spatial effects are treated to offer an in-depth understanding of Romania's regional disparities and inequalities. This application illustrates how the choice of the adequate spatial modelling approaches can facilitate the analysis of the contemporary challenges in which space plays an essential role. Moreover, a temporal assessment of these disparities and their underlying spatial processes is presented, which, from a methodological point of view, sheds light on the application of an incipient space-time predictive approach. The findings in this sub-chapter set a precedent for future research into of the spatial processes of health disparities.

2.3. USE CASE 3. APPLICATION OF A CROSS-SECTION SDEM MODEL - EXPLORING THE SPATIAL CLUSTERING AND SPILLOVER EFFECTS OF COVID-19 VACCINATION UPTAKE IN ROMANIA: AN ANALYSIS AT MUNICIPALITY LEVEL

This section advances on the empirical application of spatial and space-time methodologies to assess the spatial patterns of the vaccination uptake and its determinants, focusing on a different research question: How do socio-economic, labour market, social, and health-related factors spatially influence Covid-19 vaccine hesitancy at the municipal level in Romania? The application's findings are presented from Mare et al. (2024) with the intention to exemplify the relevance, choice and specification of more elaborated methods that enable examination of the spatial effects of the vaccination conditioned by multiple factors. In this case, I seek for evidence of local spatial spillovers, hence the disturbance factor together with all independent variables are spatially lagged in a SDEM model (LeSage and Pace, 2009 and Elhorst, 2014).

Once again, Moran's I statistics are employed for the detection of global and local spatial autocorrelation patterns (Griffith, 2003, and Anselin, 1995) of the vaccination behaviours. Still, the approach differs from the Covid-19 incidence case presented in sub-chapter 2.1, as only two time periods' vaccination data is available, and, therefore, analysed. The spatial autocorrelation of the temporal changes between the two moments is treated using differential LISA, which allows the identification of significant spatial clusters of the vaccination rollout over time.

Taking another methodological step forward towards more complex space-time econometrics, this sub-chapter addresses robustness validation of both the spatial model employed and the spatial weights matrix. In this sense, multiple spatial weights matrices are computed out of the geographical information of the municipalities. Multiple spatial models are computed for each spatial weights matrix specification, as per the general to specific modelling approach restriction of the SDEM to SLX and SEM . The resulting estimates are statistically compared using multiple criteria: AIC, log-likelihood, Breusch-Pagan, and the pseudo-R2, LR, spatial Hausman.

All results considered; this empirical study contributes to the literature of public health interventions' spatial distribution as well as to the literature of spatial statistics. I argue this is due to an extensive analysis of the spatial patterns conditioned by numerous factors and due to the rigorous validation of the spatial modelling specifications. What is more, the approach comes with evidence-based insights of the spatial clustering and the inter-municipal contagion and diffusion of vaccination behaviour, insights that come with important implications and recommendations towards public strategies tailored to the spatial dependencies imposed by the pandemic and it's socio-economic channels.

2.4. USE CASE 4. APPLICATION OF A SPATIAL PANEL SDEM MODEL - EVALUATION OF THE SPACE-TIME EFFECTS OF COVID-19 ON HOUSEHOLD LOANS AND SAVINGS IN ROMANIA

This sub-chapter is based on Belbe et al. (2024) and addresses a research gap by considering a spatial panel modelling approach in which the Covid-19 pandemic acts as a factor and not a dependent, as seen in the previous empirical studies. What is more, the research delves into the space-time effects of the pandemic on Romania's county-level banking sector. This implies that, while the previously presented use cases are focused more on the specification and temporal evolution of spatial autocorrelation and tackle space-time dependency on a secondary plan, the current sub-chapter primarily directs the attention on the inclusion of both space and time into the specification of the final predictive model.

This application showcases a distinct methodological approach, hence instead of general to specific modelling, the analysis of spatial dependence starts with estimating the simplest model, OLS, for a selection of key moments of the pandemic. The methodology progressively increases in complexity with the addition of the average of the monthly cross-section regressions estimated in different ways: pooled OLS, cross-sectional FE, time FE and the two-way FE model. At all stages of this exploratory modelling phase, the spatial weights matrix is attached to allow the detection of spatial dependence in different forms (Anselin, 1988, Elhorst, 2014). What is more, spatial and serial autocorrelation are both identified and accounted for via different means: individual and pooled global Moran's I statistics (Beenstock and Felsenstein, 2019) and functional boxplots (Sun and Genton, 2011). Moreover, the methodology includes continuous monitorization of the autocorrelation patterns in all models' residuals, including their squared form.

From the simple OLS models, the methodology progresses towards the estimation of a more general model: SDEM with individual and time-specific fixed effects to control for unobserved space-time heterogeneity. Here I showcase the estimation, validation and interpretation of local spillovers and of the spatial autoregressive processes in the error term which align with the expectation that there are dependencies caused by unobserved factors. The modelling process finalizes with this approach due to a good spatial fit of the models' estimates. All methods are adapted to a lower spatial resolution than previous use cases: counties.

I use this study to highlight the importance of space-time econometrics in exploiting the multifaceted impacts of global disruptions. In the analysis outlined in this section, the pandemic proves to significantly influence the banking sector in both space and time. The methodological approach as well as its corresponding results contribute with insights to policymakers and financial institutions, once again stressing on the importance of county-level heterogeneities and spatial spillovers.

2.5. USE CASE 5. APPLICATION OF A SPATIAL PANEL AND OF A DYNAMIC SPATIAL PANEL DURBIN MODEL: EVALUATION OF THE SPACE TIME EFFECTS OF THE ECONOMIC STABILITY UPON THE HEALTH SYSTEM PERFORMANCE IN THE EU COUNTRIES

This section is based on the book chapter *Integrating Health System Performance and Economic Stability: A Geospatial and AI-Driven Approach to Transparency in FinTech*[6] and is intended to showcase the applicability of the most advanced modelling techniques from the literature of Space-time Econometrics, namely the SDM for spatial panel and the SDM for

[6] In process of publication to Springer as part of the book Transparency In FinTech

dynamic spatial panel data (LeSage and Pace, 2009; Elhorst, 2014; Shi and Lee, 2017). The analysis moves away from the Covid-19 empirical cases and focuses on the issue of transparency in FinTech using the lens of highly explainable econometric procedures coupled with "black-box" AI techniques (von Eschenbach, 2021). What is more, instead of modelling individual behaviour (microeconomics), this is a study of macroeconomics patterns, hence an assessment of global spatial spillover effects of the GDP, life expectancy and net income on the health expenditures in the European Union member states.

With the application of the spatial panel SDM, the thesis evolves towards the inclusion of the cross-sectional and time-FE in a model that accounts for the spatial dependency imposed by the dependent. Similar to the previous sub-chapter (2.4) I model here cross-sectional data over time treating the spatial autocorrelation by introducing different spatial interaction effects in the model that allows the estimation of the panel data structures as a two-ways fixed effects. Moreover, as it was the case for sub-chapter 2.3, the spatial weights matrix specification is addressed with multiple models results simulation to ensure connectivity for isolated countries. The second spatial model fitted with the data in this study assesses dynamics on top of the estimates of the previous model and exemplifies how the space-time interactions can be treated when shifting from a static model to a dynamic one. No longer do I model the spatial panel as a collection of cross-sectional observations, but I explicitly account for temporal dynamics through the lagged dependent variable.

The space-time modelling dimension addressed here has important implications for policymakers, and once again highlights the importance of space when modelling socio-economic phenomena with spatiotemporal dependencies. As transparency in FinTech is the main topic in this book chapter, the study introduces the use of AI to address potential extensions of the highly explainable econometrical spatial panel models to enable model interpretability. Therefore, one of the main contributions is for the literature of FinTech, essential for policymakers, researchers, and public health officials to understand how to attain explainable AI-based modelling and prediction systems for space-time data at multinational and sub-national levels. The framework covered in the book relies on geospatial methodologies' combinations from two complementary disciplines: Econometrics and AI. Due to the econometrical nature of the overall objectives of this thesis, the AI-based framework is only introduced at a high level in this sub-chapter, leaving the reader to follow a more in-depth description upon the publication of the book chapter.

CONCLUSIONS

In this research I aimed at taking a step forward towards the assembly of cutting-edge methodologies for space-time polygon data, their potential extensions, limitations and advantages. Therefore, an overview of the state-of-the-art in spatial and space-time econometrics is provided, followed by empirical research applied on top of these methodologies from the simpler to the most complex. The empirical setting switches from one context to another: from the effects of and upon the Covid-19 pandemics to the health system resilience given by economic wealth. Moreover, the applications cover multiple spatial resolutions: from very high given by local geographies of municipalities to counties and then to a very low resolution given by EU's member states.

First, this research tackled issues of interest related to nowadays' econometrics: spatial and space-time autocorrelation, spatial and space-time heterogeneity, multicollinearity, specification of the spatial weights matrix, model estimation and inference, data quality and availability, and model transparency. Second, the empirical applications explore and model relationships between real economic and socio-health phenomena, demonstrating benefits and challenges of advanced space-time econometrics. Moreover, these case studies showcase how informed decision-making and policy formulation can be achieved when using the right methodologies and accounting for the relevant spatial effects depending on the phenomena under study, spatial and temporal resolution, and on the research objectives.

In line with my objectives, I have systematically addressed the stated research questions by showing how advanced modelling can overcome the limitations of traditional and simple cross-sectional or time series. The empirical investigations demonstrate how spatial autocorrelation, heterogeneity, cross-sectional and temporal dependencies influence model quality and interpretation. At all times I address the importance of space and, consequently, of selecting the appropriate neighbourhood specifications.

Amongst the limitations of the research, data availability was a significant constraint. This is because econometric models rely on high spatial and temporal granularity data to effectively capture the relationships and spatial effects between variables as patterns might differ or simply be hindered when assessing data at low spatial and temporal resolutions. In some cases, I needed to proxy different phenomena of interest, as data was not reported at a high temporal granularity, which simply restricted the areal of econometric techniques that could be used. To overcome this, the latest data values available were used or the analysis focused on data at a lower spatial and/or temporal granularity. At times, multiple factors were disconsidered due to a high number of missing values present in the dataset.

I must stress that this thesis' empirical application research ends with dynamic spatial panel data modelling, whilst the dynamic spatial panel data model with common factors (Elhorst, 2022) is "a beast of its own" that warrants a dedicated study on their own.

As a future research stage, my intention is to step forward from the econometrics, hence statistical based modelling approaches, towards machine learning (ML)-based and hybrid (such as combinations between ML and statistical) space-time modelling. Whether ML and, implicitly data driven models, can outperform the conventional statistical and numerical approaches, is still an issue under debate and further comparative studies could help to better address this question. I also aim to further contribute with empirical applications for the models that assume heteroscedastic errors (spatial ARCH and GARCH, see Otto et al., 2018) as a continuation of the current research on the spatial and space-time econometric modelling approaches.

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