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The German Tourism Industry During the COVID-19 Pandemic Unraveling Regional Disparities and Political Restrictions for Uneven Development on the Demand Side

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Abstract

This thesis employs dynamic spatial panel methods to delve into the multifaceted dynamics of overnight stays across various districts in Germany during the unprecedented challenges posed by the Covid-19 pandemic. The overarching goal is to dissect the intricate interplay of factors influencing deviations in overnight stays, ranging from pandemic-induced restrictions to inherent urbanisation dynamics. The study utilises monthly deviation rates from 2020 and 2021 compared to the average of 2015-2019 to assess the effects of these factors. It incorporates an index of restrictions (IOR) to quantify the severity and economic ramifications of Covid-19 measures on accommodation demand. Furthermore, it evaluates the differential impacts of urbanisation levels, distinguishing between rural, peri-urban, urban, and major urban districts, to understand and quantify their resilience to pandemic disruptions. Findings reveal significant variations in deviation rates across district categories. Rural districts generally displayed more stability, whereas major urban districts experienced the most profound declines, underscoring the heterogeneous impacts of the pandemic. The monthly relative change of overnight stays was 5% lower in major urban districts compared to rural districts. The analysis also highlights spatial dependencies, emphasising the influence of neighbouring districts on tourism patterns. Through empirical insights, the thesis provides actionable recommendations for policymakers and stakeholders in the tourism sector, aiming to enhance resilience and sustainability in the face of future crises. By identifying vulnerable districts and effective mitigation strategies, this research contributes to strategic policy decisions and planning initiatives in the tourism industry.

Abstrakt

Diese Dissertation nutzt dynamische und räumliche Panelmethoden, um die komplexen Entwicklungen der Übernachtungszahlen in verschiedenen deutschen Kreisen während der außergewöhnlichen Herausforderungen der Covid-19 Pandemie zu analysieren. Das übergeordnete Ziel besteht darin, das komplexe Zusammenspiel von Faktoren zu analysieren, die Abweichungen bei Übernachtungen beeinflussen. Dies beinhaltet die pandemiebedingten Einschränkungen, bis in zu der inhärenten Urbanisierungsdynamik. Die Studie verwendet monatliche Abweichungsraten der Übernachtungszahlen in Gaststätten und Hotels von 2020 und 2021 im Vergleich zum Durchschnitt der Jahre 2015-2019, um die Auswirkungen dieser Faktoren zu bewerten. Sie integriert einen Restriktionsindex (IOR), um die Schwere und wirtschaftlichen Auswirkungen der Covid-19 Maßnahmen auf die Nachfrage nach Unterkünften zu quantifizieren. Darüber hinaus bewertet sie die unterschiedlichen Auswirkungen von Graden der Urbanisierung und unterscheidet dabei zwischen ländlichen, peri-urbanen, urbanen und großstädtischen Kreisen, um deren Widerstandsfähigkeit gegenüber pandemiebedingten Störungen zu verstehen und zu quantifizieren. Die Ergebnisse zeigen signifikante Variationen in den Abweichungsraten zwischen den verschiedenen Kreiskategorien. Ländliche Kreise zeigten im Allgemeinen eine größere Stabilität, während großstädtische Kreise die stärksten Rückgänge verzeichneten, was die heterogenen Auswirkungen der Pandemie unterstreicht. Dementsprechend verzeichnen die großstädtischen Kreise einen Rückgang der relativen monatlichen Übernachtungszahlen von 5% gegenüber der Landkreise. Die Analyse hebt auch eine räumliche Abhängigkeiten hervor und betont den Einfluss benachbarter Kreise auf das Tourismusmuster. Durch empirische Einblicke bietet die Dissertation umsetzbare Empfehlungen für politische Entscheidungsträger und Akteure im Tourismussektor, mit dem Ziel, die Widerstandsfähigkeit und Nachhaltigkeit angesichts zukünftiger Krisen zu verbessern. Indem sie gefährdete Bezirke und effektive Minderungsstrategien identifiziert, trägt diese Forschung zu fundierten politischen Entscheidungen und strategischen Planungsinitiativen in der Tourismusbranche bei.

Table of Contents

1. Introduction

The Covid-19 pandemic has posed unprecedented challenges to the global tourism industry, profoundly affecting travel behaviours and accommodation demands. Germany, like many other nations, implemented stringent measures to curb the spread of the virus, significantly altering tourism dynamics across its districts. These measures aimed to mitigate the spread of the virus and safeguard public health regarding the potential repercussions of a pathogen of unknown nature, but they also imposed substantial economic burdens on regions heavily reliant on tourism revenues.
The impact of these measures resonates deeply within Germany, spanning its diverse federal states ("Bundesländer") and districts ("Kreise"). The pandemic's effects on tourism have varied widely, reflecting the intricate interplay of policy interventions, urbanisation levels, and local economic dependencies. Accordingly, the thesis investigates the intricate dynamics of tourism demand in Germany in 2020 and 2021. By constructing a comprehensive dataset that includes monthly variations in overnight stays for accommodations of more than 10 beds and a composite index of restrictions (IOR) reflecting the stringency of pandemic-related measures, the study aims to dissect how these factors influenced tourism activity.
Preliminary findings underscored the nuanced impact of Covid-19 restrictions on overnight stays, revealing substantial regional disparities across Germany. Urban and rural areas have exhibited distinct patterns in resilience and recovery within their tourism sectors, reflecting varying levels of urbanisation and local economic dependencies. These insights are crucial for understanding the differential impact of the pandemic on tourism dynamics at local levels.
I employed a dynamic spatial panel data analysis, incorporating both temporal variations (monthly) and cross-sectional variations (district-specific), to unravel the nuanced impacts of Covid-19 restrictions on overnight stays.

Furthermore, the research categories these dynamics comprehensively, offering valuable perspectives for policymakers and industry stakeholders navigating the complexities of the tourism sector's recovery and resilience amidst ongoing global uncertainties. By providing empirical evidence and quantitative analysis through the spatial panel method, this study aims to inform strategic planning and policy formulation to support a sustainable revival of Germany's tourism industry or any other country in the face of future pandemics or crises.

In conclusion, this thesis contributes to a deeper understanding of how external shocks, such as the Covid-19 pandemic, interact with local tourism economies. It highlights the importance of adaptive strategies and targeted interventions to foster resilience and ensure long-term economic sustainability in the tourism sector.

2. Literature Review

The tourism industry, a significant driver of the global economy, was profoundly impacted by the outbreak of the Covid-19 virus. The ensuing restrictions and political measures created a substantial shock to the industry. Historically, such shocks have had only temporary effects on the market or demand side, as suggested by Browne and Edwards (2009). This perspective is reinforced by the recent resurgence in global tourism numbers after the official end of the Covid-19 pandemic in 2023.

Several historical global diseases have significantly affected the tourism industry and obviously the national economy as well. The SARS virus, for instance, caused a short-term crisis in China, dramatically reducing tourism numbers (Zeng et al., 2005). Similarly, Kuo et al. (2008) found that tourism arrivals in Asia decreased following the SARS outbreak. Rossello et al. (2017) reported similar findings for diseases like Malaria, Yellow Fever, Dengue, and Ebola. The common pattern always was the health risk in affected regions, leading to a decline in tourism demand, as supported by Yang et al. (2020).

However, the Covid-19 pandemic is unprecedented, leading to global travel bans and lockdowns unlike any previous crisis. The extent of its impact spans multiple domains, not just health. For example, Abdullah et al. (2004) noted a 2.6% decrease in international travel during the first four months of 2003 due to SARS, with a 10% drop in March and a 50% decline in April in the Asia-Pacific region. Hong Kong was particularly affected, experiencing a 64.8% decline in March and 67.9% in April. These figures pale in comparison to the impacts of the Covid-19 pandemic.

Unlike past crises, governments played a central role during the Covid-19 pandemic, influencing the tourism market through interventions and political restrictions (Hall et al., 2020). Schmude et al. (2021) examined tourism demand side in Bavaria from January to September 2020, highlighting significant temporal and spatial variations in overnight stays during periods of decline and recovery. These variations were linked to different levels of urbanisation and tourism intensity across districts. Schmude et al. (2021) emphasised the importance of incorporating spatial and temporal dimensions into political decision-making.

Popescu et al. (2023) underscored the importance of examining the Romanian tourism industry across both 2020 and 2021. Following the peak levels of overnight stays in 2019, the tourism market faced significant challenges in recovering fully during the pandemic year of 2020. However, by 2021, tourism managers had adapted their offerings and implemented health measures, providing travellers with more confidence and time to plan their vacations. Consequently, a longer timeframe — specifically, a two-year period — is essential for a comprehensive analysis of the German tourism industry during the pandemic.

3. Data

3.1. Objectives

In this study, I employed dynamic spatial panel methods to delve into the multifaceted dynamics of overnight stays across various districts in Germany the Covid-19 pandemic. The overarching goal was to dissect the intricate interplay of factors influencing deviations in overnight stays, ranging from pandemic-induced restrictions to inherent urbanisation dynamics.

My primary objectives revolve around understanding and quantifying the diverse influence on overnight stays during times of a pandemic or any other crisis. The key points are as follow:

Evaluate the Impact of Covid-19 Restrictions (IOR): I aim to analyse the effectiveness and economic ramifications of Covid-19 restrictions, as quantified by a constructed index of restrictions (IOR), on deviations in overnight stays across districts. It is about identifying how varying levels of restrictions have shaped travel patterns and accommodation demands.

Assess the Role of Urbanisation: Through this objective, I seek to unravel the differential effects of urbanisation levels on overnight stays deviations during times of breakdown and recovery. By dissecting urban-rural divides, I aim to discern whether urban regions experienced disparate impacts compared to rural areas, shedding light on the resilience of different locales to pandemic-induced disruptions.

Analyse the Influence of Tourism Intensity: Our analysis delves into the intricate relationship between tourism intensity and overnight stays deviations. By exploring the nexus between districts' reliance on tourism activities and their observed deviations, I aim to unveil the economic vulnerability and resilience of tourism-dependent regions.

Control for Time and District-Specific Effects: To ensure the robustness of our findings, I incorporate both temporal (monthly) and cross-sectional (district-specific) variations. By accounting for unobserved heterogeneity and unique contextual factors, I aim to disentangle the underlying drivers of overnight stays deviations.

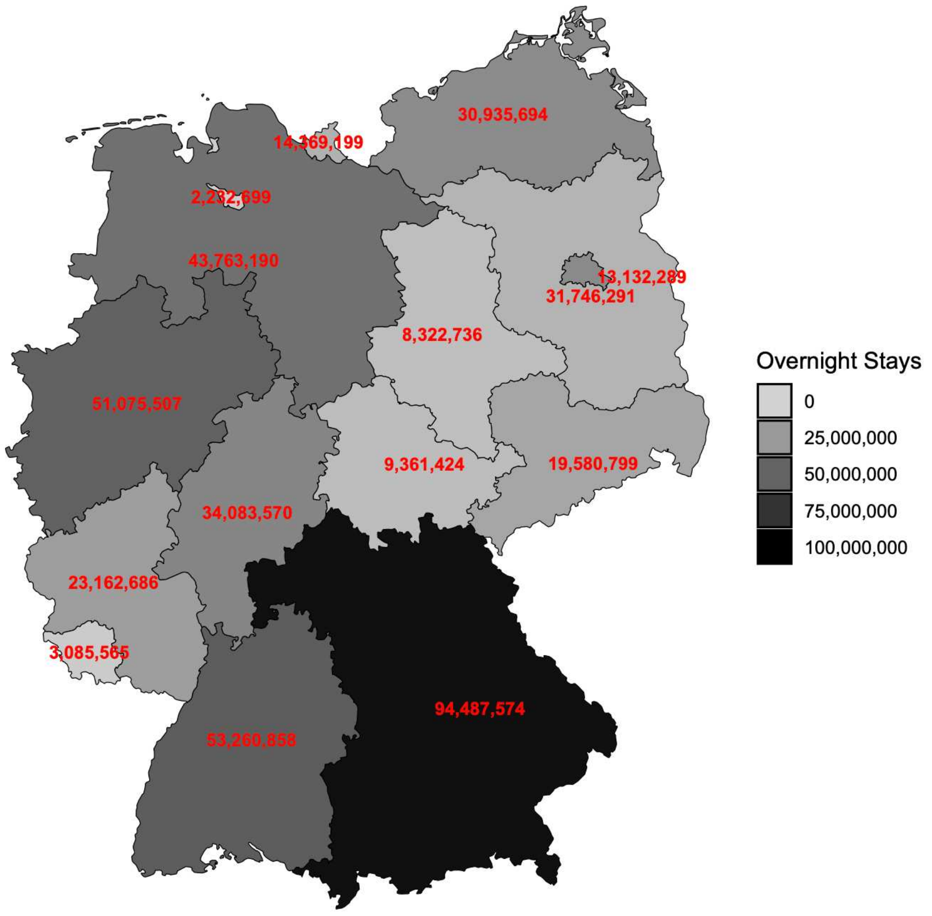
Provide Policy Recommendations: Building upon our empirical insights, I want to furnish evidence-based policy recommendations to bolster the resilience of the tourism sector for potential future crises. By identifying vulnerable districts and effective mitigation strategies, I aim to influence policy decisions and strategic planning initiatives.

Economic Losses : Another important point is to fulfil significant estimations about how the covid-19 pandemic and the corresponding restrictions affected different regions.

3.2. Study Area and Raw Data

Germany is one of the most visited countries in the world, making it an ideal study area due to the distinctive characteristics of its sixteen states, which vary significantly in population, landscape, and international arrivals. In 2023, the total sales revenue from tourism-related products and services in Germany was 338 billion euros, accounting for 8.8% of the country's GDP. Additionally, one in eight jobs in Germany is within the tourism industry. Bavaria (Bayern) leads this sector, with an average of 94,487,574 (see figure 1) yearly overnight stays between 2015 and 2019, the years preceding the Covid-19 outbreak. North Rhine-Westphalia (Nordrhein-Westfalen) and Baden-Württemberg follow as the next most prominent states in terms of tourism activity.

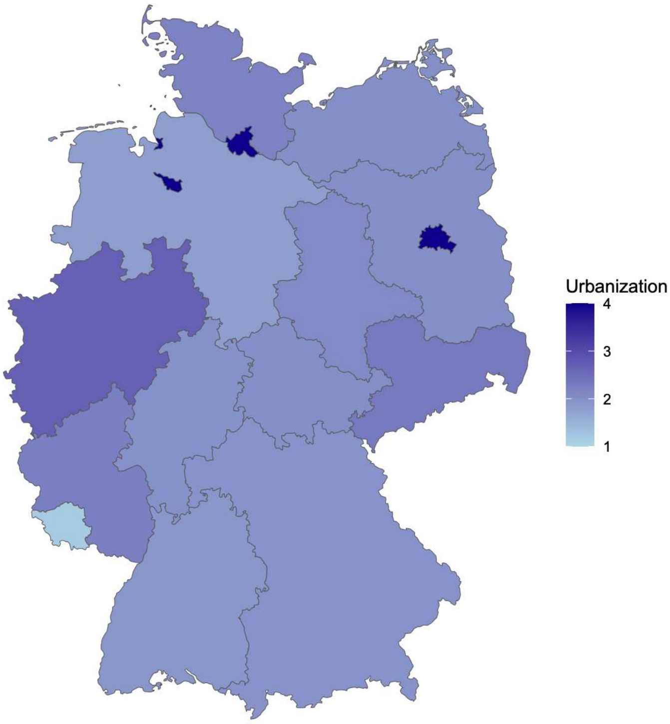
Figure 1
Annual number of overnight stays in each federal state



Source: Own Illustration

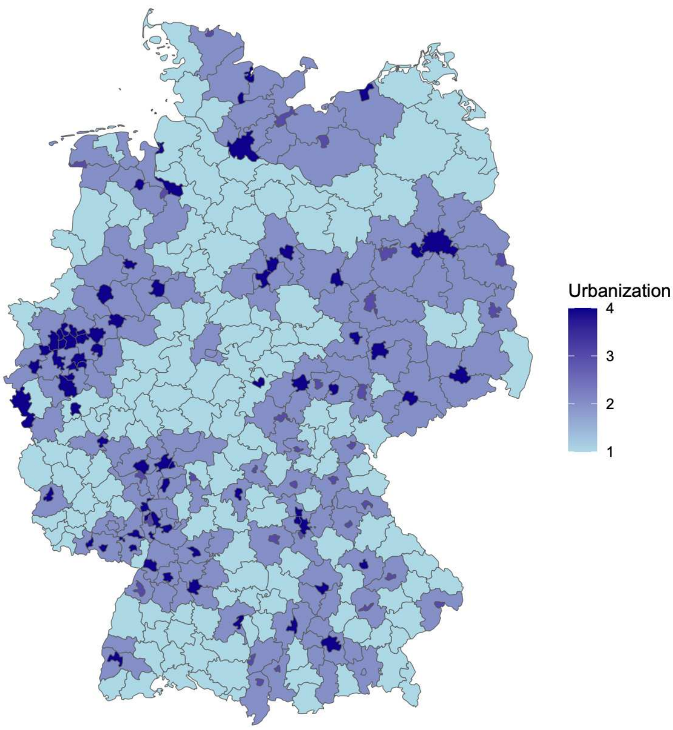
Each state in Germany is subdivided into multiple government regions (Regierungsbezirke), which comprise rural districts (Landkreise) and urban districts (Stadtkreise). For my study on tourism demand at a regional scale, I categorise each district according to its population structure and relative location to larger agglomerations. As illustrated in figure 2, I differentiate them into four classes: 1) Rural districts, with low population density and no direct proximity to major urban districts, 2) Peri-urban districts, with direct proximity to major urban districts, 3) Urban districts with up to 100,000 inhabitants, and 4) Major urban districts with more than 100,000 inhabitants. This classification follows the methodology used by Schmude et al. (2021).

Figure 2
Urbanisation in each Germany measured for each federal state



Source: Own Illustration

Figure 3
Urbanisation in Germany measured for each district



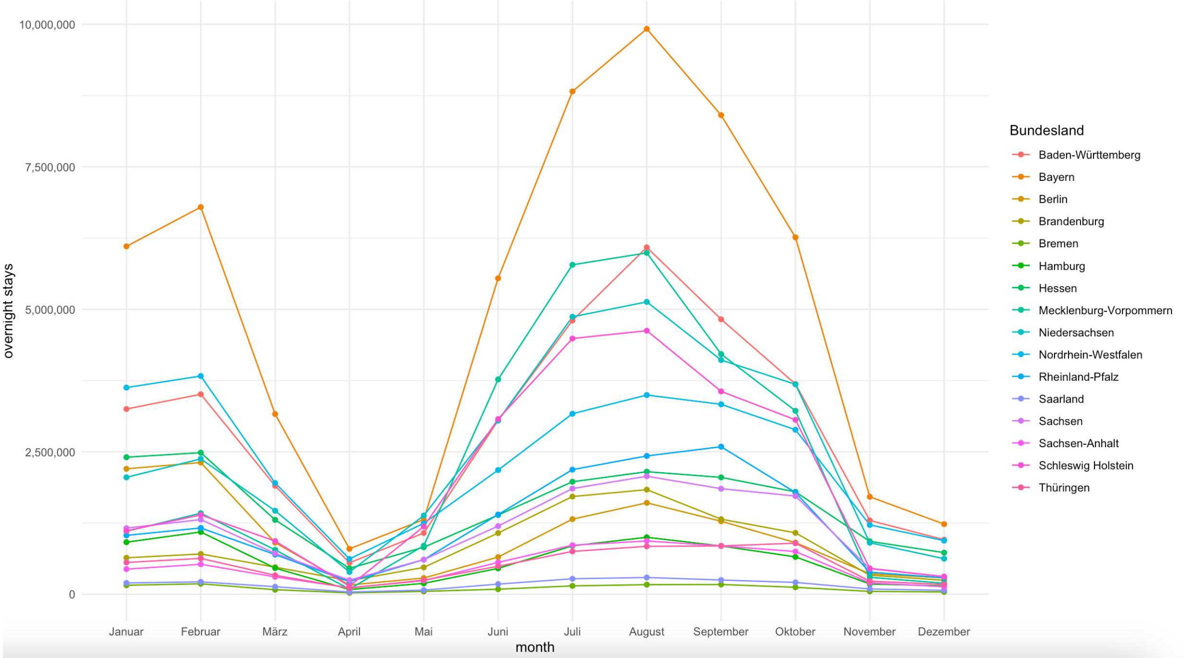
Source: Own Illustration

The federal structure of Germany provides a unique opportunity to study the heterogeneity in policy implementation and its effects across multiple administrative levels. Each of the 16 federal states (Bundesländer) has the authority to adjust public health measures according to local conditions, resulting in a diverse range of responses during the pandemic. This study specifically targets the period from 2020 to 2021, a critical timeframe for observing immediate responses to the pandemic and their repercussions. During this period, restrictions varied widely—from lockdowns and curfews to mask mandates and social distancing rules—significantly impacting the tourism sector, among other areas of economic and social life.

By examining these impacts at the district level, this study aims to provide detailed insights into how local characteristics, such as urbanisation, population density, and economic structure, influenced the effectiveness and consequences of Covid-19 restrictions. This approach not only highlights the resilience and vulnerability of different regions but also helps to understand the broader socio-economic fabric that either buffered or amplified the effects of pandemic measures. Through this analysis, we can identify patterns and draw conclusions that are vital for informing future policy decisions in similar crises.

The selection of districts as the focal point of this study combined with the federal states as political authorities, allows for a detailed assessment of localised policy impacts. This approach offers valuable lessons for managing future public health crises in a nuanced and differentiated manner across similar decentralised political systems. By analysing how varying local conditions and policy responses influence outcomes, this study aims to contribute to a more refined understanding of effective crisis management in diverse administrative contexts.

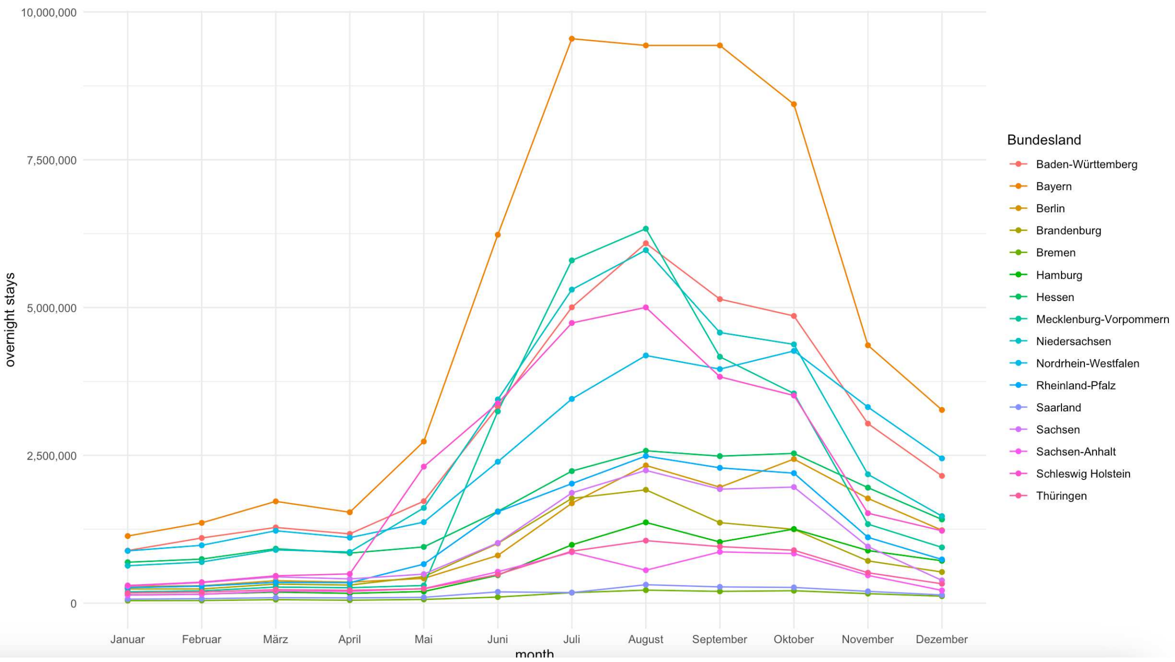
Figure 4
Monthly number of overnight stays for each state in 2020



The study evaluates the dynamics of tourism demand, illustrated by the relative change in overnight stays in 2020 and 2021 compared to the average of the preceding five years, across binary dimensions of space and time. The monthly data on overnight stays was provided by the corresponding Office for Statistics for each federal state or district. By calculating the deviation rate from the average value of the previous five years, it is possible to analyse the relative number of overnight stays before and after the outbreak of the pandemic. This analysis is conducted by spatial categories and intervening factors, identifying the varying degrees to which different regions were affected over time during phases of decline and recovery. The absolute numbers of overnight stays for each month and federal states in 2020 and 2021 are depicted in figure 4 and 5.

In January and February 2020, before the pandemic fully erupted, each state operated at habitual levels. However, in March, the tourism sector collapsed immediately following the declaration of a pandemic and the subsequent implementation of lockdowns. The number of overnight stays in each state plummeted, reaching a nadir in April. At this point, the numbers of overnight stays across states converged to a uniformly low level. In May, the number of overnight stays began a slow recovery, continuing through the summer, which can be attributed to decreasing Covid-19 infection rates and seasonal variations. However, relative differences between the states also began to re-emerge. During the winter of 2020, with the imposition of new lockdowns, the numbers of overnight stays crashed again, reaching levels similar to those in April 2020.

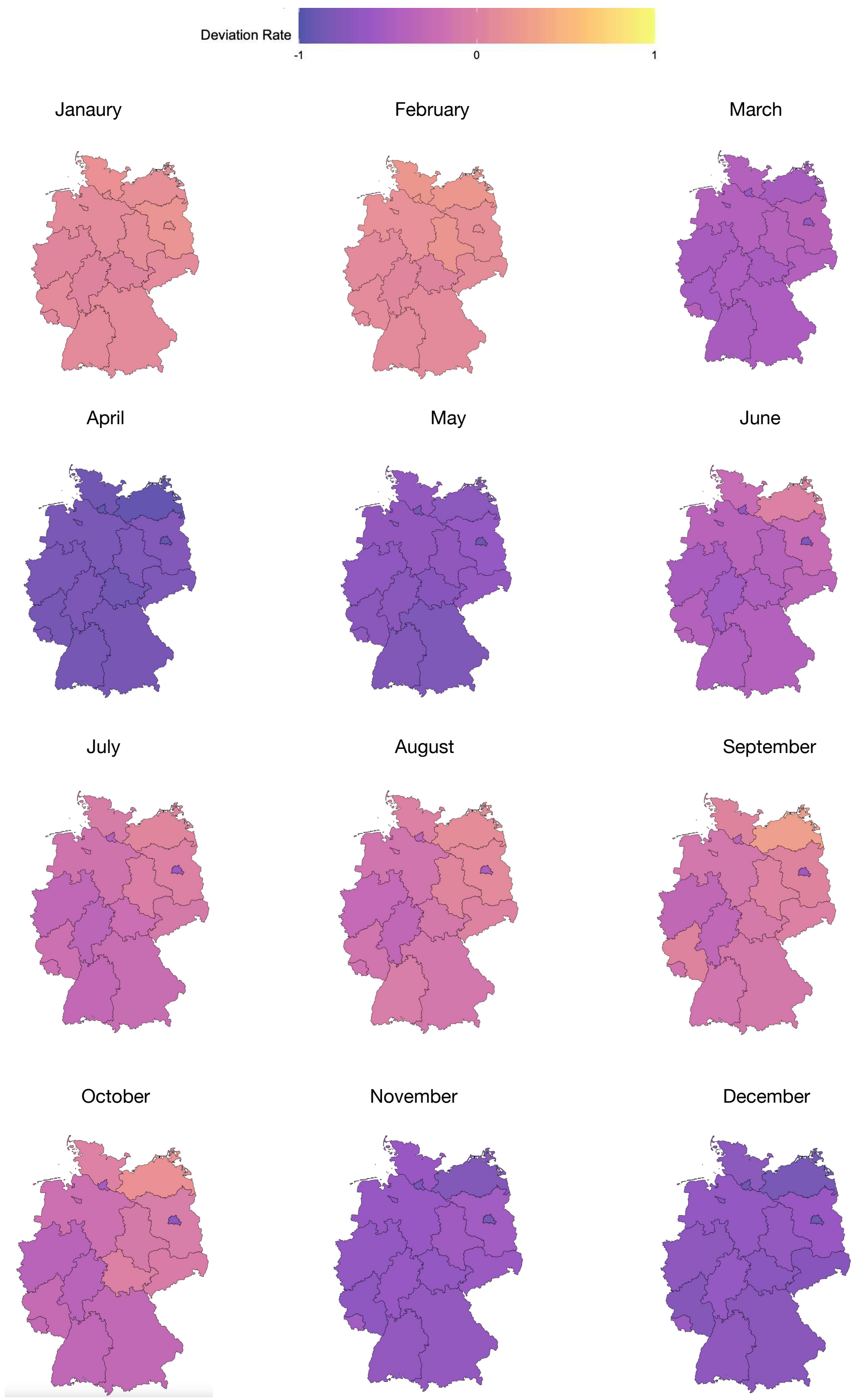
Figure 5
Monthly number of overnight stays for each state in 2021



Contrary to the first lockdown, the number of overnight stays in Germany stagnated near the bottom line until April 2021, with only slight monthly recoveries. From May 2021 onwards, a significant phase of recovery was initiated. During the summer, overnight stays reached habitual highs, and even in the following winter, the German tourism industry managed to maintain a decent level. This period of recovery reflects the adaptability and resilience of the tourism sector in response to evolving public health measures and changing traveler behaviours during the pandemic. The deviation rate of overnight stays in each state from 2020 to 2021 is illustrated in figure 6 and 7.

Figure 6

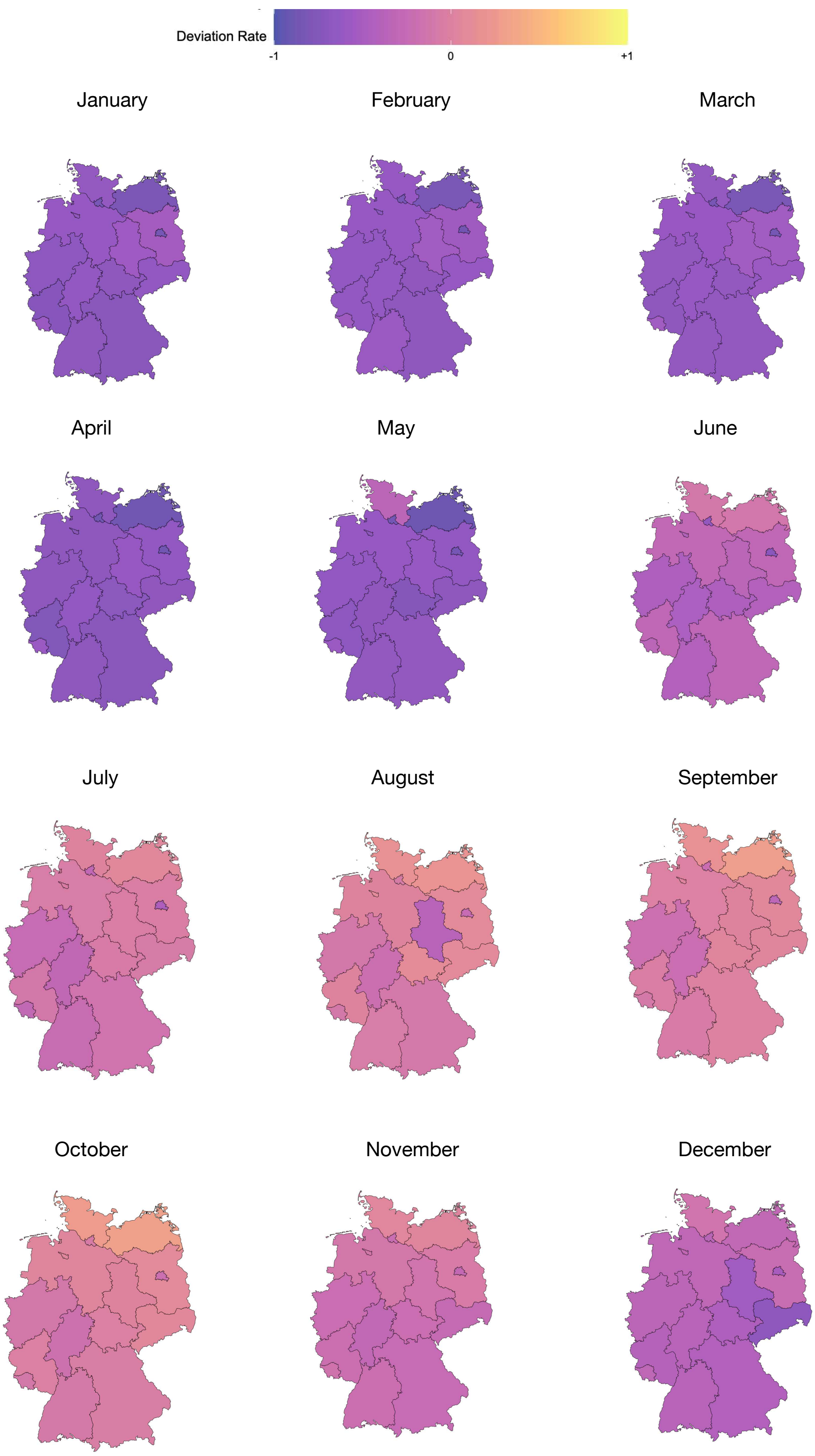
Monthly deviation of overnight stays to the preceding 5 years average for each state in 2020



Source: Own illustration

Figure 7

Monthly deviation of overnight stays to the preceding 5 years average for each state in 2021



Source: Own Illustration

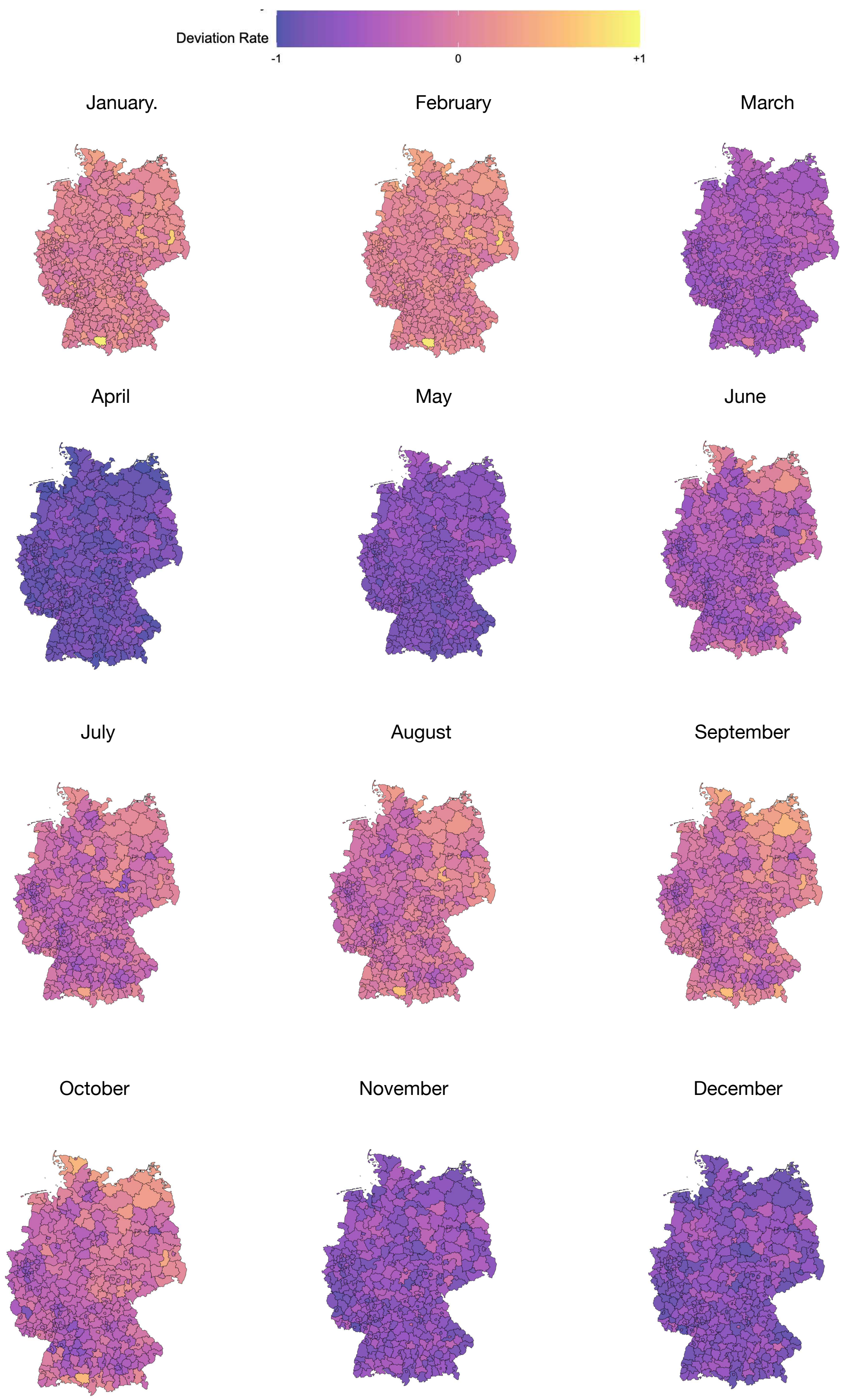
As already mentioned, the deviation rate of overnight stays in January and February 2020 from the 5-year average before is even slightly positive in most states. This indicates that the number of overnight stays in each state was equal to or even greater than the 5-year average prior. In March 2020, the number of overnight stays was already significantly lower, despite the lockdown in Germany starting only on March 22. Each state had to contend with similar deviation rates. The trough was reached in April 2020. However, there were significant differences between the 16 states. For example, the large city-states Berlin and Hamburg, had losses in overnight stays of over 93% while Brandenburg and Saxony had only a negative deviation rate of 76% and 79% during the month of April.

From May onwards, the deviation rate began to stabilise, but the states exhibited very different levels of transition. For instance, the cities of Berlin and Bremen, as well as North Rhine-Westphalia and Hesse, experienced substantial negative deviation rates over the summer term. Conversely, other states managed to stabilise in terms of overnight stays until November 2020. With the introduction of new lockdowns, overnight stays significantly decreased until August, with slight variations between the states.

In September 2021, the deviation rate started stabilising again, this time more uniformly over the summer term. By November and December 2021, the deviation rate was higher nationwide, yet it remained far from the trough observed during the previous winter term. This pattern highlights the varied impacts of Covid-19 and associated restrictions across different regions and periods, reflecting the complexity of the pandemic's influence on the tourism sector.

Figure 8

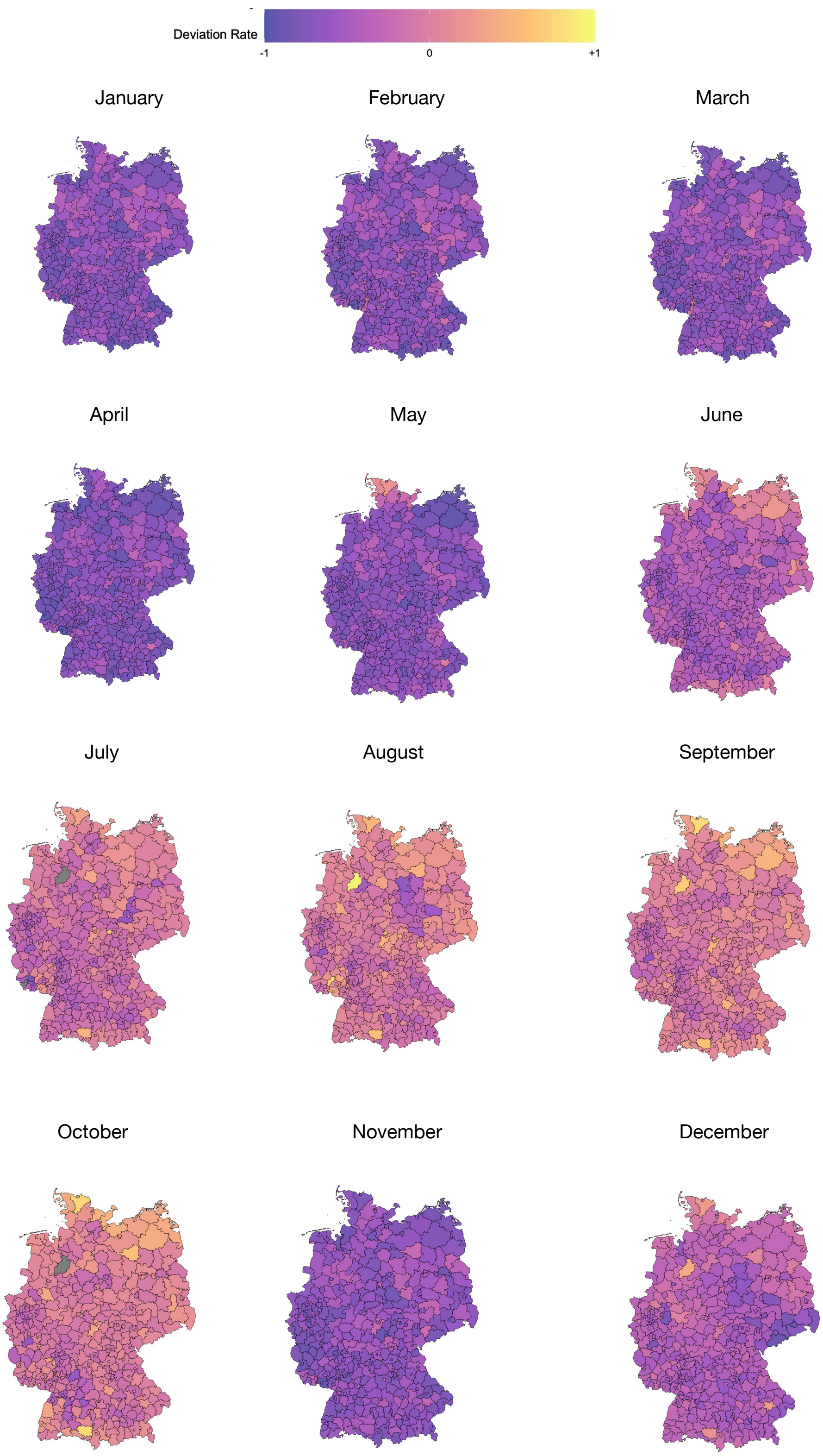
Monthly deviation of overnight stays to the preceding 5 years average for each district in 2020



Source: Own illustration

Figure 9

Monthly deviation of overnight stays to the preceding 5 years average for each district in 2021



Source: Own illustration

Figures 8 and 9 show that there are even huge differences in deviation rates across the 401 districts in Germany. The tourism industry in some districts is recovering much faster than in others. For example, in April which was the peak of the crisis, the city of Munich had a loss in overnight stays of around 90% while the district Fürstenfeldbruck only lost about 65%.

Table 1
Deviations in overnight stays in four different regional categories in Germany in 2020 in the monthly comparison to the average of the five previous years

Month		Rural Districts	Peri-Urban Districts	Urban Districts	Major Urban Districts
January	Mean	7.00%	7.50%	19.50%	12.15%
	CV	1.841	1.388	0.783	1.104
February	Mean	10.47%	9.21%	17.88%	13.68%
	CV	1.251	1.298	1.042	0.969
March	Mean	-45.79%	-45.20%	-45.80%	-51.95%
	CV	-0.228	-0.228	-0.292	-0.210
April	Mean	-84.66%	-80.55%	-82.62%	-85.02%
	CV	-0.118	-0.130	-0.126	-0.117
May	Mean	-72.52%	-69.43%	-71.53%	-75.63%
	CV	-0.142	-0.151	-0.181	-0.142
June	Mean	-35.80%	-39.06%	-40.05%	-54.46%
	CV	-0.494	-0.456	-0.450	-0.269
July	Mean	-16.02%	-19.72%	-14.75%	-32.29%
	CV	-1.038	-0.924	-1.744	-0.642
August	Mean	-9.16%	-10.51%	-3.43%	-23.83%
	CV	-1.726	-1.589	-6.974	-0.799
September	Mean	-5.19%	-12.26%	-1.66%	-24.31%
	CV	-3.482	-1.639	-10.903	-0.898
October	Mean	-17.88%	-21.23%	-19.15%	-36.85%
	CV	-1.162	-1.026	-1.010	-0.541
November	Mean	-62.48%	-61.32%	-59.92%	-69.51%
	CV	-0.215	-0.228	-0.284	-0.169
December	Mean	-68.51%	-66.91%	-68.85%	-74.86%
	CV	-0.215	-0.208	-0.227	-0.152
Annual average	MEAN	-33.38%	-34.12%	-30.86%	-41.91%
	CV	-0.477	-0.324	-1.697	-0.156

Source: Own illustration

The tables provided illustrate the mean and coefficient of variation (CV) of all deviation rates across the 4 different district categories (Rural Districts, Peri-Urban Districts, Urban Districts, and Major Urban Districts) for each month during the years 2020 and 2021. Notably, the Covid-19 pandemic's real extent, including the onset of the first lockdowns in Europe and Germany, began in March 2020.

For 2020 (table 1), the data reveals significant variation in deviation rates throughout the year. In January and February, the mean deviation rates were positive across all district categories, indicating a period before pandemic-induced lockdowns. Particularly, Urban Districts exhibited high mean deviation rates, such as 19.50% and 12.15% in January, respectively, underscoring the momentum in the tourism sector over recent years. These positive values can be attributed to the absence of lockdown measures and the typical economic and social activities during these months.

However, from March 2020, with the implementation of the first lockdowns and political measures, a sharp decline in deviation rates is observed across all district categories. Rural Districts experienced a significant drop to -45.79% in March, plummeting further to -84.66% in April, and maintaining largely negative values for the rest of the year, reaching -68.51% in December. Peri-Urban Districts followed a similar trajectory, with a substantial decline to -45.20% in March, further decreasing to -80.55% in April, and ending the year at -66.91%. Urban Districts exhibited comparable steep declines, dropping to -45.80% in March and peaking at -82.62% in April. Interestingly, urban districts showed slightly more resilience to the political measures than peri-urban districts. However, the most significant drop was observed in the major urban districts, starting at -51.95% in March, peaking at -85.02% in April, and maintaining a consistently low level throughout the entire year. These figures underscore the substantial impact of lockdowns and reduced economic activity on deviation rates from overnight stays compared to the previous 5-year average.

The coefficient of variation for 2020 indicates varying degrees of relative variability in deviation rates across the months, with notable peaks around August to October. Another discernible trend is that rural or peri-urban districts recovered much faster during the summer term from the significant drop compared to the major urban districts.

Table 2 illustrates deviations in overnight stays in four different regional categories in Germany in 2021 in the monthly comparison to the average of the five previous years. Deviation rates continued to reflect the ongoing impact of the pandemic. Rural Districts predominantly experienced negative mean deviation rates throughout the year, with the highest negative rates occurring in April

(-70.87%) and May (-65.19%). Peri-Urban Districts followed a similar pattern, with significant negative mean deviation rates in April (-67.74%) and May (-62.30%). Urban Districts showed a mix of negative and positive mean deviation rates, with significant negative rates in April (-65.92%) and May (-62.10%), but positive rates in August (5.69%), September (6.98%) and October (5.81%), indicating some recovery or fluctuation in those months. Building on observations from the previous year, with the pandemic more entrenched, urban districts demonstrated greater resilience to the crisis, especially during the summer term. Major Urban Districts exhibited negative mean deviation rates throughout the year, with the highest negative rates in April (-71.50%) and May (-69.43%). The coefficient of variation for 2021 highlights considerable relative variability in deviation rates, especially in September and October for Rural Districts (9.256, 75.490), suggesting again a period of high volatility.

Table 2
Deviations in overnight stays in four different regional categories in Germany in 2021 in the monthly comparison to the average of the five previous years

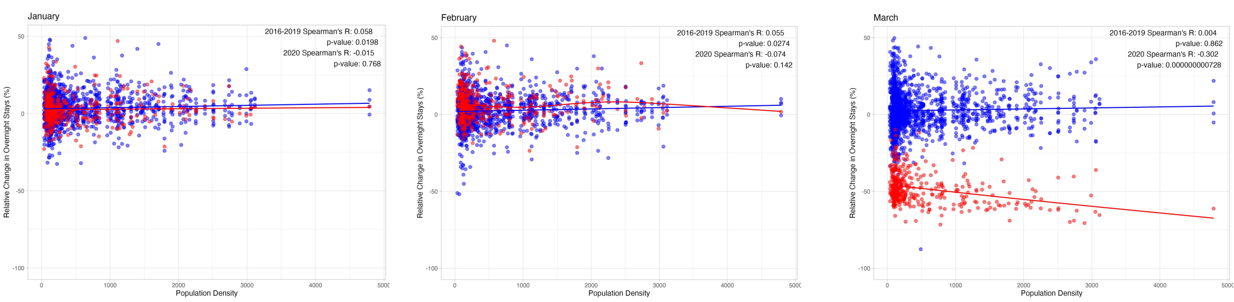
Month		Rural Districts	Peri-Urban Districts	Urban Districts	Major Urban Districts
January	MEAN	-66.40%	-64.87%	-64.02%	-72.98%
	CV	-0.221	-0.221	-0.285	-0.158
February	MEAN	-64.46%	-62.36%	-59.74%	-67.00%
	CV	-0.234	-0.257	-0.331	-0.543
March	MEAN	-63.61%	-60.31%	-57.07%	-68.23%
	CV	-0.242	-0.263	-0.341	-0.192
April	MEAN	-70.87%	-67.74%	-65.92%	-71.50%
	CV	-0.197	-0.192	-0.216	-0.177
May	MEAN	-65.19%	-62.30%	-62.10%	-69.43%
	CV	-0.221	-0.250	-0.252	-0.174
June	MEAN	-30.97%	-33.13%	-34.79%	-48.49%
	CV	-0.540	-0.578	-0.551	-0.294
July	MEAN	-9.96%	-12.49%	-11.91%	-22.20%
	CV	-2.033	-1.613	-1.541	-0.885
August	MEAN	-2.71%	-3.62%	5.69%	-8.88%
	CV	-7.066	-5.812	3.985	-2.344
September	MEAN	1.85%	-3.30%	6.98%	-11.45%
	CV	9.256	-5.725	2.215	-1.786
October	MEAN	0.26%	-2.63%	5.81%	-5.07%
	CV	75.490	-8.757	3.228	-4.852
November	MEAN	-15.65%	-18.10%	-17.73%	-23.15%
	CV	-0.966	-0.934	-0.984	-0.645
December	MEAN	-35.10%	-37.52%	-39.50%	-41.90%
	CV	-0.419	-0.496	-0.471	-0.381
Annual average	MEAN	-35.23%	-35.70%	-32.86%	-42.52%
	CV	6.051	-2.091	0.371	-1.036

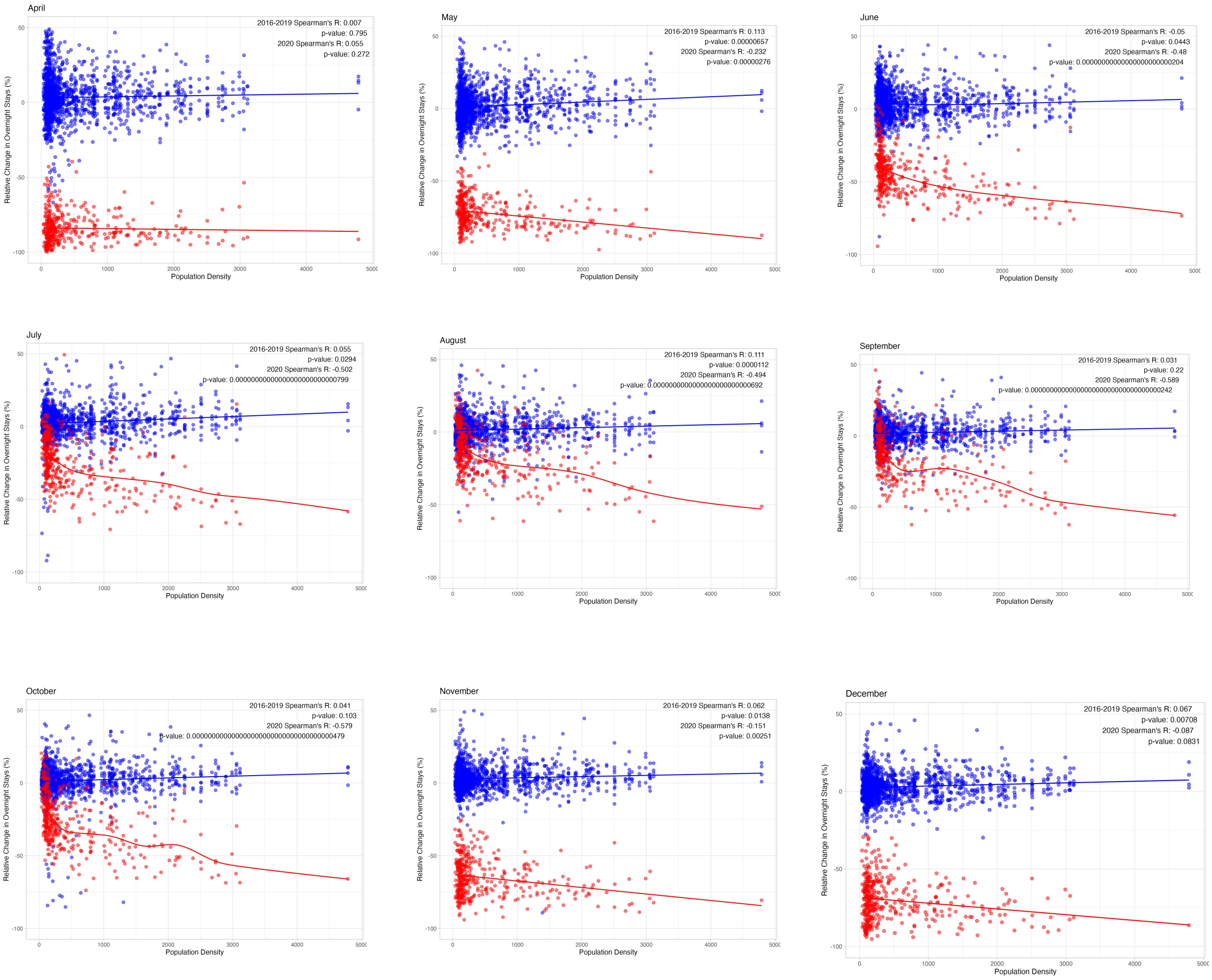
Source: Own Illustration

In summary, the analysis of deviation rates and coefficients of variation (CV) across different district categories reveals significant insights into the impact of the COVID-19 pandemic throughout 2020 and 2021. From March 2020 onward, the onset of the pandemic and subsequent lockdowns are marked by negative mean deviation rates across all district categories, with the most profound declines observed in April 2020. This period saw severe restrictions, leading to substantial negative deviations, particularly in Major Urban Districts, which consistently exhibited the highest negative mean deviation rates throughout the pandemic. The elevated coefficients of variation during these months highlight the significant volatility and uncertainty faced by these areas.

Interestingly, while Major Urban Districts suffered the most severe impacts, as evidenced by both the largest negative mean deviation rates and relatively high CVs, Rural Districts experienced the least fluctuation. Despite some negative deviations, Rural Districts generally maintained lower variability and less severe impacts compared to their urban counterparts. This suggests that rural areas were more resilient to the pandemic's disruptions, possibly due to lower population densities and fewer restrictions affecting daily life. This aspect will be examined further in the thesis. Overall, this analysis underscores the differential impact of the Covid-19 pandemic on various district categories, with Major Urban Districts bearing the brunt of the adverse effects, while Rural Districts displayed relative stability and resilience. This disparity emphasises the need for tailored policy responses that consider the unique challenges and resilience factors of different district types.

Figure 10
Relative change in overnight stays 2020 vs mean of 2016 to 2019 as a function of population density at the district level, corresponding splines, Spearman's correlation coefficient (RS) and, uncertainty (p) in Germany





Source: Own illustration

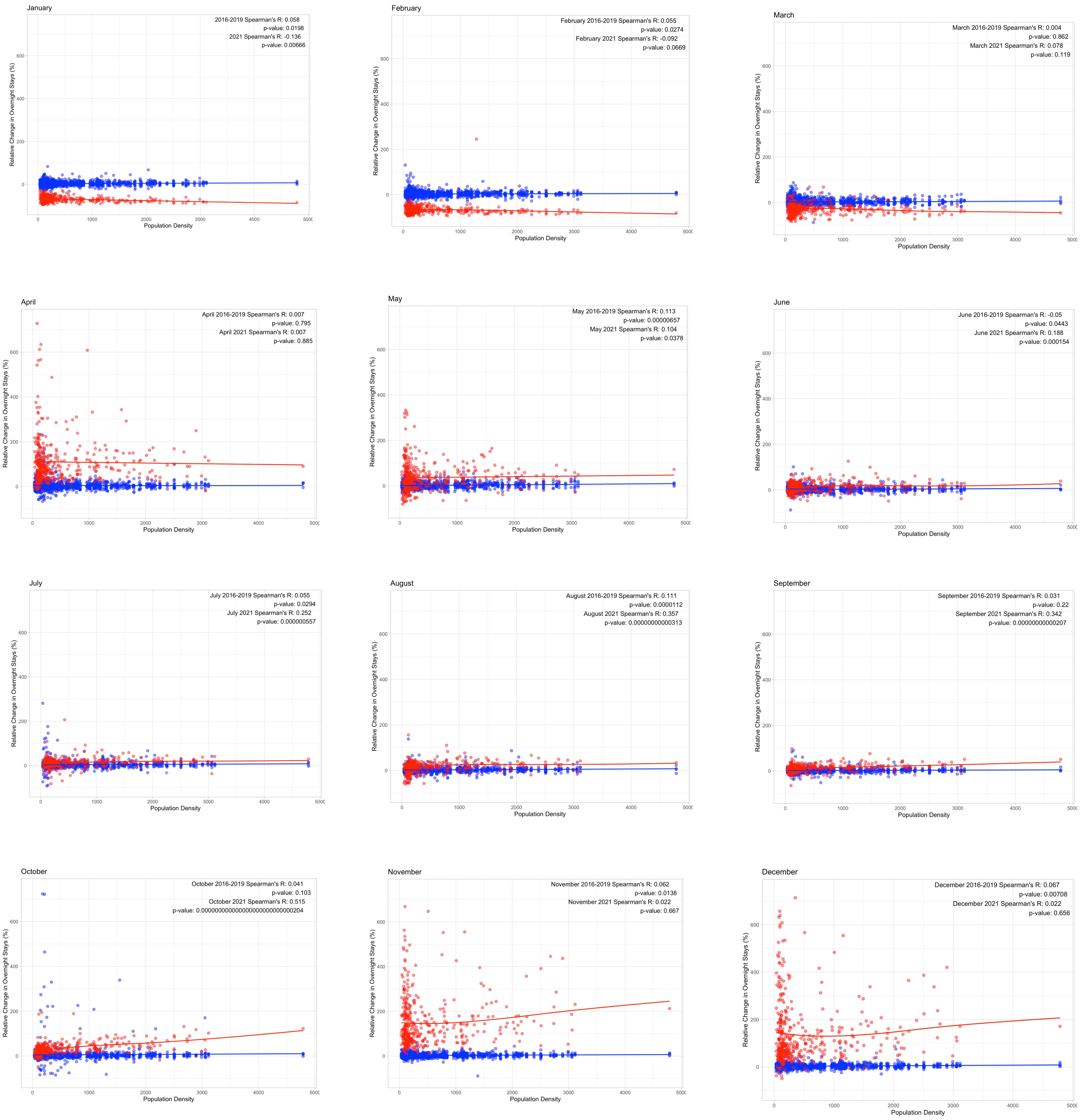
The primary variable under consideration is the relative change in the number of overnight stays from the previous year to the current year. Figure 10 illustrates these relative changes for 2020, alongside the average changes from 2016 to 2019, displayed for each month. My analysis adopts a methodology similar to Hamidi et al. (2020), with a focus on the spatial and temporal distribution of tourism demand in 2020. Specifically, for each district in Germany, I examine the relationship between population density and the relative change in overnight stays compared to the same month from the previous year. The blue points represent districts during pre-COVID times, while the red points depict the situation in 2020.

For each month, I calculated Spearman's correlation coefficient (RS) to gain insights into both the direction and strength of the relationships. The p-value (p), obtained from a two-sided correlation test using an asymptotic t-distribution approximation, helps to determine whether to accept or reject the null hypothesis of no correlation. A p-value less than 0.05 indicates a significant correlation. Additionally, a large absolute value of RS (positive or negative) signifies a strong correlation, whereas a small absolute value of RS indicates a weak correlation.

Notably, in January and February, prior to the global lockdowns, the regression curves for pre-Covid and 2020 data are very similar and even intersect, indicating similar changes in overnight stays compared to the previous year. However, from March onwards, significant differences emerge between the two curves throughout the year. From March to May, districts with higher population density were more affected by the crisis and corresponding restrictions, depicted by a nearly flat, declining red curve.

During the summer months and slightly beyond, these districts experienced a slower recovery compared to others. From July to October, districts with medium population density showed slight resistance to the decline in numbers. For the remaining months of the winter term, the situation worsened again, nearly reverting to the initial conditions observed earlier in the year.
Districts with higher population density more likely experienced stricter lockdown measures and higher infection rates, leading to a more pronounced decline in tourism compared to districts with lower population density. This could explain the flat or declining red curve in densely populated areas from March to May but also during winter term.
Rural districts might have benefited initially from increased interest in less crowded areas, whereas urban districts could have faced challenges due to density and reliance on international tourism.

Figure 11
Relative change in overnight stays 2021 vs mean of 2016 to 2019 as a function of population. density at the district level, corresponding splines, Spearman's correlation coefficient (RS) and, uncertainty (p) in Germany



Source: Own illustration

I repeat the same procedure for the year 2021, with the key difference being that I now determine the relative changes between the years 2021 and 2020 during the ongoing crisis. The results are illustrated in figure 11. The blue points again represent the districts during pre-Covid times, while the red points illustrate those in 2021. The relative change in the four-year mean remains around the 0% line.

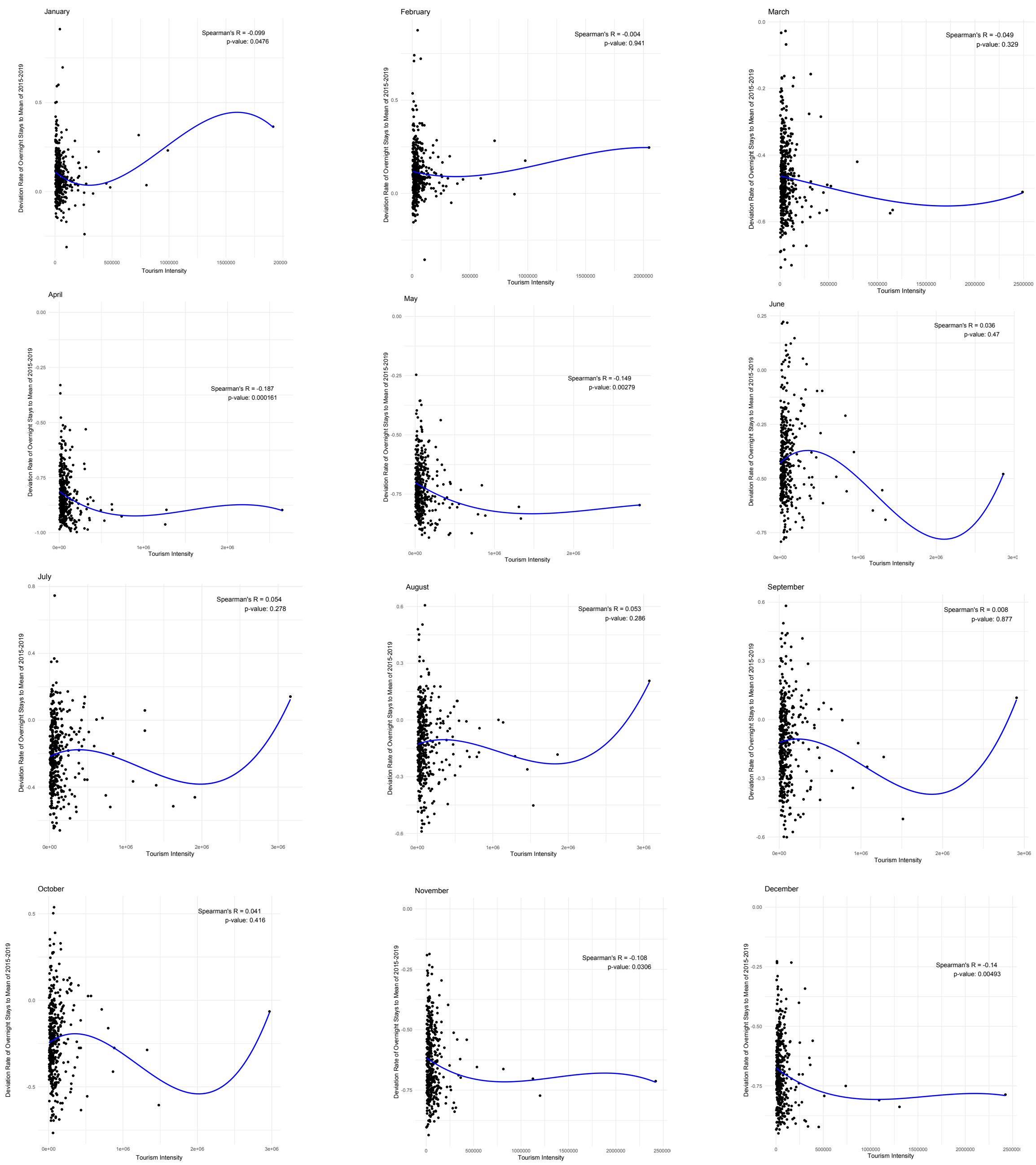
This time, the curves for January and February are not similar. The reason is that in 2021, both months fall within the pandemic period, whereas in 2020, they did not. Consequently, there is a negative relative change in overnight stays, although the gap is relatively small. In March, this gap narrows further because the first lockdown in 2020 was introduced in the middle of the month. From April onwards, there is a noticeable shift to positive values in the relative change rate for 2021. The tourism sector is slowly recovering from the crisis, even during the summer months, when the number of overnight stays was already quite high in 2020. During this phase, population density does not play a major role, as districts with both low and high population densities experience similar growth rates.

However, starting in September, during the winter months, this trend seemed to change. The relative change in most districts becomes significantly higher, and districts with higher population density recover much faster than those with a lower density. This suggests that the level of relative number of overnight stays is gradually returning to a pre-Covid19 distribution across all types of districts. One notable point is the summer recovery. From April onwards, there is a noticeable shift to positive values in relative change rates for 2021. This suggests that the tourism sector began recovering as restrictions eased and vaccination efforts increased, despite 2020 already having high numbers of overnight stays during the summer months.

Furthermore, one should highlight the similar growth across densities. During the summer phase, both low and high population density districts experienced similar growth rates. This could indicate a broader recovery trend as travellers regained confidence and were less constrained by local population densities.

Figure 12

Deviation of overnight stays in 2020 to the mean of 2015 to 2019 as a function of monthly mean tourism intensity (2015 to 2019) at the district level corresponding splines, Spearman's correlation coefficient (RS) and, uncertainty (p) in Bavaria



Source: Own Illustration

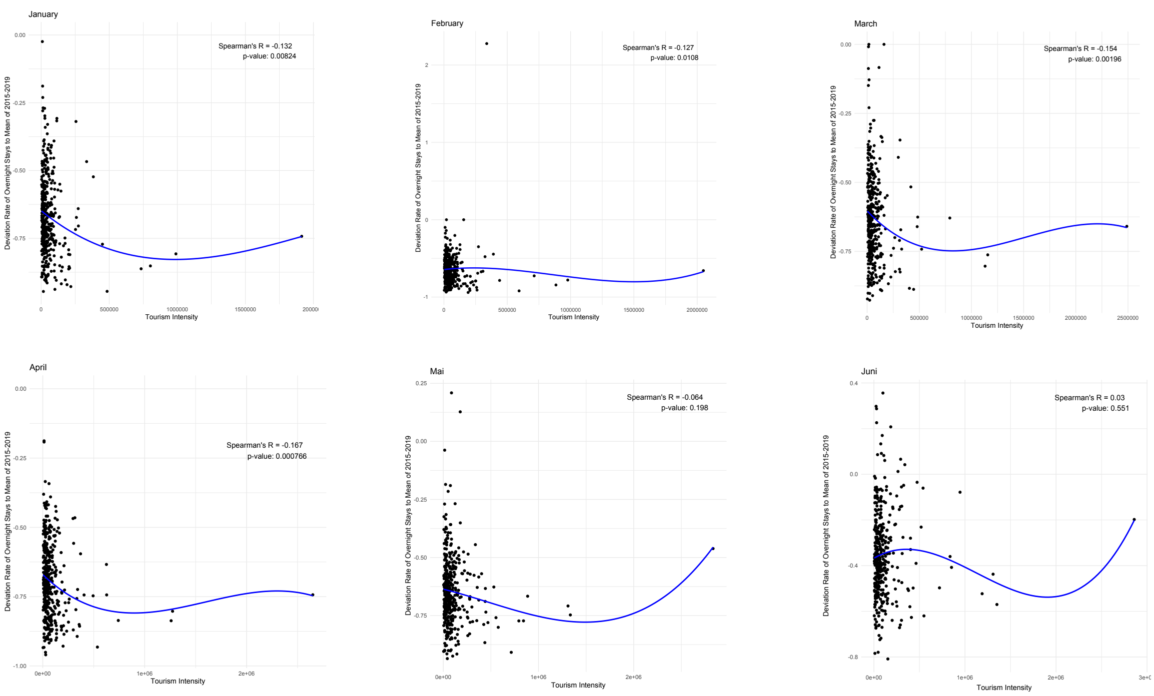
Figure 12 illustrates the impact of tourism intensity on the deviation rates of monthly overnight stays in 2020 compared to the average from 2015 to 2019. The y-axis represents tourism intensity, measured by the average monthly number of overnight stays from 2015 to 2019. Each black point on the graph represents a unique district in Germany for each month in 2020.

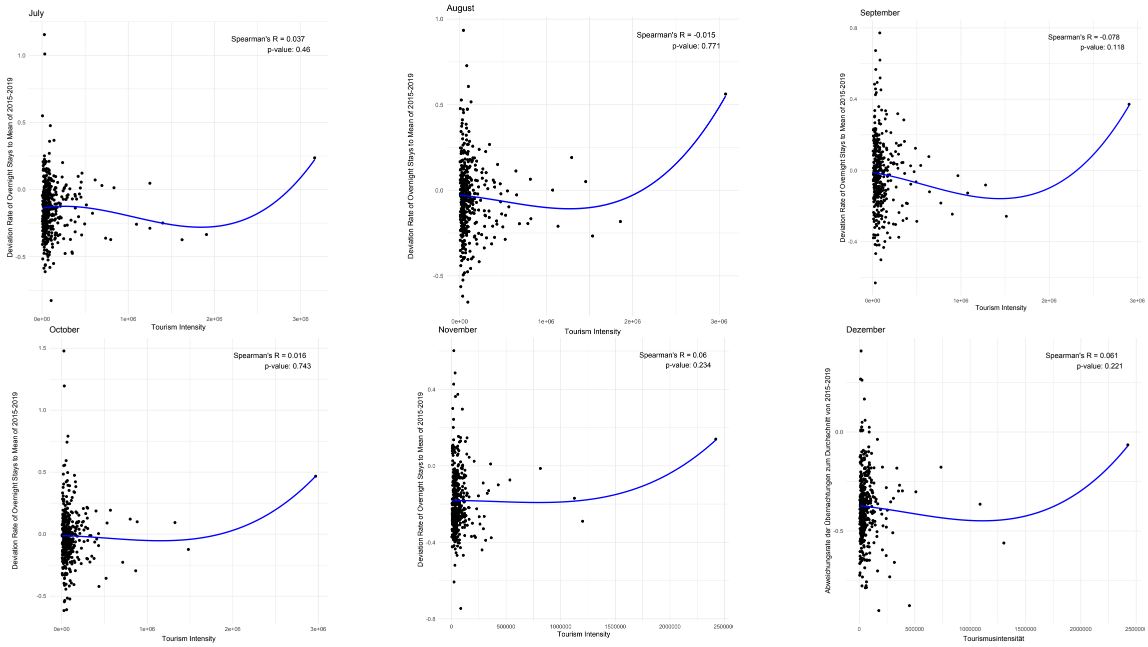
In the first two months of 2020, similar to the patterns seen with population density in Figures 10 and 11, the deviation rates exhibit R-values very close to 0, indicating stable performance. However, in March, with the onset of the first lockdowns, deviation rates sharply decline, though they do so irrespective of tourism intensity, with an R-value around 0 (-0.049).

In April and May, it becomes evident that districts with higher tourism intensity suffer more pronounced drops in demand during the peak months of the COVID-19 crisis. The R-values for these months are -0.187 and -0.149, respectively, indicating a significant negative correlation. From June 2020 onwards, during the summer months, this trend reverses. Deviation rates begin to recover, and districts with higher tourism intensity show similar or even stronger recovery trends. However, in November and December, as demand falls again, the R-values turn significantly negative once more (-0.108 and -0.14). We will examine whether this trend continues into 2021 in Figure 13.

Figure 13

Deviation of overnight stays in 2021 to the mean of 2015 to 2019 as a function of monthly mean tourism intensity (2015 to 2019) at the district level corresponding splines, Spearman's correlation coefficient (RS) and, uncertainty (p) in Bavaria





Source: Own illustration

Evidently, the trend continues with significantly negative R-values for the Spearman coefficient until April 2021. The R-values for the first 3 months in 2021 are -0.132, -0.127. and -0.154, respectively, indicating a significant negative correlation. Following this period, a pattern similar to 2020 emerges. During the summer months, demand begins to recover, and districts with varying tourism intensity show comparable recovery rates, with a slight preference for tourism-intensive districts.

However, during the winter months of 2021 (including October, November, and December), when demand sharply declines again due to high Covid-19 infection rates, there is no longer a significant trend indicating that districts with high tourism intensity are disproportionately affected. The R-values even illustrate no significant relationship at any point.

At the onset of the pandemic, people likely avoided popular travel destinations or highly-intensive districts to minimise infection risk. The pandemic might have shifted travel preferences, with people initially avoiding crowded areas but gradually returning as confidence grew in safety protocols and health measures. In other words, when the Covid-19 crisis evolved, along with the implementation of restrictions and the advent of vaccinations, people stopped avoiding popular regions in favour of less known and more remote areas again. Furthermore, tourism-intensive districts might have initially implemented stricter measures, impacting their recovery rates. They often also have better health infrastructure, which could have increased traveller's' sense of safety after the initial fear subsided. Another contributing factor could be the economic impact of the pandemic. In the early stages, many people faced financial hardships that restricted their ability to travel. However, as the economy began to recover and there was greater optimism about the economic and social future, people started to resume travel to their preferred destinations.

4. Methodology and Econometric model

The data used in this study consists of monthly deviation rates of overnight stays in various German districts (Kreise) for the years 2020 and 2021, compared to the average number of overnight stays from 2015 to 2019. Additionally, each district is assigned an urbanisation index ranging from 1 to 4 (see figure 3), representing the degree of urbanisation, and an index of restriction (IOR) ranging from 0 to 4, indicating the severity of Covid-19 restrictions for each month and each district. Given the longitudinal and spatial nature of the data, with multiple observations for each district over time and spatial dependencies between districts, a dynamic spatial panel data analysis was appropriate. The DSPD analysis allowed me to control for both time-invariant characteristics of the districts, time-specific effects, and spatial dependencies, providing more accurate and reliable estimates. Furthermore, it allows me to analyse the impact of urbanisation, the level of restriction, as well as spatial or dynamic dependencies on the deviation rate of overnight stays. Firstly the Dynamic Spatial Autoregressive Model (DSAR) was considered.

The general form of the dynamic spatial panel data regression model is:

$$
\begin{aligned}
deviation_{rate_{\{it\}}} &= \beta_0 + \beta_1 Urbanisation_{\{it\}} + \beta_2 IOR_{\{it\}} + \rho\, W\, deviation_{rate_{\{it\}}} \\
&+ \gamma\, lag_{deviation_{rate_{\{it\}}}} + \delta\, lag_{W_{deviation_{rate_{\{it\}}}}} + \mu_i + \epsilon_{\{it\}}
\end{aligned}
$$

where: $deviation\_rate_{it}$ is the deviation rate of overnight stays for district I in month t, $Urbanization_{it}$ is the level of Urbanisation for district i in month t, IOR_{it} is the index of restriction for district i in month t, $Wdeviation\_ratei_t$ is the spatially lagged dependent variable capturing the influence of neighbouring districts, ρ is the spatial autoregressive coefficient, $lag\_deviation\_rate_{it}$ is the lagged dependent variable capturing the deviation rate from the previous month, $lag\_W\_deviation\_rate_{it}$ is the weighted average of the deviation rates in neighbouring regions in the previous period, u_i represents the unobserved time-invariant district-specific effects, ϵ_{it} is the idiosyncratic error term.

The index of restriction indicates the severity of restriction implemented by the government that takes place in each federal state ranging from 0 to 4 at monthly degree. I only take into account the measures relevant for the tourism sector. The values are dependant and proportional on the exact day of new policy implementation, respectively the number of days under specific levels of restriction. Unfortunately, it is not possible to set up this index at district scale since the data and information about local restrictions as for example travel bans or 7 days incidence rates is limited. Furthermore, the most important decisions were anyway taken by authorities on federal states level or even at national level. The index is set up as follows:

Level 0: No Restrictions or recommendations

- only before the first lockdown when there had not been any political restrictions or recommendations yet

Level 1: Mild Restrictions

- Recommendations against non-essential travel and wearing masks
- No strict opening hours for bars and restaurants.
- Limited number of people per square meter in public areas.
- Possible travel restrictions or quarantine requirements for travellers from high-risk areas.

Level 2: Moderate Restrictions

- Travel allowed with conditions (e.g., testing upon arrival).
- Gatherings and events allowed with limited capacity.
- Ban on non-essential travel or quarantine requirements for travellers from high-risk areas.
- Soft restrictions for hotels and accommodations (e.g., capacity limits, closures).

Level 3: Severe Restrictions

- Significant limits on the size of gatherings and events.
- Comprehensive travel bans or mandatory quarantine for all arrivals.
- Large gatherings and public events banned.
- Hotels and restaurants allowed to open with strict capacity limits and health protocols.
- Restrictions based on high 7-day incidence rates.

Level 4: Lockdown

- Strict lockdown measures with stay-at-home orders.
- Closure of all non-essential businesses, including most tourist attractions.
- Complete closure of certain tourist facilities and attractions.
- Strict travel restrictions or travel bans.
- Hotels and restaurants closed except for essential services (e.g., takeout or delivery).

5. Results

Table 4:
Dynamic *Spatial Autoregressive (DSAR) Model: Analysing the Relative Change in Overnight Stays in Germany during years 2020 and 2021*

```
Residuals:
      Min        1Q    Median        3Q       Max
-1.818631 -0.071185 -0.001876  0.071313  2.986909

Type: lag
Coefficients: (asymptotic standard errors)
                       Estimate Std. Error z value  Pr(>|z|)
(Intercept)           0.0671744  0.0052029  12.911 < 2.2e-16
Urbanization         -0.0148057  0.0014138 -10.472 < 2.2e-16
IOR                  -0.0668245  0.0018233 -36.651 < 2.2e-16
W_deviation_rate      0.1110304  0.0017152  64.732 < 2.2e-16
lag_deviation_rate    0.6254838  0.0072641  86.107 < 2.2e-16
lag_W_deviation_rate -0.0988779  0.0017023 -58.083 < 2.2e-16

Rho: 0.0021198, LR test value: 0.065874, p-value: 0.79744
Asymptotic standard error: 0.0082165
    z-value: 0.25799, p-value: 0.79641
Wald statistic: 0.06656, p-value: 0.79641

Log likelihood: 4919.677 for lag model
ML residual variance (sigma squared): 0.020147, (sigma: 0.14194)
Number of observations: 9223
Number of parameters estimated: 8
AIC: -9823.4, (AIC for lm: -9825.3)
LM test for residual autocorrelation
test value: 0.0036647, p-value: 0.95173
```

The results of the Dynamic Spatial Autoregressive (DSAR) model analysis illustrated by table 4 indicate several important relationships between the key variables and deviation rates of the monthly number of overnight stays. The model's residuals range from -1.819 to 2.987 with a median close to zero. Urbanisation has a significant negative relationship with deviation rates (Estimate = -0.0148***), suggesting that more urbanised areas tend to have lower deviation rates during the crisis. The index of restrictions (IOR) shows a strong negative effect on deviation rates (Estimate =

-0.0688***), indicating that stricter restrictions means reducing the number of overnight stays. The spatially lagged deviation rate (W_deviation_rate) has a positive coefficient (Estimate = 0.1110***), suggesting that deviations in one region are influenced by deviation rates in neighbouring regions.

Interestingly, while the spatially lagged variable (W_deviation_rate) is significant which indicates spatial dependence, the spatial autoregressive coefficient ($\rho = 0.0021$, $p = 0.7964$) is not significant and tends towards zero. This suggests that there is no strong overall spatial autocorrelation in the data. This finding indicates that while deviations in one region significantly influence neighbouring regions, the overall spatial dependence across all regions is weak, reducing the justification for using a purely spatial model.

Additionally, we have two lag variables: the time-lagged deviation rate (lag_deviation_rate) and the spatial lag of the W_deviation_rate variable. The time-lagged deviation rate has a strong positive coefficient (Estimate = 0.6255***), capturing the effect of deviation rates from previous months. This suggests a persistent effect where higher deviation rates in previous months tend to lead to higher deviation rates in the current period. The spatial lag (Estimate = -0.0989***) shows a significant negative relationship, indicating that the lagged spatial deviations negatively influence the current deviation rates.

6. Discussion

The DSAR model results reveal important insights into the factors affecting relative overnight stays changes in the analysed regions during the pandemic. Urbanisation, with its negative coefficient, indicates that areas with higher urbanisation levels experience more negative deviation rates, which supports the hypothesis already elaborated by table 10 and 11. Districts with urbanisation levels 1 point below might suffer a deviation rate of 1.48% lower during the crisis. This suggests that highly urbanised regions may suffer more severely during economic downturns, possibly due to their greater exposure to economic fluctuations and dependency on service-oriented industries like tourism, which are more vulnerable to external shocks. Policymakers might need to develop targeted strategies to support urban areas during economic crises, focusing on diversifying economic activities and enhancing resilience.

The level of restriction (IOR), with its strong negative coefficient, shows a significant negative association with deviation rates. This indicates that higher levels of restrictions to combat the pandemic correspond to more negative deviation rates. As the IOR ranges from 0 to 4, with higher values representing stricter restrictions, this finding suggests that regions and time stamps with stricter measures experienced higher damage to the tourism industry and thus more significant economic damage. In other words, if the index of restriction rises by 1 entire point, the monthly relative number of overnight stays are going to fall by 6.68%. This highlights the trade-off between public health measures and economic performance, suggesting a need for balanced policies that mitigate the economic impact while effectively controlling the pandemic.

What do these numbers and estimations tell us about potential financial losses to the country? The number of overnight stays in Germany in 2019 was around 496 million. Based on own calculations the average price of a room for a night in Germany is around 70 euros. This would result in a annual volume of sales of 34.720 billion euros. Based on the model, this would mean that major urban districts have a loss in overnight stays of 4.44% higher than rural district. This would then be equivalent to a loss in revenue of around 1.54 billion euros in 2020. Furthermore, one further degree of restriction would then be equal to a further loss of above 2.31 billion euros.

The spatially lagged variable's positive and significant coefficient underscores the influence of neighbouring regions' deviation rates on a region's economic performance. This spatial dependence suggests that regional economic policies should consider the broader spatial context, as economic conditions in one area can spill over to adjacent regions. This phenomenon is omnipresent during the pandemic as the right choice of accommodation during vacation might have been essential. months during the crisis.

The time-lagged deviation rate's strong positive coefficient illustrates the dynamic dependence on subsequent months during the crisis, suggesting persistent effects where higher deviation rates in previous months lead to higher deviation rates in the current period. Conversely, the significant negative coefficient for the spatially lagged time-lagged deviation rate indicates that deviations in neighbouring regions in previous periods can have a dampening effect on current deviation rates. It is possible that regions with past high deviations experienced a period of adjustment and normalisation. As these regions stabilised, their neighbouring areas could have benefited from reduced uncertainty and volatility, thus showing a dampening effect in their current deviation rates. This reflects a delayed positive adjustment effect that manifests as a negative coefficient in the time-lagged context.

Another point could be the contagion and mitigation effects. While the spatial lag effect is typically positive, suggesting that economic shocks or deviations spread across regions, the negative coefficient here might indicate that, over time, the initial shocks experienced by one region led to heightened awareness and more proactive measures in neighbouring regions. As a result, the past shocks might have eventually contributed to stabilising the neighbouring regions.
The fundamental activities influencing the tourism sector hit the market in both, the region itself and the neighbouring regions with little delay and similar intensity. However, smaller changes may influence the decision making of tourists and deliver the necessary time to deviate the accommodation planing to neighbouring regions.

Overall, the DSAR model's findings emphasise the critical role of urbanisation, economic disparity, and spatial dependencies in shaping deviation rates of overnight stays. These insights can inform policymakers in designing strategies to foster economic stability and reduce regional disparities, taking into account the interconnected nature of regional economies. The results of the DSAR model support its use in analysing spatial economic data and developing informed regional policies. I computed additional robustness checks to confirm the findings.

7. Robustness Checks

To ensure the robustness of my Dynamic Spatial Autoregressive (DSAR) model, I conducted the following key checks:

1. **Moran's I Test for Spatial Autocorrelation**: I performed Moran's I test to detect any spatial patterns in the model residuals. This verified the assumption of spatial independence in the residuals.
2. **Standard Panel Data Analysis**: I conducted a standard panel data analysis using fixed and random effects models. This comparison with non-spatial panel models helps assess whether spatial dependence significantly influences the results and validates the conclusions drawn from the DSAR model.
3. **Dynamic Spatial Error Model Specification**: I also specified and compared a Spatial Error (DSER) model alongside the DSAR model. This comparison helps assess whether the SAR model or SE model provides a better fit for the data.
4. **Spatial Autoregressive Model (SAR) (without spatial and time lags) :** I remove the spatial and time lags for further analysis.
5. **Yearly Comparison (2020 and 2021)**: I separately analysed and compared the DSAR model results for the years 2020 and 2021. This comparison evaluates how the model performs across different years, ensuring consistency and identifying any temporal variations.
6. **Model Restricted to Bavaria**: I restricted the analysis to data specifically from Bavaria. This focused analysis allowed me to examine regional dynamics within Bavaria and their impact on the SSAR model results. Bavaria represents the federal state with the most important tourism industry in Germany.
7. **Phases of decline and Phases of recovery:** As I could already illustrate before, urbanisation has a different scale of impact depending on the different phase during the

crisis. Thus, in this part I distinct between phases of decline and phases of revery while employing the DSAR model.

These robustness checks were essential to validate the DSAR model's assumptions, evaluate its performance over time and across regions, and ensure the reliability of the model's conclusions.

Table 5

Moran's I Test for Spatial Autocorrelation in the residuals

```
        Moran I test under randomisation

data:  sar_residuals
weights: extended_listw

Moran I statistic standard deviate = -0.03588, p-value = 0.5143
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
    -3.591854e-04     -1.084363e-04      4.883948e-05
```

Table 5 above shows the Moran's I test for spatial autocorrelation in the residuals of the DSAR model. The results indicate a slightly negative spatial autocorrelation with a Moran's I value of -0.0363. Moran's I values typically range from -1 (indicating perfect dispersion) to +1 (indicating perfect correlation), with 0 indicating a random spatial pattern. A negative value here suggests that the residuals in the model are somewhat spatially dispersed. However, the magnitude of the value is close to zero, suggesting that the negative autocorrelation is very weak.

Furthermore, the p-value of 0.5143 indicates that the results are not statistically significant. In other words, there is no strong evidence to reject the null hypothesis of spatial randomness. This suggests that the residuals do not exhibit significant spatial autocorrelation and the DSAR model has done a good job accounting for spatial dependencies in the data.

Overall, the results indicate that there is no significant spatial autocorrelation in the residuals of your DSAR model. The weak negative value of Moran's I suggests a slight spatial dispersion, but the p-value confirms that this is not statistically significant. This supports the conclusion that your

DSAR model is appropriately capturing the spatial dependencies in the data, and the residuals are spatially random.

The panel model in Table 6 in the appendix provides notably higher estimations, particularly evident in the coefficient for IOR (-0.138***), indicating its ability to capture nuanced effects across time and entities. However, the Dynamic Spatial Autoregressive Model (DSAR) also contributes critical insights by considering spatial and temporal dependencies essential for understanding tourism activities' interconnected nature and the spillover effects of restrictions.

The DSAR model reveals a coefficient of 0.111*** for the spatially lagged variable, highlighting significant spatial interactions where deviation rates in one area are influenced by neighbouring areas. This spatial dimension, crucially addressed by the DSAR model, remains unaccounted for in the panel model. This disparity underscores the DSAR model's relevance, particularly in contexts where spatial effects play a pivotal role.

While the panel model excels in capturing temporal effects, its omission of spatial dependencies limits its ability to comprehensively analyse interconnected impacts across diverse regions. Thus, while the panel model provides robust estimations of temporal dynamics, the DSAR model's inclusion of spatial considerations makes it indispensable for exploring broader regional interactions.

Table 7 in the appendix shows results of the Spatial Autoregressive (SAR) model without any time or spatial lags. Urbanisation has a significant negative relationship with deviation rates (Estimate = -0.036***). The Index of Restrictions (IOR) shows a strong negative effect on deviation rates (Estimate = -0.140***). The spatially lagged deviation rate (W_deviation_rate) has a positive coefficient (Estimate = 0.056***). The significant spatial autoregressive coefficient (ρ = 0.0068***) confirms the presence of spatial dependence in the data, in this case justifying the use of a spatial model. The model's residuals range from -0.794 to 2.880 with a median close to zero. Overall, the estimates are significantly stronger to the negative side if we do not consider the dynamic aspect.

Table 8
Dynamic Spatial Error Model (DSEM): Analysing the Relative Change in Overnight Stays in Germany from 2020 to 2021

```
Residuals:
       Min         1Q     Median         3Q        Max
-1.8191037 -0.0711611 -0.0017575  0.0712360  2.9867534

Type: error
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error z value  Pr(>|z|)
(Intercept)           0.0664068  0.0042659  15.567 < 2.2e-16
Urbanization         -0.0148099  0.0014139 -10.474 < 2.2e-16
IOR                  -0.0668173  0.0018230 -36.653 < 2.2e-16
W_deviation_rate      0.1110389  0.0017149  64.749 < 2.2e-16
lag_deviation_rate    0.6255626  0.0072578  86.191 < 2.2e-16
lag_W_deviation_rate -0.0988803  0.0017024 -58.082 < 2.2e-16

Lambda: 0.0012949, LR test value: 0.0069888, p-value: 0.93338
Asymptotic standard error: 0.015482
    z-value: 0.083642, p-value: 0.93334
Wald statistic: 0.006996, p-value: 0.93334

Log likelihood: 4919.647 for error model
ML residual variance (sigma squared): 0.020147, (sigma: 0.14194)
Number of observations: 9223
Number of parameters estimated: 8
AIC: -9823.3, (AIC for lm: -9825.3)
```

Table 8 shows the Dynamic spatial error model (DSEM) which serves as a robustness check to the Dynamic spatial Autoregressive (DSAR) model by examining the sensitivity of the results to the specification of spatial dependence. Unlike the DSAR model, which assumes spatial lag effects in both the dependent variable and the error term, the DSEM specifies spatially autocorrelated errors while treating the dependent variable as exogenously determined.
Both the DSEM and DSAR models were employed to examine spatial dynamics in deviation rates across regions, aiming to uncover significant factors and spatial dependencies influencing these rates.

In the DSEM, which addresses spatial autocorrelation in the error terms, again significant relationships were observed: Urbanisation (-0.014***), Index of Restriction (-0.067***), and spatially lagged deviation rate (0.111***). λ, indicating spatial autocorrelation in errors, was estimated at 0.0013 (p=0.9334) which suggests that the spatial autocorrelation effect is minimal and the result even not significant.

The DSAR model, incorporating spatial lag effects in both the dependent variable and error term, exhibited similar significant coefficients for Urbanisation, IOR, and spatially lagged variable, echoing findings from the DSEM.

These results collectively underscore the robustness of spatial modelling approaches in capturing and explaining regional deviations, emphasising the persistent influence of spatial factors on regional outcomes. Both models exhibit robust and similar findings across key variables, validating the consistency of results. Spatial autocorrelation is addressed differently in each model, with SEM directly testing for autocorrelation in error terms through Lambda and SAR estimating rho for spatial lag effects.

The Dynamic Spatial Autoregressive (DSAR) models for the years 2020 (table 9 in the appendices) and 2021 (table 10 in the appendices) were computed separately to analyse differences in spatial dynamics influencing deviation rates of overnight stays across these years. This analysis aims to provide insights into how urbanisation and restrictions impacted deviation rates during different phases or years of the pandemic.

In 2020, the DSAR model again showed significant relationships for several key variables. Urbanisation had a coefficient of -0.020***, indicating a negative impact on deviation rates. The index of restriction (IOR) had a coefficient of -0.098***, demonstrating a strong negative influence. The spatially lagged deviation rate (W_deviation_rate) had a coefficient of 0.098***, highlighting a positive spatial lag effect where deviation rates in neighbouring regions positively influenced each other. The model's ρ parameter was 0.008, indicating no strong spatial dependence in the errors.

In 2021, the DSAR model revealed some changes in the relationships among the variables. Urbanisation had a coefficient of -0.009***, still indicating a negative impact on deviation rates but less pronounced than in 2020 and the p-value is explicitly higher. This suggests that highly urbanised areas continued to experience lower deviation rates, although the effect was weaker as already illustrated by table 10 and 11 before. The tourism industry managed in the second year of the pandemic to slowly return to the initial conditions. The IOR had a coefficient of -0.066***, showing a strong negative influence, although slightly less than in 2020, meaning that restrictions continued to significantly reduce overnight stays but the impact is mitigated. The spatially lagged deviation Rate (W_deviation_rate) had an estimationt of 0.083***, indicating a positive spatial effect, though also weaker compared to 2020. The ρ parameter was 0.021, again indicating no strong spatial dependence in the errors.

Comparing the results of 2020 and 2021, it is evident that the negative impact of urbanisation on deviation rates is consistent across both years, though the effect is stronger in 2020 (-0.0379***) compared to 2021 (-0.0130***). This indicates that highly urbanised areas tend to have lower deviation rates in overnight stays, with the effect being more pronounced during the initial year of the pandemic (2020) compared to the following year (2021). The tourism industry managed to return slowly to the initial situation.

Overall, the models for 2020 and 2021 individually provide consistent results in the significance and direction of the coefficients for Urbanisation, IOR, and the spatially lagged variable. These findings reinforce the robustness of the spatial modelling approach and emphasise the persistent influence of spatial factors on regional deviation rates. The absence of significant spatial dependence in the ρ parameter and LM test values for both years suggests that the primary spatial effects are captured by the included covariates, validating the robustness of these models in capturing regional dynamics. These insights deepen our understanding of regional tourism dynamics across different phases of the pandemic and can inform policymakers in designing strategies to foster economic stability and resilience.

The DSAR model restricted for the state of Bavaria (table 11 in the appendices) has again similar results to the previous models.

Table 12

D*SAR Model: Analysing the Relative Change in Overnight Stays during months of decline in overnight stays between 2020 and 2021*

```
Residuals:
       Min         1Q     Median         3Q        Max
-1.8779548 -0.0662603  0.0039928  0.0769095  3.0016116

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error  z value  Pr(>|z|)
(Intercept)         -0.2099665  0.0124447 -16.8720 < 2.2e-16
Urbanization        -0.0148872  0.0022464  -6.6273  3.42e-11
W_deviation_rate     0.0875084  0.0024128  36.2691 < 2.2e-16
lag_deviation_rate   0.6500104  0.0104842  61.9992 < 2.2e-16
lag_W_deviation_rate -0.0847933  0.0027144 -31.2380 < 2.2e-16

Rho: -0.012288, LR test value: 0.51792, p-value: 0.47173
Asymptotic standard error: 0.016966
    z-value: -0.72425, p-value: 0.46891
Wald statistic: 0.52453, p-value: 0.46891

Log likelihood: 1992.373 for lag model
ML residual variance (sigma squared): 0.021675, (sigma: 0.14722)
Number of observations: 4010
Number of parameters estimated: 7
AIC: -3970.7, (AIC for lm: -3972.2)
LM test for residual autocorrelation
test value: 8.773, p-value: 0.0030573
```

Table 13

D*SAR Model: Analysing the Relative Change in Overnight Stays during months of recovery in overnight stays between 2020 and 2021*

```
Residuals:
      Min        1Q    Median        3Q       Max
-1.018739 -0.073170 -0.011911  0.062070  1.403802

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error  z value  Pr(>|z|)
(Intercept)          0.0402648  0.0062846   6.4068 1.486e-10
Urbanization        -0.0081612  0.0023167  -3.5228  0.000427
W_deviation_rate     0.1124115  0.0054974  20.4482 < 2.2e-16
lag_deviation_rate   0.6547851  0.0117879  55.5472 < 2.2e-16
lag_W_deviation_rate -0.0724546  0.0039463 -18.3601 < 2.2e-16

Rho: 0.041458, LR test value: 5.4843, p-value: 0.019188
Asymptotic standard error: 0.018067
    z-value: 2.2947, p-value: 0.021753
Wald statistic: 5.2655, p-value: 0.021753

Log likelihood: 1847.383 for lag model
ML residual variance (sigma squared): 0.018501, (sigma: 0.13602)
Number of observations: 3208
Number of parameters estimated: 7
AIC: -3680.8, (AIC for lm: -3677.3)
LM test for residual autocorrelation
test value: 0.85846, p-value: 0.35417
```

Dynamic Spatial Autoregressive (DSAR) models were computed to analyse overnight stays deviation rates across urban and non-urban areas during 2 distinct phases: decline and recovery of tourism. In this model, the index of restriction is excluded as the degree of restriction chosen by political authorities is strongly dependent on the two phases.

The decline phase, shown in table 12, includes the months March, April, May, June, October, November, December in 2020 and January, February, March, April, May, November, and December in 2021. The residuals showed moderate variability (-1.878 to 3.002). The intercept was at -0.210***. Model coefficients highlighted a significant negative effect of urbanisation (-0.015***), suggesting again lower deviation rates in highly urbanised areas. The effect of the spatially lagged variable was positive (0.088***), indicating an influence of neighbouring districts on deviation rates.

The recovery phase includes July, August, and September in 2020 and June, July, August, September, and October in 2021. During the recovery phase illustrated by table 13, residuals exhibited reduced variability (-0.019 to 1.404), indicating less heterogeneity. The intercept significantly deviated towards 0+, suggesting that there are some positive deviation rates during that phase. Urbanisation continued to show a negative effect (-0.008***), but this effect is slightly less negative compared to the decline phase, indicating that highly urbanised areas are not as severely impacted during the recovery. The reasoning behind this phenomena I identified already in table 10 or 11 and between the years 2020 and 2021. The spatially lagged variable again strongly influenced deviation rates (0.112***).

In summary, both phases highlighted that highly urbanised areas tend to exhibit lower deviation rates in overnight stays. However, this negative effect is slightly less pronounced during the recovery phase, indicating that urbanised areas are not as severely impacted during recovery compared to the decline phase. The trend illustrated in Tables 10 and 11 is supported by the DSAR model. These findings deepen our understanding of regional tourism dynamics across phases of decline and recovery.

Table 14: Summary of models and estimations

Independant variables	(1) Intercept	(2) Urbanization	(3) IOR	(4) Spatially lagged variable	(5) time lags	(6) spatial lags
DSAR	0.067*** (0.005)	-0.015*** (0.001)	-0.067*** (0.002)	0.111*** (0.002)	0.625*** (0.007)	-0.099*** 0.002
DSEM	0.066*** (0.004)	-0.015*** (0.004)	-0.067*** (0.002)	0.111*** (0.002)	0.626*** (0.007)	-0.099*** 0.002
SAR (no lags)	0.147*** (0.006)	-0.036*** (0.002)	-0.140*** (0.002)	0.056*** (0.002)	/	/
Panel	0.114*** (0.005)	-0.0162*** (0.002)	-0.137*** (0.002)	/	0.385*** (0.006)	/
2020 (DSAR)	0.080*** (0.008)	-0.020*** (0.002)	-0.098*** (0.003)	0.098*** (0.002)	0.529*** (0.011)	-0.093*** 0.002
2021 (DSAR)	0.094*** (0.007)	-0.009*** (0.002)	-0.066*** (0.003)	0.083*** (0.004)	0.664*** (0.009)	-0.073*** 0.003
Bavaria (DSAR)	0.083*** (0.009)	-0.015*** (0.003)	-0.074*** (0.003)	0.111*** (0.004)	0.599*** (0.014)	-0.101*** 0.004
Decline (DSAR)	-0.210*** (0.012)	-0.015*** (0.002)	/	0.088*** (0.002)	0.650*** (0.010)	-0.085*** 0.003
Recovery (DSAR)	0.040*** (0.006)	-0.008*** (0.002)	/	0.0112*** (0.005)	0.655*** (0.012)	-0.072*** 0.004

*** $p < 0.01$, ** $p < 0.005$, * $p < 0.1$

Table 14 presents the estimated coefficients from multiple models that analyse the impact of urbanisation and political restrictions on the deviation rate in tourism. The models included are the Dynamic Spatial Autoregressive Model (DSAR), the Dynamic Spatial Error Model (DSEM), a panel model, a simple Spatial Autoregressive Model (SAR) without any time or spatial lags, as well as specific models for the years 2020 and 2021 and models discerning between revery and decline phases. The coefficients provided are for urbanisation, IOR, time lags, spatial lags and a spatially lagged variable, which is included only in the DSAR and DSEM models. The spatially lagged variable coefficient captures the influence of the deviation rate in one area on the deviation rates in neighbouring areas.

The table indicates that urbanisation has a significant similar negative impact on the deviation rate of overnight stays across all models. The coefficients for urbanisation are slightly different between all models but they are always negative, suggesting that higher urbanisation levels are associated with lower, often negative deviation rates in tourism during the pandemic.

The IOR also has consistently negative coefficients, indicating that stricter restrictions lead to higher deviation rates. The spatially lagged variable in the DSAR and DSEM models has positive coefficients (4 % for both), indicating that the deviation rate in one area is positively correlated with the deviation rate in neighbouring areas. This highlights the importance of spatial interactions, which are not captured by simple panel models. Similarly for the spatial and time lags where the significant coefficient highlight the importance of temporal dependencies across regions.
The specific models for 2020 and 2021 show similar trends, with slightly varying coefficients, accounting for the temporal dimension of the data. The model for Bavaria shows coefficients similar to the other models, indicating that the results are robust and not skewed by regional peculiarities.

Finally, table 15 in the appendix shows the results of the DSAR model when putting focus on the factor Urbanisation. The reference category in this case is urbanisation level 1 which are rural districts. The estimates for level 2 (peri-urban districts), level 3 (urban district) and level 3 (major urban districts) are + 0.007*, - 0.01* and - 0.05***. The relative change in overnight stays is 5% lower in major urban districts compared to rural districts. Urban districts, in general, show a 1% lower rate. Interestingly, peri-urban districts exhibit a slightly higher deviation rate by 0.7%. This suggests that the urbanisation effect is weaker in less urbanised areas. Additionally, the significance of the results is notably weaker for urbanisation factors 1 and 2. It's important to note that peri-urban districts border major urban areas. During the pandemic, people tended to avoid highly urbanised regions and sought accommodations in less densely populated areas. As a result, the tourism industry in these bordering regions benefited from an influx of visitors.

8. Conclusion

The analysis conducted using the Dynamic Spatial Autoregressive (DSAR) model has provided critical insights into the determinants of deviation rates in monthly overnight stays during the Covid-19 pandemic. It reveals significant variations both temporally and spatially on demand side. It is evident that urbanisation, government restrictions, spatial and temporal dependencies play pivotal roles in shaping tourism dynamics amidst the crisis. Urbanisation demonstrates a notable impact, with higher levels consistently associated with lower deviation rates. Monthly overnight stays were about 5 percentage points lower in major urban districts compared to rural ones. This finding underscores urban areas' resilience during economic downturns, though with heightened susceptibility to external shocks, particularly in service-oriented industries.

Government restrictions exhibit a robust negative correlation with deviation rates, indicating that stricter measures aimed at pandemic control significantly impeded tourism activities. This highlights the delicate balance required between stringent public health measures and mitigating economic impacts. In the second year the effect of restrictions on the overnight stays already mitigated compared to the first one.

The analysis of phases (decline and recovery) in tourism further elucidates these dynamics. During the decline phase, urbanisation continued to correlate negatively with deviation rates. However, it has a nuanced effect suggesting varying impacts across different phases of crisis. The damaging effect to the tourism industry by the factor urbanisation is almost doubled during the decline phase. The effect slightly diminished, reflecting stabilising economic conditions and policy adaptations over time.

Spatial dependencies were prominently featured in the DSAR model, illustrating that deviations in one region significantly influence those in neighbouring areas. This spatial autocorrelation underscores the interconnected nature of regional economies, while temporal dependencies, such as those from the time lags or spatial lags, further highlight the dynamic interactions over time. These findings emphasise the need for integrated policy responses that account for both spatial spillovers and temporal dynamics.

Robustness checks, including Moran's I test and comparisons with a Dynamic Spatial Error Model (DSEM), validated the reliability of the DSAR model. These checks underscore the necessity of spatial modelling approaches for accurately capturing regional dynamics in the tourism sector.
For the spatial analysis of overnight stays, we anticipate minimal limitations regarding validity. Possible inaccuracies in official statistics may arise from delays in receiving reports or incomplete submissions from individual accommodation facilities. However, these potential issues might be mitigated by utilising district-level and monthly data. The findings and conclusions of this study are applicable to various spatial entities. Given the heterogeneous nature of Germany's tourism industry, which encompasses multiple facets, these insights can be projected to other countries. This transferability is especially valuable in regions with significant spatial disparities in tourism activity.

Government measures, such as subsidies or crisis relief aid, should not be uniformly distributed across an entire region but should instead be tailored to fit regional specificities. The implications for policy are profound, suggesting that policies should support urban areas in diversifying their economies and enhancing resilience. Furthermore, policies must strike a delicate balance between stringent public health measures and mitigating economic impacts, recognising the spatial and temporal interdependencies that characterise regional economies. Future research could explore alternative spatial modelling techniques or incorporate additional variables to further enhance model accuracy.

In conclusion, this study provides critical insights for crisis management in the tourism sector, informing evidence-based policymaking that considers specific spatial and economic dynamics. By doing so, policymakers can better navigate crises and support sustainable tourism recovery strategies. One thing is certain: the Covid-19 pandemic had devastating financial and economic consequences for Germany as a whole. Moving forward, the objective for potential future pandemics is to learn from the past and minimise potential losses through better preparedness or decision making potentially based on the numbers provided by this research.

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10. Appendices

Table 6

Panel Data: Analysing the Relative Change in Overnight Stays in Germany from 2020 to 2021

```
Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.0347950 -0.0945436  0.0015218  0.0993744  3.0551675

Coefficients:
                    Estimate Std. Error  z-value  Pr(>|z|)
(Intercept)        0.1141025  0.0050464  22.6106 < 2.2e-16 ***
Urbanization      -0.0162336  0.0016569  -9.7974 < 2.2e-16 ***
IOR               -0.1377909  0.0016745 -82.2876 < 2.2e-16 ***
lag_deviation_rate  0.3849125  0.0064622  59.5639 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    989.4
Residual Sum of Squares: 276.03
R-Squared:      0.72101
Adj. R-Squared: 0.72092
Chisq: 23825.4 on 3 DF, p-value: < 2.22e-16
```

Table 7

Spatial Autoregressive (SAR) Model - without lags: Analysing the Relative Change in Overnight Stays in Germany during years 2020 and 2021

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.793906 -0.125436 -0.011556  0.111887  2.882081

Type: lag
Coefficients: (asymptotic standard errors)
                  Estimate Std. Error z value  Pr(>|z|)
(Intercept)      0.1470812  0.0059821  24.587 < 2.2e-16
Urbanization    -0.0361939  0.0018018 -20.087 < 2.2e-16
IOR             -0.1401743  0.0020903 -67.058 < 2.2e-16
W_deviation_rate  0.0556297  0.0015531  35.818 < 2.2e-16

Rho: 0.0068005, LR test value: 18.22, p-value: 1.9683e-05
Asymptotic standard error: 0.0015992
    z-value: 4.2525, p-value: 2.1136e-05
Wald statistic: 18.084, p-value: 2.1136e-05

Log likelihood: 2385.284 for lag model
ML residual variance (sigma squared): 0.035657, (sigma: 0.18883)
Number of observations: 9624
Number of parameters estimated: 6
AIC: -4758.6, (AIC for lm: -4742.3)
LM test for residual autocorrelation
test value: 20.272, p-value: 6.7191e-06
```

Table 9

DSAR Model: Analysing the Relative Change in Overnight Stays in Germany in 2020

```
Residuals:
       Min         1Q     Median         3Q        Max 
-0.5942986 -0.0821896 -0.0044961  0.0813350  0.8692952 

Type: lag 
Coefficients: (asymptotic standard errors) 
                      Estimate Std. Error  z value  Pr(>|z|)
(Intercept)          0.0797272  0.0075030  10.6261 < 2.2e-16
Urbanization        -0.0204426  0.0020740  -9.8565 < 2.2e-16
IOR                 -0.0976163  0.0028762 -33.9398 < 2.2e-16
W_deviation_rate     0.0976367  0.0022064  44.2524 < 2.2e-16
lag_deviation_rate   0.5287069  0.0114180  46.3048 < 2.2e-16
lag_W_deviation_rate -0.0931969  0.0023124 -40.3026 < 2.2e-16

Rho: 0.0077339, LR test value: 0.44223, p-value: 0.50605
Asymptotic standard error: 0.011758
    z-value: 0.65778, p-value: 0.51068
Wald statistic: 0.43267, p-value: 0.51068

Log likelihood: 2302.401 for lag model
ML residual variance (sigma squared): 0.020613, (sigma: 0.14357)
Number of observations: 4411 
Number of parameters estimated: 8 
AIC: -4588.8, (AIC for lm: -4590.4)
LM test for residual autocorrelation
test value: 2.2155, p-value: 0.13663
```

Table 10

D*SAR Model: Analysing the Relative Change in Overnight Stays in Germany in 2021*

```
Residuals:
       Min         1Q     Median         3Q        Max 
-1.9496879 -0.0647454 -0.0062552  0.0561758  2.9701661 

Type: lag 
Coefficients: (asymptotic standard errors) 
                      Estimate Std. Error  z value  Pr(>|z|)
(Intercept)          0.0935482  0.0068937  13.5702 < 2.2e-16
Urbanization        -0.0088282  0.0018226  -4.8438 1.274e-06
IOR                 -0.0663834  0.0025225 -26.3166 < 2.2e-16
W_deviation_rate     0.0827822  0.0035060  23.6116 < 2.2e-16
lag_deviation_rate   0.6637694  0.0090168  73.6150 < 2.2e-16
lag_W_deviation_rate -0.0725274  0.0031248 -23.2106 < 2.2e-16

Rho: 0.021021, LR test value: 3.8455, p-value: 0.04988
Asymptotic standard error: 0.010674
    z-value: 1.9693, p-value: 0.048914
Wald statistic: 3.8783, p-value: 0.048914

Log likelihood: 2901.515 for lag model
ML residual variance (sigma squared): 0.017529, (sigma: 0.1324)
Number of observations: 4812 
Number of parameters estimated: 8 
AIC: -5787, (AIC for lm: -5785.2)
LM test for residual autocorrelation
test value: 0.57755, p-value: 0.44727
```

Table 11

DSAR Model : Analysing the Relative Change in Overnight Stays in Bavaria for the years 2020 and 2021

```
Residuals:
       Min          1Q      Median          3Q         Max
-0.56792582 -0.06973213 -0.00093465  0.06969273  0.60285060

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error  z value  Pr(>|z|)
(Intercept)          0.0853182  0.0094287   9.0488 < 2.2e-16
Urbanization        -0.0147904  0.0029824  -4.9593 7.076e-07
IOR                 -0.0738660  0.0029941 -24.6708 < 2.2e-16
W_deviation_rate     0.1108330  0.0035711  31.0357 < 2.2e-16
lag_deviation_rate   0.5990672  0.0136904  43.7581 < 2.2e-16
lag_W_deviation_rate -0.1007133  0.0036589 -27.5259 < 2.2e-16

Rho: 0.036713, LR test value: 6.9148, p-value: 0.0085485
Asymptotic standard error: 0.013711
    z-value: 2.6777, p-value: 0.0074128
Wald statistic: 7.1701, p-value: 0.0074128

Log likelihood: 1387.478 for lag model
ML residual variance (sigma squared): 0.016657, (sigma: 0.12906)
Number of observations: 2208
Number of parameters estimated: 8
AIC: -2759, (AIC for lm: -2754)
LM test for residual autocorrelation
test value: 8.5301, p-value: 0.0034933
```

Table 15

DSAR Model: Analysing the Relative Change in Overnight Stays in Germany for the years 2020 and 2021 with focus on factor Urbanisation

```
Residuals:
      Min         1Q     Median         3Q        Max
-1.7857702 -0.0700580 -0.0017682  0.0717094  2.9934151

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error  z value Pr(>|z|)
(Intercept)          0.0438292  0.0047062   9.3131  < 2e-16
Urbanization2        0.0071958  0.0035075   2.0515  0.04021
Urbanization3       -0.0096081  0.0058366  -1.6462  0.09973
Urbanization4       -0.0491865  0.0043387 -11.3366  < 2e-16
IOR                 -0.0663444  0.0018507 -35.8486  < 2e-16
W_deviation_rate     0.1117565  0.0017394  64.2485  < 2e-16
lag_deviation_rate   0.6166482  0.0073325  84.0984  < 2e-16
lag_W_deviation_rate -0.0973293  0.0017095 -56.9333  < 2e-16

Rho: 0.0023805, LR test value: 0.083523, p-value: 0.77258
Asymptotic standard error: 0.008198
    z-value: 0.29038, p-value: 0.77153
Wald statistic: 0.08432, p-value: 0.77153

Log likelihood: 4949.107 for lag model
ML residual variance (sigma squared): 0.020019, (sigma: 0.14149)
Number of observations: 9223
Number of parameters estimated: 10
AIC: -9878.2, (AIC for lm: -9880.1)
LM test for residual autocorrelation
test value: 0.019323, p-value: 0.88945
```