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Exploring the relationship between Airbnb and traditional accommodation for regional variations of tourism markets

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Abstract
The relationship between Airbnb-based and traditional accommodation is mainly documented for key tourist destinations with a large tourism sector, while there is almost no evidence on this for other destinations. This article focuses on regional variations in the relationship between Airbnb-based and traditional accommodation across primary and secondary tourist destinations in Norway. Through an exploratory cluster analysis and a panel vector autoregressive (PVAR) model with forecast error decomposition of shocks (unobserved effects), it finds evidence of spillovers from Airbnb-based accommodation to traditional accommodation in secondary destinations. The demand for traditional accommodation is positively affected by Airbnb demand in the long run. Interestingly, a smaller effect is found with the supply-side of regional tourism markets in the Norwegian secondary tourist destinations. The growth of Airbnb may, thus, spur growth in the general tourism sector in such less frequented destinations.

Keywords
Airbnb, cluster analysis, FEVD, regional variations, shared accommodation, traditional accommodation

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Introduction

The abundant literature on Airbnb's presence in tourist destinations highlights both positive and negative effects of the global sharing economy player on tourism markets (Dogru et al., 2019; Oskam and Boswijk, 2016). However, the literature is biased because most empirical studies focus on primary destinations that host a large or growing tourism sector, including shared accommodation services. Examples discussed are the European capital cities of Berlin, Amsterdam, Vienna and Paris (e.g. Heo et al., 2019) or non-capital cities, such as Barcelona and Utrecht (Ioannides et al., 2019). As the Paris case illustrates (Heo et al., 2019), Airbnb's presence is a strong driver for tourism growth over there. Dogru et al. (2020) illustrate the positive effects that Airbnb's supply in major metropolitan regions in the United States has on employment growth in the hospitality, tourism and leisure industries. At the same time, Airbnb's growth also creates negative effects in these destinations such as price increases for all accommodation types (Dogru et al., 2019), the crowding-out of established accommodation providers (Zervas et al., 2017), the crowding-out of residents (Ferreira et al., 2019) and congestion effects due to overtourism (Gurran et al., 2020).

Contrary to this stream of literature with a focus on key or primary tourist markets, the potential effects of Airbnb on established accommodation providers in less developed tourist destinations are rarely documented in the literature (notable exceptions are Falk et al., 2019; Lima, 2019; Strømmen-Bakhtiar et al., 2020; Vinogradov and Strømmen-Bakhtiar, 2019). This article uses the concept of secondary tourist destinations (Tsogas et al., 2019) to frame destinations that are no mainstream targets for national or international travellers and differentiate them from primary destinations. Secondary tourist destinations host threshold-level activities in tourism and hospitality because of highly visited tourist sites (Leick et al., 2020) or existing niche markets that can be developed (Choomgrant and Sukharomana, 2017). In such regional contexts, Airbnb-based tourism may spur tourism in general and, indirectly, foster the development of traditional accommodation (hotels, pensions, bed and breakfast pensions (B&Bs), camping sites, cabins, etc.) by attracting more visitors.

To date, there is almost no indication from the theoretical or empirical literature concerning the influence of Airbnb-based tourism on traditional accommodation providers, and *vice versa*, in regionally variegated contexts (cf. Guttentag and Smith, 2017; Zervas et al., 2017). What the literature indicates (Heo et al., 2019) is that the relationship between Airbnb- and hotel-based accommodations is highly complex. For instance, a study by Morales-Perez et al. (2020) on regional tourism markets in Catalonia, Spain, highlights that, while Airbnb's supply is rather a complement than a competitor to traditional accommodation in regions outside of bigger cities, its growth is highly dependent on municipal regulation. Consequently, our point of departure in this article is the research gap on the interrelationship between Airbnb-based and traditional tourism through the lodging and hospitality industry in less developed tourism markets. The understanding of this specific relationship for regional variations of tourism markets promises to be of interest to both scholars and policymakers.

Beginning with supply–demand predictions, we investigate regional variations in the relationship between Airbnb-based and traditional accommodation for primary and secondary tourist destinations. We use county-level data for Norway and classify the tourist destinations into two distinct clusters of primary and secondary destinations. By means of a panel vector autoregression (PVAR) analysis and forecast error variance decomposition (FEVD), these clusters are compared concerning the relationship studied and their association with regional tourism markets.

The exploratory findings indicate that Airbnb-based and traditional accommodations in all regional markets are mostly explained by shocks (measured as unobserved effects and interpreted as innovations) within their own sectors. For example, supply-side shocks to traditional accommodation influence traditional accommodation, but not Airbnb-based accommodation, and vice versa. Nevertheless, there are spillovers both on the demand- and supply-side between the different accommodation types, notably in the secondary destinations of Norway. The results suggest that the factors affecting the demand for Airbnb bookings also imply changes in demand for traditional accommodation and can spur general tourism in secondary destinations in the longer run. This indicates a demand-side relatedness of the two accommodation types in secondary tourist destinations as well as a supply-side relatedness, which is, however, weaker than the demand-side relatedness. In both cases, the effects go from Airbnb-based to traditional accommodation, rather than the other way around.

With these findings, the article contributes to the existing empirical literature on Airbnb and tourism markets in two respects: First, it illustrates core differences between primary tourist destinations (Gurran et al., 2020; Ioannides et al., 2019) and secondary destinations in terms of less developed tourism markets, which have been overlooked in the existing literature. Second, it also contributes to a better understanding of the characteristics of secondary tourist destinations and their operationalisation (Tsogas et al., 2019).

The remainder of this article is organised as follows: The second section provides a literature review, presents the theoretical background and establishes the hypotheses. The third section summarises the context for general tourism, notably in secondary tourist destinations of Norway. The fourth section describes the methodology and research design, and the fifth section presents the descriptive statistics and empirical computations, including their discussion. Finally, the sixth section provides conclusions, public-policy implications, limitations and suggestions for future research.

Literature review

Tourism in secondary tourist destinations

It is common with destination marketing approaches to differentiate between regional markets within countries (Dwyer et al., 2009), and various criteria are used for this market segmentation (Perles-Ribes et al., 2020). Besides key destinations in a country, which we call primary destinations, the concept of 'secondary tourist destinations' is used in the tourism marketing literature. It is, however, poorly defined. Tsogas et al. (2019: 240) provide one of the most clear-cut definitions by framing a secondary tourist destination as 'a destination where the tourists are staying overnight or for a few days in comparison to the number of their total staying in the primary destination'. Tsogas et al. (2019) and McKercher and Wong (2004) show that the shorter overnight stays of visitors in a secondary tourist destination, compared to main destinations, can be explained by the different motivational factors attracting tourists to secondary destinations (Lau and McKercher, 2006).

Apart from the duration of stays, Tsogas et al. (2019) use the notion of independent travellers, who self-arrange their travels outside organised excursions and trips and plan only minimal transportation and accommodation services in advance. Lau and McKercher (2006), moreover, found that the route planning of tourists typically focuses on main tourist destinations as a key base from where they explore secondary tourist destinations. Hence, such destinations are not visited intentionally for the sake of abundant tourist-pulling attractions and accommodation services (Vengesayi et al., 2009), but they are included in a broader travel plan of visitors (Liu, 1999). As Choi et al. (2007) argue, the decisions about travels to such destinations are usually embedded in flexible and tentative decision-making processes, compared to the more intentional travel decisions for primary tourist destinations that involve more fixed and advance planning.

In the light of these characteristics, the concept of secondary tourist destinations is a powerful lens to depict the attractiveness and competitiveness of less developed tourist markets (cf. Buhalis, 2000; Dwyer and Kim, 2003). To consider the Norwegian context, a secondary tourist destination is framed as follows in this article (cf. Buhalis, 2000; Choi et al., 2007; Lau and McKercher, 2006; McKercher and Wong, 2004; Tsogas et al., 2019): It is no key target in a country for national and international travellers and does not face a high demand for tourism that would account for significant tourism growth. Nevertheless, tourism activities in a secondary destination may reach a stable minimal level, indicated by the number of overnight stays and expenditures by visitors (as demand-side indicators) and the accommodation infrastructure, such as the hotels and their profitability (as supply-side indicators).

In the present article, it is argued that the presence of Airbnb-based accommodation in less developed tourist destinations can spur tourism (Oskam and Boswijk, 2016) without necessarily generating the negative effects that are observed in primary destinations, notably urban and metropolitan tourism markets (Strømmen-Bakhtiar and Vinogradov, 2020; Wachsmuth and Weisler, 2018). Hence, it is necessary to explore the regional variations concerning the effects of Airbnb on tourism markets.

The sharing economy and its effects on accommodation services

Airbnb represents the main global sharing-economy provider of tourist accommodation and its seemingly unlimited growth[1] affects both the supply- and demand-side of regional tourism markets (Cheng, 2016). Most of these positive and negative effects have been empirically confirmed for primary tourist destinations but not to the same extent for secondary destinations: Dogru et al. (2019) and Strømmen-Bakhtiar and Vinogradov (2019) demonstrate for primary tourist destinations that the shared accommodation provider has taken market shares from the lodging industry. At the same time, Airbnb's supply has also been associated with employment growth in the hospitality and tourism sector of major urban destinations in the United States (Dogru et al., 2020). Airbnb's presence, moreover, has led to the gentrification of rental space inside cities in primary tourist destinations, driving up rents and crowding out the long-term rental demand (Cocola-Gant and Gago, 2019; Gurran and Phibbs, 2017; Wachsmuth and Weisler, 2018). Regardless of the destination type, the growth of Airbnb has the potential to be beneficial for a regional tourism sector by enabling job and income opportunities for private households (Fang et al., 2016). It might also lead to the attraction of new types of tourists (Bilgihan and Nejad, 2015; Paulauskaite et al., 2017) and a better visibility of the destination, which can result in more incoming travellers (Strømmen-Bakhtiar and Vinogradov, 2019).

For secondary tourist destinations, such as rural-peripheral regions (Lane and Kastenholz, 2015; Pablo-Romero and Molina, 2013), the role of Airbnb as a shared accommodation provider for tourism markets has not been fully captured yet (Postma and Schmuecker, 2016; Yun et al., 2017). Only a handful of studies directly address the effects of Airbnb on secondary tourist destinations. While some of these studies point to negative effects (Falk et al., 2019), others claim overall benefits (Gössling and Lane, 2015).

Falk et al. (2019) put forward that in rural regions, Airbnb would be a strong and direct competitor to the distribution model of established accommodation providers (cf. Oskam and Boswijk, 2016). By contrast, Gössling and Lane (2015), who empirically analysed the effect of internet-based booking systems on a rural tourist destination in Norway in the pre-Airbnb times, found overall positive effects of the new booking platform on the regional tourism market. They argue that multiple positive effects were associated with the introduction of the online booking system such as the higher price transparency, lower entry barriers for new tourists to the destination and a higher visibility of the accommodation providers, that is, a potential larger demand by incoming tourists. The only negative effect they found was that the rating system on the online booking platform made the destination and its accommodation providers vulnerable to the user ratings (Gössling and Lane, 2015). Interestingly, a fiercer competition between the established providers was not confirmed in this study.

Furthermore, Morales-Perez et al. (2020) suggest that Airbnb and traditional accommodation providers are complementary outside bigger cities. Finally, Lee et al. (2020) demonstrate that Airbnb's growth is spurred by the existence of tourism clusters within and across regions. Altogether, the scarce empirical evidence points to multiple and unclear effects of Airbnb on traditional accommodation providers in secondary tourist destinations. The opposite direction of the relationship has not been discussed at all in the extant literature.

Traditional versus Airbnb-based accommodation and tourism markets

From the viewpoint of economic theory, Airbnb represents a disruptive innovation in the tourism service provision (Guttentag, 2015), which can have a strong impact on tourism markets through supply- and demand-side effects. The entry of Airbnb into a regional tourism market can, thus, be considered as a shock to the sector: From a supply-side perspective, the presence of Airbnb can have positive partial effects on the tourist market because the new accommodation providers supplement the existing supply of tourist services with a broader and more diversified offer (Cheng, 2016; Cheng and Jin, 2019). Since Airbnb-based suppliers may be motivated by the outlook to generate extra income (Jiao and Bai, 2020), the higher supply in a tourist destination can leverage tourism growth based on the broader range of amenities offered for tourists, which may imply subsequent demand-side effects (cf. Deller, 2006; Naldi et al., 2015). Moreover, Airbnb influences the demand for accommodation services in the tourist destination (cf. Gunter and Önder, 2018) by attracting various types of travellers: travellers booking otherwise with low-cost hotels and those looking for alternative experiences such as uniqueness, authenticity and local customs outside the established accommodation providers (Mody et al., 2017; Paulauskaite et al., 2017). Hence, Airbnb's presence might lead to extra demand because of additional visitors coming to the destination.

In primary tourist destinations where there is a strong tourism market with sufficient traditional accommodation providers and demand by tourists, Airbnb might buffer a rise in demand as an additional supplier (Vengesayi et al., 2009). This effect is less evident for secondary destinations. Due to a lower demand for tourist services in a secondary tourist destination, Airbnb's extra supply to such a limited tourism market will supposedly rather lead to fiercer competition with traditional accommodation providers (cf. Oskam and Boswijk, 2016) because the already low demand may be diverted to the new competitor. In this scenario, Airbnb-based and traditional accommodation in a secondary tourist destination would be substitutes, competing for the few tourists (cf. Falk et al., 2019). However, it is also likely that new tourist groups might be attracted to secondary

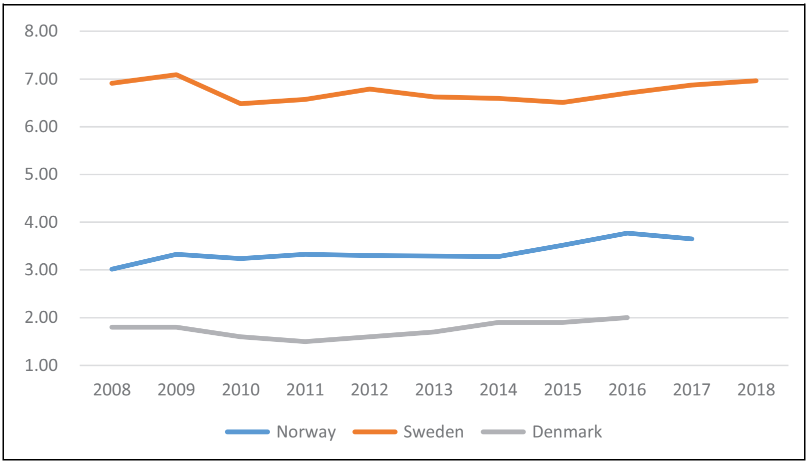

Figure 1. A comparison of tourism-related GDP as a share of total GDP in Norway versus the other countries in Scandinavia.
Source: Organisation for Economic Co-operation and Development (OECD, 2019a).

destinations through Airbnb. Airbnb-based accommodation would then be additive or complementary to the existing accommodation (Gyódi, 2019), expanding the market potential in the destination and supporting tourism growth through offering various services to a broader group of visitors.

The context of tourism in Norway

This section explains the background and motivation for selecting Norway as a country in Scandinavia[2] for this study by, first, showing the importance of tourism for the country and, second, presenting related literature about tourism in Norway. As Figure 1 highlights, Norway is one of the leading countries in Scandinavia regarding the contribution of tourism to the national GDP. Tourism in Norway increased consistently from 2008 to 2017, with its share in total GDP rising by 21%.

In addition, an OECD (2019b, 2019c) comparison of GDP and unemployment rate, two key economic indicators, across Scandinavia found that Norway has a higher GDP than the OECD average (OECD, 2019b)[3] and its unemployment rate is lower than the average unemployment rate of OECD countries (OECD, 2019c). With its good economic performance, compared to other Scandinavian and OECD countries, both in terms of general economic and tourism development, Norway represents an appropriate context to study the topic addressed in this article.

Indeed, the related literature on tourist destinations in Norway confirms that tourism in Norway takes place in both primary (e.g. the capital city of Oslo and its surroundings) and secondary destinations (InnovasjonNorge, 2019). According to Flognfeldt (1999), many international visitors to Norway prefer multisite trips from primary destination bases, and a significant proportion of travelling consists of passing through secondary tourist destinations during day trips or short overnight stays (for instance, rural regions; Hammer, 2008). Mei (2014) stresses the importance of experience-based tourism in the case of a rural secondary tourist destination in Norway. These findings highlight that both tourism activities in primary and secondary destinations matter for Norway. Finally, a survey among travellers to Norway in 2019 (InnovasjonNorge, 2019) shows

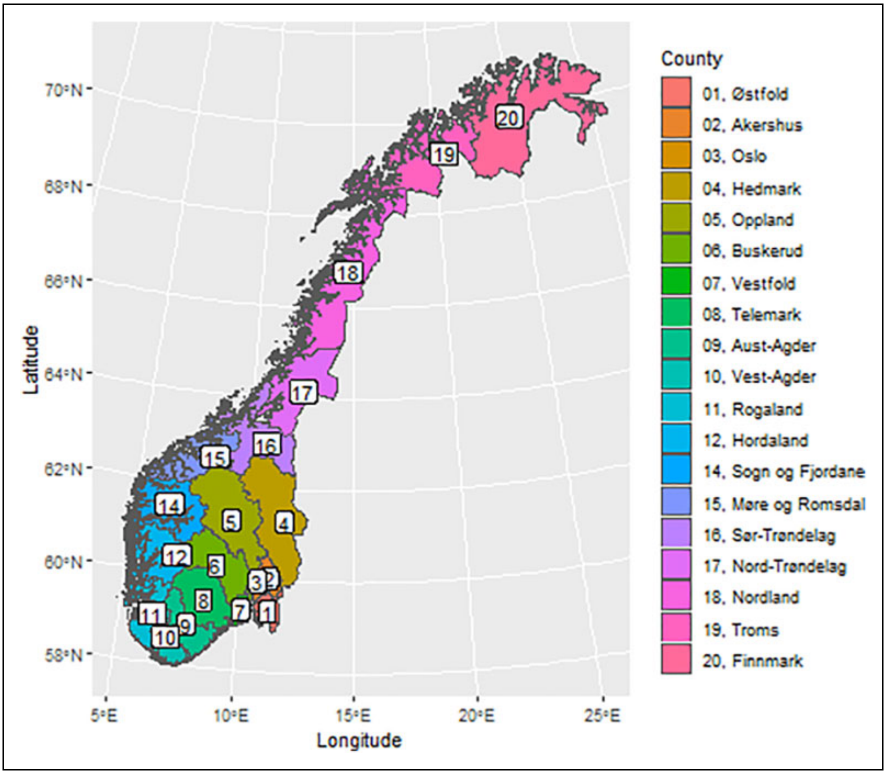

Figure 2. County numbers and names 1972–2017.
Source: Kartverket (Norwegian Mapping Authority), Creative Commons 0.

that 36% of those who have been booking Airbnb-based accommodation all over Norway also book hotels, much rather than other accommodation types. This points to a competitive relationship between Airbnb-based accommodation and the lodging industry in Norway.

Method and data

Data

To investigate this relationship for secondary compared to primary Norwegian tourist destinations and study how this relationship is associated with general economic development of the regional tourism markets, monthly data on Airbnb listings in Norway (January 2010 to March 2018) stemming from Airdna[4] are analysed. Until the end of 2017, Norway consisted of 19 counties (Figure 2 and Online Appendix) of varying geographical and population size. These counties are used as the geographical unit in this study. We aggregated the data on the reported number of bookings for each Airbnb unit over the last 12 months for each month and county. This provided a monthly panel data of Airbnb bookings for each county from 2010 to 2017, which were subsequently merged with data on regional tourism and economic activity from Statistics Norway (number of overnight stays of guests at hotels and camping sites, etc.) and the Norwegian Labour and Welfare Administration (unemployment data). The unemployment rate is used as a measure of general economic activity in the region. Since the number of Airbnb bookings is quite low or even zero for a lot of counties at the beginning of the sample, the data set was trimmed prior to the merger.[5]

The final panel set contained monthly observations for Airbnb bookings, overnight stays, the number of guests in traditional accommodation types and the unemployment rate for a total of 19 Norwegian counties between January 2012 and December 2017. These variables were selected since all of them are available both at a monthly rate and on the county level, which is a precondition to match the highly granular Airbnb data used in this article.

Method

The data outlined in 'Data' section were used to analyse dependencies by taking into consideration variations across time and geographical scope. A cluster analysis was applied (Romesburg, 2004; see the next section for the outline of this procedure) to separate the 19 counties into primary and secondary destinations, which resulted in a separate panel for each cluster. We subsequently estimated a PVAR model, which considers dynamics over time and variation across counties, to compare the two clusters. Using the PVAR model allows us to treat both Airbnb and traditional accommodation as endogenous variables. Furthermore, using a vector autoregression (VAR) specification eliminates the endogeneity problem as well as the problem of omitted variable bias, that is, the need to include more proxy variables (cf., for instance, Guerello, 2014). By using time- and county-fixed effects, we are able to control for factors which are equal across counties over time, such as national economic factors. Moreover, factors that remain constant over time but are county-specific can be controlled for, such as the population and income distribution (which do not show much variation over the relatively short sample used).

The PVAR model can be summarised as $y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{i,t-l} + Bx_{i,t} + Cs_{i,t} + \varepsilon_{i,t}$ where y represents the endogenous variables, x represents the predetermined variables and s denotes exogenous variables. We estimate such a PVAR model for each cluster, using the R package *panelvar* (Sigmund and Ferstl, 2019). Since a PVAR model is estimated for both the supply and demand side of accommodation, a total of four different PVAR models are used to compare effects between traditional and Airbnb-based accommodation in primary *versus* secondary destinations. The forward orthogonal transformation is applied to control for fixed effects, as it is preferred over first-difference transformation (Hayakawa, 2009).

Furthermore, the PVAR model is used for a FEVD, as outlined in Lütkepohl (2005). This allows us to investigate how much of the forecast error of each variable can be explained by exogenous shocks (unobserved effects) to the variables in the model. For example, it can be explored whether there are differences in how exogenous shocks related to traditional or Airbnb-based accommodation affect these two variables in primary compared to secondary destinations, provided by differences between the two clusters. The forecasting error is represented by $y_{i,t+s} - \hat{y}_{i,t+s|t}$ where the hat denotes forecasted values and $|t$ indicates a forecast provided by information up to time t. The forecasting error of a two-variable PVAR is affected by shocks to each of the two variables, and the forecasting error for each variable in the PVAR can be explained by shocks to each of the two variables in the PVAR. Through the FEVD, we can calculate how much each variable in the PVAR system is contributing to the forecast error of each variable (cf. Hamilton, 1994: 323). For instance, a forecast error for Airbnb demand (i.e. the model's disability to forecast Airbnb demand) may be caused mainly by shocks or unobserved effects to Airbnb demand but also by shocks to the demand of traditional accommodation. We calculate the FEVD as a forecast for 12 months ahead to capture the potential dynamics of the FEVD. This enables investigating short-run (1 month) and long-run (12 months) effects.

The PVAR model is estimated and a FEVD is performed for each of the two clusters, both for the supply and demand side of tourism. This enables us to investigate how shocks to Airbnb and traditional accommodation are affecting each other on the supply and demand sides of the regional tourism market. For the demand side, the model is estimated using Airbnb bookings and the number of overnight stays with traditional accommodation; for the supply side, we use the number of Airbnb listings and the number of rooms (including lodging in hotels, on camping sites and other cabins for rent). We also control for unemployment as a proxy for general economic development and regional business cycles by including unemployment as a predetermined variable. Moreover, monthly dummy variables are included to control for seasonal effects. All variables are in the first difference of their logarithms since the PVAR models need to be estimated using stationary variables with all eigenvalues of the autoregressive matrix being less than unity (Sigmund and Ferstl, 2019). The lag length is chosen based on the model that gives the lowest value on information criteria while also satisfying the eigenvalue stability condition. With this setting, four PVAR models are established: one model for supply and demand, for each of the two clusters. We perform a FEVD for each of these models to investigate how shocks to Airbnb and traditional accommodation may affect these two sectors.

In addition, we incorporate spatial effects by extending the PVAR model with lagged spatial effects, which results in an estimation of the reduced form spatial vector autoregressive model as shown by Beenstock and Felsenstein (2007). This yields the model $y_{it} = \mu_i + \sum_{l=1}^{p} A_l y_{i,t-l} + Bx_{i,t} + Cs_{i,t} + w_i \sum_{q=1}^{r} D_q y_{j,t-q} + \varepsilon_{i,t}$ where the lags of the endogenous variables pertaining to other counties are added as a new term to the standard PVAR model. The weighting matrix w_i is constructed by a contiguity matrix weighing the bordering counties. This also includes borders in the sea such as the Norwegian *Oslofjord*, an outlet of the North Sea that separates the counties of Østfold and Vestfold through its natural border. This makes it possible to control for tourism in bordering counties belonging to the other cluster, for example, counties bordering Oslo, which may, by themselves, not be assigned to the cluster of primary destination, but benefit from tourism in the capital region.

Results

Descriptive statistics

The resulting empirical analysis explores the relationship between Airbnb-based and traditional accommodation for Norwegian tourist destinations at the county level. Regarding the demand for touristic accommodation, a high degree of heterogeneity can be observed across destinations. This is true for the total demand for both Airbnb bookings (Figure 3) and traditional accommodation (Figure 4), the latter being measured as the total overnight stays with accommodation providers, excluding Airbnb bookings. In a similar vein, a supply-side indicator of the traditional accommodation sector, the turnover of accommodation companies, which shows the monetary size of the tourism sector and thereby its ability to accommodate incoming tourists, confirms the heterogeneity in overall tourism among Norwegian counties (Figure 5).

For example, the capital city of Oslo (county number 3) and the region with the second-largest Norwegian city of Bergen (Hordaland; county number 12) have both the highest average number

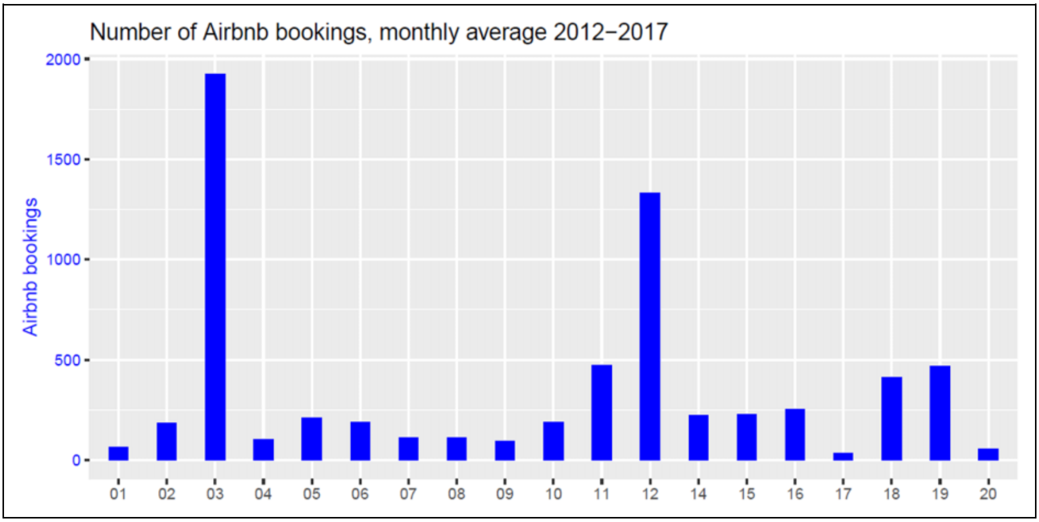

Figure 3. Total number of Airbnb bookings in the last 12 months for the 19 Norwegian counties, monthly average 2012–2017.

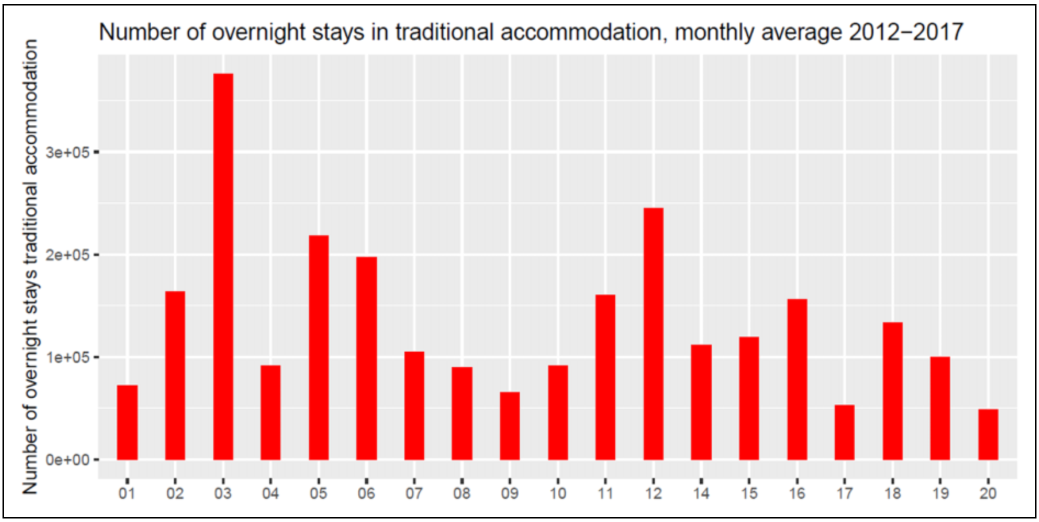

Figure 4. Average monthly number of overnights stays in traditional accommodation types (hotels, camping, etc.) for the 19 Norwegian counties 2012–2017.

of Airbnb bookings for all months in the sample and a high amount of traditional accommodation bookings because these regions are the most popular tourist destinations for all different kinds of travellers visiting Norway. Airbnb has also a high presence in other counties (11 = Rogaland, 14 = Sogn and Fjordane, 15 = Møre and Romsdal, 16 = Sør-Trøndelag, 18 = Nordland and 19 = Troms), which is in line with the pattern of demand observed there for traditional accommodation.

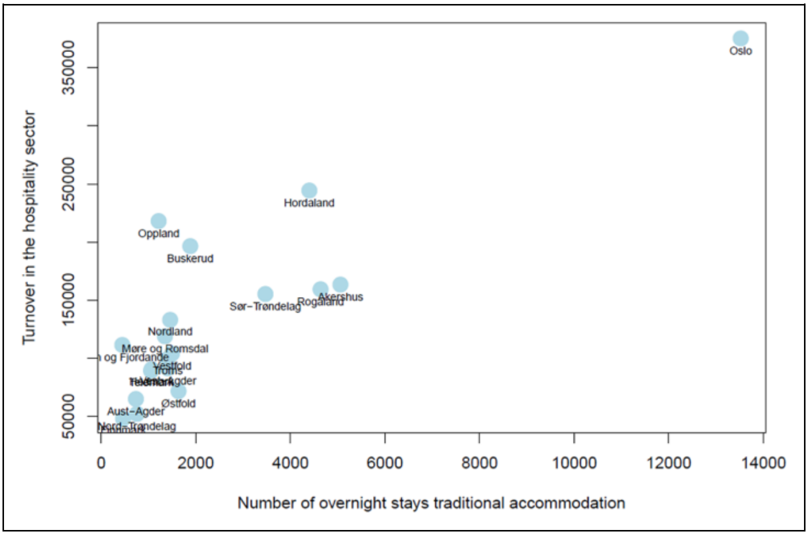

Figure 5. Scatterplot between turnover in the hospitality industry and number of overnight stays in traditional accommodation. Monthly mean for each county between 2012 and 2017.

Moreover, many Norwegian counties are characterised by a relatively high demand for traditional accommodation but less so for Airbnb bookings: 4 = Hedmark, 5 = Oppland, 6 = Buskerud, 7 = Vestfold, 8 = Telemark, 9 = Aust-Agder and 10 = Vest-Agder.

Interestingly, some counties also show a relatively high (low) number of Airbnb bookings, but a low (high) number of traditional accommodation overnight stays. Hence, there appear to be counties where there is Airbnb-based tourism even though there is a relatively low demand for traditional accommodation and counties with higher demand for traditional accommodation but a relatively low degree of Airbnb bookings. This may reflect the fact that tourism with traditional accommodation providers and Airbnb-based supply and demand in tourism markets behave differently in different Norwegian regional tourism markets, here, counties.

Finally, the turnover of hospitality companies is relatively high in regions with a high number of overnight stays (Figure 5), which illustrates the volume of the tourism market and the incentives for accommodation suppliers. However, some counties have a relatively low number of overnight stays while the turnover in the hospitality sector is not correspondingly low. This latter constellation may indicate that there can be room for developing tourism markets.

Cluster analysis

Since the descriptive statistics point to heterogeneity in both the supply- and demand-side indicators for tourism markets in Norway (Table 1), including Airbnb bookings, these differences will be more thoroughly investigated by means of a cluster analysis. Based on the average number of overnight stays, arrived guests, turnover in the hospitality industry and accommodation-related companies, the Norwegian counties are grouped into two clusters: cluster 1 with 7 counties and cluster 2 with the remaining 12 counties (Tables 2 and 3).

Table 1. Cluster number of each Norwegian county based on the cluster analysis.

County number	County name	Cluster number
1	Østfold	2
2	Akershus	1
3	Oslo	1
4	Hedmark	2
5	Oppland	1
6	Buskerud	1
7	Vestfold	2
8	Telemark	2
9	Aust-Agder	2
10	Vest-Agder	2
11	Rogaland	2
12	Hordaland	1
14	Sogn og Fjordane	2
15	Møre og Romsdal	2
16	Sør-Trøndelag	2
17	Nord-Trøndelag	2
18	Nordland	2
19	Troms	2
20	Finnmark	2

Table 2. Summary statistics and *t* tests of mean difference for the two cluster groups.

	Arrived guests	Overnight stays[1]	Number of accommodation companies[2]	Turnover hospitality industry[3]
Average value in cluster 1	104,671.60	219,060.04	190.39	4,280.46
Average value in cluster 2	33,438.48	95,606.19	152.83	989.52
Standard deviation cluster 1	47,839.19	77,657.77	79.49	2,636.41
Standard deviation cluster 2	15,005.27	29,268.31	75.36	365.21
Test statistic	4.85	5.01	1.028	4.34
p Value	0.000***	0.000***	0.319	0.000***

Source: Statistics Norway.
[1]Average number of monthly overnight stay. [2]Average turnover in million NOK for overnight industries. [3]Average turnover in million NOK for hospitality industries (restaurants and bars, etc.). Data spans from 2012 to 2017.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

From the cluster classification, it can be observed that the counties in cluster 1 have, on average, significantly more tourism, as measured by all of the three indicators ‘arrived guests’ and ‘overnight stays’ (demand-side indicators) and ‘turnover in the hospitality industry’ (supply-side indicator), compared to those in cluster 2 (Table 2). This allows us to define cluster 1 to consist of counties with primary tourist destinations, whereas cluster 2 consists of counties with secondary destinations in Norway. As Figure 6 confirms, the classification into a two-cluster result is appropriate, when considering the drop in the total within sum of squares (‘elbow method’). We

Table 3. Forecast error variance decomposition demand shocks for the estimated PVAR models.

	Cluster 1 Variance decomp of dlogAirbnbBookings	Airbnb bookings dlogOvernightStays	Cluster 2 Variance decomp of dlogAirbnbBookings	Airbnb bookings dlogOvernightStays
1	1.000 [1.000]	**0.000** [0.000]	1.000 [1.000]	0.000 [0.000]
2	0.995 [0.990]	**0.005** [0.010]	0.996 [1.000]	0.004 [0.000]
3	0.863 [0.981]	**0.137** [0.019]	0.996 [1.000]	0.004 [0.000]
4	0.864 [0.981]	**0.136** [0.019]	0.996 [1.000]	0.004 [0.000]
5	0.852 [0.979]	**0.148** [0.021]	0.996 [1.000]	0.004 [0.000]
6	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
7	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
8	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
9	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
10	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
11	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
12	0.851 [0.979]	**0.149** [0.021]	0.996 [1.000]	0.004 [0.000]
	Variance decomp of dlogAirbnbBookings	Overnight stays (trad) dlogOvernightStays	Variance decomp of dlogAirbnbBookings	Overnight stays (trad) dlogOvernightStays
1	0.009 [0.017]	0.991 [0.983]	**0.007 [0.113]**	0.993 [0.887]
2	0.008 [0.019]	0.992 [0.981]	**0.184 [0.310]**	0.816 [0.690]
3	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
4	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
5	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
6	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
7	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
8	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
9	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
10	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
11	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]
12	0.011 [0.019]	0.989 [0.981]	**0.186 [0.310]**	0.814 [0.690]

Note: FEVD when including spatial effects in square brackets. Forecast errors caused to some extent by shocks to the other sector (i.e. Airbnb for traditional accommodation and vice versa) are boldfaced. FEVD: forecast error variance decomposition; PVAR: panel vector autoregressive.

also perform several tests to choose the best number of clusters by using the R package *NbClust* (cf. Charrad et al., 2014). Among the 23 tests, 10 propose three clusters, while 6 propose two clusters. However, when choosing three clusters, the third cluster only contains the Norwegian municipality of Oslo. We decided for the two-cluster approach because having a group of regions in each cluster allows us to use the same panel-based analyses.[6]

Forecast error variance decomposition (FEVD)

Tables 3 and 4 provide the FEVD for the forecasts of the four endogenous variables in our PVAR model (up to 12 months ahead) for each cluster. The FEVD for the demand side (Table 3) provides forecasts for Airbnb bookings and the number of overnight stays with traditional accommodation

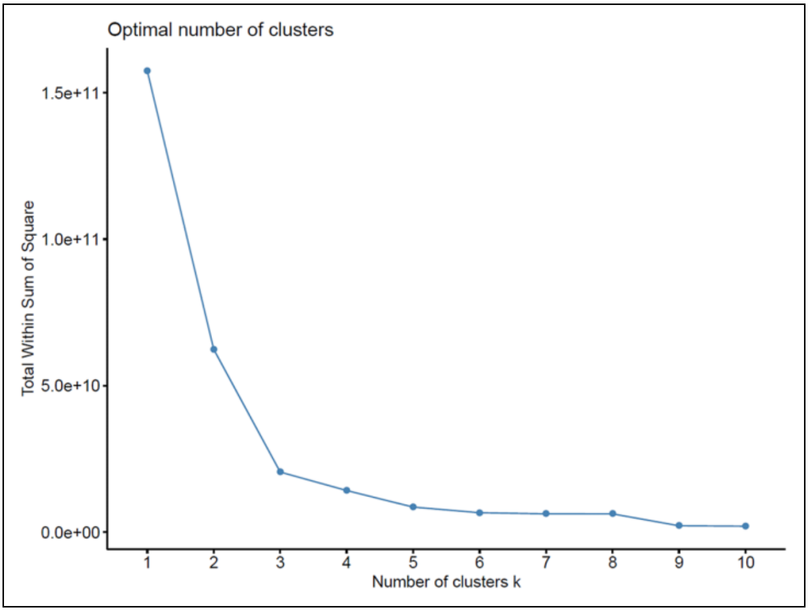

Figure 6. Total within sum of squares given the number of clusters (using the variables the average number of overnight stays, arrived guests, turnover in the hospitality industry and accommodation-related companies).

providers. Forecasts for the number of Airbnb properties and the number of available rooms with traditional accommodation providers are given in Table 4. The FEVD for each of the 12 months yields how much of the forecast error (i.e. forecasts that cannot be explained by the PVAR model) pertains to shocks (unobserved effects) which will be interpreted as innovations in the Airbnb-based and the traditional accommodation sector, respectively. The FEVD (Tables 3 and 4) is estimated with (in square brackets) and without taking spatial effects into account.

The top-left panel in Table 3 illustrates the variance decomposition of the forecast of Airbnb bookings in cluster 1 (primary tourist destinations), and the 12 rows show how much the forecast error of Airbnb bookings can be explained by shocks (unobserved effects) to Airbnb bookings or overnight stays (measured in log differences) 1 through 12 months ahead. The one-step-ahead forecast is explained 100% by shocks to Airbnb bookings and not at all (0%) by traditional overnight stays, while the 12-step-ahead (long-run) forecasts are explained to 85.1% by shocks to Airbnb bookings and 14.9% by shocks to traditional accommodation. Hence, the forecast error of Airbnb bookings is mostly explained by shocks to Airbnb bookings, with another 15% by unobserved effects in the traditional accommodation sector. However, when controlling for spatial effects, the effect of shocks on the demand for traditional accommodation is reduced to 2.1% in the long run. This leads to the assumption that tourism in neighbouring counties may influence Airbnb demand.

Additionally, the bottom-right panel of Table 3 shows that the long-run forecast error of overnight stays with traditional accommodation providers in secondary destinations (cluster 2) is explained to 81.4% by shocks to overnight stays, compared to 18.6% of the shocks to Airbnb bookings, and to 31% and 69%, respectively, when controlling for spatial effects. Hence, the

Table 4. Forecast error variance decomposition supply shocks for the estimated PVAR models.

	Cluster 1 Variance decomp of dlogNumberPropAirbn	Airbnb properties dlogTradSupply	Cluster 2 Variance decomp of dlogNumberPropAirbn	Airbnb properties dlogTradSupply
1	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
2	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
3	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
4	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
5	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
6	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
7	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
8	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
9	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
10	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
11	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
12	1.000 [1.000]	0.000 [0.000]	1.000 [1.000]	0.000 [0.000]
	Variance decomp of dlogNumberPropAirbn	Supply trad acc. dlogTradSupply	Variance decomp of dlogNumberPropAirbn	Supply trad acc. dlogTradSupply
1	0.013 [0.002]	0.987 [0.998]	0.004 [**0.018**]	0.996 [0.982]
2	0.016 [0.004]	0.984 [0.996]	0.007 [**0.059**]	0.993 [0.941]
3	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
4	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
5	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
6	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
7	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
8	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
9	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
10	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
11	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]
12	0.016 [0.004]	0.984 [0.996]	0.007 [**0.063**]	0.993 [0.937]

Note: FEVD when including spatial effects in square brackets. Forecast errors caused to some extent by shocks to the other sector (i.e. Airbnb for traditional accommodation and vice versa) are boldfaced. FEVD: forecast error variance decomposition; PVAR: panel vector autoregressive.

forecast of the demand for traditional accommodation which is not explained by the model is mostly explained by shocks to traditional accommodation, while Airbnb-induced demand causes nearly one-third of the forecast error.

Discussion

The FEVD results (Tables 3 and 4) allow us to estimate whether and to which extent supply or demand of one accommodation type contributes to the forecast error of each variable and subsequently can be explained by shocks to the same or another accommodation type. For instance, Chen and Chang (2018) found that social media presence and advertising create a sense of media richness and purchase intention, which increases the number of Airbnb bookings and would refer to a shock within the sector of Airbnb-based accommodation. Hence, we can measure whether the forecast error of Airbnb bookings is mainly explained by shocks to Airbnb or shocks to traditional accommodation occurring on the demand side of the market (Table 3). An example of the latter case would be an increase in tourism in a region or over time due to exogenous factors, such as better profiling of a region as a tourist destination, which would imply that more tourists are attracted to traditional accommodation types (cf. Cardenas-Garcia et al., 2015) and, thereby, increase Airbnb demand as well. The same argumentation can be applied to the supply side (Table 4) by looking at how the forecast error of traditional accommodation is explained by shocks related to the number of available rooms or Airbnb units.

For secondary destinations, the results do not confirm a competitive relationship between the two accommodation types (Fang et al., 2016), but rather show an innovation effect of Airbnb-induced demand on the demand for traditional accommodation. It might, however, also suggest a negative effect in that Airbnb growth could lead to a decrease in demand for traditional accommodations in such regions. We believe this is not the case based on further observations. In particular, the findings that the long-run forecast error is explained up to 31% by Airbnb bookings and that growth both in Airbnb and traditional accommodation is observed on average over the entire sample speaks for a higher likelihood of a positive effect from Airbnb-based demand to the demand for traditional accommodation in secondary tourist destinations. This allows us to conclude that Airbnb growth may, indeed, spur a general demand for tourism services in secondary tourist destinations, as, for instance, Strømmen-Bakhtiar and Vinogradov (2019) found evidence of.

On the supply side of the regional tourism markets (Table 4), the forecast errors for Airbnb supply and the supply of traditional accommodation seem to be affected mostly by shocks within their own segment, that is, Airbnb and traditional accommodation, respectively. After controlling for spatial effects, only 6.3% of the forecast error of the supply of traditional accommodation are explained by shocks to Airbnb supply. This result could indicate that the supply side of the tourism market is more rigid than the demand side, even though the supply of Airbnb listings would be able to react quickly. An example of this dynamic would be private households providing new accommodation by opting to list available space, even if it is only for periods when housing space such as a house, an apartment or a cabin is unused.

All in all, the results in Tables 3 and 4 showing the FEVD estimation indicate that Airbnb bookings and traditional overnight stays in the two clusters are mostly explained by shocks to their own sectors (i.e. unobserved effects to Airbnb bookings and traditional overnight stays, respectively), with some exceptions. By itself, this does not allow us to conclude whether the relationship between the two supply-side market segments is additive (cf. Morales-Perez et al., 2020) or competitive. The PVAR model found no significant effects in the regression results that indicate short-run effects between the variables. The FEVD, however, shows that there are unobserved effects in the long run on the demand side of the regional tourism market between Airbnb-based and traditional accommodation, caused by innovations, specifically, positive effects from Airbnb-based tourism on traditional accommodation (and thereby tourism in general) in secondary destinations. To a minor extent, there is also evidence of such innovations and long-term effects on the supply side, which suggests that Airbnb growth may spur growth in the traditional accommodation sector in the long run, as is documented by Dogru et al. (2020). In summary, the findings of our analysis point more to an additive than a competitive relationship between the two accommodation types, both on the demand- and supply-side of tourism markets outside of primary destinations.

Conclusions, policy implications, limitations and research outlook

Main conclusions and public policy implications

This article explores the relationship between Airbnb-based and traditional accommodation across variegated regional tourism markets, that is, secondary *versus* primary tourist destinations. This rationale is motivated by a gap in the empirical literature concerning the effects between Airbnb-based and traditional accommodation outside key tourist destinations, which are framed as secondary tourist destinations in this article. To explore the regional variations of this relationship, we conducted an empirical study of Norwegian counties that were classified as primary and secondary destinations by means of a cluster analysis. A subsequent PVAR model estimation and pertaining FEVD analysis empirically tested the relationship studied in the short and long run, considering county- and year-fixed effects as well as spatial spillover effects between primary and secondary tourist destinations.

Our main findings indicated that while the effects between the Airbnb-based and the traditional accommodation segment are very small, there are some notable spillover effects between the segments in secondary tourist destinations. In particular, the demand for traditional accommodation seems to be positively affected by Airbnb demand in the long run, and there is also an indication of a positive effect spilling over from the supply of Airbnb locations to the supply of traditional accommodation. The observation of both effects suggests that the growth of Airbnb may spur the growth of the established tourism sector in secondary destinations.

Based on these exploratory results, we conclude that the public policy implications for regional tourism markets with secondary tourist destinations are to include the development of Airbnb supply and demand in tourism and regional planning considerations. For instance, the presence of Airbnb-based suppliers and bookings, respectively, in a less developed tourism region can have a positive effect on overall tourism development in the area. In the long run, our results suggest that this effect might increase the demand for and even the supply of traditional accommodation in such secondary destinations. Traditional players in regional tourism, such as small, family-owned hotels, B&Bs and camping sites, are typically important for tourism development (cf. Getz and Carlsen, 2005) and might benefit from a higher demand for accommodation services. A growing Airbnb-based market segment in such destinations can help attract new types of visitors to the under-developed tourism market.

To determine the need for policy action on a local and regional level, such as the regulation of Airbnb, it will be necessary to explore the specific motivations and characteristics of tourists using either Airbnb or traditional accommodation in secondary tourist destinations; this will provide more robust information about the level of competition or complementarity between the providers of the two accommodation types in regional tourism markets.

Research outlook

As this study provides merely an initial mapping of how the relationship between Airbnb-based and traditional accommodation in regionally variegated tourism markets might look like, future research is needed in – at least – four areas: First, it is necessary to investigate empirically with more case studies whether a rise in Airbnb bookings as a demand-side shock might divert the generally low demand for established service providers in secondary tourist destinations because there might be limitations to demand-side tourism growth. The presence of smaller accommodation providers in secondary destinations (cf. Getz and Carlsen, 2005) may be an explanation for why we find supply-side differences between primary and secondary tourist destinations. The nature of the traditional accommodation providers should, thus, also be explored in more depth with regard to the specific relationship – and whether it is of a more competitive or additive nature between Airbnb suppliers and small accommodation companies.

Second, factors from outside tourism markets such as pricing, trust, quality of the accommodation, flexibility related to the booking, the variety or width of accommodation selection for travellers in a destination, the presence of amenities, the convenience of the booking platform and the customer's prior experiences might influence both accommodation types in secondary tourist destinations. For instance, Butler and Hannam (2012) have shown the specific booking and mobility choices of independent travellers to rural Norway. Inspired by their research, it could be worthwhile to analyse which share of bookings with Airbnb and traditional accommodation providers stem from independent compared to organised travellers and how these shares might affect the demand for the accommodation providers in different markets. In addition, the finding of a weak relation on the supply-side might be associated with the distinct motivations of persons offering accommodation services through Airbnb. These motivations are not necessarily related to the intentional provision of tourist services, but they could simply be grounded in the wish to generate extra income or to use free housing space more flexibly than through long-term rental contracts.

Third, an important limitation of this study is the single-country setting that includes only Norwegian tourist destinations. Future research should extend this study to other countries in Northern Europe with significant tourism activities or establish a comparative cross-country research design to validate the findings for Norway about Airbnb-based and traditional accommodation and their relationship for variegated regional tourism markets for other countries. Finally, future studies should consider additional indicators such as the share of tourism in GDP to classify and describe different types of tourist destinations. Such additional measures could not be included in the present empirical study because many of the county-level data used to describe tourism markets were not available on the monthly frequency needed for our analyses. Since the concept of secondary tourism destinations is not well-defined, this represents another avenue for future research in the field of tourism economics and marketing.

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Notes

1. This article was written between September 2019 and February 2020, at a time when the consequences of the Covid-19 virus pandemic on global tourism markets, including sharing-economy companies such as Airbnb, could not be anticipated. We are aware that some of the arguments put forward here might no longer hold in the light of the ongoing pandemic.

2. The Scandinavian countries consist of Norway, Denmark and Sweden, while the Nordic countries also include Finland and Iceland.
3. The official Organisation for Economic Co-operation and Development countries are Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States (World Population Review, 2020).
4. The data were received upon a special request from the research team.
5. The Airbnb observations for 2010 and 2011 were removed. Because of the change in some counties (with a merger of two counties due to municipal reforms in Norway) from January 2018 on, we also removed observations from 2018.
6. This decision is also supported by the widely used elbow method, which represents one of the 23 tests performed for the cluster analysis.

Supplemental material

Supplemental material for this article is available online.

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