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Measuring price dynamics of package holidays with transaction data

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Non-technical summary

Research Question

In traditional price collection, offer prices from pre-defined price representatives usually are collected at fixed points in time every month. For package holidays, which are made up of both travel and accommodation (hotel) services, the sample size of the offer data is currently limited due to the high effort required for manual price collection in German price statistics. Therefore, no official price indices broken down by individual holiday destination are available at present. An alternative to collecting offer prices consists in using price data from actual bookings of international package holidays recorded in electronic booking systems as used by online travel agencies or at traditional high street travel agencies. The aim of this paper is to investigate the chances and challenges when compiling a price index out of transaction data for flight package holidays, which reflect very heterogeneous seasonal services in price statistics.

Contribution

The contribution of this paper is to compile a transaction-based experimental price index, which can be subdivided into relevant holiday destinations, thus allowing for a detailed economic interpretation of the underlying price movements of package holidays. Thereby, a various set of index aggregation methods is applied, which include hedonic regressions, stratification, and also a multilateral index method, to the relatively new field of measuring prices of (bundled) services by transaction data.

Results

This paper shows that, by means of transaction data, it is possible to efficiently calculate several experimental price indices that can be disaggregated by holiday destination and therefore allow interpreting movements in the overall index of international package holidays. All five methods under consideration follow a similar pattern in terms of rates of change and volatility, so that the selection of the method does not influence the overall movement of the series. Moreover, the destination-based price indicators are robust to different data filters, such as controlling for the same hotel or the same meal category and room type over time.

Nichttechnische Zusammenfassung

Fragestellung

Im Rahmen der traditionellen Preismessung werden Angebotsdaten vordefinierter Preisrepräsentanten zu bestimmten Zeitpunkten innerhalb eines Monats erhoben. Im Falle der Pauschalreisen, also der Kombination aus Reise- und Beherbergungsdienstleistungen, ist die Stichprobengröße der Angebotsdaten aufgrund des hohen Aufwands in der momentan manuellen Erfassung im Rahmen der deutschen Preisstatistik begrenzt. Aus diesem Grund werden derzeit keine amtlichen Preisangaben nach Urlaubsregion veröffentlicht. Eine Alternative zur Erhebung von Angebotsdaten besteht in der Nutzung von Preisdaten aus Transaktionen über elektronische Buchungssysteme, welche sowohl von Online-Reiseanbietern als auch von traditionellen stationären Reisebüros verwendet werden. Ziel dieser Studie ist es, die Möglichkeiten und Herausforderungen eines transaktionsbasierten Preisindex für Flugpauschalreisen zu untersuchen, welche aus Sicht der Preisstatistik sehr heterogene saisonale Dienstleistungen darstellen.

Beitrag

Der Beitrag der Studie ist die Erstellung eines experimentellen Preisindex basierend auf Buchungsdaten, der nach relevanten Urlaubsregionen unterteilt werden kann und somit eine detaillierte ökonomische Interpretation der Preisentwicklung von Pauschalreisen erlaubt. Hierbei wird ein Kranz von Methoden zur Indexbildung wie hedonische Regressionen, Stratifizierung sowie eine multilaterale Methode auf das relativ junge Feld der Preismessung anhand von Buchungsdaten im Bereich (kombinierter) Dienstleistungen angewandt.

Ergebnisse

Die Studie zeigt, dass Buchungsdaten effizient die Herleitung verschiedener experimenteller Preisindizes nach Urlaubsregion ermöglichen; dies erlaubt eine tiefergehende Interpretation der Preisbewegungen von Pauschalreisen. Alle fünf untersuchten Methoden zeigen eine ähnliche Preisentwicklung hinsichtlich der Veränderungsraten und Volatilität über die Zeit, so dass die Methodenwahl die gemessene Preisdynamik kaum beeinflusst. Zudem erweisen sich die regionalen Preisindikatoren robust hinsichtlich verschiedener Datensatzrestriktionen, wie der Kontrolle für das gleiche Hotel oder der gleichen Verpflegungs- und Zimmerkategorie über die Zeit.

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Abstract

In Germany, package holidays are an important driver of consumer prices. Several challenges arise when measuring the price development of these bundled travel and accommodation services, such as the quality of accommodation and the timing of booking. Statistical practices are currently based on sampling offer prices. By using actual bookings, this paper analyses the possibilities and challenges in compiling a price index out of transaction data for flight package holidays. Our dataset comprises both online bookings and bookings made via stationary travel agencies on a daily basis. The large sample size allows for a disaggregation by individual holiday destination. Several methodological issues such as product definition, the grouping of unstructured text information, and weighting are addressed. Moreover, various index aggregation methods are analysed, which include hedonic regressions, stratification, and also a multilateral index method. Applied to six major holiday destinations for German travellers, all transaction-based methods under consideration exhibit similar price dynamics, pointing to robust results for destination-based price indicators for package holidays.

Keywords: Consumer prices, transaction data, hedonic regressions, quality adjustment, multilateral index number methods.

JEL-Classification: C14, C43, E31.

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1 Motivation

In traditional price collection, offer prices from pre-defined price representatives are usually collected at fixed points in time every month. The more complex a given good or service is, the more manual work is required by a national statistical institute (NSI) in setting-up a sufficiently large selection of price representatives. This is especially true for bundles of different services, such as package holidays, which are made up of both travel and accommodation (hotel) services and have a lot of price-determining characteristics such as the category of the hotel as well as the meal type, the room or the departure airport. Moreover, travel-related prices such as the flight can fluctuate heavily within a given month.

In German price statistics, package holidays have a weight of 2.7 % in the Harmonised Index of Consumer Prices (HICP) as of 2019. However, due to their high volatility and strong seasonality, package holidays have a noticeable effect on the German and even the euro area inflation rate. The Federal Statistical Office (Destatis) currently uses a global distribution system from information technology (IT) provider Amadeus (Amadeus Germany GmbH) — as applied by travel agencies — to collect offer prices of package holidays. The sample size is limited due to the high effort required for manual price collection. Therefore, it is currently not possible to publish price developments broken down by holiday destinations, rather, broad subindices are published for 'Domestic package holidays' (ECOICOP 09.6.0.1) and 'International package holidays' (ECOICOP 09.6.0.2).[1]

An alternative to collecting offer prices consists in transaction data by using actual bookings of international package holidays recorded in the Amadeus IT booking systems, which are used by online travel agencies or at traditional high street travel agencies.[2] The aim of this paper is to investigate the possibilities and challenges when compiling a price index out of transaction data for flight package holidays,[3] which are very heterogeneous

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[1] The goods and services in the HICP follow the European classification of individual consumption according to purpose (ECOICOP). For an overview of this classification, see: https://ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=LST_NOM_DTL&StrNom=COICOP_5&StrLanguageCode=EN&IntPcKey=&StrLayoutCode=HIERARCHIC&IntCurrentPage=1.

[2] Note that transaction prices are generally in line with the basic price definition in the HICP: 'The prices used in the HICP should be purchaser prices, which are the prices actually paid by households' (see Eurostat, 2018, p. 30).

[3] Besides flight package holidays, the German HICP subindex for package holidays also consists of domestic package holidays, shorter city trips to other European countries and cruises (see Section 2), which were not the subject of this study.

seasonal services.[4] Due to the large sample size of the underlying transaction dataset, the resulting experimental price index could be subdivided into relevant holiday destinations, thus allowing for a more detailed economic interpretation of the underlying price movements of package holidays. In particular, such destination-based price indicators could help to disentangle the overall price trend in package holidays from short-term movements for a given holiday destination, which would provide a high level of value added for consumer price analysis. This paper also contributes through the application of the most recent index aggregation methods, which include hedonic regressions, stratification, and a multilateral method, to the relatively new field of measuring prices of (bundled) services by transaction data.

The paper is structured as follows: Section 2 describes the current official practice in measuring prices of package holidays by the Federal Statistical Office, which is based on offer prices. Section 3 presents the transaction dataset from Amadeus and comments on the challenges of processing these data for the purpose of price statistics. Section 4 discusses various methods commonly used to measure prices, as well as newer index methods that have recently been developed on the basis of scanner data. Section 5 compares the price indices derived from the various methods for six major holiday destinations of German travellers. Section 6 concludes and provides an outlook on the feasibility of destination-based price indicators for package holidays.

2 Current official practice for the German HICP

In official price statistics, package holidays reflect a bundled cost of travel and accommodation services sold in one transaction, for example a return flight in combination with a seven day hotel stay. By convention, the price of a package holiday enters the official HICP always in the month during which the holiday takes place and not in the month during which the holiday is booked (see Eurostat, 2018, Chapter 12.5). Nevertheless, the timing of when the booking was made (for example early or last minute bookings) is an important price determinant of a package holiday. Thus, official price statistics typically use booking prices from different points in time ahead when compiling a price index for a given travel month.

To calculate the official HICP subindex for package holidays, the German Federal Statistical Office collects offer prices. This data represent a very detailed specified sample of trips, with the aim of ensuring a pure price comparison. According to the EU regulation, two methods are allowed for calculating indices for package holidays: the

[4] Although interesting on its own, this paper does not analyse the seasonality of package holidays itself such as the imputation of out-of-season package holidays.

fixed weights method (also known as strict annual weights) and a class-confined seasonal weights method.[5] Before the German national CPI was revised and rebased to 2015 = 100 in February 2019, the class-confined seasonal weights method was used, with a different summer and winter sample. From reporting year 2015 onwards, the official HICP subindex for package holidays is based on the fixed weights method, where the missing prices for out-of-season months are imputed.[6]

Table 1 provides an overview of the elementary aggregates of the German HICP for package holidays (ECOICOP 09.6). The sample for the subindex for 'international package holidays' consists of holidays from Germany to six holiday destinations (the Balearic Islands, the Canary Islands, Greece, Turkey, Egypt and the Dominican Republic) with a duration of 7-14 days and to two countries for shorter city trips. Moreover, the international aggregate includes cruises. For most holiday destinations, there exist three strata: summer, winter, and whole-year strata. Missing prices for the summer sample for a given holiday destination are imputed using the winter or the whole-year sample and vice versa (counter-seasonal estimation). For two holiday destinations, there is only a summer or winter sample and missing prices are imputed using all other available prices (all-seasonal estimation).

Table 1: Elementary aggregates for the German HICP subindex for package holidays (09.6)

ECOICOP	Weight of 09.6 (%)	Coverage	Sample period
09.6.0.1 Domestic package holidays	5.60	Germany only, travel by train or car	Summer/winter
09.6.0.2 International package holidays			
International flight package holidays (7 to 14 days)	76.95	Four holiday destinations	Summer/winter/whole year
		Two holiday destinations	Summer or winter only
City trips		Two holiday destinations	Whole year
Cruises	17.45	Combination of flight and open-sea cruise	Summer only

[5] See European Commission Regulation No 330/2009, Article 2, as well as Eurostat (2018), Chapter 7.1 on seasonal products and Chapter 12.5 on flights and package holidays.

[6] Switching to CPI basis 2015 and using the fixed weights methods improved the interpretability of the previous month's rate of change in April, May and November of a year. At the same time, it increased the seasonal profile of the package holiday price index, with higher index values in the summer and lower values in the winter season. See also Eurostat (2019) and Deutsche Bundesbank (2019).

In German price statistics, offer prices for international package holidays are collected from the booking system START Amadeus[7] via the internet and cover roughly 300 price representatives. Booking codes from tour operators are used to identify a product offer with pre-defined attributes (for example hotel XXXX, all inclusive, double room with sea view, for two persons and ten days, with departure flight from Frankfurt am Main). The price representatives are calculated using three offer prices (three inquiries at different points in time in advance of a given departure) for the winter/summer sample or 21 offer prices (three inquiries in advance of seven departure days) for the whole-year sample. In total, about 1 500 to 3 000 offer prices (depending on the timing of public holidays) are included in the price calculation for a given travel month.

The resulting German HICP subindex for package holidays exhibits a high degree of volatility, as shown in **Figure 1**. The annual rate of change from January 2016 onwards ranges between -9 and +14 percentage points and is therefore more volatile than other seasonal HICP components, such as clothes or unprocessed food.[8] From the perspective of a data user, a more detailed breakdown by holiday destinations would be helpful in interpreting such price movements.[9] From an international perspective, the weight of package holidays in the German HICP (2019: 2.7 %) is one of the highest among European countries, with higher values only observed in Iceland (6.3 %), the United Kingdom (4.2 %) and Cyprus (3.2 %). Because of its weight and volatility, the challenges of measuring prices for package holidays with transaction data and how to derive prices for bundled services, which are generally more complex than supermarket goods, are very important to Germany, but may be relevant to other (European) NSIs as well.[10]

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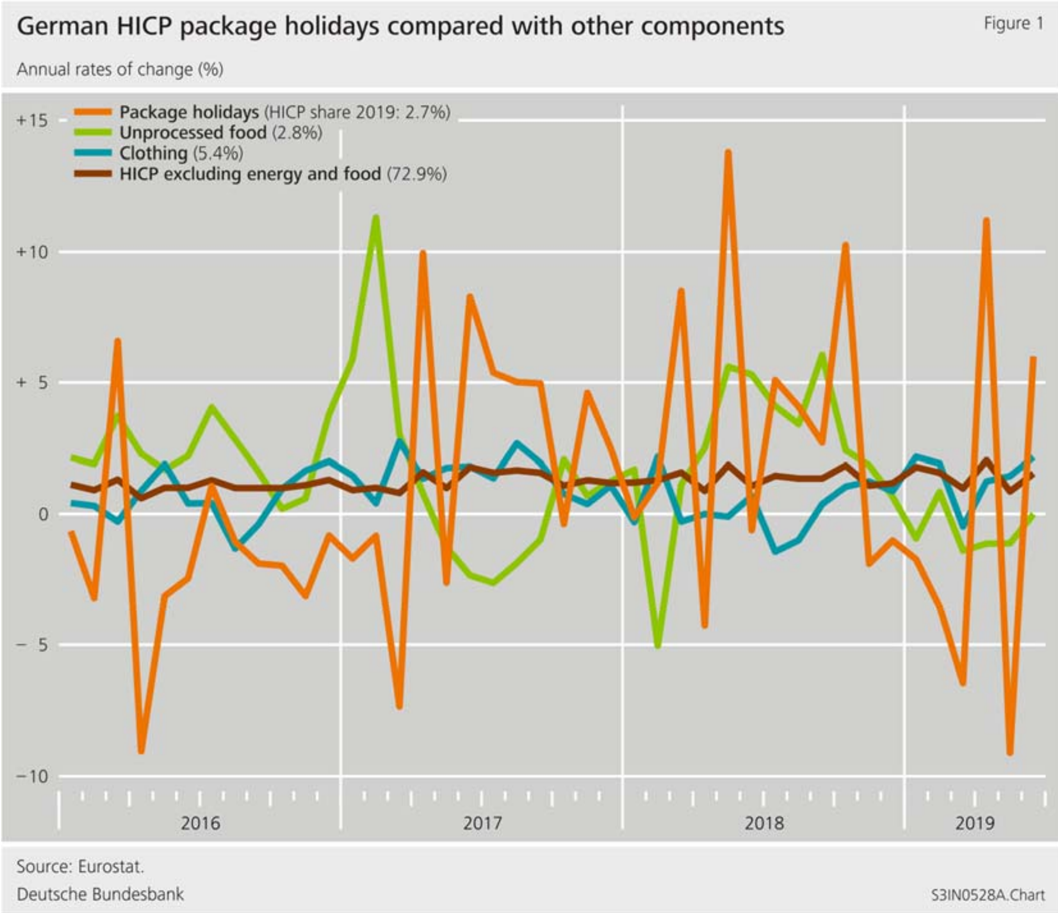
[7] The booking system *START Amadeus* is used by traditional high street travel agencies to handle booking transactions for package holidays (see Section 3 for more information on the data provider). In contrast, the offer prices for city trips are collected manually from different online travel agencies, whereas for cruises, catalogue prices are compiled.

[8] Amongst others, possible contributors are Easter and/or the Pentecost holidays, which vary from year to year (unlike Christmas).

[9] See also Deutsche Bundesbank (2017) for a comment on the impact of HICP package holidays on core inflation in Germany.

[10] To the best of our knowledge, only the Dutch and Swedish NSIs have already implemented a transaction-based price index for package holidays in their regular index production (see, for instance, Johansson and Tongur (2019)). Both NSIs use a method that is similar to the *traditional stratification* method in this paper (see Section 4.3.2).



3 Description of the Amadeus dataset

The Amadeus IT Group operates an IT system for sales and marketing in the field of travelling. The underlying dataset for Germany contains around 3.7 million transaction prices per year for flight package holidays of German travellers in the period from 2013 to 2018. The data are collected via the Amadeus booking system, which is used by online travel portals as well as traditional high street travel agencies in Germany.[11] For each transaction, information on price determinants such as the accommodation, holiday destination and number of travellers is given.[12] The data are made up of both online and offline (in other words, via traditional high street travel agencies) bookings. The offline data constitute the larger component (see **Figure 2**) and usually contain two to three times as many observations as online data, but they do not contain detailed information on meal types, room categories, car rentals or travel insurance. Given the different levels of

[11] According to the economic newspaper *WirtschaftsWoche* (issue 27/2018), Amadeus has a global market share of 43 %. See Nagengast, Bursian and Menz (2019) for an application of the Amadeus dataset in analysing the role of dynamic pricing for exchange rate pass through.

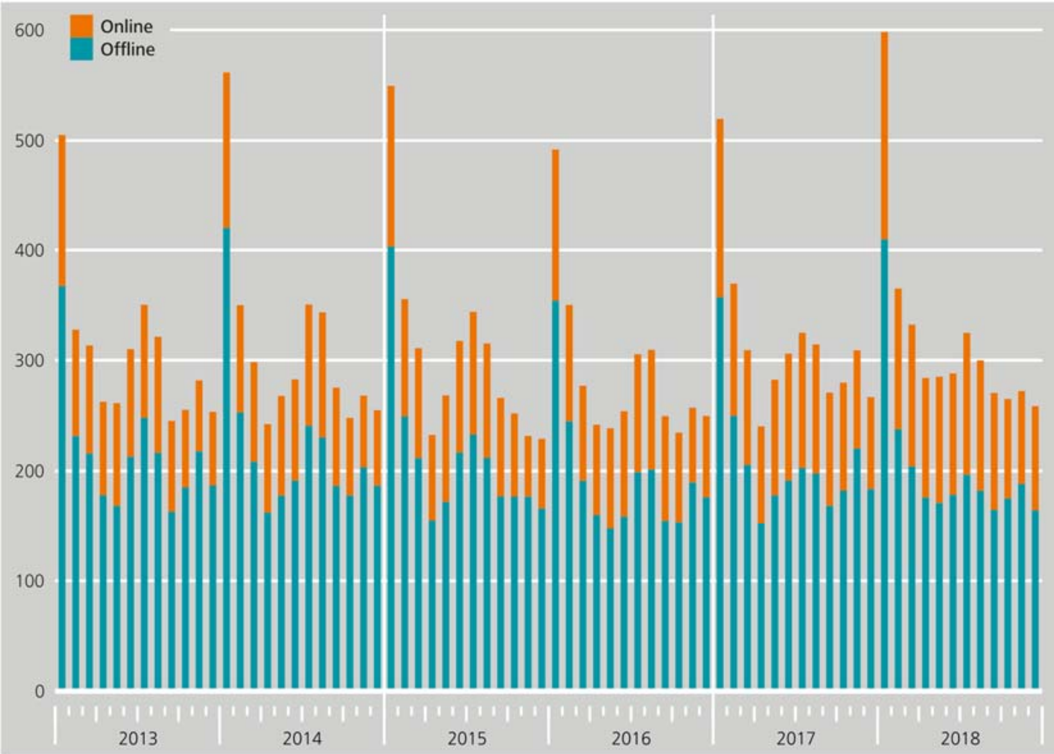
[12] For an overview of variables from the data provider, see **Table A.1** in the Appendix. **Table A.2** lists the additional variables created for this paper.

information provided as well as the possibility of different pricing methods, it may make sense to examine the online and offline booking channels separately when measuring prices.

Number of offline and online transactions per booking month

Figure 2

Thousands



Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH.
Deutsche Bundesbank

S3IN0409.Chart

Datasets that have not been compiled primarily for the purpose of price statistics may exhibit a multitude of irregularities. The transaction dataset may, for instance, be incomplete or contain incorrect entries. For example, in about 10 % of offline bookings, the holiday destination is missing. There are also cases in which the travel date ($travelDate$) is earlier than the booking date ($transactionDate$). Incorrect entries of this kind are filtered out beforehand.[13] Moreover, outliers in the Amadeus dataset concerning the price and the duration of the package holiday are also excluded. Corresponding to the first and 99th percentile of transactions, outliers for prices per person per day are defined as those under EUR 27 or those over EUR 427 and outliers concerning the duration of the package holiday as those less than two days or more than

[13] Cancellations, which are available for offline bookings only, are not included in the analysis.

22 days. Overall, after adjusting for outliers, roughly 3.4 million observations per year remain for holidays in the period from 2013 to 2018.

In addition to data cleansing and outlier adjustment, it is also necessary to categorise the unstructured text information in some variables of the (more detailed) online bookings. For example, more than 100 different variations exist for the online variable $mealType$. Across the entire dataset, the number of different variations for the variable $roomCategory$ is even higher, at 80 000. In order to categorise this level of variety, it is necessary to use string matching techniques like substring searches where the categories are defined manually in advance.[14] Identifying children's prices, for which no set definition exists across all tour operators, represents another challenge. While offline bookings contain information on whether children are part of the booking, and if so, how many ($childrenCount$), for online bookings an assumption must be made based on the reported ages of the travellers ($travellersAges$). In the following, children were defined as travellers less than 16 years of age.

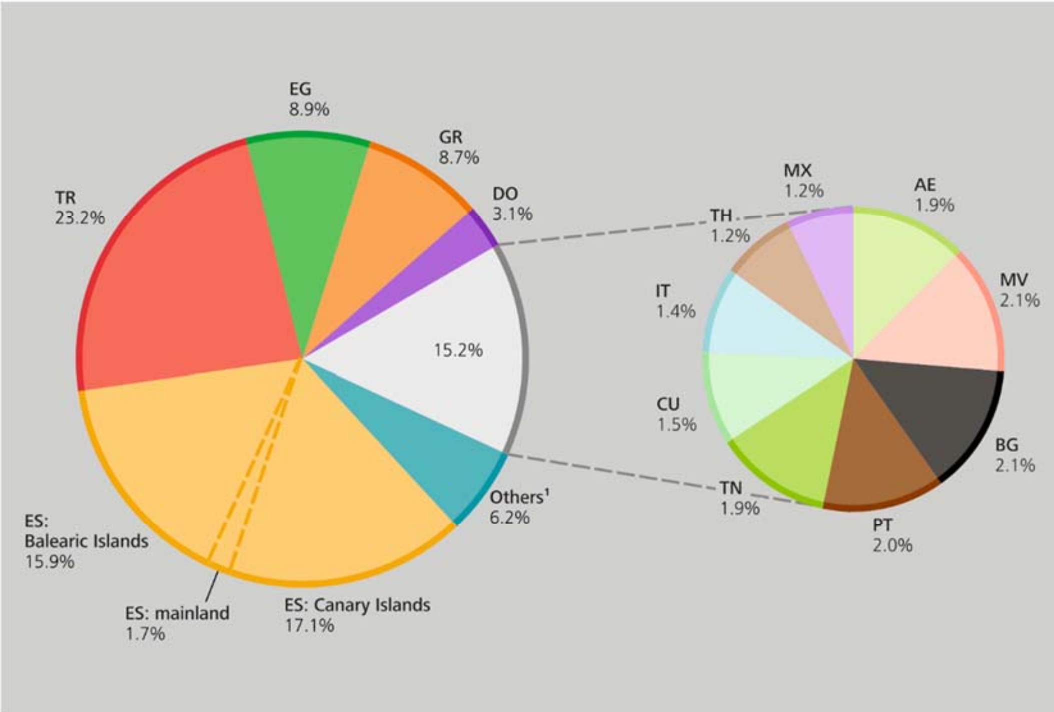
Measured by total revenue in 2015 (and excluding cruises), the most popular destinations for German travellers were Turkey (23.2 %), the Canary Islands (17.1 %), the Balearic Islands (15.9 %), Egypt (8.9 %), Greece (8.7 %) and the Dominican Republic (3.1 %), as shown in **Figure 3**. These six destinations together account for more than three quarters of the total revenue for German package holidays. For a disaggregation of price dynamics by destination, it therefore makes sense to focus exclusively on these six destinations.[15] The revenue shares of the nine next most visited destinations were less than 2 % and all had fairly similar shares (range: 1.1 percentage points).[16] Using the transaction dataset, it is possible to derive a set of stylised facts for the German travel market. Based on data for 2015, the typical package holidaymaker travels with one other person (64 %) and without children (80 %), flies from Düsseldorf (16 %), Frankfurt (14 %) or Munich (11 %), stays for 7 or 14 days (35 % and 19 %, respectively) in a four-star hotel (59 %), and pays an average of EUR 92 per person per day.

A peculiarity of the HICP for package holidays is that bookings can, in principle, be made up to a year before departure and the timing of a booking can have an impact on the price.

[14] See **Table A.3** for the categorisation of the variable *roomType*, which follows a kind of 'dictionary'. For the production of statistical data, this dictionary would need to be updated from time to time.
[15] In the following, these six holiday destinations form the variable *topArea*.
[16] Note that the share of total revenue attributed to the six principal destinations shifted considerably over the observed period up to 2018. For example, Turkey's share fell by over half from 2013 to 2017, whereas the share of bookings for Greece and the Dominican Republic rose by roughly the same factor. In 2018, Turkey's share recovered, whereas the share of bookings for the Dominican Republic returned to its level for 2013.

For the period under review, **Figure 4** shows that over 20 % of all bookings had already been made half a year prior to the month of travel. On average, half of the bookings had already been made three months or more in advance. The price per person per day is 3 % more expensive than average for those holidaymakers who make their booking 6 or 12 months before departure, whereas the price falls sharply if the booking is made within two months of the departure date.

Revenue shares of package holidays by destination in 2015* — Figure 3

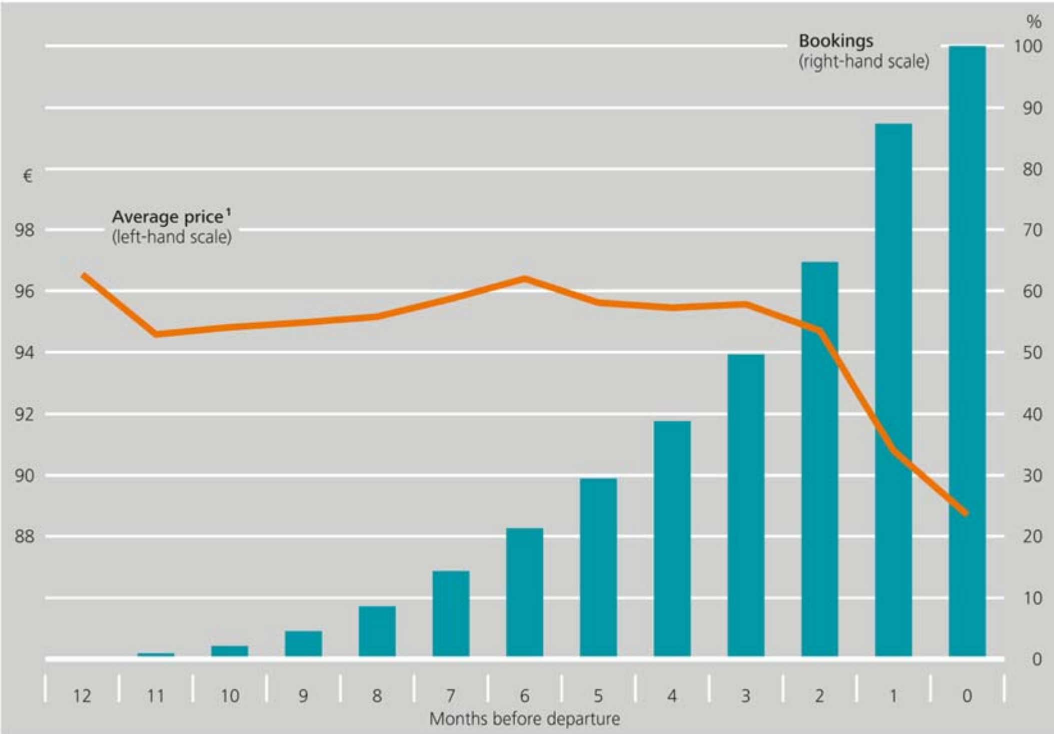


Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH. * Without cruises. **ES** Spain, **TR** Turkey, **EG** Egypt, **GR** Greece, **DO** Dominican Republic, **AE** United Arab Emirates, **MV** Maldives, **BG** Bulgaria, **PT** Portugal, **TN** Tunisia, **CU** Cuba, **IT** Italy, **TH** Thailand, **MX** Mexico. **1** Holiday regions with a transaction weight of less than 1%.

Deutsche Bundesbank — S3IN0503.Chart

Bookings and average price by number of months before departure* Figure 4

2013 – 2018



Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH. * Without cruises. **1** Expressed in € per person and day.

Deutsche Bundesbank S3IN0504A.Chart

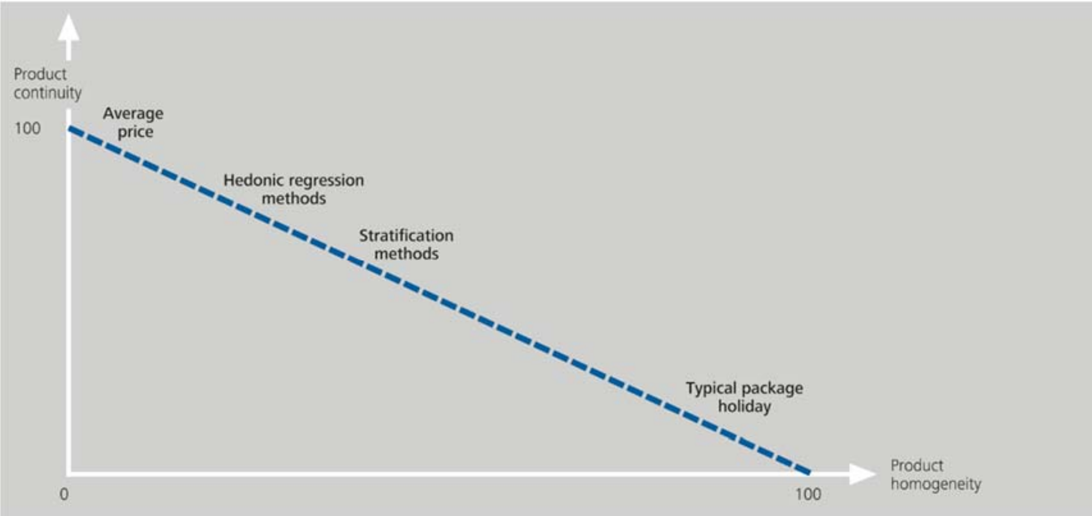
4 Methods of price measurement

An ideal price index would be based on a basket of goods which compares prices of exactly the same product over time. However, transaction price data typically lack a prior product mapping, leaving it to the price statistician to define similar products within a given dataset. This process can be considered in terms of two dimensions for 'product continuity' and 'product homogeneity', when comparing transactions between any two periods. In the context of package holidays, two extrema are at hand (see **Figure 6**). A simple *average price* across all bookings would have the highest *product continuity*, in other words a high share of observations used over time. Still, it might be heavily affected by compositional changes in the underlying bookings, and therefore not provide a high degree of *product homogeneity* in terms of comparing similar package holidays. In contrast, the price statistician could only select transactions which correspond to a (pre-defined) *typical package holiday.* This approach coincides basically with the current official practice of collecting prices only for a given price representative. When applied to transaction data, it however does not provide a high enough number of bookings used over time to have a sound basis for any disaggregation by destination.

In the following, Section 4.1 will illustrate an average price with a high continuity of bookings, but a low degree of product homogeneity. Consequently, two main approaches in constructing a transaction-based price index are considered, both with the aim of achieving a balance between product continuity and homogeneity (see **Figure 5**). The first class of models will be based on *hedonic regression methods*, which estimate a price or index value by controlling for price-determining characteristics (Section 4.2). The second class of models is based on increasing the homogeneity of the bookings used by employing s*tratification methods* (Section 4.3).

Hypothetical trade-off between product continuity and homogeneity* Figure 5

%



* Product continuity refers to the degree of product match in terms of observations, when comparing a given month with a base period. Product homogeneity refers to the degree of similarity of items within a given product.

Deutsche Bundesbank S3IN0537.Chart

4.1 Unit Value Price Index

The simplest approach to construct a price index is a *unit value price index*, which basically compares average prices over time. In the context of package holidays, the price per person per day (PPD) as given by the variables $travellerCount$ and $duration$ is computed for each transaction. Consequently, the average PPD for a given holiday destination is defined by:

$$\overline{PPD}_t = \frac{1}{N_t} \cdot \sum_{i=1}^{N_t} \frac{\frac{totalPrice_{i,t}}{travellerCount_{i,t}}}{duration_{i,t}}, \tag{1}$$

where $i = 1, \ldots, N_t$ denotes the number of transactions in period t.[17] For comparison purposes, the series of average prices are rebased to $2015 = 100$. The resulting unit value price index, I_t^{UV}, in period t is given by:

$$I_t^{UV} = \frac{\overline{PPD}_t}{\overline{PPD}_{2015}} \cdot 100. \qquad (2)$$

The *unit value price index* is often applied in the context of export and import price indices and is suitable for aggregating identical, homogeneous products such as fuel and electricity (see, for instance, IMF (2009)). However, for more complex or heterogeneous products, this index would suffer from a *unit value bias* related to compositional changes in the underlying basket of goods. An example for this bias consists in more (costly) bookings for five-star hotel rooms in period 1 than in base period 0 for a given holiday destination. Even in the case of constant prices, a *unit value price index* would signal a price increase in period 1 simply related to the compositional changes in the hotels booked between both periods. Nevertheless, the *unit value price index* uses most of the transactions (see **Figure 5**) and is drift-free by construction in comparison with chain-linked price indices; therefore, it can serve as a simple benchmark method for the following (more sophisticated) price index methods.

4.2 Hedonic regression methods

Hedonics are a group of regression techniques, which describe the price of a given good or service as a function of several (observed) attributes, each having a marginal contribution to the overall price. In official statistics, hedonics are widely used in order to estimate a quality-adjusted price, for example in the context of residential house prices (see ILO et al. (2004); Triplett (2006); Eurostat (2013)). In the following, two different hedonic methods are tested with bookings of package holidays. The first method is *double imputation* (see Section 4.2.1), where prices are estimated for the base period as well as the comparison period. The second method is the *time dummy model* (see Section 4.2.2), where the index is directly derived from the coefficient of a time dummy variable in the regression.

4.2.1 Double imputation

Hedonic regression techniques can be used to estimate prices for products which are available in the base period 0 but are no longer available in the comparison period t. To

[17] Note that this implies a proportional relationship between the total price and both the number of days and the number of travellers. However, the price of a package holiday might be better reflected by a fixed-cost (travel-related) component and a non-proportional increase for additional travellers and/or days. This assumption is relaxed in the hedonic regression models in the next section.

account for this fact, German official price statistics use the *double imputation* technique[18] for the house price index[19] and price indices of electronic products such as notebooks or smartphones, since the life cycle of innovative products is typically only a few months. Similarly, package holidays have a high churn, because they are rarely observed with exactly the same attributes in two successive periods. Some of the reasons for this are the numerous characteristics of package holidays as well as the seasonality of holiday destinations; for example, the number of bookings for Greece declines drastically during the winter season. Consequently, the *double imputation* is performed for package holidays on the basis of estimated prices for both the base period (year 2015) and a given comparison month t.[20] Prices are estimated using the ordinary least squares method for the base year and for month t. Consequently, the observations of month t are used to estimate prices for the base year (using the regression coefficients of the base year) and prices for month t (using the regression coefficients of month t). In contrast to electronic products, the underlying regression model for package holidays is regarded as stable over a longer period of time, since the price-determining variables rarely change.[21]

The Amadeus dataset contains several price-determining variables, as listed in **Tables A.1 and A.2**. In a first step, the variable selection of the regression model per holiday destination was done by analysing adjusted R^2 and its minimum and maximum range, indicating the explanatory content of the regression model. To avoid multicollinearity, the variance inflation factor (VIF) and significance of coefficients were checked. Moreover, the coefficients had to be stable and plausible over time, for example a coefficient of the four-star hotel dummy should be *ceteris paribus* smaller than the coefficient of the five-star hotel (see also Appendix A.3). Various combinations of variables were tested. For the variables $travellerCount$, $duration$ and $bookTime$, three transformations were considered (continuous, log-transformation, or categorised), with the best option to use logarithmic values for all three variables. Moreover, in estimating a price properly, the *double imputation* method requires to capture the additional effect of public holidays — besides the typical holiday season — during a given travel month

[18] Typically, the starting point for the concept of *double imputation* is an A-, B- and C-sample, where the B-sample contains all products that are present in both base period 0 and comparison period t, and products of A- or C-sample are not present in either the base period (C-sample) or the comparison period (A-sample). However, the concept of the A-, B- and C-sample is not applicable for package holidays, since there is no B-sample available. See Linz et al. (2004) for further details on the *double imputation* technique applied by the Federal Statistical Office.

[19] See Eurostat (2017), Section 6.1.2.

[20] By contrast, for electronic products, January is chosen as a base period and the index is chain-linked annually. This allows an annual adjustment of the regression model to integrate new price-determining features. See Destatis (2009).

[21] A change in the hedonic regression model for package holidays would only be necessary if, for example, the data provider changes the variables listed in **Table A.1**.

on the total price. Therefore, a dummy variable ($isHoliday$) is generated that equals 1 if Easter, Pentecost or Christmas falls during a given package holiday and 0 otherwise.[22] Overall, a model comprising variables $travellerCount,\ duration,\ bookTime,$ $channel,\ star,$ and $isHoliday$ gave the best results, with an average adjusted R^2 per holiday destination ranging between 0.704 and 0.785 (see **Table A.4**).[23] The final regression model comprising both online and offline bookings is subsequently defined as:

$$\begin{aligned}\ln(totalPrice_{i,t}) \\ &= \beta_0 + \beta_1 \ln(travellerCount_{i,t}) \\ &+ \beta_2 \ln(duration_{i,t}) + \beta_3 \ln(bookTime_{i,t}) \\ &+ \beta_4 \mathrm{D}(channel_{i,t}) \\ &+ \beta_5 \mathrm{D}\left(star_{one_{i,t}}\right) + \beta_6 \mathrm{D}\left(star_{two_{i,t}}\right) + \beta_7 \mathrm{D}\left(star_{three_{i,t}}\right) \\ &+ \beta_8 \mathrm{D}\left(star_{five_{i,t}}\right) + \beta_9 \mathrm{D}\left(isHoliday_{i,t}\right) + \varepsilon_{i,t},\end{aligned} \tag{3}$$

where Equation (3) is estimated for the base year 2015 and each comparison travel month t separately. Consequently, the Jevons formula is used for index calculation, in other words, the geometric mean of the estimated price relative of period t and base period 0, such that the index value for hedonic regression, I_t^{DI}, reads as follows:

$$I_t^{DI} = \left(\prod_{i=1}^{N} \frac{\widehat{P}_{i,t}}{\widehat{P}_{i,0}} \right)^{\frac{1}{N}}. \tag{4}$$

Note that $mealType$ and $roomCategory$ are also important price-determining variables, but are available for online bookings only. As a robustness exercise, a more detailed regression specification based on online transactions was estimated:

[22] For example, the coefficient for $isHoliday$ was 0.28 for the Canary Islands in December 2015, thus, the price of a package holiday is about 28 % higher for travelling at Christmas than for travelling before or after Christmas. Alternatively, one could also include public school holidays as an explanatory variable, although the date of these can vary considerably across the German Federal States.

[23] The Federal Statistical Office also calculates other hedonic indices, which have an adjusted R^2 about 80 % (for complex products like servers) and nearly 100 % (for simple products like RAM modules). However, possible price-determining characteristics of package holidays such as hotel rating, hotel facilities or the exact location of a hotel are not available from the Amadeus dataset. Thus, an adjusted R^2 of about 0.75 for a complex product like package holidays seems to be acceptable.

$$
\begin{aligned}
\ln(totalPrice_{i,t}) \quad & \quad (5) \\
= \beta_0 + \ & \beta_1 \ln(travellerCount_{i,t}) \\
& + \beta_2 \ln(duration_{i,t}) + \beta_3 \ln(bookTime_{i,t}) \\
& + \beta_4 \,\mathrm{D}\left(star_{one_{i,t}}\right) + \beta_5 \,\mathrm{D}\left(star_{two_{i,t}}\right) + \beta_6 \mathrm{D}\left(star_{three_{i,t}}\right) \\
& + \beta_7 \,\mathrm{D}\left(star_{five_{i,t}}\right) + \beta_8 \,\mathrm{D}(seaView_{i,t}) \\
& + \beta_9 \,\mathrm{D}\left(highStandard_{i,t}\right) \\
& + \beta_{10} \mathrm{D}(lowStandard_{i,t}) + \beta_{11} \,\mathrm{D}(allInclusive_{i,t}) \\
& + \beta_{12} \,\mathrm{D}\left(breakfastOnly_{i,t}\right) + \beta_{13} \mathrm{D}\left(isHoliday_{i,t}\right) + \varepsilon_{i,t},
\end{aligned}
$$

where additional dummy variables for the room and meal category were included. In the special case of Greece, due to a lack of bookings during the winter season, it is only possible to estimate a price index for the period May to October for each year.[24]

4.2.2 Time Dummy Model

The second hedonic method is the *time dummy model*, which also constitutes a regression approach. Contrary to the *double imputation* technique, no prices are estimated, but the price index is derived directly from the time dummy coefficient. For the *time dummy model*, the same regression model as in Equation (3) is taken, except for $isHoliday$. The effect of public holidays has to be measured as a price change and is therefore already included in the time dummy variable.[25] The *time dummy* regression model is given by:

$$
\begin{aligned}
\ln(totalPrice_{i,t}) \quad & \quad (6) \\
= \beta_0 + \ & \beta_1 \ln(travellerCount_{i,t}) \\
& + \beta_2 \ln(duration_{i,t}) + \beta_3 \ln(bookTime_{i,t}) \\
& + \beta_4 D(channel_{i,t}) \ + \beta_5 \,\mathrm{D}\left(star_{one_{i,t}}\right) \\
& + \beta_6 \,\mathrm{D}\left(star_{two_{i,t}}\right) + \beta_7 \,\mathrm{D}\left(star_{three_{i,t}}\right) \\
& + \beta_8 \,\mathrm{D}\left(star_{five_{i,t}}\right) + \gamma D_{i,t} + \varepsilon_{i,t},
\end{aligned}
$$

where $D_{i,t}$ denotes the time dummy which equals 0 for the base period and 1 for the comparison travel month t.[26] The regression is estimated using all observations from the

[24] To calculate a price index for the whole year for Greece, one possible solution would consist of a regression model with joint dummy variables for Greece and the Balearic Islands as Mediterranean euro area holiday destinations. However, the results were more plausible when using a single regression model for each holiday destination.

[25] Including $isHoliday$ in the *time dummy model* could also lead to multicollinearity, because both the time dummy variable and $isHoliday$ measure a seasonal effect.

[26] Here, we use only one time dummy and compare two periods, so the result is a bilateral index. It would also be possible to include more periods and extend the regression model by using more than one time dummy.

base period (January) and month t. The *time dummy model* index, I_t^{TD}, is directly derived from the exponential of the coefficient of the time dummy, γ, such that:

$$I_t^{TD} = e^{\hat{\gamma}}. \tag{7}$$

The final index series is chain-linked in January by applying the growth rate to the previous index value.[27]

4.3 Stratification methods

An alternative to setting-up a regression model consists of dividing a sample into homogeneous strata and to consequently compute an average price within a given stratum. The following sections are dedicated to this *stratification approach.* As a first step, Section 4.3.1 deals with the definition of homogeneous strata or products in the context of package holidays by a quantitative approach. In a next step, Section 4.3.2 presents a traditional bilateral stratification approach based on a comparison of two periods, whereas Section 4.3.3 presents a multilateral approach, the *GEKS* method recently applied to supermarket scanner data, which compares several periods in computing a price index.

4.3.1 Product definition by a quantitative approach

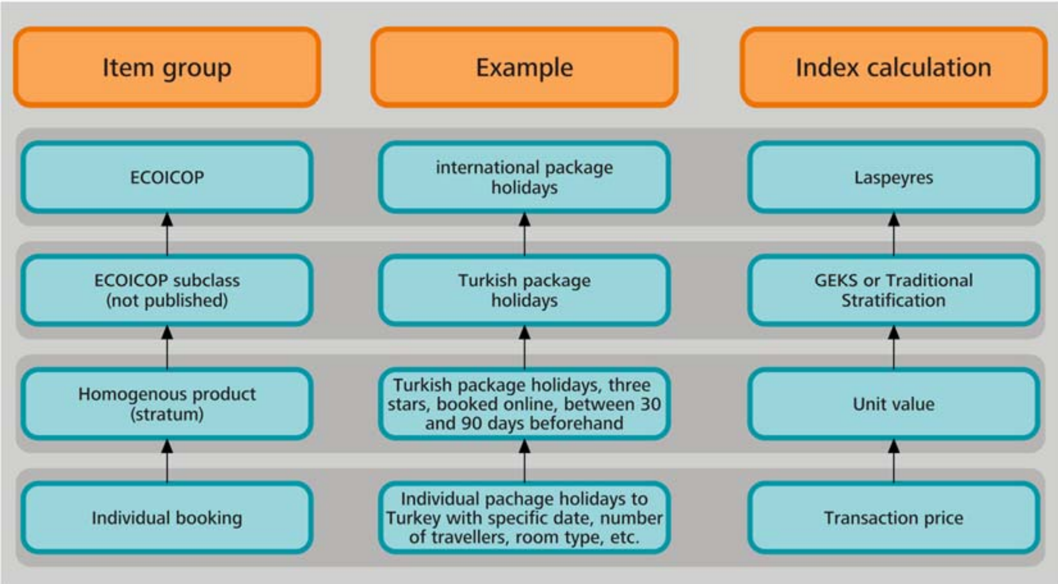
In price statistics, a proper product definition is key. This is especially true for stratification methods as these methods group the underlying data according to their price-determining characteristics. Thereby, it is important to distinguish between items and products. More specifically, several items form one product.[28] All items have certain characteristics of attribute variables and the question is which variables are important for product distinction and which ones can be neglected. Obviously, this problem is very much dependent on the product market and especially on the corresponding rate of churn.

[27] Hill (2011) suggests using a correction factor in the index calculation, because of a bias in the price index, which results from the fact that $E[e^{\hat{\gamma}}] \neq e^{\hat{\gamma}}$. However, in the present application, the effect of the correction factor was quite small so the factor was not included in the final model.

[28] A prominent application is in the field of clothing. While a single blue t-shirt of a certain brand with an individual Global Trade Item Number (GTIN) is an item, all blue t-shirts of any brand may form the product 'blue t-shirt', irrespective, for example, of the fabric or pattern. This product can be grouped again with t-shirts of other colours and other products to an ECOICOP subclass for 'men's shirts'.

Item hierarchy in the context of package holidays

Figure 6



Source: Own illustration following Chessa (2016).
Deutsche Bundesbank

S3IN0559.Chart

Figure 6 illustrates the relationship between items and products in the context of package holidays. The right-hand column underlines the fact that the product definition at a lower level is not related to the index method since this calculation is performed at a higher aggregation level. In the second column, for illustrative purposes, some package holidays would form, for instance, the homogeneous product ‘Turkish package holidays in three-star hotels, booked online within 30 to 90 days of departure’. This product again may form, along with several others, an ECOICOP subindex called ‘Turkish package holidays’. Note that the Federal Statistical Office currently only publishes at a higher aggregation level (domestic and international package holidays). But if the sample covers a sufficient number of observations, it might also be feasible to publish subindices at a more detailed ECOICOP level such as by holiday destination to allow for a more detailed economic interpretation of the volatile prices of package holidays.

As a quantitative measure for the selection of price-determining variables for product definition, Chessa (2019) developed *Match Adjusted R Squared* (MARS). This measure weighs the two sides of product definition: product homogeneity and product continuity in comparison with a given base period. Thereby, product homogeneity among a specific product group is defined as the deviation of the average price, whilst assuming that homogeneous items do not vary much in price. Product continuity is defined as the share of products that are available in the base period as well as in the comparison period. Both measures are normalised to one. If, for example, a product definition is based only on the item level (in other words every single package holiday transaction), then product homogeneity equals one, but product continuity declines as new items appear on the market.[29] Equally, if a product definition just aggregates all items to one product, the continuity is always one, but homogeneity would equal zero.[30] Multiplying the values for product continuity and homogeneity yields the balance measure of MARS. This multiplication is similar to a classical loss function since product homogeneity increases as continuity decreases and vice versa.

Applying this to package holidays, with n different product variables such as $duration$ and accommodation category, there are 2^{n} different combinations forming a product definition at hand (not considering the number of attributes of a specific variable). By using PPD instead of $totalPrice$ as the price variable, it is possible to omit two variables from the combinatorial problem ($duration$ and $travellerCount$).[31] The variable $bookTime$ was grouped in order to avoid a too detailed product definition.[32] Moreover, since the shares of one- and two-star accommodations were relatively small in terms of the total revenue (for example less than 1 % and 2 % respectively in 2015), these bookings were removed beforehand. Likewise, the computation was only performed by using the 12 travel months for 2015, which also serves as the base period for the following price indices. Using the results from hedonic regressions above as a starting point, six variables ($topArea$, $star$, $channel$, $bookTime\_Class$, $depAirport$ and $weekday$ of departure) were considered as variables for product definition.[33] Thus, $2^6 = 64$ possible product definitions were tested.

[29] This assumption is made implicitly for calculating the *double imputation* method (see Section 4.2.1), because no package holiday is grouped with another. Thereby, the lack of product continuity is handled by estimating the missing prices.

[30] This assumption is made implicitly for the *unit value price index* (see Section 4.1), because no distinction between items is made.

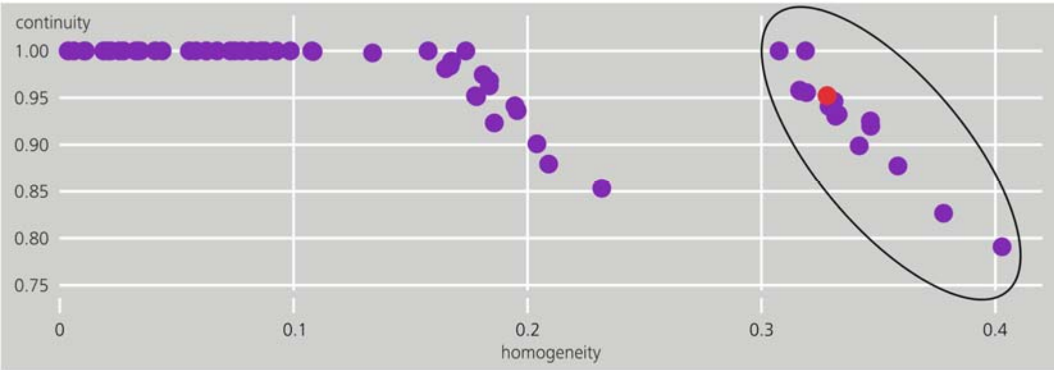
[31] Alternatively, transactions could be categorised by duration and the number of travellers. This would however largely increase the number of strata and therefore reduce product continuity.

[32] As shown in **Figure 4**, the width of possible classes grows by increasing days before departure. Following this, the first group of bookTime_Class is from 15 to 30 days, the second from 31 to 90, the third class from 91 to 180, and the fourth class captures all bookings made more than 180 days in advance of departure.

[33] Note that seasonal variables like winter and summer season are not considered; they would create artificial breaks or discontinuities and therefore decrease the value of product continuity drastically. An alternative would be to stretch the base period to the entire previous year instead of just the previous month. However, this exercise is left for further research.

Continuity and homogeneity of several product definitions following Chessa (2019)

Figure 7



Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH; average values of 2015. The product definition highlighted in red was selected for the subsequent analysis. For illustration purpose, one outlier combination with homogeneity = 1 (i.e., every package holiday represents an own product class) is excluded.

Deutsche Bundesbank

S3IN0538.Chart

Figure 7 depicts the average value of product continuity and homogeneity for the 64 tested product definitions in 2015. By concept, a combination in the upper right corner, where product continuity and homogeneity equal one, would be best (see the circled set of points).[34] Moreover, a higher weight for product homogeneity seems to be more suitable for the heterogeneous product category of 'package holidays'.[35] Based on the results in **Table A.5** and the hedonic regression analysis before, a combination of variables is chosen which also exhibits a high number of items per product. In Figure 7, this combination is marked in red, according to which a product in the context of package holidays is well defined by the variables $topArea$, $star$, $channel$ and $bookTime\_Class$. Moreover, $travellerCount$ and $duration$ are included implicitly by using PPD rather than $totalPrice$ as the price variable. Overall, these findings define the strata and the data filters that are used in the following two stratification methods.

4.3.2 Traditional stratification

The *traditional stratification* approach tries to overcome the unit value bias of an average price by grouping transactions into several homogeneous classes before calculating the unit value. In terms of package holidays, transactions that have similar price-determining characteristics are sorted into the same class or stratum. In the following, for each holiday destination as given by $topArea$, the strata are formed by $star$, $channel$ and

[34] Note that it is not feasible to multiply the values for product continuity and homogeneity in **Figure 7** in order to calculate MARS, since these represent averages from the 12 monthly values in 2015.

[35] In the model from Chessa (2019), this can be thought as a loss function in an additive composition including a parameter λ for manual weighting.

$bookTime\_Class$, which is consistent with the set of variables approved by the results of the previous section and also the *hedonic regression*. The next step is to calculate in each stratum the average PPD in period t (see Equation 1) and to normalise the resulting series to $2015 = 100$.[36] In this manner, for each holiday destination, $M = 24$ strata are constructed resulting in 24 elementary price indices, $I_{m,t}^{TS}$.

The aggregation of those elementary price indices to an overall price index for the corresponding holiday destination can be affected by using either a weighted or unweighted mean. In some destinations, certain classes account for only a very small revenue share. For example, there tend to be less package holidays to three-star hotels in Turkey or five-star hotels on the Balearic and Canary Islands, respectively. Thus, an unweighted average price would be biased towards the under-represented classes. For this reason, the weighting is based on the total revenue shares of the individual class in 2015, as given by the transaction data. Finally, for each holiday destination the overall price index according to *traditional stratification*, I^{TS}, in period t is given by:

$$I_t^{TS} = \sum_{m=1}^{M} w_m \, I_{m,t}^{TS}, \qquad (8)$$

where w_m represents the 2015 revenue share of each stratum $m = 1, \dots, M$.

In addition to the baseline version described above, two alternatives of *traditional stratification* are considered. First, bookings are grouped by $iffCode$, which is the numeric identifier of the accommodation booked. Following this, the strata can be formed by $iffCode$, $channel$ and $bookTime\_Class$.[37] This selection of variables refines the baseline model above. Since the focus is now at the individual hotel level, the variable $star$ can be neglected. For each of the six destinations, a large number of hotels are available, but concerning product continuity, it is reasonable to select the favoured ones. Therefore, for each holiday destination, only the top 25 hotels as measured by their revenue shares in 2015 are included in the calculation. Accordingly, the number of strata rises to $M = 200$, with 200 elementary price indices calculated and weighted together as described above. Second, by using only the online data, it is also possible to form the strata by using the variables $star$, $D(seaView)$, $D(AllInclusive)$ and $bookTime\_Class$ to include price-determining information about meal and room categories.[38] In this way, the resulting number of strata is

[36] An additional stratification by *duration* and *travellerCount* would also be possible (for example one strata for 7-day package holidays and another one for 14-day package holidays). As a result, *totalPrice* could be used as the relevant price variable instead of *PPD*. However, this would strongly reduce the number of observations per stratum.

[37] It is also reasonable to stratify by *iffCode, bookTime_Class* and *depAirport* (using the three largest German airports, for instance). However, the results were very similar to the stratification by *iffCode, channel* and *bookTime_Class*.

[38] To cover meal type, only the variable *D(AllInclusive)* is included because some meal categories such as “breakfast only” would have none to very low observations for some holiday destinations. Regarding room

$M = 48$, with 48 elementary price indices calculated and weighted in the same way as described above. For both alternatives, in case of missing bookings for a given period, the weights of the respective strata are set to zero and distributed proportionally across the remaining strata.

4.3.3 GEKS

The origin of the following method goes back to Gini, Eltetö, Köves and Szulc (*GEKS*) and was adopted by Ivancic, Diewert and Fox (2011) to apply to the growing field of scanner data in price statistics.[39] As in the previous approach, the price variable is PPD and the sample is stratified to calculate a unit value per stratum. The difference between *GEKS* and the *traditional stratification* approach lies in the index aggregation; instead of using the fixed weights from the year 2015, the monthly revenue shares of each stratum were used. Moreover, *GEKS* is a multilateral method, which compares more than two time periods to each other in computing a price index. The main advantage from multilateral methods is that these are transitive and therefore generally free from chain drift.[40]

In particular, in the current month T, *GEKS* compares all months $t = 1, \dots, T$ with the base month 0 using a geometric mean of a set of index ratios comprising the Fisher index of month 0 divided by the Fisher index of month T whereas the base period iterates from 0 to T.[41] Given any period $t = 0, \dots, T$, the *GEKS* index between base period 0 and comparison period t, $I_{0,t}^{GEKS}$, is defined by:

$$I_{0,t}^{GEKS} = \prod_{z=0}^{T} \left(\frac{P_{0,z}^{Fish}}{P_{t,z}^{Fish}} \right)^{\frac{1}{T+1}}, \tag{9}$$

where $I_{t,z}^{Fish}$ represents the Fisher index between period t and z, whereas T stands for the current month. The Fisher index is given by:

$$I_{t,z}^{Fish} = \sqrt{I_{t,z}^{L} \cdot I_{t,z}^{Pa}} = \sqrt{\frac{\sum_{i=1}^{N_{t,z}} p_z^i \, q_t^i}{\sum_{i=1}^{N_{t,z}} p_t^i \, q_t^i} \cdot \frac{\sum_{i=1}^{N_{t,z}} p_z^i \, q_z^i}{\sum_{i=1}^{N_{t,z}} p_t^i \, q_z^i}}, \tag{10}$$

with $I_{t,z}^{L}$ as the Laspeyres index and $I_{t,z}^{Pa}$ as the Paasche index between period t and z. Furthermore, p_t^i and q_t^i denote the price and the quantity of product i sold in month t.

---

category, it is reasonable to use only the indicator variable for sea view to guarantee a sufficiently high number of observations. For the same reason, the variable *star* is included instead of *iffCode*.

[39] Introduced already in the mid-1960s, this index concept is also used to measure purchasing power parities (see OECD and Eurostat (2012) for an overview).

[40] Note that also hedonic regression methods can in principle be constructed in a multilateral way, which is, however, not the case in this paper.

[41] Note that instead of a Fisher index, a Törnqvist index could also be applied.

Lastly, $N_{t,z}$ stands for the total number of products that are sold in month t as well as in month z. As reflected in formula (9), multilateral indices inherit ongoing revisions; in the next period $T+1$, the value of $I_{0,t}^{GEKS}, (t\ = 0, \dots, T)$ might be different to its value in period T since the product is expanded by one factor. To avoid revisions of already published price indices, Ivancic et al. (2011) propose a chain-link. This is done by recalculating the indices for all other months with the help of the new month and applying the growth rate of the new month to the previously published index values (so-called movement splice). Additionally, the authors propose a rolling window in order to give more recent index values a higher weight in the current index calculation. Hence, T reflects also as the size of the rolling window. In the present application, the length of the rolling window was set to 13 months.[42] Note that no dumping-filter was applied, because data cleansing was done beforehand (see Section 3).[43]

5 Comparison of results

In the following, price indices based on the five different methods (*unit value price index*, *double imputation*, *time dummy model*, *traditional stratification* and *GEKS*) are evaluated concerning their overall seasonal pattern, volatility and robustness with respect to different data filters. Ideally, all price indices follow a similar pattern for a given holiday destination, so that to a large extent the selection of the method does not influence the overall movement of the series. In this case, the decision on the preferred method could in principle be based on the volatility of the annual rates of change. Moreover, the resulting transaction-based price indices are compared with the official price index, which uses offer prices. For this purpose, for each method, the underlying dataset excludes last minute bookings ($bookTime \leq$14) as well as non-German departure airports ($D(GermanAirport)$ = 0), which is consistent with the current official practice as described in Section 2 and is therefore considered for comparison purposes as well.

Figure 8 shows transaction-based price indices according to the different methods for the six major holiday destinations (the Balearic and Canary Islands, Turkey, Greece, Egypt, and the Dominican Republic). Overall, the resulting price indices for package holidays in a given destination have the same seasonal pattern, with typically higher prices during summer months in Germany and lower prices during winter months. However, there are some

[42] See Van Loon and Roels (2018) for an overview of different chain-linking methods. Besides the movement splice, the fixed base moving window proposed by Lamboray (2017) was tested. The results were very similar. Following de Haan and Krsinich (2018), a window length of 13 months is the smallest that can deal with seasonal products. In the present case, the window initially starts in January 2014 and ends in January 2015 (for Greece, from May to October 2014 and May 2015).
[43] In German price statistics, the *GEKS* method was applied by Bieg (2019) to supermarket scanner data.

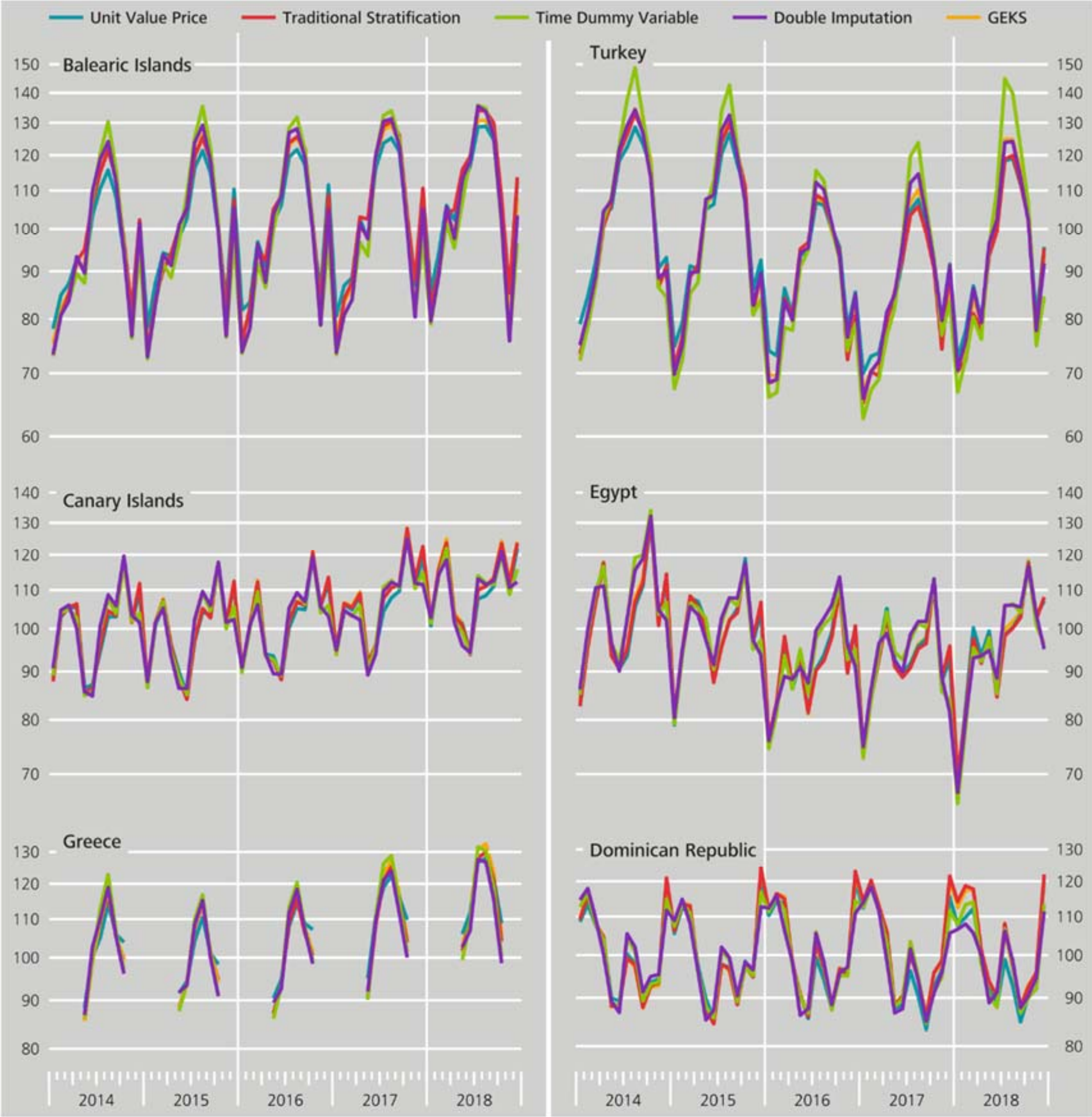
differences across methods within specific destinations. For instance, at the end of each calendar year, the price trend for the Canary Islands based on *double imputation* differs from the price trends for the other methods. For Egypt, both methods of *hedonic regression* differ at the end of the year. For Turkey, the *time dummy model* exhibits a higher volatility in comparison with the other methods. For the Dominican Republic, the fourth quarter of 2017 and the first quarter of 2018 show differences between almost all methods. Note that although the concept of the *GEKS* as a multilateral index is very different from the bilateral indices, it provides similar results.

To have a closer look at the differences in dynamics between methods, the next step is to analyse the annual rates of change, in other words the percentage change between a given month and the same month of the previous year. For this purpose, descriptive statistics are calculated for each method and holiday destination. The *unit value* approach is generally less volatile; however, it is also considered to exhibit the lowest degree of product homogeneity over time (see **Figure 5**). The arithmetic mean (MEAN) indicates whether the price indices have the same trend over time, whereas the standard deviation (SD) as well as the minimum (MIN) and the maximum (MAX) indicate the volatility of the annual rates of change. In **Table 2**, the (absolute) lowest SD, MIN and MAX of a given holiday destination are highlighted in green. At a first glance, *traditional stratification* and *double imputation* perform well in terms of these descriptive statistics. The latter exhibits the lowest volatility as indicated by the standard deviation. However, it also appears that the performance of each method seems to depend on the holiday destination under consideration. Whereas for the Canary Islands and Egypt, *double imputation* performs best, in the Balearic Islands and Greece, *traditional stratification* seems to perform well. Note that the largest variation across methods is found for the Dominican Republic, where — in contrast to the other holiday destinations — the sign of the average rate of change (MEAN) differs between methods.

Comparison of different methods of price measurement

Figure 8

2015 = 100, log scale



Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH.
Deutsche Bundesbank

S3IN0527.Chart

Table 2: Descriptive measures of different index methods by holiday destination

Annual growth rates, 2014 - 2018		Unit Value Price	Hedonic Regressions		Stratification	
			Double Imputation	Time Dummy Variable	Traditional Stratification	GEKS
Canary Islands	Mean	2.4	2.1	2.3	2.6	2.8
	SD	4.7	**3.8**	4.8	5.0	**5.0**
	Min	-8.7	**-6.7**	-8.0	-9.6	**-9.3**
	Max	17.1	**14.7**	18.4	**17.5**	18.1
Balearic Islands	Mean	3.2	2.7	2.3	3.3	2.5
	SD	4.7	6.4	**5.3**	**4.3**	4.6
	Min	-8.4	-12.8	**-8.5**	**-7.8**	-8.4
	Max	19.5	25.8	**20.5**	**18.1**	19.0
Turkey	Mean	-2.1	-2.1	-1.8	-2.2	-1.9
	SD	8.2	**8.3**	9.9	**8.8**	9.1
	Min	-16.3	**-16.8**	-21.0	**-17.4**	-18.5
	Max	17.9	**19.6**	21.0	**16.6**	18.2
Greece	Mean	3.4	2.4	2.6	3.2	3.6
	SD	5.5	**5.8**	6.0	**5.3**	5.7
	Min	-5.9	-9.1	**-6.1**	**-5.5**	-5.7
	Max	16.9	**18.2**	18.6	**16.0**	18.2
Egypt	Mean	-1.5	-2.3	-2.6	-1.7	-1.6
	SD	7.9	**7.0**	8.0	**7.3**	7.9
	Min	-19.4	**-15.9**	-18.1	**-17.6**	-18.5
	Max	21.8	**16.9**	20.8	**18.2**	20.9
Dominican Republic	Mean	-0.3	-0.5	-0.3	0.7	0.6
	SD	3.4	3.3	**3.0**	3.4	**3.2**
	Min	-7.7	-8.8	**-7.1**	**-7.9**	-8.1
	Max	8.4	**5.5**	5.8	7.9	**7.8**

Note: Based on the annual rates of change from January 2014 to December 2018.

In addition, several robustness tests related to the data itself as well as to the model specifications were performed. Results for different data filters are shown in the Appendix for *double imputation* and *traditional stratification* (**Figures A.2 and A.3**, respectively).[44] Using all of the transaction data including last minute bookings (those made 14 days or less before departure) as well as including non-German departure airports did not affect the index values in a noticeable way. Moreover, excluding bookings with an accompanying child (aged less than 16 years), which might comprise a tour operator-specific discount on the package holiday, did not impact the resulting series. By using online bookings only, a more detailed regression Equation (5) was estimated for the *double imputation* method (see Section 4.2.1). Evidently, using the additional information on the meal type (for example 'all inclusive') or the room category does not seem to change the resulting hedonic price index. Finally, two alternatives of the *traditional stratification* approach were tested: a more detailed stratification for online bookings by including also the information on the meal type and room category as well as a stratification at the individual hotel level (see Section 4.3.2). Whereas the resulting annual

[44] For a detailed description of the robustness exercise concerning different datasets, see **Table A.6**.

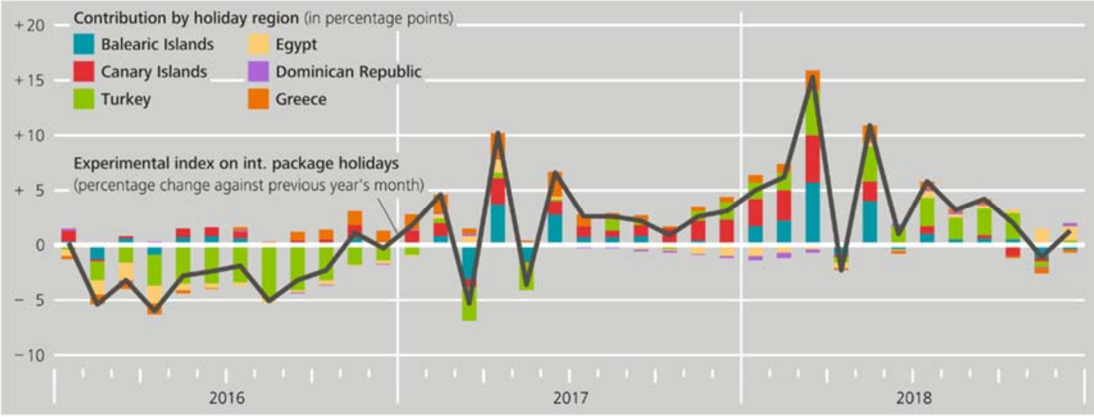
rates of change of the first alternative closely resemble the rates of the baseline version of *traditional stratification*, stratification at the individual hotel level differs quite greatly in some periods and is also more volatile (see **Figure A.4** in the Appendix). For the Balearic Islands, the resulting rates of change deviate notably during winter months. This is due to the sharp drop in observations, noting that hotels booked during the winter season are generally different to those booked during the summer season.[45] Similarly, the annual rates of change for Turkey differ widely during the winter season of 2017/2018. Overall, the number of observations for these alternative specifications decreases considerably; in comparison with the baseline versions, only one quarter to one third of the data is used (see **Table A.7** in the Appendix). Therefore, in the remaining analysis, only the baseline versions of the *double imputation* and the *traditional stratification* method are considered.

The destination-based price indicators allows for a detailed economic interpretation of the overall price trend for international package holidays. In this sense, **Figure 9** plots an experimental price index based on the baseline version of the *double imputation* method, by aggregating the six destination-based price indicators using their average revenue shares from 2015-2016. It becomes clear that the negative price trend in 2016 as well as the recent peak in the summer of 2018 in international package holiday prices was primarily driven by developments in Turkey. During the beginning of the sample, the latter experienced a decline in bookings as a response to several terroristic attacks and increasing political uncertainty, with bookings recovering in the summer season of 2018. Obviously, this was accompanied by a similar movement in prices for package holidays in Turkey. Due to the resulting shift in German travellers' preferences, the Balearic and Canary Islands and, to a lesser extent, Greece, could at the same time increase their prices for package holidays during 2017 and 2018.[46]

[45] Most of the top 25 hotels have no observations in the winter months (November to February). The remaining top 25 hotels have only a small proportion of their observations during this period. This leads to 'unusual' prices and accordingly to more volatile rates of change.

[46] See also Section 3 on revenue shares per holiday destination over time. Note that, in calculating the contributions to growth, the weight of a given holiday destination was held constant (average 2015-2016 revenue share).

Experimental index for international package holidays and contributions from holiday regions — Figure 9



Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH. The experimental index is based on the "double imputation" method and consists of six holiday regions, which are weighted together by their respective revenue share (2015-2016 average).
Deutsche Bundesbank S3IN0536.Chart

Finally, the transaction-based indices are contrasted with the official price index for international package holidays (ECOICOP 09.6.0.2), which is based on offer prices and is currently only reported at the aggregate level. For an approximate comparison, the transaction-based indices for the six holiday destinations are used to calculate an overall index for package holidays abroad according to the calculation procedure of the official index.[47] As described in Section 2, the official price index consists of these six holiday destinations for international flight package holidays, but also includes city trips and cruises. The latter two are not calculated with Amadeus transaction data; instead, the official (confidential) subindices are used.[48] Similarly, transaction-based indices for Greece and cruises during the winter season are imputed by using all available subindices (all-seasonal estimation). For the Dominican Republic, the official subindex imputes the summer months whereas the transaction-based indices for this holiday destination are also based on actual bookings during the summer season.[49] For all five transaction-based methods under consideration, a corresponding index for international package holidays is calculated by summing up the eight subindices using the official weighting scheme.

Figure 10 depicts the annual rates of change for all five transaction-based indices together with the current official index. Note that a comparison of the latter can be only made from January 2016 onwards, since a new computation method was introduced (with data back

[47] Note that the official weighting scheme at this detailed level is not published.
[48] Concerning cruises, in the transaction data there is only information on the destination airport, but not on the room category (for example, inside or outside cabin), which is obviously an important price determinant when booking a cruise. City trips might be calculated with the Amadeus data, but this is left for further research.
[49] This does not only affect price movements for the Dominican Republic but also indices for Greece and cruises, because out-of-season months are imputed using the all-seasonal estimation.

to January 2015). Concerning the annual rates of change as shown in the upper part of Figure 10, there are only four periods (out of a total of 36), when the algebraic sign of the respective rate of change diverges across the five transaction-based methods. In contrast, the official method deviates in 11 out of the 36 periods from the sign for the rate of change indicated by the majority of transaction methods. Concerning month-on-month rates of change from February 2015 onwards, the five methods do not differ in any of the 47 periods in terms of their signs for the rate of change, reflecting the dominance of the seasonal pattern in the series. The official method deviates only in four out of the 47 periods. Finally, descriptive statistics for the annual rates of change are shown in **Table 3**. Evidently, all methods have a smaller standard deviation when compared with the official method. Concerning the different indices, *double imputation* has the lowest standard deviation; however, the differences between methods fall within a rather small range.

Comparison of transaction-based pseudo indices with current sub-index „International Package Holidays“ (ECOICOP 09.6.0.2) Figure 10

Source: Destatis; Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH. For each transaction-based method, the elementary indices on six holiday regions were aggregated together with the official (confidential) elementary indices "city trips" and "cruises" by using the official fixed-weighting scheme.

Deutsche Bundesbank S3IN0535A.Chart

Table 3: Comparison of transaction-based methods with current national practice (percentage change against previous year's month)

	HICP Int. package holidays (09.6.0.2)	Unit Value	Double Imputation	Time Dummy	Traditional Stratification	GEKS
MEAN	4.3	3.1	3.2	3.5	3.3	3.4
SD	5.3	4.3	**4.1**	4.5	**4.3**	4.4
MIN	-9.7	-6.4	-6.1	**-5.8**	-7.5	**-6.7**
MAX	14.3	13.7	**13.1**	13.6	**13.4**	14.0
Q 0,25	-2.5	-1.4	-1.8	**-1.8**	**-1.2**	-1.5
Q 0,75	4.9	4.2	**3.5**	3.8	4.2	**4.0**

Note: Based on the annual rates of change from January 2016 to December 2018, since the method of the official price index changed in 2015. For each transaction-based method, the elementary indices for six holiday destinations were aggregated together with the official (confidential) elementary indices for 'city trips' and 'cruises' by using the official weighting scheme.

All in all, the transaction-based methods presented above generate similar price indices, which do not vary a lot over time. This is in contrast to the current method that is based on offer prices, where differences compared with the transaction-based methods become apparent during certain periods (see **Figure 10**). The reasons for these differences are hard to judge. One reason might be the different underlying principles of price comparison. The current official method is based on a pure price comparison of identical price offers over time by tracking the same booking code in each month, in other words quality changes should not influence price developments. Methods that are based on transaction data also try to compare like with like but define identical products for package holidays in a broader way.[50] Thus, transaction-based methods might not eliminate heterogeneity in bookings to a sufficient degree and might therefore suffer from model uncertainty caused by structural shifts and substitution effects. Moreover, price collection that is based on offer prices might be prone to sampling uncertainty as in the case of every statistic that is based on samples. In that sense, the transaction-based indices cover a more universal dataset by using approximately 50 to 100 times more observations per year than the current official practice (see **Table A.7**).

[50] Note that there is currently an on-going discussion in price statistics about the appropriate definition of 'homogeneous products' being a challenge when using new digital data sources. See, for instance, Zhang et al. (2019) as well as Nilsson and Ståhl (2019).

6 Summary

This paper has shown that, by means of transaction data, it is possible to calculate efficiently several experimental price indices that can be disaggregated by holiday destination, therefore allowing the interpretation of movements in the overall price index for international package holidays. All five methods under consideration follow a similar pattern, from which the official price index based on offer prices deviates at some points in time.

Concerning the difference between transaction-based and offer-based methods, there remain some open questions. In comparison with offer prices, it is not clear to what extent the given transaction-based methods perform sufficiently well in terms of varying sample and quality adjustment, notably regarding incomplete information such as the exact room type. Whereas transaction-based methods might suffer from 'model uncertainty', there is always a potential 'sample uncertainty' when using offer prices. Moreover, it is not sure whether the sampled offer prices represent a transaction. A quantification of both effects has to be based on a comparison between transaction prices and offer prices at the level of individual bookings, which is beyond the scope of this paper. Note that it would also be fruitful to extend research on measuring prices to cruises as these are thought to be an important driver of price developments in the German package holiday market; this would require more detailed information, for example on the cabin category booked. Moreover, transaction data from other global distribution systems or even from tour operators themselves could make the analysis more robust.

Concerning an implementation of the current transaction-based methods in statistical production and the publication of destination-based price indicators, several important issues have to be noted. If one states that a pure price comparison can only be achieved via Laspeyres-like methods, then some of the methods presented are not fully in line with the current HICP regulation. The *GEKS* method applied in this paper relies heavily on a Fisher index that uses changing weights due to the underlying Paasche index. Nevertheless, Eurostat is currently working on adapting the current legal framework to allow for other price index formulae beyond Laspeyres. Finally, concerning a more detailed breakdown of the German HICP for package holidays, note that this aim might also be accomplished with offer data. The Federal Statistical Office is currently extending their price collection to a larger number of price representatives per destination and to a larger number of travel days per month by means of an automated interface to the Amadeus booking system. Hence, a future disaggregation by holiday destination could also be developed based on offer data. Nonetheless, in the case of offer data, collected prices still need to be aggregated using external weight information, for example survey or also transaction data concerning the time of booking. In this sense, transaction data, which already contain weight information on a very detailed level, might be more convenient.

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Appendix

A.1 Overview of variables

Table A.1: Description of variables in Amadeus dataset

Variable	Description	Online	Offline	Type
Information on the accommodation				
iffCode	Numeric identifier of the accommodation booked	Y	Y	numeric
accomCategory	Classification of the standard of the accommodation (star rating)	Y	Y	numeric
accomName	Name of accommodation (for example, 'Sea View hotel')	Y	Y	alphanumeric
isCruise	Accommodation represents a cruise ('Y' or 'N')	Y	Y	categorical
Information on the holiday destination				
accomLocation	Location (lowest level of geography) for the accommodation (for example Playa de Palma)	Y	Y	alphanumeric
accomProvince	Region of the accommodation (for example Balearic Islands)	Y	Y	alphanumeric
accomCountry	Country of the accommodation (for example Spain)	Y	Y	alphanumeric
Information on the flight				
travelDate	Date on which travel is booked to start	Y	Y	date
depAirport	3-letter IATA code of the departure airport	Y	Y	alphanumeric
destAirport	3-letter IATA code of the destination airport	Y	Y	alphanumeric
Information on the booking process				
tourOperatorId	Numeric identifier of the tour operator	Y	Y	numeric
channel	Source of the booking ('online' or 'offline')	Y	Y	categorical
status	Status of the booking ('booked' or 'cancelled')	Y	Y	categorical
transactionDate	Date on which the booking is made	Y	Y	date
postcode_travelAgency	Postcode of the traditional high street travel agency	N	Y	numeric
Information on the travellers				
travellerCount	Number of travellers for the booking	Y	Y	numeric
childrenCount	Number of children for the booking	N	Y	numeric
travellerAges	List of ages for each of the travellers	Y	N	alphanumeric
Information on the transaction price				
totalPrice	The selling price of the booking expressed in EUR	Y	Y	numeric

duration	Length of the holiday expressed as a number of days	Y	Y	numeric
mealType	A classification of the level of service provided at the accommodation (for example ‘all inclusive’)	Y	N	alphanumeric
roomCategory	Description of the accommodation booked (for example ‘with sea view’)	Y	N	alphanumeric
hasTravelInsurance	Total price includes travel insurance (‘Y’ or ‘N’)	Y	N	categorical
hasHireCar	Total price includes car hire (‘Y’ or ‘N’)	Y	N	categorical

Table A.2: Description of newly defined variables

Variable	Description	Type
travelMonth	Month of travelDate	numeric
bookingMonth	Month of transactionDate	numeric
bookTime	Difference between travelDate and transactionDate in number of days	numeric
bookTime_Class	bookTime divided into four classes (up to 30, between 31 and 90, between 91 and 180, higher than 180)	numeric
PPD	Price per person per day	numeric
children	Number of children (offline) and travellers less than 16 years of age (online)	numeric
star	accomCategory divided into five classes (one to five stars)	numeric
D(star_one) to D(star_five)	Dummy variables for a given star category (1 or 0)	categorical
D(online)	Online booking only (1 or 0)	categorical
D(GermanAirport)	destAirport is located in Germany (1 or 0)	categorical
topArea	Balearic Islands, Canary Islands, Turkey, Greece, Egypt or the Dominican Republic	alphanumeric
D(doubleRoom)	Indicator variable (see Table A.3)	categorical
D(seaView)	Indicator variable (see Table A.3)	categorical
D(highStandard)	Indicator variable (see Table A.3)	categorical
D(lowStandard)	Indicator variable (see Table A.3)	categorical
D(allInclusive)	Indicator variable on whether $mealType$ is ‘all inclusive’ or ‘Vollpension’ (1 in both cases) or not (0)	categorical
D(breakfastOnly)	Indicator variable on whether $mealType$ includes breakfast only or not (1 or 0)	categorical
D(isHoliday)	Easter and Pentecost Sunday or Monday or Christmas within the travel period (1 or 0)	categorical
weekday	Day of departure date (Monday, …, Saturday, Sunday)	categorical

Table A.3: Categorisation of the variable 'roomCategory'

Indicator variable	Double room	High standard	Low standard	Sea view
text string	2-zimmer	deluxe	spar	meers
	2 zimmer	superior	eco	mb
	dz	penth		meerb
	2 raum	villa		sea view
	2 räume			seaview
	doppel			meer-u
	zweizimmer			
	zweibett			
	double room			
	doubleroom			
	2er			
	2 be			

Note: The indicator variable equals 1 if the variable roomCategory (converted into lowercase letters) contains one of the pre-defined text strings, and 0 otherwise. The text strings are defined according to the most frequent entries (top 100 values).

A.2 Hedonic regression models: Stability of coefficients and goodness of fit

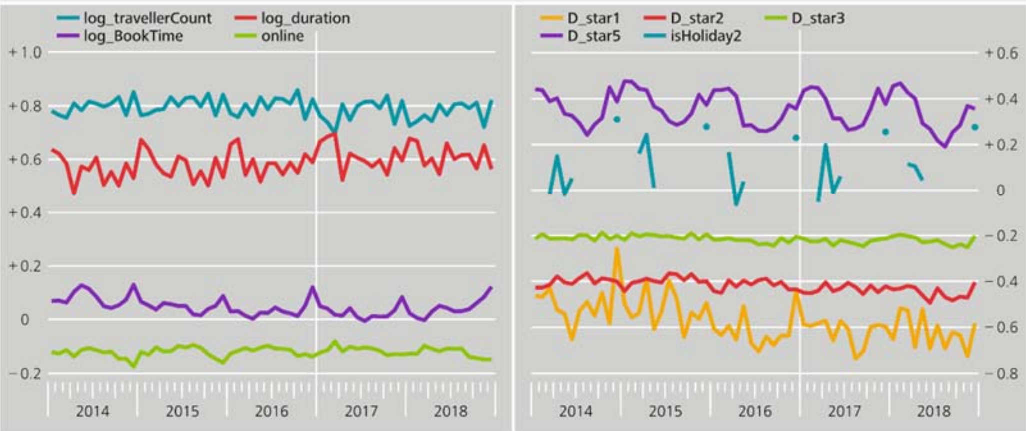
As a necessity to the hedonic regression models in Section 4.2, the resulting coefficients have to be stable and plausible from an economic perspective. Coefficients of the *double imputation* model for each of the six holiday destinations are shown in **Figure A.1**. On the left-hand side, there are the coefficients for the variables $travellerCount$, $duration$, $bookTime$, D_online and $isHoliday$. As expected, all coefficients are positive, in other words the price of a package holidays increases with the number of travellers, the duration, the number of days the package has been booked in advance and if the holiday covers a period including one (or more) public holidays. One exception is for online bookings, signalling that a package holiday booked online is on average 8.4-11.9 % cheaper (depending on the holiday destination) than a package holiday booked offline via a traditional, high street travel agency. Concerning volatility over time, it has to be kept in mind that package holidays have a seasonal pattern, which will be reflected in volatile coefficients and partly also in a seasonal pattern.[51]

[51] For Greece and Turkey, note that the magnitude of the coefficients on $travellerCount$ and $duration$ exhibit a negative correlation during the summer months. Evidently, demand (also from non-German travellers) during this period is higher for these holiday destinations, which seems to rebalance the pricing

The right-hand side of **Figure A.1** shows the coefficients for the accommodation category of the underlying hotel, as indicated by one up to five stars. The benchmark in the regression model (3) is a four-star hotel, so five-star hotels are on average expected to be more expensive, whereas one- to three-star hotels are expected to be cheaper. This condition is fulfilled for nearly all holiday destinations. Besides this, the coefficient of a three-star hotel should on average be higher than for a two-star hotel, and the coefficient of a two-star hotel higher than for a one-star hotel. For most holiday destinations, this is true, but one- and two-star hotels are not common for all holiday destinations and therefore have only a small number of observations. This is reflected in the coefficients of one-star hotels, which are not stable for the Canary Islands and Turkey; for some months, these are higher than for two-star hotels or even positive, and they also exhibit missing values. The same problem occurs for two-star hotels in Egypt and the Dominican Republic. For example, the standard deviation of the coefficient for a two-star hotel in Egypt is higher ($\sigma = 0.09$) than for a three-star hotel ($\sigma = 0.02$) or a five-star hotel ($\sigma = 0.05$). The volatility of some regression coefficients (for example two-star hotels in Egypt) has only a minor effect on the index, because its implicit weight is very small. Concerning regular statistical production, the hedonic regression model could be adapted and optimised for each holiday destination. Nevertheless, most of the coefficients are stable and show a similar seasonal pattern.

Stability of regression coefficients over time (Double Imputation method)
Canary Islands

Figure A.1



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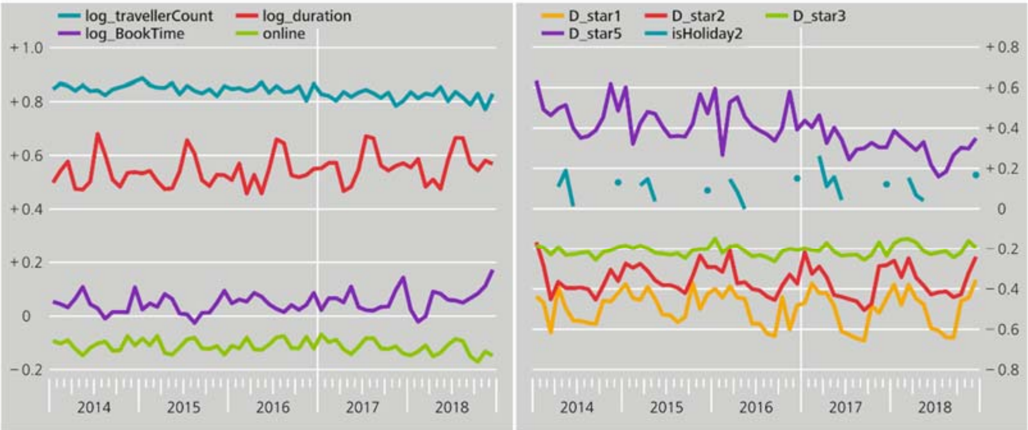
S3PR0519D.Chart

scheme of tour operators concerning an extra day of stay and the number of travellers for the package holiday.

Stability of regression coefficients over time (Double Imputation method)
Balearic Islands

Figure A.1



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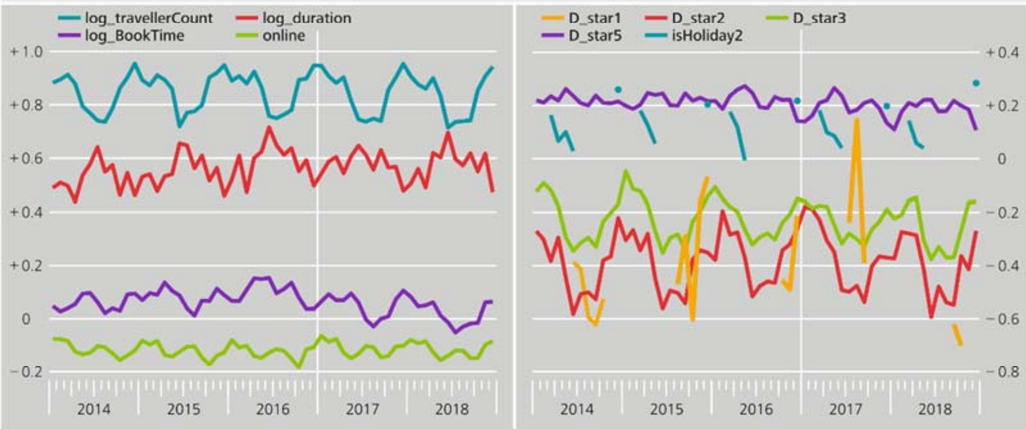
Stability of regression coefficients over time (Double Imputation method)
Turkey

Figure A.1

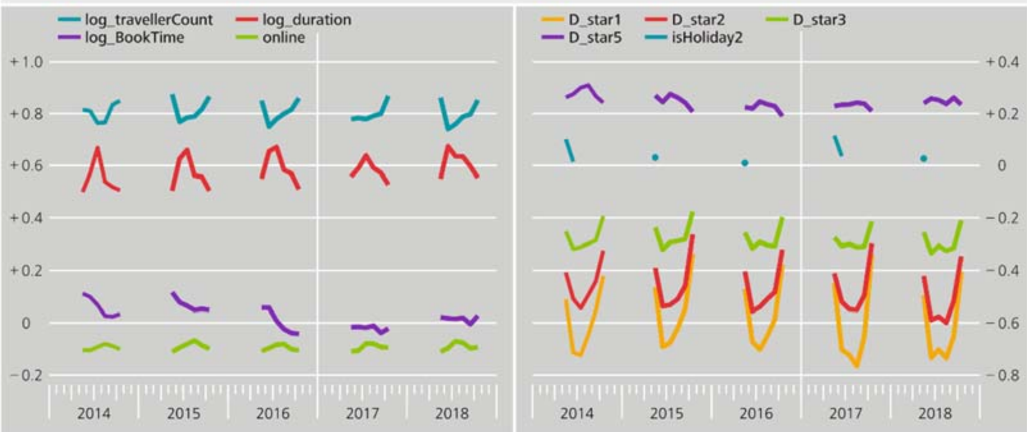


Deutsche Bundesbank

S3PR0519E.Chart

Stability of regression coefficients over time (Double Imputation method)
Greece

Figure A.1

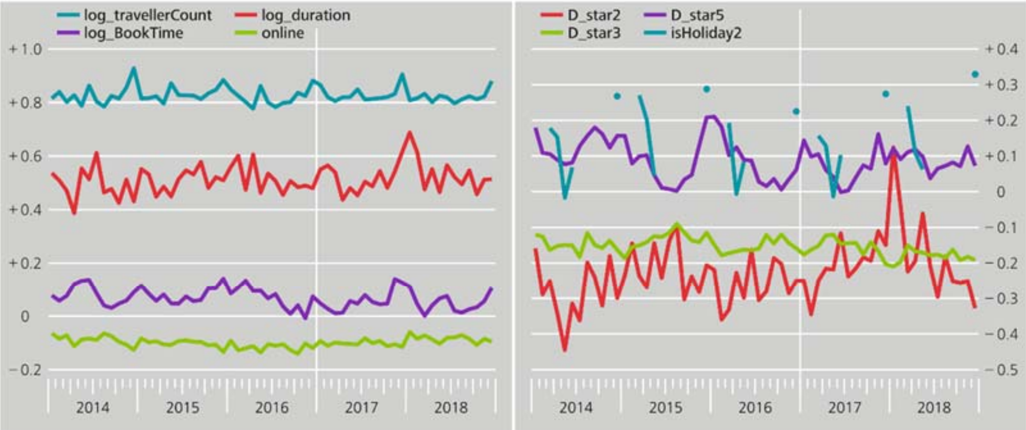


Deutsche Bundesbank

S3PR0519C.Chart

Stability of regression coefficients over time (Double Imputation method)
Egypt

Figure A.1

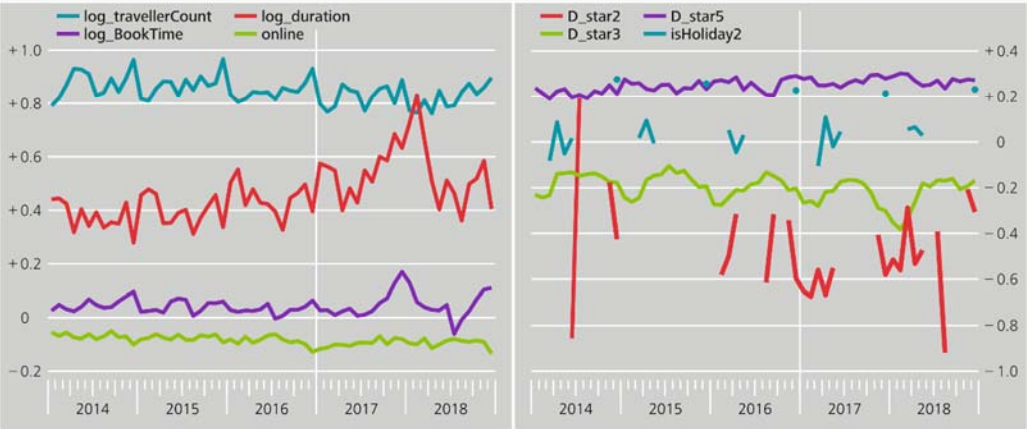


Deutsche Bundesbank

S3PR0519A.Chart

Stability of regression coefficients over time (Double Imputation method)
Dominican Republic

Figure A.1



Deutsche Bundesbank

S3PR0519B.Chart

Table A.4: Adjusted R² by holiday destination

Destination/ Method	Double Imputation		Time Dummy Model	
	Mean	Max-Min Range	Mean	Max-Min Range
Balearic Islands	0.769	0.161	0.730	0.206
Canary Islands	0.721	0.113	0.677	0.118
Turkey	0.772	0.147	0.794	0.092
Greece	0.753	0.118	0.695	0.156
Egypt	0.704	0.205	0.717	0.175
Dominican Republic	0.785	0.121	0.720	0.099

A.3 Detailed result on product definition following Chessa (2019)

Table A.5: Top 10 results of MARS for the product definition of package holidays

No. of combination	topArea	star	channel	bookTime _Class	depAirport	weekday
1	1	1	1	1	1	1
2	1	1	1	1		1
3	1	1	1	1	1	
4	1	1		1	1	1
5	1	1	1		1	1
6	1	1	1			
7	1	1	1			1
8	1	1	1	1		
9	1	1		1		1
10	1	1			1	1

No. of combination	Number of products	Mean of items per product	MARS	Homogeneity	Continuity
1	10681	193.2	0.33	0.40	0.79
2	1008	2047.5	0.33	0.35	0.93
3	1582	1304.6	0.32	0.35	0.92
4	5423	380.6	0.32	0.38	0.83
5	2752	750.0	0.32	0.36	0.88
6	36	57330.1	0.32	0.32	1.00
7	252	8190.0	0.32	0.33	0.95
8	144	14332.5	0.32	0.33	0.95
9	504	4095.0	0.32	0.33	0.93
10	1379	1496.7	0.31	0.34	0.90

Note: This table shows the top-ten results from MARS following Chessa (2019). The values of MARS are calculated as the average of 12 monthly MARS values in 2015. Combination no. 8 (highlighted in green) was taken for the main analysis in this paper.

A.4 Robustness of data filters and model specification

Table A.6: Construction of datasets (R1-R4) for robustness analysis

Data filters used / Data set	R1	R2	R3	R4
Excluding outliers as defined by the price per person per day and $duration$	X	X	X	X
German departure airports only		X	X	X
Travellers > 16 years				X
Excluding last minute bookings (within 14 days before departure)		X	X	X
Online transactions only			X	

Note: R2 denotes the baseline data set used in the main analysis of the paper. R3 (online transactions only) also includes a more detailed regression equation for *Double Imputation*, as shown in Equation (5).

Table A.7: Number of observations used

Holiday destination	Data set R2			Data set R3 (only online transactions)		
	Unit Value	Double Imp./ Time Dummy	Trad. Strat./ GEKS	Double Imp.[a)] mealType/roomType	Trad. Strat.[b)] mealType/roomType	Trad. Strat.[c)] (top 25 hotels)
Balearic Islands	491,382	470,069	446,394	129,434	118,350	70,715
Canary Island	482,836	465,688	441,382	138,697	127,716	124,569
Turkey	658,706	637,694	633,795	200,131	197,587	102,828
Greece	245,870	233,191	220,939	77,680	71,179	38,445
Egypt	282,563	267,814	267,588	94,386	94,203	122,220
Dom. Republic	50,190	47,802	47,801	14,210	14,209	32,737
Total	**2,211,547**	**2,122,258**	**2,057,899**	**654,538**	**623,244**	**491,514**

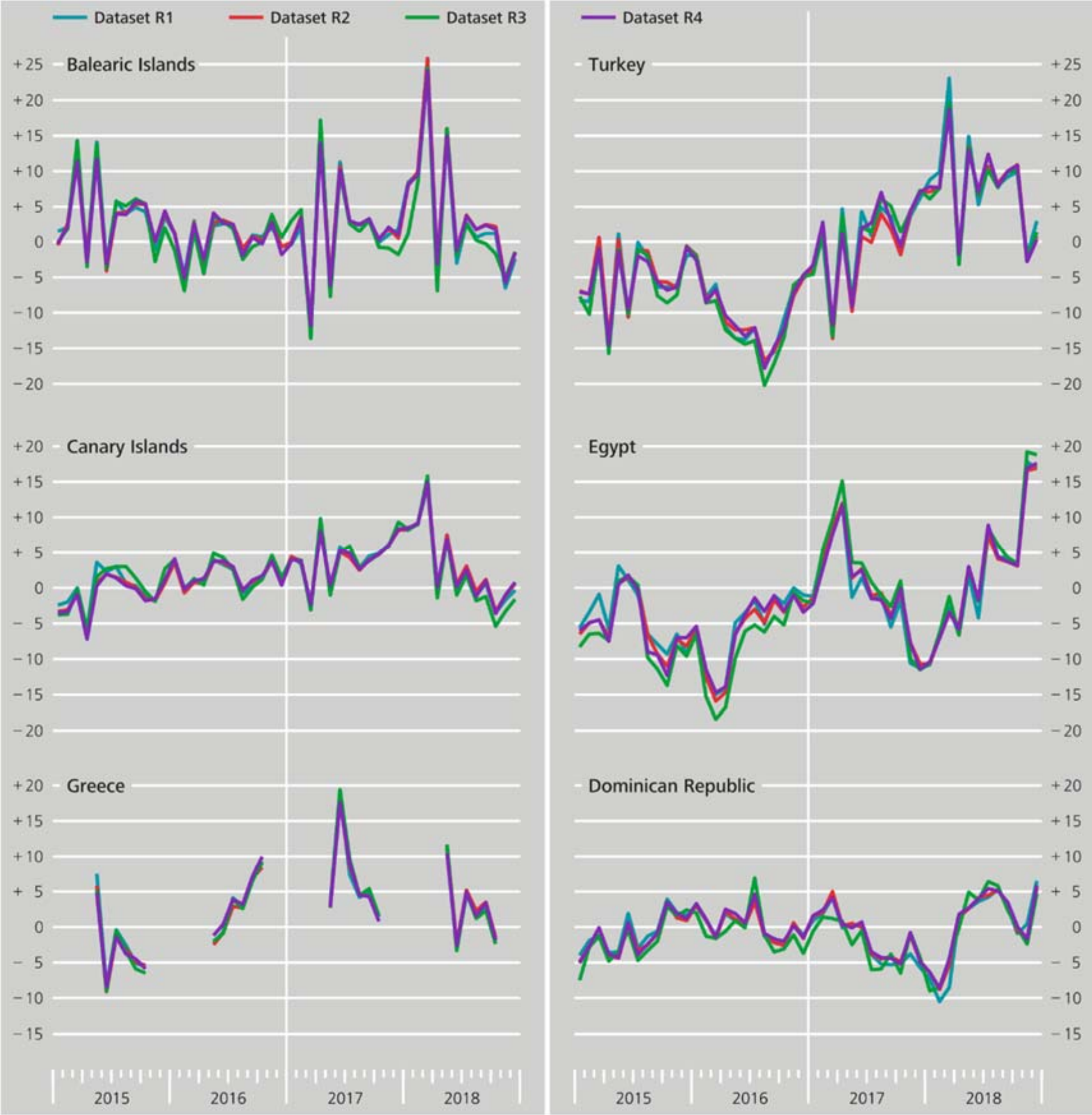
Note: a) *Double Imputation* based on the more detailed regression model in Equation (5). b) *Traditional Stratification* according to $star$, $D(seaView)$, $D(AllInclusive)$ and $bookTime\_Class$ ($M = 48$ strata). c) *Traditional Stratification* based on top 25 hotels in each holiday destination (as measured by their revenue share in 2015) according to $iffCode$ and $bookTime\_Class$ ($M = 200$ strata).

Note: See **Table A.6** for a description of the different data sets. R2 denotes the baseline data set used in the main analysis of the paper.

Comparison of the annual rates of change for Double Imputation using different datasets

Figure A 3

Percent

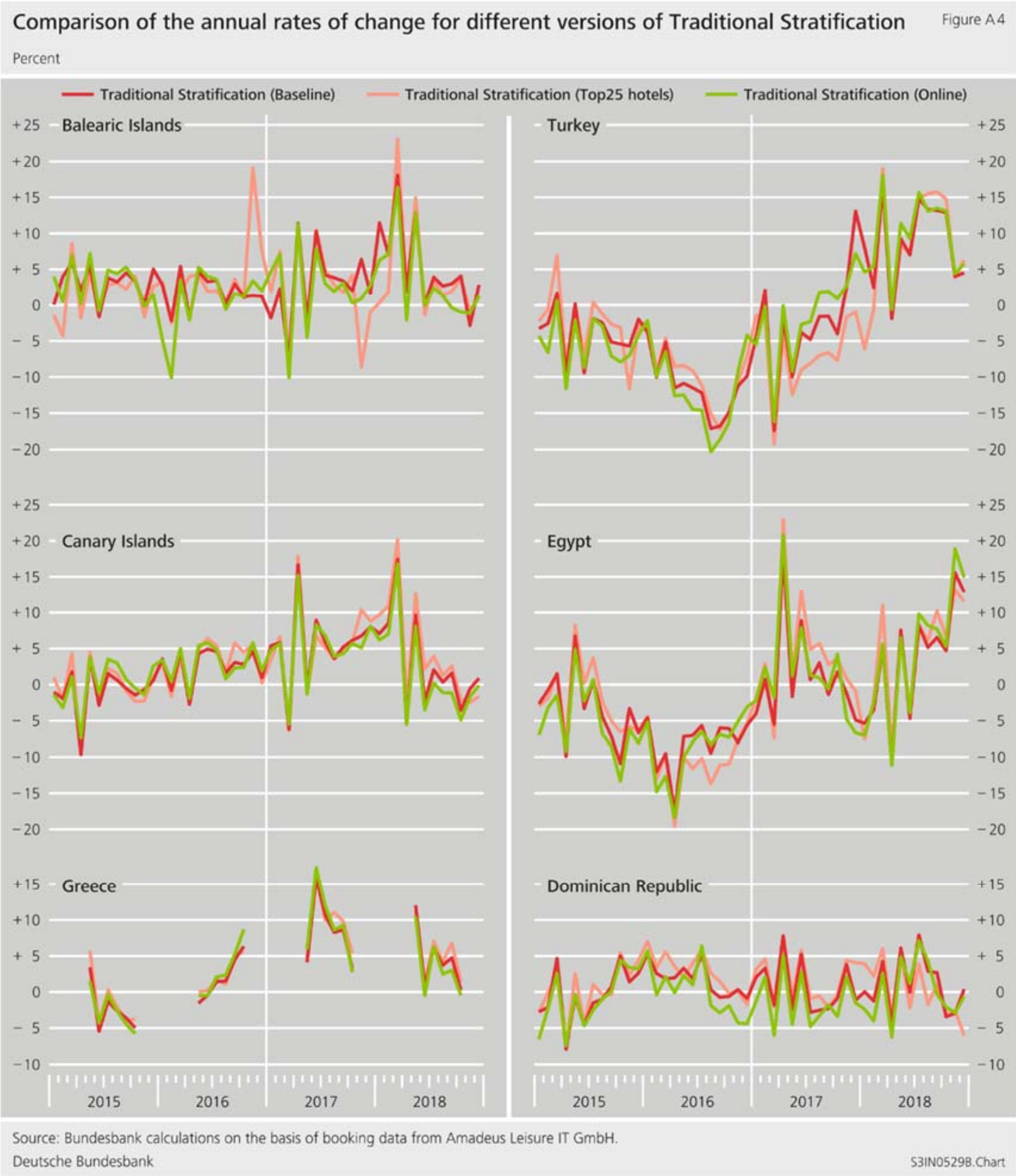


Source: Bundesbank calculations on the basis of booking data from Amadeus Leisure IT GmbH.

Deutsche Bundesbank

S3IN0529.Chart

Note: See **Table A.6** for a description of the different data sets. R2 denotes the baseline data set used in the main analysis of the paper. R3 (online bookings only) also includes a more detailed regression equation, as shown in Equation (5).



Note: The baseline index refers to the *Traditional Stratification* as used in the main body of this paper. Moreover, two alternatives are shown: i) a stratification at the hotel level (by $iffCode$, $channel$ and $bookTime\_Class$, $M = 200\ strata$) based on the top 25 hotels in each holiday destination (measured by their revenue share in 2015), and ii) a more detailed stratification by $star$, $D(seaView)$, $D(AllInclusive)$ and $bookTime\_Class$ ($M = 48\ strata$) for online bookings only.