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Abstract

This paper introduces a novel travel performance indicator derived from tourist reviews available online, utilizing text mining techniques. The time series generated is integrated as an explanatory variable into a small-scale empirical model of travel revenue and expenditure in the Czech Republic's balance of payments. The significance of online reviews for nowcasting is validated through various machine learning algorithms. The study also addresses empirical challenges, including trends in review data, the impact of the COVID-19 pandemic, and occasional methodological changes in official statistical series, and outlines strategies to overcome these obstacles. The findings suggest that the proposed model is a valuable addition to the Czech National Bank's nowcasting framework. To the best of our knowledge, this is the first study to combine text analysis with nowcasting of a BoP item, specifically travel services.

JEL Codes: C53, C83, F17.
Keywords: Balance of payments, text mining, travel services.

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1. Motivation

The growing uncertainty surrounding future economic and geopolitical developments has heightened the need for short-term forecasting techniques and increased demand for data sources that are available with minimal lag or in real time. Over the past few decades, nowcasting models[1] have gained widespread popularity, particularly in macroeconomic forecasting. These models are based on constructing a macroeconomic dataset that is correlated with the target variable but can be accessed with a shorter publication delay or at a higher frequency. When appropriate explanatory variables are selected, dynamic estimation procedures can provide quick, reliable, and unbiased forecasts for very short time horizons. As a result, nowcasting has become a crucial tool for central banks and empirically driven researchers, particularly for real-time GDP growth forecasts.

Recent advancements in big data processing techniques have opened new opportunities for nowcasting applications. Although nowcasting is designed to be an automated procedure that can generate forecasts almost instantaneously, the macroeconomic indicators used as independent regressors are often published with a delay. In this context, text mining offers a significant advantage, enabling researchers to develop their own data collection algorithms and update forecast indicators in real time. This is particularly valuable for forecasting exercises conducted on a fixed schedule. For instance, at the Czech National Bank (CNB), forecasts are prepared quarterly and published shortly after the monetary policy meetings of the Bank's board.

This research aims to develop a two-stage nowcasting model for travel revenue and expenditure by combining text mining techniques[2] for data collection with machine learning methods for the estimation process. Our primary focus is on travel services data from the Czech Republic's balance of payments (BoP). In the first stage, we apply a text mining procedure to scrape web reviews related to travel services, transforming them into a time series indicator that reflects Czech inbound and outbound tourism. In the second stage, we employ several machine learning models—using our newly constructed Google reviews indicator—to produce nowcasts for the unobservable first quarter. Travel services is one of the variables the CNB regularly estimates as part of its quarterly BoP forecast. By utilizing alternative data sources with no publication delay, this model has the potential to enhance the accuracy of near-term forecasts for this current account item.

Our contribution to the economic literature is twofold: (i) the development of a new leading indicator for travel based on text mining, and (ii) the introduction of a novel model for nowcasting travel in nominal terms. Our goal is to find an easily collectible and free-of-charge high-frequency indicator for travel services and to use it to build a monthly-frequency model that provides insights about short-term travel services dynamics. In this way, we hope to improve the accuracy of the preliminary data. The challenges posed by data limitations may explain why nominal trade has historically received limited attention from forecasters, and travel services is no exception. To the best of our knowledge, very few nowcasting models have focused on travel, and those that do typically rely on volume indicators such as the number of tourist arrivals. This study is the first to propose a quarterly nowcast for travel services in value terms.

We demonstrate that the newly developed indicator has good nowcasting properties. However, its application is not without challenges. First, prior to the COVID-19 pandemic, the number of online reviews followed a clear upward trend, likely due to the gradual adoption of information

[1] Nowcasting means the prediction of the very near future. For data available with a lag, nowcasting could also denote current period forecasting or backcasting.
[2] Text mining, or data mining, is an automatized process for extracting particular information from a large number of texts available electronically.

technologies such as smartphones, which made writing reviews more accessible and convenient. Second, the pandemic caused significant disruption to international travel.[3] This had a direct impact on the corresponding BoP series. Finally, periodic methodological changes in the official time series present additional complexities. Our econometric approach is designed to address these issues, and we show that text mining offers a promising tool for nowcasting travel services in BoP statistics. By improving the forecasting of this component, our model can contribute to the broader current account forecast[4] regularly produced by the Czech National Bank.

The remainder of the paper is organized as follows. The next section provides an overview of relevant literature on the application of text mining in nowcasting. Section 3 describes the data used in the study: the nowcasted series, the main explanatory variable (the number of reviews), and additional data that we use. Section 4 presents the econometric model and the results. Finally, section 5 concludes, and additional materials are provided in the Appendix.

2. Literature Review

Web-based data has become a valuable tool for nowcasting macroeconomic variables, offering timely, granular, and diverse insights into consumer behavior and business activity. Various platforms offer vast amounts of user-generated content, including ratings, comments, and visit patterns, which can serve as proxies for economic indicators such as consumer confidence, retail sales, and tourism flows. For example, positive sentiment in reviews may correlate with higher spending, while changes in visit frequency to specific business categories could indicate shifts in economic activity. Unlike traditional economic data, which often come with significant publication lags, these sources provide data in real time, making them effective supplements for nowcasting and forecasting models used by policymakers.

Web-based data has proven useful across a wide range of applications for empirical analysis. Classical references include Varian (2014) and Choi and Varian (2012). Contemporary applications extend to nowcasting economic activity (Glaeser et al., 2017), unemployment (Aaronson et al., 2022; Mulero and Garcia-Hiernaux, 2023; D'Amuri and Marcucci, 2017), and prices or inflation (Seabold and Coppola, 2015; Bleher and Dimpfl, 2022). Information collected from the web has also been applied to nowcasting specific economic variables, such as car sales (Fantazzini and Toktamysova, 2015), monetary policy spillovers (Wohlfarth, 2018), migration (Avramescu and Winiowski, 2021; Bronitsky and Vakulenko, 2024), and microeconomic consumer choices (Yalcinkaya and Just, 2023). Nevertheless, Fenga (2020) warns that web-based data should be used with caution, as they may present numerous sources of uncertainty and instability, based on technical, psychological, and linguistic factors.

In the context of tourism, web data has been used primarily to nowcast and forecast metrics such as hotel occupancy and the number of tourist arrivals. Some studies were conducted during the pre-pandemic period, i.e., prior to spring 2020, while the sample of other studies incorporates the COVID-19 pandemic.

[3] Tourism was among the industries most affected worldwide by the COVID-19 pandemic. It took five years to return to the 2019 level. According to UNWTO estimated figures, global tourist arrivals reached about 99% of the 2019 level in 2024, while nominal receipts from tourism slightly surpassed that level in 2023 and continue to grow. Czech travel services follow roughly similar patterns.
[4] The general principles of the current account forecasting model are described in Babecká Kucharčuková and Brůha (2020).

For studies based on data before spring 2020, structural breaks due to the pandemic were not an issue. One early contribution, Antolini and Grassini (2019), employed Google Trends data to predict tourist arrivals in Italy. Similarly, Cevik (2020) used internet search data to forecast arrivals from the U.S. to the Bahamas, demonstrating that such data outperformed not only purely statistical models, but also models incorporating macroeconomic data such as U.S. personal income and real exchange rates.

More recent studies include the pandemic period. For instance, Rashad (2022) used Google data to forecast UK visitors to Dubai, controlling for the pandemic with a dummy variable. Their model also included GDP growth, real exchange rates, and lagged dependent variables. Zhang and Lu (2022) analyzed hotel room demand in Hong Kong during the pandemic using an autoregressive lag model and simulated various pandemic scenarios. Their model incorporated hotel room rates and exchange rates as determinants. A more involved approach to addressing structural uncertainty was adopted by Liu et al. (2024), who used time-varying parameter models to forecast tourist arrivals in Hainan province.

While most studies focus on real quantities, a limited number—which are more relevant for our research—target nominal variables. For example, Ting et al. (2022) used real-time tourism data from Google Trends to nowcast service consumption in Taiwan. They constructed diffusion indexes from various keywords and employed a dynamic factor model. However, their sample (2004–2020) does not address whether the empirical model's coefficients were stable before and during the pandemic.

In summary, web-based data have been applied to predict various tourism-related indicators, predominantly focusing on real quantities. Significant differences exist among studies in terms of methodological sophistication, the variables included, and the treatment of structural instability. This is the inspiration for our research, which targets an indicator—balance of payments (BoP) travel services—in value terms. We explicitly control for potential instability and focus on variables available with minimal publication delays, hence excluding data such as GDP growth and personal income. Detailed discussions of the variables selected for our model are presented in the following section.

3. Data Description

3.1 How to Measure Travel Performance from a Country Perspective

International tourism can be measured in nominal terms, i.e., as the amount of money spent by a resident of a given country abroad,[5] as well as in volume terms—using statistics on arrivals, the number of nights spent at a hotel, and survey and other sources. While recording money flows in the Czech Republic is the responsibility of the Czech National Bank (CNB), volume indicators are

[5] All transactions recorded in the BoP statistics are transactions between residents and non-residents. In the case of travel, it is permanent residence that determines which transaction is considered "domestic" or "foreign." Obviously, most of a country's residents have citizenship of that country, so citizenship can be used as a proxy when information about residence permits is not available. Hence, for simplicity, some terms in this paper are used with minor inaccuracies: "foreigner" means a non-resident and "Czech" denotes a Czech resident, while "travel" and "tourism" are used as synonyms. Note also that the definition of "travel" in the balance of payments statistics is much wider than the traveling and recreation usually associated with the term. It includes private trips for treatment and recreation and visits to relatives (all considered personal travel), as well as studying (comprising school fees and scholarships), short-term business trips and congress tourism, and trips undertaken by seasonal cross-border workers (all considered business travel). The share of business travel is usually much lower than that of personal travel.

Table 1: Overview of Tourism Indicators Available for the Czech Republic

Tourism indicator (source)	Frequency	Latest data*	Published	Lag
Hotel occupancy** in the Czech Republic (CZSO) - Number of guests - Number of guest overnight stays - Average length of stay	monthly	6/30/2025	8/8/2025	39 days
Domestic and outbound tourism of Czech residents (CZSO) - Number of trips (including abroad) - Number of long trips - Number of short trips - Number of business trips - Trips by destination (in CZ, abroad) - Average expenditure per long/short trip, trip with/without overnight stay	quarterly	3/31/2025	6/30/2025	91 days
Tourism services. Total and by geographical breakdown, Balance of Payments Statistics (CNB) - Revenues—non-resident spending in CZ, nominal, CZK - Expenditures—resident spending abroad, nominal, CZK	quarterly	1Q 2025	6/13/2025	74 days
Air passenger transport by type of schedule, transport coverage and country (Eurostat) - Number of passengers, all nationals—arrivals - Number of passengers, all nationals—departures	monthly	1Q 2025	8/18/2025	199 days
Tourism Satellite Account (CZSO), without resident/non-resident breakdown - Share of tourism in GDP, GVA, employment - Consumption (expenditure) by type of tourism	annual	12/31/2023	2/28/2025	> 12 months
Report based on GSM data (tourdata.cz)	one-off	Jun–Jul/2024	2025	—
Prague Airport—press releases	irregular			

* as of Sep 1, 2025
** the same data are available for the occupancy of all collective accommodation establishments

published by the Czech Statistical Office (CZSO).[6] The two institutions work with each other. The CNB's statistical department also uses CZSO statistics for cross-checking data, in addition to its own data sources, which consist of—among other things—payment card transaction records and information from exchange offices. Data on other services is also helpful. Specifically, information about traveling abroad is checked and completed using transportation statistics.

On top of this, the CZSO estimates the economic importance of the tourism industry within the Tourism Satellite Account framework[7] and publishes information such as gross value added and employment in the Czech tourism industry (domestic and inbound tourism). The data from the Tourism Satellite Account is available at yearly frequency and therefore cannot be used for nowcasting monthly BoP series (see Table 1).

[6] Czech Statistical Office: `https://csu.gov.cz/tourism`
[7] available at `https://csu.gov.cz/tourism_satellite_account`

In our analysis, we are interested primarily in travel credits and debits in the Czech BoP statistics. The credit side of travel services records the expenditure of non-residents in the Czech Republic, or, in other words, receipts from inbound tourism. Since the Czech economy receives money (foreigners pay for services), such transactions for the Czech Republic are treated as revenues or exports. The same logic is applicable on the debit side of travel services, i.e., the expenditure of Czech residents abroad—from the Czech perspective, outbound tourism is treated as spending or imports. The territorial structure also matters. By and large, the more tourists that visit a country, the more money the country receives. However, tourists from countries with higher (lower) income per capita than the Czech Republic may have higher (lower) expenditure per capita than Czechs abroad. The purpose of tourism also matters: while sightseeing tours make up a significant proportion of tourism to the Czech Republic, Czechs go abroad mainly to the seaside. This asymmetry in travel flows speaks for separate analyses of the credit and debit sides.

The asymmetric structure also contributed to a travel surplus in the pre-COVID years. Before the outbreak of the COVID-19 pandemic, the tourism balance was a significant contributor to the overall current account balance. At that time, the positive tourism balance amounted to roughly one third of the total services surplus and about one tenth of the goods and services surplus. Due to ever-increasing dividend outflows, the current account surplus was low, and the positive travel balance was thus beneficial in terms of the external balance. The anti-epidemic measures hit travel revenue and expenditure hard, with inbound travel falling more than outbound travel. The suspension of long-haul air transport contributed significantly to this, in the context of the different territorial structure of travel revenue and expenditure (see Babecká Kucharčuková and Žd'árský (2022) for more details). As a result, the significant positive contribution of travel services to net exports evaporated in the first year of the pandemic and still is hovering around zero (see Figure A2 in the Appendix).

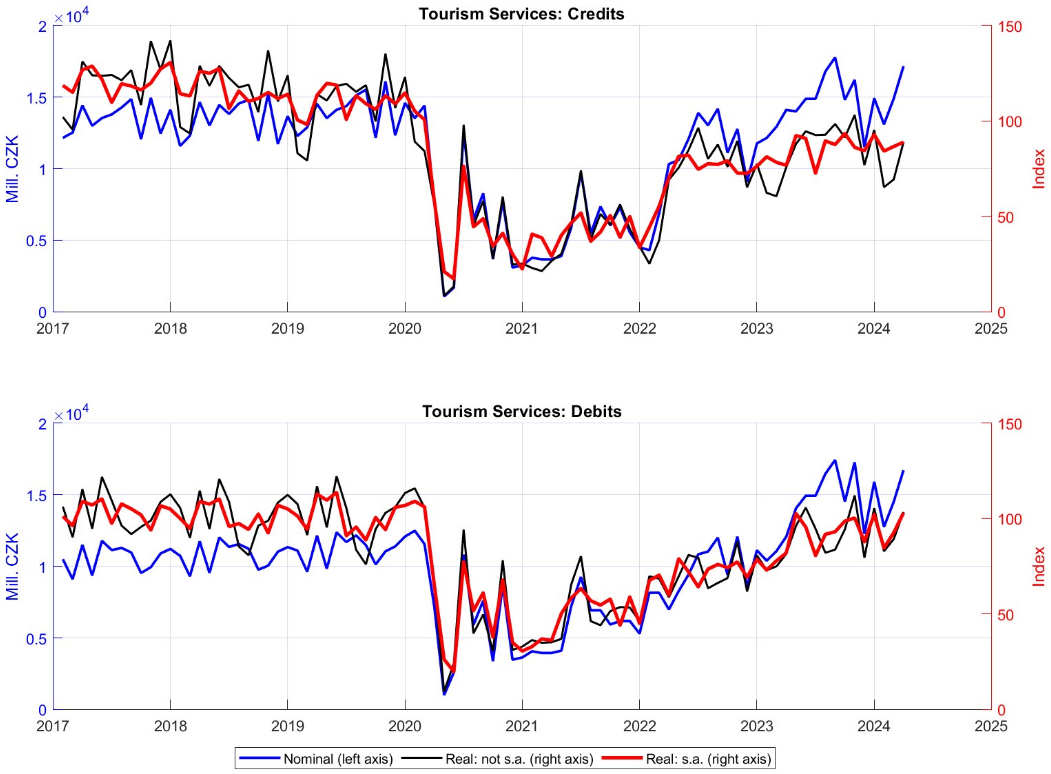
3.2 BoP Travel Services Data

Detailed data on the BoP for trade in services is available at quarterly frequency and can be accessed through the publicly available CNB database, ARAD, with a publication lag of approximately 75 days. Each quarterly figure undergoes revisions between one and seven times. Monthly data for the latest observable quarter are revised retrospectively at the time of the quarterly data release, which takes place one month after the complete monthly data for that quarter becomes available.

For the nowcasting model, we use monthly travel revenues (credits) and travel expenditures (debits) in CZK. The estimation covers the period from January 2017 to June 2024. The time series we aim to nowcast are published in nominal terms and are not seasonally adjusted. There are no official seasonal adjustments or price i ndexes available for these series, even at lower frequency. To address seasonality, we apply the STL seasonal adjustment method (Cleveland et al., 1990) and use two Harmonized Index of Consumer Prices (HICP) indexes to convert the time series into real terms—the *package domestic holidays* index for the credit side and the *package international holidays* index for the debit side. These indexes are sourced from Eurostat.

Figure 1 displays the original official series (in blue, left-hand scale), the real deflated series (in black, right-hand scale), and the real seasonally adjusted series (in red, right-hand scale). The real seasonally adjusted series enter our nowcasting model. After the nowcasting is done, the series are transformed back to nominal unadjusted levels.

Figure 1: Travel Services Credits and Debits



3.3 Text Mining Data

High-frequency leading indicators for travel data can be obtained in several ways. We intentionally focus on on-line sources to test how informative they could be for our research. We search for information that is closely correlated with travel expenditure, is easily accessible, and is available with the shortest possible delay. In this respect, online customer reviews represent an interesting case study.[8]

Online customer reviews first appeared 30 years ago.[9] Since then, their popularity has increased steadily. The development and success of customer reviews have been supported by continuous technical improvements to this service (by sellers and major search engines), the steadily increasing availability and accessibility of the internet (ensured by internet providers), and the expansion of online social networks (reflecting the growing attractiveness and importance of online communication).

Nowadays, tourists' activity can be traced through search engines and web applications such as Tripadvisor, Airbnb, Booking.com, Uber, Mapy.com, and many others. In order to avoid double

[8] Another possibility to obtain high-frequency and short-delay data is the analysis of payment card transactions (Crispino and Mariani, 2023). Although this is a very attractive source of information, the data are neither easily accessible nor free of charge.
[9] Amazon introduced this service in 1995; see https://www.aboutamazon.com/news/amazon-ai/amazon-improves-customer-reviews-with-generative-ai, an online article published on August 14, 2023. To the best of our knowledge, this is the earliest evidence of a customer or product review.

counting, we looked for a single web tool that gathers a large amount of information and is well known to both foreign and Czech tourists. In this respect, we excluded Mapy.com, which lacks reviews from outsiders, as well as Tripadvisor, which does not provide enough reviews from Czech users. We also need to differentiate tourists by nationality, which is possible on Booking.com. However, data collection is not straightforward on Booking.com and Airbnb because information about a particular property may be hidden at any time once it is fully booked. All things considered, the most suitable platform for our analysis is Google Maps, which provides a fairly large dataset that covers both Czech tourists abroad and foreign tourists visiting the Czech Republic.

In order to transform reviews into leading indicators, we need to collect at least three parameters: when the review was published, how many people wrote a review during a given period, and the nationality of the reviewers. Then, by counting the reviews by date, and separately for Czech nationals and foreigners, we obtain two Google review indicators to serve in our econometric analysis as leading indicators for BoP travel services: one for debits (Czech reviews) and the other for credits (non-Czech nationals' reviews).

Similar to the BoP data, Google reviews were collected for the period from January 1, 2017 to June 30, 2024. This starting date was chosen for several reasons. First, it was necessary to cover the period before, during, and after the COVID-19 crisis, i.e., to make the sample as long as possible. At the same time, going further into the past would have brought with it the problem of missing data for certain locations and places, especially for Czech-written reviews abroad, which are not the most popular among Czech citizens. These reviews retrieved from Google Maps are written by people for specific places and rated using symbols (stars) or verbal ratings. Google Maps contains millions of reviews for millions of places around the world.

The Outscraper.com[10] program was used to obtain the necessary input to our Google review indicators. It collects information based on the texts of individual reviews and relevant metadata information: review id, review location, user id, and others.[11] We searched for all kinds of reviews—positive, negative, and neutral. The context is not important for the analysis; it is the number of reviews over a given period that matters.

The text of the review serves solely to distinguish Czech reviewers from other nationals. As long as there are no review attributes directly linked to the author's nationality, we search for specific words that could indicate the Czech language. In this respect, words such as "hotel," "menu," "auto," and "taxi," which appear in many languages, are poor candidates, as are words with different meanings in Czech and other languages but written similarly: for instance, "host" in Czech means "guest," "pension" refers to a "guesthouse," and "smoking" denotes a men's formal suit. Last but not least, the words should be frequently used by reviewers. Thus, two keywords were selected: "místo" ("place," "location") and "jídlo" ("food," "meal," "dish," or "course"). They were applied to count all reviews about places outside the Czech Republic. As for the Czech locations reviewed, all contributions written in Czech were removed from the analysis. Here, we can assume that most reviews written in the Czech Republic in a language other than Czech will not be written by a citizen of the Czech Republic living here.

[10] https://outscraper.com/

[11] For this analysis, the key parameters were the query (query), the name of the place (name), the ID of the place to which the review belongs (place_id), the ID of the review itself (review_id), the text of the review itself (review_text), and the time with the date of the specific review (review_datetime_utc).

The location selection criteria differ for reviews by foreigners in the Czech Republic and Czech citizens abroad. For inbound tourism, the 21 most visited places in the Czech Republic with the highest number of reviews were selected, most of them situated in Prague, Kutná Hora, or Český Krumlov. Among them are popular cafés, restaurants, and hotels, historical monuments, Prague Zoo, and other attractions, as well as Václav Havel Airport. In total, this resulted in more than 112,000 reviews in languages other than Czech.

While the Czech Republic is attractive from the perspective of sightseeing tours, Czechs primarily travel to seaside destinations such as Croatia, Italy, Bulgaria, Egypt, and Greece. The locations visited by Czech tourists were therefore determined based on the most popular holiday destinations, reflecting the asymmetry between inbound and outbound tourism.[12]. In addition, other countries and locations were included to capture Czech tourists' journeys outside the summer tourist season. Thus, reviews from winter resorts, exotic destinations, and major European cities were also analyzed. We collected more than 44,000 reviews.

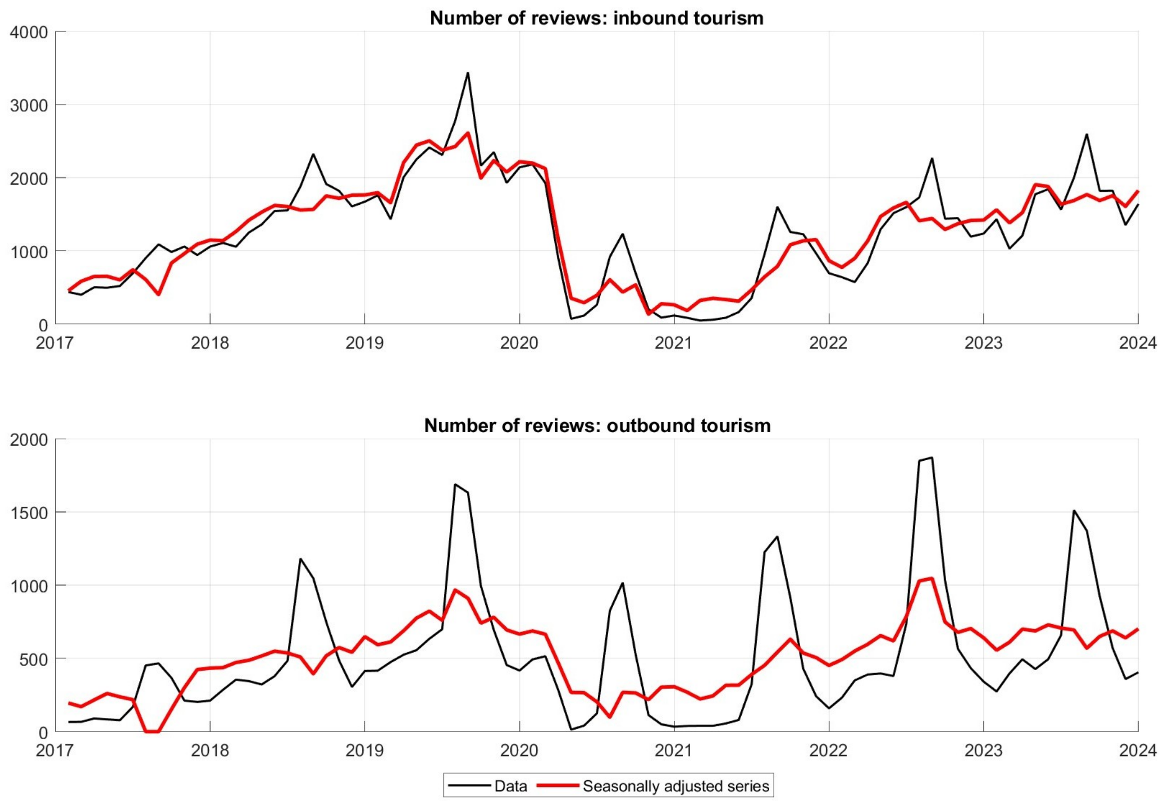
For two specific locations,[13] the necessary data from January 1, 2017 to August 11, 2018 and from January 1, 2017 to August 5, 2017, respectively, were missing. This problem was solved by imputing the missing data. The imputation was simply based on the number of reviews for the listed venues and the percentage change of all other venues for the given periods. Thus, the missing data in specific months was calculated as the number of reviews multiplied by the ratio of the number of reviews for the previous period. For example, for January 2017, 38 reviews were imputed for Restaurant U Fleků. This figure was based on the number of reviews for January 2018 multiplied by the year-over-year change (0.38) in all reviews for all locations for the same period. As the total number of reviews imputed was 2,923, the impact of the imputed data was not material to the overall analysis.

The time series of the number of reviews for both sides are displayed in Figure 2. The reviews exhibit a clear seasonal pattern, so we use the same seasonal adjustment as for the BoP series. The number of reviews exhibits clear upward trend prior to 2020, a drop during the pandemic, and then a slow recovery.

How do these data relate to the official BoP series? First, we compute the raw correlation between the two series. The correlation coefficient for the credit side (inbound travel) is 0.53 (significant at 1%), while that for the debit side is 0.26 (significant at 5%). Given the structural breaks in the series, we consider the correlation to be high. Nevertheless, to address the dramatic impact of the pandemic on tourism and the slow upward trend in the number of reviews before 2019, we compute a simple time-varying measure of correlation using exponential forgetting. Figure 3 displays both the full-sample correlation and an exponentially weighted measure of time-varying correlation.[14] Obviously, the time-varying correlation is weakest for the beginning of the sample, where the number of reviews was likely rising due to diffusion and the growing adoption of smartphones in the population. From 2022 on, the correlation seems high and stable.

[12] This can be found in OBIEE—the publicly available database of the Czech National Bank or the Czech Statistical Office.
[13] Restaurant U Fleků and Prague Zoo.
[14] The time-varying correlation is estimated using an exponentially weighted covariance estimator with decay factor $\lambda = 0.95$; see, for example, RiskMetrics Group (1996).

Figure 2: Number of Reviews



3.4 Additional Data

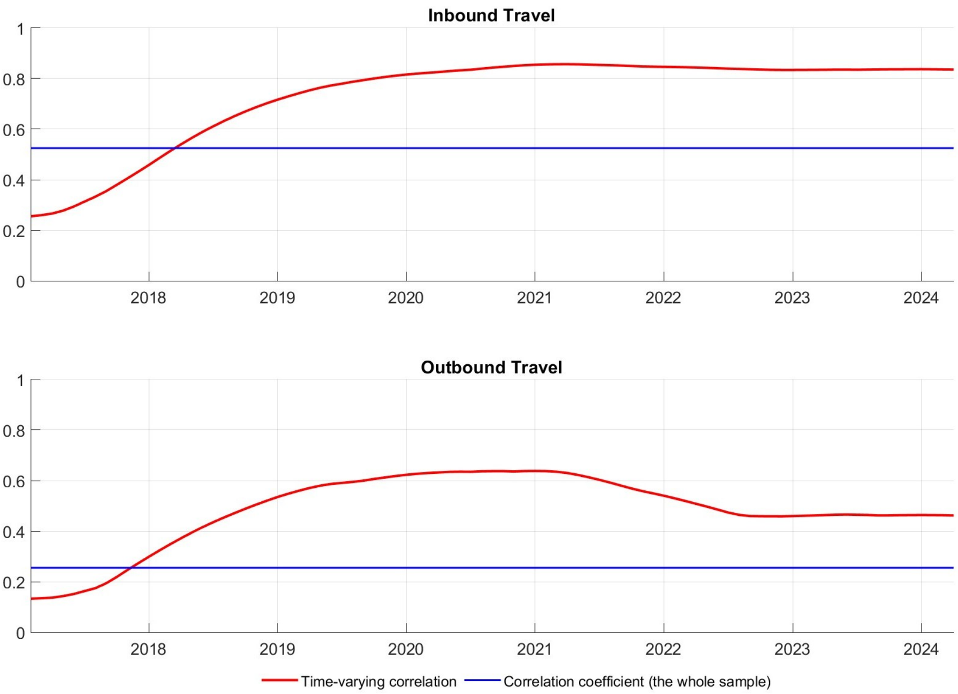
The number of reviews alone may not be sufficient to reasonably nowcast travel revenue and expenditure. We therefore carefully select candidates for other controls.[15] There are several reasons for this.

First, our sample includes the period of the COVID-19 pandemic. Governments in most countries reacted by introducing a number of measures that *inter alia* restricted the movement of people. International travel both for tourism and for business trips was restricted partly due to the anti-pandemic measures and partly voluntarily. Some tourism activities were realized in the home country rather than abroad. To deal with this, we use the **stringency index**—see Mathieu et al. (2020)—to measure the severity of the restrictions. The stringency index is a standard measure.

One may wonder whether the decrease in the number of reviews is sufficient to capture the decline in travel (as implicitly assumed by, for example, Ting et al. (2022)). There is reason to conjecture that the elasticity of the decrease in the number of reviews may be different from that of travel. This could be due to psychological factors: if traveling is scarce, one may be more inclined to write a review on each occasion compared to when one travels frequently. It is then an empirical question

[15] In the next section, we consider a set of methods, such as Lasso, that can help in selecting relevant regressors. Although very useful, these techniques are not a magic wand, as they fail to find the appropriate model if one enters everything possibly related to the procedure. This has been noticed by practitioners and is confirmed by recent research; see, for example, Shen and Xiu (2024). Careful preselection of predictors thus seems to be necessary.

Figure 3: Correlation between Reviews and the BoP Series



whether the inclusion of the stringency index is necessary. Our empirical results in the next section show that this is indeed the case. This is similar to the findings of Rashad (2022). However, unlike in that study, the stringency index is used as a continuous indicator to capture the intensity of travel restrictions, while Rashad (2022) uses a dummy variable.

Third, some studies identify additional variables that can help explain the tourism indicators. In our paper, we consider only those which become available with a small publication lag. Hence, we exclude indicators such as real GDP and personal income or consumption. Based on our reading of the literature (see section 2), we consider the inclusion of two of them: the economic sentiment indicator and the real exchange rate. For the debit side, we use the Czech sentiment indicator, while for the credit side, we employ a weighted average of the sentiment indicators of European countries.[16] The real exchange rate is deflated by the same price indexes as those used to construct the "real" BoP series on travel services (see subsection 3.2).

Fourth, there is a **clear upward trend in the number of reviews** prior to the pandemic. This trend is due to the learning process whereby people started to use IT, mainly smartphones, that made writing reviews more convenient. This upward drift ended around the pandemic and did not continue after it. The fact that the drift did not continue after the pandemic can be explained by sufficiently profound penetration of IT and people's experience gained during the pandemic.[17] See section 4 for its specification.

[16] This may be imperfect, as foreigners from other countries may travel to Czechia. The advantage of using just EU sentiment indicators is their common methodology. In previous versions, we also tried to include various US and global sentiment indicators. Conditional on using the European ones, these did not prove useful.
[17] Indeed, there is ample evidence that the pandemic was a trigger for going on-line—for working, shopping, and even leisure activities. The evidence also suggests that a significant part of this effect has been permanent. For the case of the Czech Republic, see, for example, Brůhová Foltýnová and Brůha (2024).

Finally, there are **occasional changes in methodology** for the official series. These methodological changes stem from changes in the CNB's internal model. One such change took place in 2022 and resulted in a structural break in the time series, as the series were not back-recalculated. To deal with this issue, we introduce a dummy variable for observations after 2022.

The last two variables are considered to capture unmodeled trends. The reader may wonder whether the use of a time-varying parameter model, as in Liu et al. (2024), would be preferable to the inclusion of these trends. We explore this possibility in the next section.

4. Econometric Analysis

Our empirical framework is based on the relationship between web reviews and travel services. In general terms, the framework reads as follows:

$$y_t = \mathscr{M}(\mathscr{R}_t, \mathscr{X}_t, \beta), \tag{1}$$

where y_t is the nowcasted variable, $\mathscr{R}_t$ is the number of reviews, $\mathscr{X}_t$ is the vector of additional controls, $\mathscr{M}$ is the empirical model, and β are parameters.

We consider two sets of the nowcast model. The first set contains models with time-invariant parameters, where we capture the pre-COVID trend and methodological changes using trend and time dummies. The models in the second set are estimated without these variables, but the parameters are allowed to vary in time.

The models depend on parameters β, whose estimation may depend on one or more hyperparameters ϑ. The model parameters estimated using the information available at time t are then a function of data $\mathscr{D}_t = (\mathscr{R}_t, \mathscr{X}_t)$—composed of the reviews $\mathscr{R}_t$ and the other controls $\mathscr{X}_t$—and the hyperparameters ϑ: $\beta_t = F(\mathscr{D}_t, \vartheta)$. The parameters estimated in real time thus vary even if the underlying model is time-invariant, as the data available change. To set the hyperparameters, we do a standard out-of-sample exercise over a grid of possible values and we choose the one with the lowest RMSE.[18] In more detail, let $y_{t+1|t}(\beta, \mathscr{M}) = y_{t+1|t}(F(\mathscr{D}_t, \vartheta), \mathscr{M}) \stackrel{def}{=} \mathscr{M}(\mathscr{R}_{t+1}, \mathscr{X}_{t+1}, F(\mathscr{D}_t, \vartheta))$ be the forecast of the variable y_{t+1} given the estimate based on the information available at time t, given the hyperparameter ϑ, and given a model $\mathscr{M}$. The pseudo real-time out-of-sample RMSE is then:

$$\text{RMSE}(\vartheta, \mathscr{M}) = \sqrt{\frac{1}{T-\tau} \sum_{t=\tau}^{T} \Big(y_{t+1} - y_{t+1|t}(F(\mathscr{D}_t, \vartheta), \mathscr{M}) \Big)^2},$$

and for the model $\mathscr{M}$ we choose the hyperparameter ϑ^* such that:

$$\vartheta^*_{\mathscr{M}} = \arg\min_{\vartheta \in \Theta} \text{RMSE}(\vartheta, \mathscr{M}).$$

[18] Surprisingly, a sizeable proportion of the studies that employ machine learning techniques for nowcasting do not report how the hyperparameters were set. Another significant part of the studies just use the default values available in statistical libraries. We do not use this option, as the default values (even if present) may differ across the various libraries. We thus select the hyperparameters in a data-driven way.

τ is the starting period (in our paper, we chose $\tau = 24$, i.e., the first two years of the sample) and Θ is the set of admissible values for the hyperparameters.

Furthermore, we evaluate the forecast accuracy of the machine learning models considered relative to the standard benchmark, ARIMA. To formally assess differences in predictive performance, we apply the Diebold and Mariano (1995) test under two alternative loss functions. Specifically, we consider the quadratic loss (L^2) criterion, which emphasizes larger forecast errors by penalizing them more heavily, as well as the absolute loss (L^1) criterion, which provides a more robust measure against outliers. This dual approach allows us to examine whether the proposed models deliver significantly improved accuracy across different evaluation metrics.

4.1 Time-invariant Models

First, we consider models with time-invariant parameters. They read as follows:

$$y_t = \beta_0 + \beta_1 \mathscr{R}_t + \beta_2 \mathscr{S}_t + \beta_3 \mathscr{I}_{t\geq 2022} + \beta_4 \mathscr{T}_t + \mathscr{X}_t \beta_r + \varepsilon_t, \tag{2}$$

where y_t is real seasonally adjusted travel expenditure, $\mathscr{R}_t$ is the number of reviews, $\mathscr{S}_t$ is the stringency index, $\mathscr{I}_{t\geq 2022}$ is a dummy variable that takes the value of one for months in the year 2022 or later (motivated by the methodological change in the official series), $\mathscr{T}$ is the time trend (motivated by the slow diffusion of IT), which is defined as $\mathscr{T}_t = \Phi(t|2018.5; 0.5)$, where $\Phi(x|\mu, \sigma)$ is the cumulative density function of the normal distribution with mean μ and standard deviation σ. $\mathscr{X}_t$ is the vector of additional controls (discussed in the previous section). β are unknown parameters.

We are interested in whether the reviews are in fact useful for nowcasting BoP travel expenditure. To assess that, we apply a set of machine learning techniques to model (2) to select relevant predictors. They include elastic net, a robust version of elastic net, and the smoothly clipped absolute deviation model. These models can identify unimportant predictors by setting the corresponding coefficients to zero, and thus guard against overfitting. This is achieved by imposing a penalty function on the usual least-square objective.

In more detail, the elastic net estimator is defined as follows:

$$\min_{\beta} \sum_{t=1}^{T} \left(y_t - \beta_0 - \sum_i X_{it} \beta_i \right)^2 + \lambda \left(\alpha \sum \beta_i^2 + (1-\alpha) \sum_i |\beta_i| \right), \tag{3}$$

where $\lambda > 0$ and $\alpha \in [0, 1]$ are two hyperparameters. If $\alpha = 1$, the elastic net collapses to the ridge regression, while if $\alpha = 0$, it corresponds to lasso. The L^1 penalty $\sum_i |\beta_i|$ encourages sparsity by shrinking some of the coefficients exactly to zero, similarly to lasso. The L^2 penalty $\sum \beta_i^2$ encourages small—but not necessarily zero—coefficients, which helps in handling correlated variables, similar to ridge regression. When the predictors are highly correlated, lasso may arbitrarily select one variable from the group, while ridge tends to shrink them together. Elastic net selects groups of correlated predictors together, which can result in a more stable and interpretable model in the presence of correlation among the predictors.

Like all methods whose objective contains a quadratic function, elastic net may be sensitive to unusual observations. We cannot exclude such a situation, as our sample contains the pandemic period with dramatic shocks to travel and tourism. Therefore, we consider the robust version of elastic net. The robust version can be achieved by using iteratively reweighed observations. In each iteration, the following version of elastic net is estimated:

$$\min_{\beta} \sum_{t=1}^{T} \varpi_t \left(y_t - \beta_0 - \sum_i X_{it}\beta_i \right)^2 + \lambda \left(\alpha \sum \beta_i^2 + (1-\alpha) \sum_i |\beta_i| \right), \tag{4}$$

where ϖ_t are weights on the observations aimed at eliminating the large influence of atypical observations. We use the biquadratic function to set the weights, and the iteration starts from the non-robust version of elastic net. In more detail, if ε_t are residuals from the previous iteration, the weights in the next iteration are given as:

$$\varpi_t = \begin{cases} (1-(\varepsilon_t/h)^2)^2 & \text{if} \quad \varepsilon_t/h < 1 \\ 0 & \text{otherwise} \end{cases},$$

and we set $h = 8\text{median}(|\varepsilon_t|)$.

Regardless of whether the ordinary or robust version is used, the combination of penalties L^1 and L^2 in (3) shrinks some of the coefficients exactly to zero and the remaining ones toward zero. The shrinkage of the parameters toward zero is a general property of convex penalties L^q for $q \geq 1$. This may lead to biased estimates when the true coefficient values are large. Alternatively, one can use a non-convex penalty that avoids shrinking large coefficients too much. This leads to less biased estimates for large coefficients, while still encouraging sparsity in the model.

Moreover, elastic net also sometimes selects too many variables (false positives) because of its convex penalty function. This is true for lasso (when $\alpha = 0$) and even more so for the general case of $\alpha > 0$. Non-convex penalties can handle variable selection more effectively by penalizing small coefficients more heavily and large coefficients less heavily, leading to fewer false positives and more accurate selection of important variables. One of the most commonly used non-convex penalties is the smoothly clipped absolute deviation (SCAD) penalty proposed by Fan and Li (2001). The estimator is defined as follows:

$$\min_{\beta} \sum_{t=1}^{T} \left(y_t - \beta_0 - \sum_i X_{it}\beta_i \right)^2 + \sum_i \mathscr{C}_{\lambda,\gamma}(\beta_i), \tag{5}$$

where the penalty reads as follows:

$$\mathscr{C}_{\lambda,\gamma}(x) = \begin{cases} \lambda |x| & \text{if} \quad |x| \leq \lambda \\ -\frac{x^2+2\gamma\lambda+\lambda^2}{2(\gamma-1)} & \text{if} \quad \lambda < |x| \leq \gamma\lambda \\ 0.5(\gamma+1)\lambda^2 & \text{if} \quad |x| > \gamma\lambda \end{cases}. \tag{6}$$

The penalty depends on two hyperparameters $\lambda > 0$ and $\gamma > 1$. The first determines the degree of shrinkage for small values, while the second determines the region of no penalization.

In total, we report the results of three machine learning techniques: elastic net, robust elastic net, and SCAD. We use the out-of-sample exercise described above to set the hyperparameters of these estimators. We report the point estimates of the parameters, the RMSE, and the MEA statistics evaluated for the hyperparameters that provided the lowest out-of-sample RMSE. Moreover, we also run two OLS regressions. The first one contains the four variables that we chose based on our a priori reasoning. The second one contains the regressors selected by the SCAD method. For the OLS estimators, we also report the p-values.[19] For the two OLS regressions, we also computed the out-of-sample RMSE and MAE statistics.

Table 2 provides the estimation results for revenues from travel services. The number of reviews is selected by all the machine learning techniques and is significant for both OLS regressions. The coefficient value according to most estimates is around 27. If we translate this to average 2024 nominal terms, it means that an increase of 100 in the number of reviews is expected to increase travel services revenues by CZK 0.5 billion. The other coefficients (if present) have the expected signs: the stringency index is negative, consumer sentiment is positive, and depreciation of the real exchange rate increases revenues from travel services.

The method with the most accurate pseudo real-time out-of-sample prediction according to RMSE is elastic net, while for MAE it is the robust version of the elastic net. This is not surprising, as the robust version disregards large outliers. SCAD performs worse. The value of hyperparameter α is close to 1, meaning that the winning model is closer to ridge regression than to lasso, which is not a surprise in light of recent research (Shen and Xiu, 2024). Both elastic net models outperform the ARIMA benchmark according to the Diebold–Mariano test under both loss functions at 10% significance.

Table 3 provides the results for expenditure on travel services. All the machine learning techniques select the number of reviews, but it does not have statistical significance for OLS on the conventional level. The coefficient according to elastic net, which is our preferred technique, is around 6. If we translate it to average 2024 nominal terms, it means that an increase of 100 in the number of reviews is expected to increase travel services expenditure by CZK 100 million. The other coefficients (if present) have the expected signs: the stringency index is negative, consumer sentiment is positive, and depreciation of the real exchange rate reduces expenditure on travel services—the likely channel is the relative price effect. Real exchange rate depreciation increases the cost of traveling abroad relative to domestic alternatives. Among the methods, the clear winner is the SCAD approach from the perspective of both RMSE and MAE. The winning SCAD model outperforms the ARIMA benchmark according to the Diebold–Mariano test under both loss functions at 5% significance.

As the choice of hyperparameters may be crucial, for the sake of sensitivity analysis, we also report the estimation result for the case where the shrinkage parameter λ is multiplied by 10 and multiplied by 0.1. This yields more shrinkage and less shrinkage, respectively, than in the cross-validated case. The results are available in Tables A1 and A2 in the Appendix.

4.2 Models with Time-varying Parameters

We also consider models with time-varying parameters. In this case, the econometric specification reads as follows:

$$y_t = \beta_{0,t} + \beta_{1,t}\mathscr{R}_t + \beta_{2,t}\mathscr{S}_t + \mathscr{X}_t\beta_{r,t} + \varepsilon_t, \tag{7}$$

where now the parameters are time varying but trends and time dummies are not included. We inquire whether the possibility of time variation in the parameters can be a substitute for the inclusion of trends.

[19] For machine learning techniques, we do not report any measure of the statistical significance of the coefficients. This is because these techniques select relevant regressors, so it does not make sense to test whether the coefficients are different from zero.

There is a plethora of methods that can be used to estimate models with time-varying parameters. They range from simple models with rolling or recursive windows to sophisticated Bayesian models. All the results of all these models depend on some a priori settings: rolling estimation depends on the length of the window, while the results of Bayesian models depend on the prior distributions used.

We focus on two approaches that each depend on a single hyperparameter. The key advantage of such methods is that the hyperparameter can be selected in a data-driven manner using pseudo real-time out-of-sample RMSEs, in a way analogous to common practices in machine learning. Another strength is their parsimony: only one hyperparameter needs to be determined. This stands in contrast to Bayesian techniques, which require the specification of numerous prior details (means, standard deviations, and possibly other parameters).

First, we adopt the recent approach of Goulet Coulombe (2025), who considers a time-varying regression of the form:

$$\min_{\beta} \sum_{t=1}^{T} \left(y_t - \beta_0 - \sum_i X_{it} \beta_{it} \right)^2 + \lambda \sum_{t=2}^{T} ||\beta_t - \beta_{t-1}||_2^2 .$$

The hyperparameter λ governs the degree of variation in the coefficients β. A larger value of λ imposes a stronger penalty on changes across periods, thereby enforcing smoother dynamics, while a smaller value allows the coefficients to vary more freely over time. Goulet Coulombe (2025) further demonstrates that the time-varying parameter problem can be reformulated as a large ridge regression, which substantially accelerates the computation.

Second, we consider the additive smoothed coefficient model of Li and Racine (2007), which solves the time-varying parameters as a solution to the following weighted OLS:

$$\beta_\tau = \arg\min \sum_{t=1}^{T} \kappa(\tau - t, h) \left(y_t - X_t \beta_t \right)^2 ,$$

where $\kappa(\tau - t, h)$ is a kernel with bandwidth h. We use the Gaussian kernel and the bandwidth h is the hyperparameter.

To mitigate the risk of overfitting, we selected the regressors to be included in the model. Specifically, we evaluated the model using a subset of regressors. This analysis involved five models: one incorporating all four regressors and four additional models each excluding one regressor. For each model, we calculated the out-of-sample RMSE using the optimized hyperparameter specific to each model. While models with multiple regressors removed were also considered, their forecasting performance was significantly lower, leading us to focus exclusively on these five models.

Tables 4 and 5 report the results of the first class of time-varying models. For each model, we report the mean of the time-varying parameters over the full sample and the mean over the post-COVID sample, i.e., after 2022. For the revenue (credit) side, the winning model contains the number of reviews, the stringency index, and the consumer sentiment index. The mean of the coefficient for the number of reviews is similar to the estimate of the elastic net, which is the winner among the time-invariant models (see Table 2). The model with time-varying parameters has a lower RMSE than the time-invariant model with trends and time dummies. If reviews are not included, the out-of-sample RMSE is much higher. Moreover, the DM test reveals that models with reviews beat the ARIMA benchmark at least at the 10% significance level.

For the expenditure side, the winning model with time-varying parameters includes the number of reviews, the stringency index, and the real exchange rate (see Table 3). The forecasting performance is better for the model with time-varying parameters, and the number-of-reviews coefficient is much higher than for the best time-invariant model based on the SCAD estimator.

Tables 6 and 7 present the results of the time-varying models with smoothed coefficients. On the revenue side, the winning model selects the same predictors as before: the number of reviews, the sentiment indicator, and the stringency index. The coefficient on the number of reviews is numerically close to that obtained from the ridge-based time-varying model. Both RMSE and MAE are lower for the smoothed coefficient specification, and the Diebold–Mariano test indicates significantly better forecasting accuracy relative to the ARIMA benchmark at the 5% level for both the L^2 and L^1 loss functions. On the expenditure side, the winning model includes all four predictors considered, but its forecasts are not statistically superior to those of the ARIMA benchmark.

In both cases, it seems that time variation of the parameters is a good substitute for various trends and time dummies. We therefore opt for this option. Figure 4 displays the data (the original non-seasonally adjusted series in nominal terms) and the forecasts produced by the two best models: the one with time-varying parameters and the one for a time-invariant model. The forecasts are converted to nominal terms and seasonality is added. Apparently, the empirical models considered in this paper can deal with the issues identified in our research, i.e., the slow upward trend in reviews before the pandemic, the drastic fall in travel services during the pandemic, and occasional methodological changes. The reviews thus prove useful for nowcasting BoP travel services series. It is also apparent that models with time-varying parameters exhibit larger prediction errors at the beginning of the sample and are more reliable after the COVID-19 pandemic.

Figure 4: Predictions by Preferred Methods

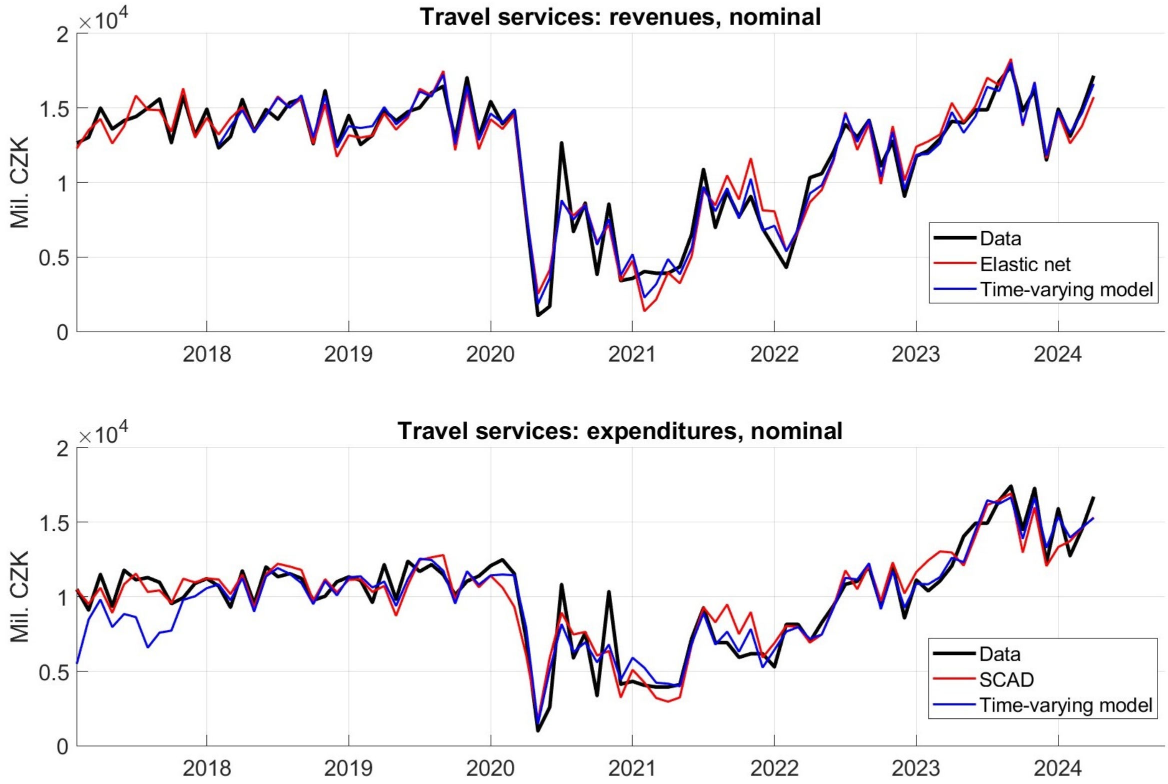


Table 2: Estimation of the Revenue Side

Variable	Elastic net	Elastic net (robust)	SCAD	OLS 1		OLS 2	
				Estimate	p-value	Estimate	p-value
Google reviews	27.908	29.439	28.267	28.855	2.0985e-12	27.978	1.77e-11
Stringency index	-30.473	-26.651	-29.137	-30.943	0.0064277	-30.406	0.0075531
Dummy$\geq$ 2022	-5.3371	-4.5577	-4.7585	-9.5629	0.0011491	-5.4031	0.22443
Pre-2019 trend	-57.998	-60.519	-58.804	-60.684	3.0788e-16	-58.1	7.8804e-13
Cons. sentiment	3.159	3.3057	3.2293			3.13	0.20931
Real exchange rate	0.048461	-0.07608	0				
Hyperparameters	$\alpha = 1.00$	$\alpha = 1.00$	$\gamma = 4.99$				
	$\lambda = 0.2184$	$\lambda = 0.1053$	$\lambda = 3.11$				
RMSE	10.8900	10.9915	11.5230	10.9549		10.9915	
MAE	8.2424	8.1322	8.5903	8.1804		8.2322	
DM test (L^2)	0.0675*	0.0671*	0.0734*	0.0588*		0.0671*	
DM test (L^1)	0.0825*	0.0826*	0.1049	0.0736*		0.0826*	

Note: The DM test reports the p-value of the one-sided test for superior forecasting accuracy relative to the ARIMA benchmark. Results are shown for both loss functions.

Table 3: Estimation of the Expenditure Side

Variable	Elastic net	Elastic net (robust)	SCAD	OLS 1		OLS 2	
				Estimate	p-value	Estimate	p-value
Google reviews	6.8556	4.3492	6.0583	7.9041	0.43346	7.7556	0.40631
Stringency index	-65.532	-66.327	-68.505	-82.667	9.5753e-14	-63.021	1.3204e-08
Dummy$\geq$ 2022	8.5777	0.34409	8.8488	-9.5629	0.0039081	11.211	0.072908
Pre-2019 trend	-7.7267	-5.4019	-5.3385	-9.6424	0.15213	-7.1953	0.2496
Consumer sentiment	8.6004	5.1164	8.822			9.4899	0.00023891
Real exchange rate	-0.62081	0	0				
Hyperparameters	$\alpha = 1.00$	$\alpha = 0.90$	$\gamma = 4.99$				
	$\lambda = 0.1246$	$\lambda = 0.6787$	$\lambda = 9.98$				
RMSE	15.0466	14.8027	13.8682	16.0150		15.5118	
MAE	10.5861	10.4187	10.2945	11.8887		10.5944	
DM test (L^2)	0.4431	0.3631	0.0232	0.6876		0.5664	
DM test (L^1)	0.4939	0.4151	0.0360	0.8119		0.5078	

Note: The DM test reports the p-value of the one-sided test for superior forecasting accuracy relative to the ARIMA benchmark. Results are shown for both loss functions.

Table 4: Estimation of the Revenue Side: Time-Varying Model

Variable	Full model		Submodel 1		Submodel 2		Submodel 3		Submodel 4	
	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID
Google reviews	26.268	22.31	25.673	20.948	26.515	22.188	28.455	25.545		
Stringency index	-11.996	-16.254	-14.555	-19.844	-17.039	-21.515			-74.127	-73.946
Consumer sentiment	6.4687	1.5296	5.9533	1.0184			7.2868	1.391	7.2272	2.9817
Real exchange rate	1.7833	0.21692			0.31814	-0.42953	1.8577	0.19896	0.70182	0.14357
RMSE	10.917		10.774		11.038		11.203		12.484	
DM test (L^2)	0.0662*		0.0561*		0.0340**		0.0782*		0.1807	
DM test (L^1)	0.0665*		0.0328**		0.0168**		0.1005		0.4256	

Note: The table reports the mean of the time-varying parameters for each model. The first column reports the mean over the full sample and the second column reports the mean over the post-COVID sample, i.e., after 2022. The DM test reports the p-value of the one-sided test for superior forecasting accuracy relative to the ARIMA benchmark. Results are shown for both loss functions.

Table 5: Estimation of the Expenditure Side: Time-Varying Model

Variable	Full model		Submodel 1		Submodel 2		Submodel 3		Submodel 4	
	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID
Google reviews	18.7950	19.6653	20.7315	21.6997	17.9173	17.2808	21.6242	23.7413		
Stringency index	-23.4911	-32.3483	-22.1351	-30.2086	-36.1806	-46.8839			-70.6693	-70.8578
Consumer sentiment	6.7976	1.2654	9.1569	2.1133			8.3915	0.3015	3.8700	2.1874
Real exchange rate	-0.9723	-1.2214			-2.2011	-1.5139	-1.4039	-1.6940	-1.9793	-0.1020
RMSE	13.6299		13.9925		13.2833		14.4041		13.9485	
DM test (L^2)	0.3764		0.4261		0.2189		0.5089		0.3794	
DM test (L^1)	0.7733		0.9243		0.7294		0.9304		0.9732	

Note: The table reports the mean of the time-varying parameters for each model. The first column reports the mean over the full sample and the second column reports the mean over the post-COVID sample, i.e., after 2022. The DM test reports the p-value of the one-sided test for superior forecasting accuracy relative to the ARIMA benchmark. Results are shown for both loss functions.

Table 6: Estimation of the Revenue Side: Additive Smoothed Coefficient Model

Variable	Full model		Submodel 1		Submodel 2		Submodel 3		Submodel 4	
	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID
Google reviews	24.5808	26.2107	20.1557	28.0087	25.7361	29.1560	26.4003	26.2509		
Stringency index	-12.5784	-1.5034	-12.0079	1.1226	-13.3455	-3.5816			-26.2636	-15.8839
Consumer sentiment	3.7741	10.8835	4.9447	13.8183			4.4667	12.7631	8.1008	23.1574
Real exchange rate	-2.7717	14.2787			-1.7217	17.3517	2.5766	13.3180	25.3568	29.2789
RMSE	10.5698		10.4357		10.5998		10.9064		12.1784	
MAE	7.8180		7.6068		7.8322		7.6511		9.1396	
DM test (L^2)	0.0375		0.0393		0.0383		0.0483		0.1162	
DM test (L^1)	0.0161		0.0151		0.0178		0.0276		0.2156	

Note: The table reports the mean of the time-varying parameters for each model. The first column reports the mean over the full sample and the second column reports the mean over the post-COVID sample, i.e., after 2022.

Table 7: Estimation of the Expenditure Side: Additive Smoothed Coefficient Model

Variable	Full model		Submodel 1		Submodel 2		Submodel 3		Submodel 4	
	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID	full	post-COVID
Google reviews	14.4758	7.4261	15.2822	9.7303	17.4708	13.4111	23.7145	15.9198		
Stringency index	-28.7186	-21.9388	-29.1488	-22.4623	-34.5757	-34.6622			-34.5119	-22.3010
Consumer sentiment	7.9369	21.0094	9.2749	25.7331			8.5698	22.6576	8.7537	22.4419
Real exchange rate	17.7542	28.5494			19.7475	36.9806	16.9433	24.0660	22.9532	30.3478
RMSE	14.5354		14.4593		14.7099		15.1506		15.2043	
MAE	10.1244		10.2782		10.3987		11.2259		11.0489	
DM test (L^2)	0.2639		0.2573		0.2980		0.3233		0.2708	
DM test (L^1)	0.2212		0.2888		0.3323		0.7114		0.2378	

Note: The table reports the mean of the time-varying parameters for each model. The first column reports the mean over the full sample and the second column reports the mean over the post-COVID sample, i.e., after 2022.

5. Conclusion

In this paper, we introduce a novel indicator for nowcasting time series related to travel services in balance of payments (BoP) statistics. This indicator leverages the number of web reviews for tourist attractions. On the credit side (travel service revenues), the analysis focuses on reviews written in languages other than Czech for attractions located in the Czech Republic. Conversely, for the debit side (travel service expenditure), we target reviews written in Czech for attractions located abroad. To the best of our knowledge, this is the first study to apply web reviews as a tool for BoP nowcasting.

The use of web reviews as a nowcasting indicator presents several challenges. First, there is a pre-COVID upward trend driven by the diffusion of IT, which likely facilitated writing reviews. Second, the COVID-19 pandemic caused significant disruption to international travel. Lastly, the time series data are occasionally affected by methodological adjustments, adding further complexity to the analysis.

To address these challenges, we explored various econometric models to evaluate the potential of web reviews as a nowcasting tool. Specifically, we implemented machine learning models with carefully chosen regressors, including time trends and time dummies. Additionally, we employed a model with time-varying coefficients that excluded time trends. In both approaches, the number of web reviews consistently emerged as a significant predictor. Based on these findings, we conclude that the volume of web reviews contains meaningful information for nowcasting BoP time series.

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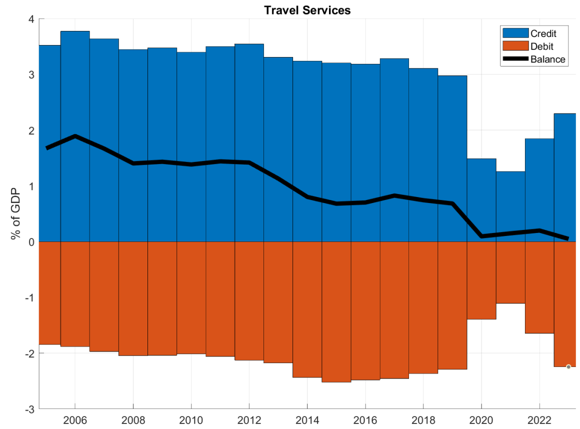
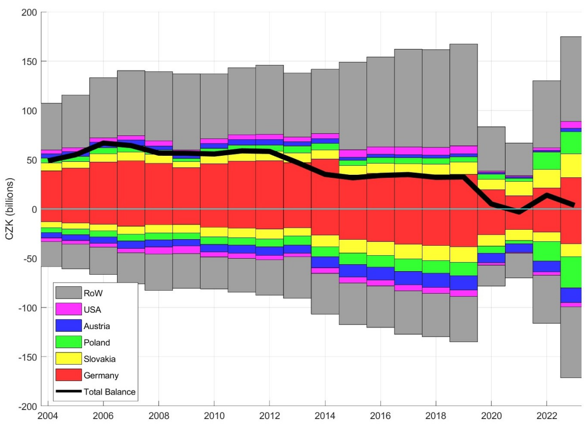
Appendix A: Additional Figures and Tables

Figure A1: Travel Services as a Percentage of GDP



Note: Prior to the pandemic, travel services contributed positively to the current account balance. This contribution evaporated in the first year of the pandemic and as of now is still hovering around zero.

Figure A2: Geographical Distribution of Travel Services



Note: The chart displays the geographical distribution of travel services revenue and expenditure for the most important countries and the rest of the world. Bars above the zero line correspond to revenues and bars below the zero line to expenditure.

Table A1: Estimation of the Revenue Side: Sensitivity to Hyperparameters

Variable	Elastic net		Robust elastic net		SCAD	
Google reviews	27.979	27.196	28.923	25.298	27.988	28.702
Stringency index	-30.389	-31.303	-28.026	-37.301	-30.4	-26.556
Dummy$\geq$ 2022	-5.3936	-4.772	-4.6233	-5.024	-5.4405	-3.8503
Pre-2019 trend	-58.102	-56.962	-59.492	-52.265	-58.182	-59.018
Consumer sentiment	3.1323	3.4248	3.4318	4.2989	3.1088	3.6303
Real exchange rate	0.050969	0.023271	-0.030754	0	0.023794	0
Hyperparameters	$\lambda = 0.02184$	$\lambda = 2.184$	$\lambda = 0.01053$	$\lambda = 1.053$	$\lambda = 0.311$	$\lambda = 31.1$
RMSE	10.9912	11.1496	10.9944	11.1951	11.5880	12.3822
MAE	8.2334	8.5045	8.2465	8.5410	8.7410	9.1002

Note: This table provides the sensitivity results for the estimation of the revenue side w.r.t. the hyperparameter of the model. Only parameter λ was varied. The parameter related to the number of reviews is rather stable to variation in hyperparameters.

Table A2: Estimation of the Expenditure Side: Sensitivity to Hyperparameters

Variable	Elastic net		Robust elastic net		SCAD	
Google reviews	9.0588	0	9.2179	0	9.2093	5.4283
Stringency index	-62.25	-74.959	-61.625	-32.721	-61.957	-64.694
Dummy$\geq$ 2022	10.784	0	10.587	0	11.036	10.061
Pre-2019 trend	-9.6736	-1.0574	-9.4875	-2.0987	-9.7303	-6.9984
Consumer sentiment	9.4717	4.9092	9.4376	1.411	9.5629	9.257
Real exchange rate	-0.87725	0	-0.76939	0	-0.85283	09
Hyperparameters	$\lambda = 0.0125$	$\lambda = 1.246$	$\lambda = 0.0678$	$\lambda = 6.787$	$\lambda = 0.99$	$\lambda = 99.8$
RMSE	15.0710	15.4234	15.0469	19.9317	14.0166	14.3565
MAE	10.5251	10.4610	10.5360	14.0498	10.2587	10.3639

Note: This table provides the sensitivity results for the estimation of the expenditure side w.r.t. the hyperparameter of the model. Only parameter λ was varied. For the winning model, i.e., the model with the SCAD penalty, the number of reviews stays in the model with non-zero coefficients even when the shrinkage hyperparameter is multiplied by 10.

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