Exploring the predictive ability of LIKES of posts on the Facebook pages of four major city DMOs in Austria

WIFO Research Seminar, Austrian Institute of Economic Research

Vienna, Austria, September 15, 2020

Ulrich Gunter, Irem Önder, Stefan Gindl

Agenda

- Motivation
- Data
- Rival Forecast Models
- Forecasting Exercise
- Forecast Evaluation Results
- Conclusion

- *Appendix:*
  - *In-Sample Goodness-of-Fit Measures*
  - *Detailed Forecast Accuracy Results per City*

Motivation

Facebook’s Potential Role in Forecasting

- Pertaining to user-generated content (UGC), Facebook is one of the largest social networks, with more than 2.7 billion monthly active Facebook users (as of June 2020; Zephoria, 2020)
- Although Facebook is a very popular social media platform generating big data (in the form of posts, shares, reactions such as LIKES, etc.), data from this platform have not often been used in tourism demand forecasting
- Traditional tourism demand drivers (e.g., own price, competitors’ prices, income; Song et al., 2009) can suffer from a publication lag
- On the other hand, the majority of business decisions in the tourism industry require reliable (i.e., accurate) and timely tourism demand forecasts (Song et al., 2009), which is also due to the perishable nature of tourism products and services (Frechtling, 2001)

Purpose of this Study (1)

- Consequently, this study investigates the (pseudo) out-of-sample predictive ability of LIKES of posts on the Facebook pages of four major city destination management organizations (DMOs) in Austria for forecasting actual total tourist arrivals (total domestic and total foreign) to these destinations
- The cities under scrutiny are Graz, Innsbruck, Salzburg, and Vienna, which received the highest number of annual total tourist arrivals out of the nine Austrian provincial capital cities for six consecutive years from 2012 to 2017 (TourMIS, 2018)

Purpose of this Study (2)

- The rationale behind this investigation is that if those LIKES are expressions of decision-relevant reactions to meaningful information provided by the city DMOs (i.e., a useful predictor of actual tourism demand), including the information contained in these reactions in the information set available to the forecaster at the forecast origin should result in more accurate tourism demand forecasts (i.e., LIKES are assumed to Granger-cause actual tourism demand; Granger, 1969; Lütkepohl, 2005)
- Moreover, (potential) tourists gather information about their destination of interest prior to the actual trip, with the Internet being characterized by comparably low search costs, ergo allowing tourists to forage information (Pirolli and Card, 1999; Gunter and Önder, 2016) with only little effort (Zipf, 2012; Önder et al., 2020)

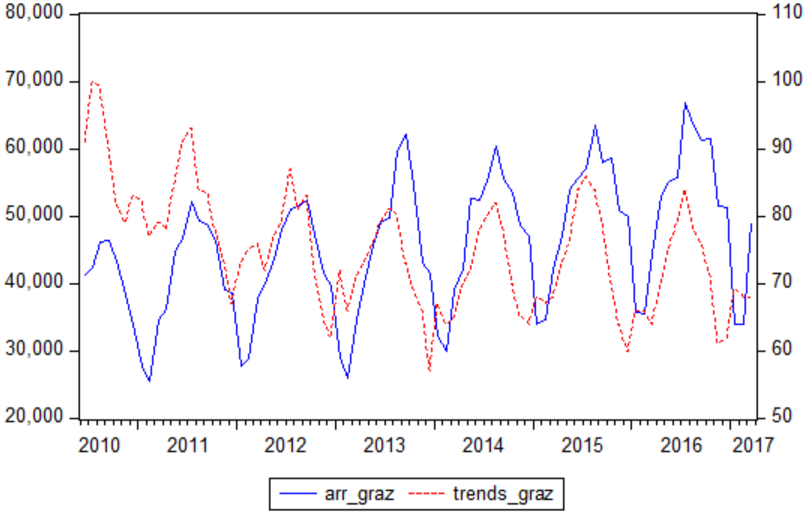
Contribution to the Literature

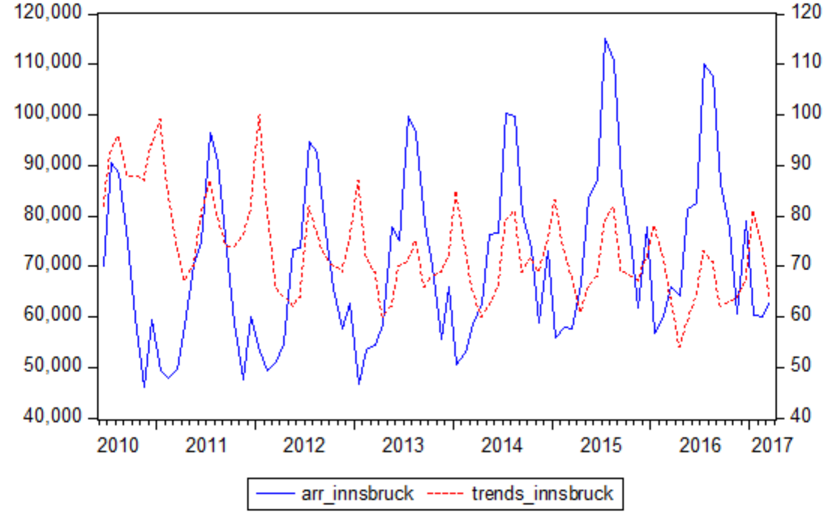
- Besides the first-time use of Facebook LIKES in tourism demand forecasting, the joint investigation of the predictive ability of two different types of big data (or web-based predictors) in tourism demand forecasting – the novel LIKES from the *UGC data* category and the well-established Google Trends from the *transaction data* category according to Li, Xu et al. (2018) – is one of the main contributions of the present study
- A broader contribution of this research is the investigation of the predictive ability of any type of big data in tourism demand forecasting for important Austrian city destinations beyond Vienna

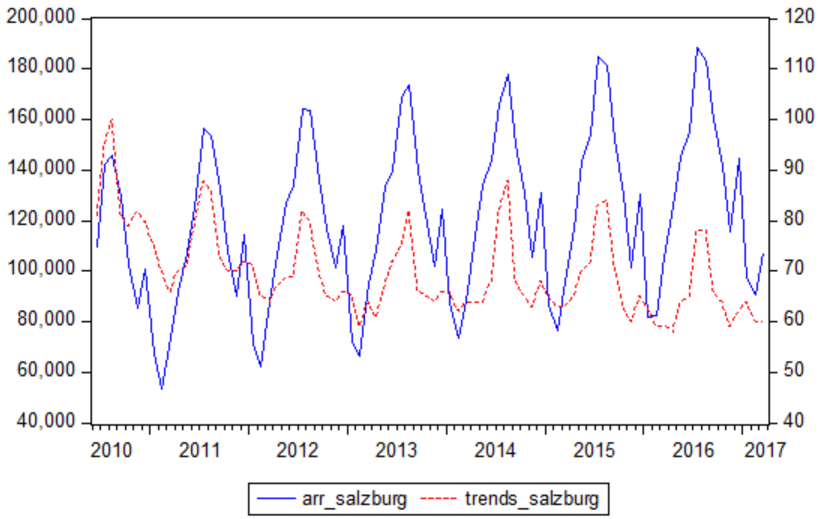
Data

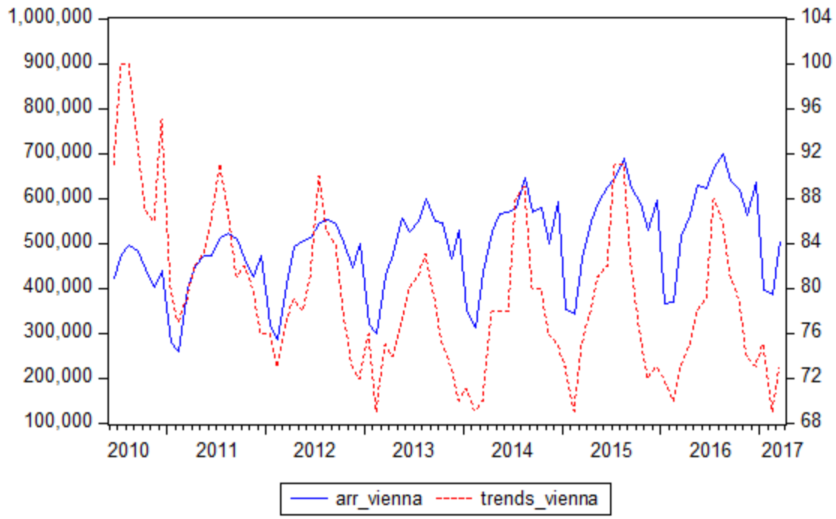
Data (1)

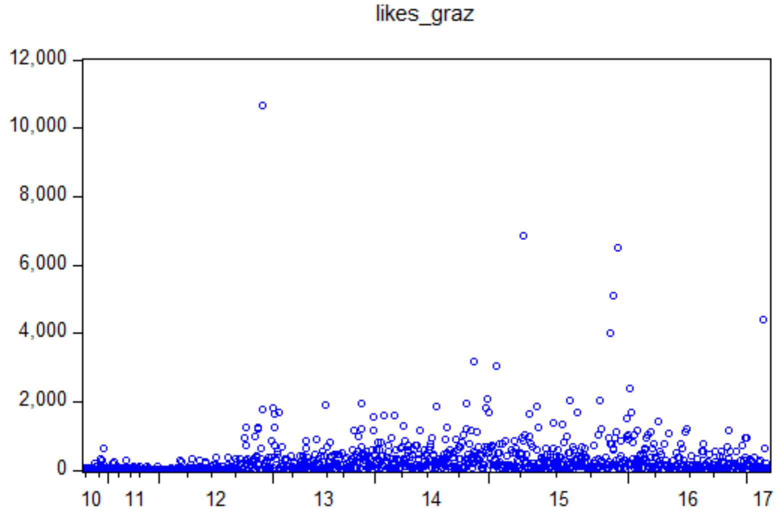
- The sample period ranges from 2010M06 to 2017M02
- As a measure for actual tourism demand in the four cities, *monthly* total tourist arrivals (domestic and all foreign sources markets to all paid forms of accommodation) are employed
- The first – potential – web-based predictor of tourism demand, the *daily* LIKES of posts on the Facebook pages of the four cities under scrutiny, were retrieved using Facebook's Graph Application Programming Interface (API) employing a self-programmed crawling system
- The second – 'gold standard' – web-based predictor of tourism demand, the *monthly* Google Trends indices for the four cities under scrutiny (web search index under the 'travel' category for worldwide searches in English), were retrieved from Google LLC
- All variables are seasonally adjusted by applying moving average filters before they are further employed in the forecast evaluation (including the monthly aggregate of the daily LIKES)

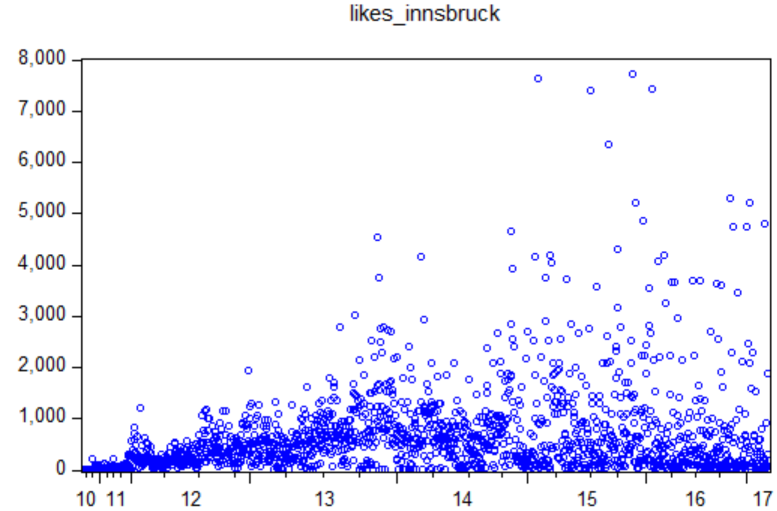

arr_graz
trends_graz

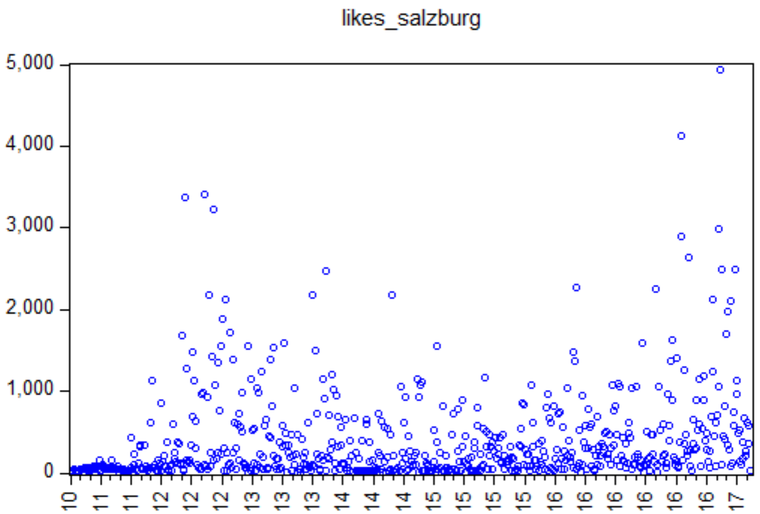

arr_innsbruck
trends_innsbruck

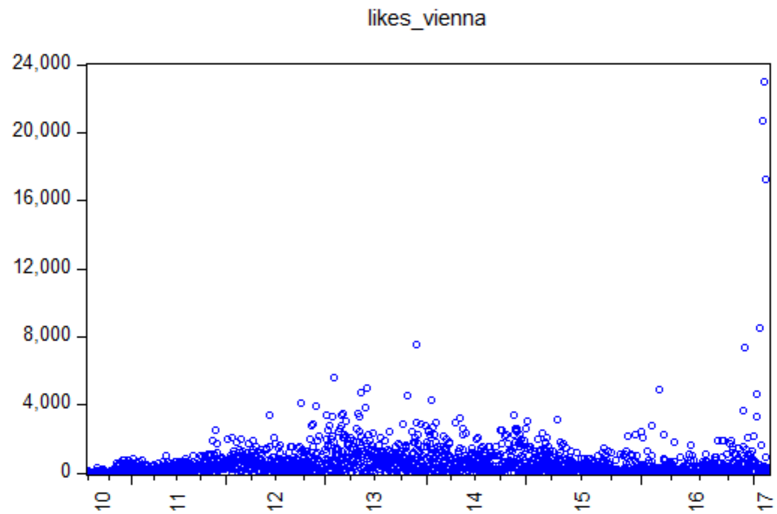

arr_salzburg
trends_salzburg


arr_vienna
trends_vienna


likes_graz
12,000
10,000
8,000
6,000
4,000
2,000
0
10 11 12 13 14 15 16 17


likes_innsbruck
8,000
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
10 11 12 13 14 15 16 17


likes_salzburg
5,000
4,000
3,000
2,000
1,000
0


likes_vienna
24,000
20,000
16,000
12,000
8,000
4,000
0
10 11 12 13 14 15 16 17

Data (2)

- Augmented Dickey-Fuller (ADF) tests of the seasonally adjusted variables are conducted including a constant and a linear trend
- The null hypothesis of the ADF test (i.e., presence of a non-seasonal unit root) is rejected for total tourist arrivals to all four cities and for LIKES across cities at the 0.1% significance level
- Concerning the Google Trends data, however, the null hypothesis of the ADF test is only rejected for Innsbruck (at the 5% significance level) and for Vienna (at the 1% significance level)
- To remain consistent across cities and forecast models and to prevent information loss due to over-differencing in the case of the two non-affected cities (Smith and Yadav, 1994; Hyndman and Khandakar, 2008) all variables are employed in levels (while still allowing for trending behavior in the data)

Rival Forecast Models

Models Including LIKES and/or Google Trends (1)

- Due to presumably dynamic nature of the data-generating process (DGP) and to allow for habit persistence and expectations in consumption (albeit having to ignore potential unobserved heterogeneity), the autoregressive distributed lag (ADL) model class is employed (Engle and Granger, 1987; Song et al., 2009)
- The optimal lag orders per city and variable out of a maximum initial lag order equal to 12 are obtained by the Bayesian information criterion (BIC) through automatic model selection

Models Including LIKES and/or Google Trends (2)

- Taking into account the daily frequency of the original LIKES data and to fine-tune their lag structure, the mixed data sampling (MIDAS) model class is also employed (Ghysels et al., 2005, 2006; Andreou et al., 2010)
- The R-MIDAS-AR model specifications employ a non-exponential Almon lag polynomial (Almon, 1965) with four shape parameters as weighting function for temporal aggregation of the high-frequency lags of the LIKES data, while the optimal number of high-frequency lags per city out of a maximum of 60 days is also automatically selected
- Besides that, they also include low-frequency lags of the dependent variable (and current values and low-frequency lags of Google Trends indices)

Pure Time-Series Benchmarks

- Representatives of the autoregressive moving average (ARMA; Box and Jenkins, 1970), the error-trend-seasonal (ETS; Ord et al., 1997; Hyndman et al., 2002, 2008), and the naïve model classes (i.e., the naïve-1 benchmark) are included as pure time-series benchmarks
- The optimal ARMA and ETS specifications are obtained by the BIC through automatic model selection
- The different possible combinations of LIKES and Google Trends in one ADL or MIDAS model result in a total of eight rival forecast models

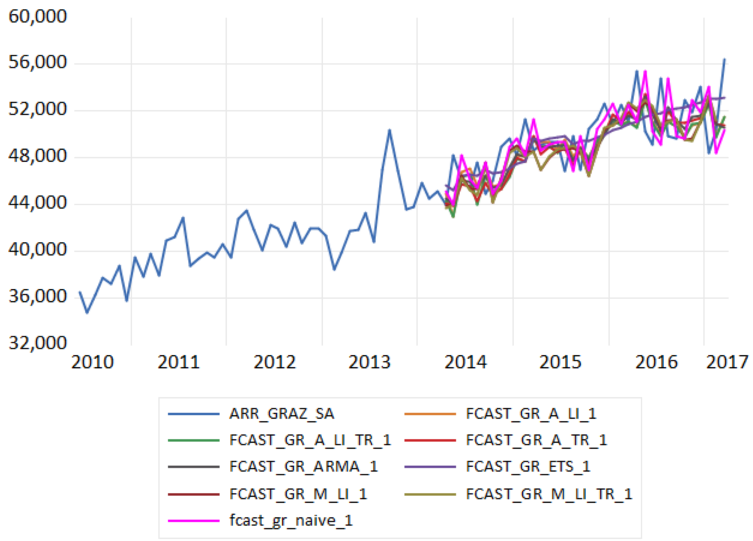
Forecasting Exercise

Forecasting Exercise (1)

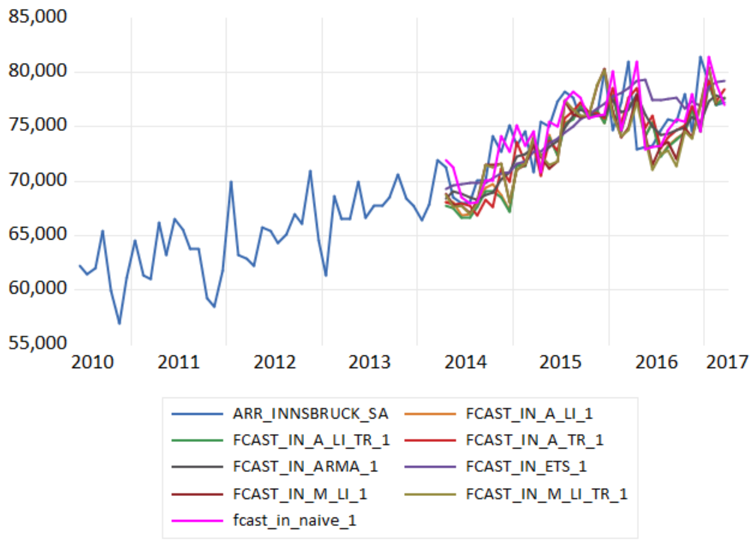
- The forecasting exercise is carried out by employing expanding estimation windows in order to replicate a 'natural' forecasting problem, whereby the forecaster seeks to use all information available up to the forecast origin
- The forecast horizons which are evaluated range from short-term to long-term, i.e., from h = 1, h = 2, h = 3, h = 6, h = 12, to h = 24 months ahead
- This results, per city, in 35 forecasts for the period 2014M04 – 2017M02 for h = 1, 34 forecasts for the period 2014M05 – 2017M02 for h = 2, …, and 12 forecasts for the period 2016M03 – 2017M02 for h = 24

Forecasting Exercise (2)

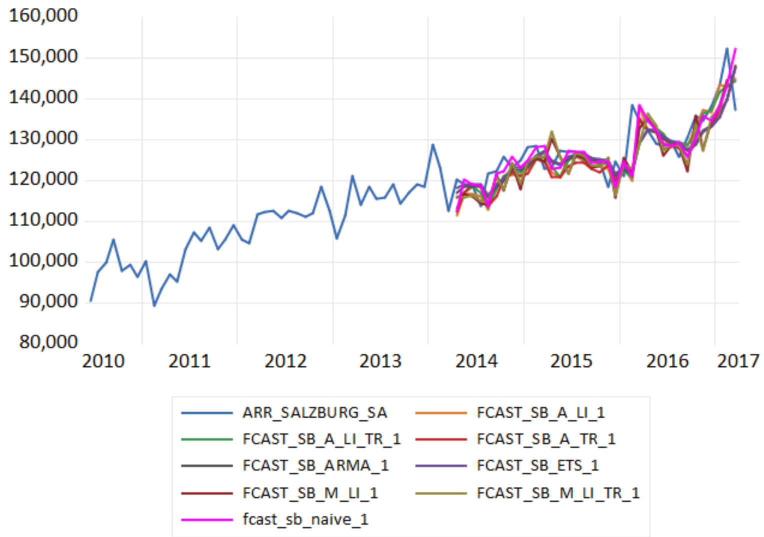
- For each city and forecast horizon, the (pseudo) out-of-sample ex-post accuracy of all eight rival forecast models is evaluated in term of the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE)
- Moreover, the forecast encompassing test by Chong and Hendry (1986) and Timmermann (2006) is employed to investigate whether the naïve-1 benchmark encompasses all the information contained in the remaining forecast models to investigate if more sophisticated forecast models are meaningful in the first place



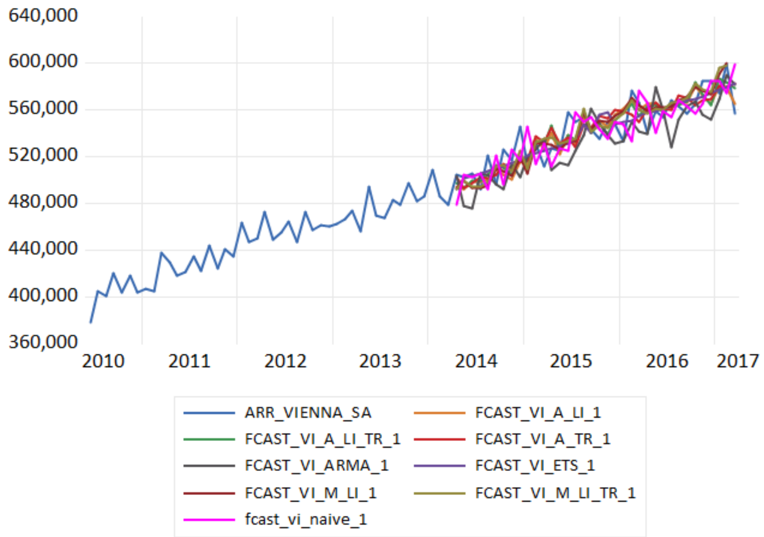
60,000
56,000
52,000
48,000
44,000
40,000
36,000
32,000
2010
2011
2012
2013
2014
2015
2016
2017
ARR_GRAZ_SA
FCAST_GR_A_LI_1
FCAST_GR_A_LI_TR_1
FCAST_GR_A_TR_1
FCAST_GR_ARMA_1
FCAST_GR_ETS_1
FCAST_GR_M_LI_1
FCAST_GR_M_LI_TR_1
fcast_gr_naive_1



85,000
80,000
75,000
70,000
65,000
60,000
55,000
2010
2011
2012
2013
2014
2015
2016
2017
ARR_INNSBRUCK_SA
FCAST_IN_A_LI_1
FCAST_IN_A_LI_TR_1
FCAST_IN_A_TR_1
FCAST_IN_ARMA_1
FCAST_IN_ETS_1
FCAST_IN_M_LI_1
FCAST_IN_M_LI_TR_1
fcast_in_naive_1



160,000
150,000
140,000
130,000
120,000
110,000
100,000
90,000
80,000
2010
2011
2012
2013
2014
2015
2016
2017
ARR_SALZBURG_SA
FCAST_SB_A_LI_1
FCAST_SB_A_LI_TR_1
FCAST_SB_A_TR_1
FCAST_SB_ARMA_1
FCAST_SB_ETS_1
FCAST_SB_M_LI_1
FCAST_SB_M_LI_TR_1
fcast_sb_naive_1



640,000
600,000
560,000
520,000
480,000
440,000
400,000
360,000
2010
2011
2012
2013
2014
2015
2016
2017
ARR_VIENNA_SA
FCAST_VI_A_LI_1
FCAST_VI_A_LI_TR_1
FCAST_VI_A_TR_1
FCAST_VI_ARMA_1
FCAST_VI_ETS_1
FCAST_VI_M_LI_1
FCAST_VI_M_LI_TR_1
fcast_vi_naive_1

Forecast Evaluation Results

Forecast Evaluation Results (1)

- While the time-series benchmarks perform best for Graz and Innsbruck across forecast horizons and forecast accuracy measures, the ADL models incorporating only LIKES as well as both LIKES and Google Trends outperform their competitors in most cases for Salzburg
- For Vienna, the MIDAS model including both LIKES and Google Trends produces the smallest RMSE, MAE, and MAPE values for most forecast horizons, which is followed by the ADL model with both LIKES and Google Trends
- Therefore, for at least two of the four Austrian cities under scrutiny, incorporating *complementary information* originating from two different web-based predictors within appropriate dynamic forecast model classes is worthwhile in order to produce more accurate tourism demand forecasts

Forecast Evaluation Results (2)

- In addition, the null hypothesis of the forecast encompassing test by Chong and Hendry (1986) and Timmermann (2006) of the naïve-1 benchmark containing all the information enclosed in the remaining forecast models is rejected at least at the 10% significance level in 18 out of 24 cases across cities and forecast horizons
- Incorporating Google Trends indices has been shown to deliver accurate tourism demand forecasts for the city of Vienna (Önder and Gunter, 2016; Önder, 2017); therefore, the present results complement the findings of previous studies from the literature

Conclusion

Some Limitations and Areas for Future Research (1)

- The study is limited to only four Austrian cities, to a specific time period, to tourist arrivals as a tourism demand measure, and to the aggregate of the total domestic and total foreign source markets
- However, it can be completely replicated by applying the same methodology to different data sets in order to ascertain whether the forecast evaluation results differ for different destinations inside and outside of Austria, for different time periods, for different measures of tourism demand, for different information criteria, and for data disaggregated at the source market level
- Evaluating the ex-ante accuracy of all eight rival forecast models would be of interest as well

Some Limitations and Areas for Future Research (2)

- Once data on Facebook LIKES become available at the disaggregate source market level, future research will be able to investigate the properties of the different source markets in greater detail
- Also the potential predictive ability of the other reaction types available on Facebook – namely ANGRY, CARE (introduced only during the COVID-19 pandemic), HAHA, LOVE, SAD, and WOW – would be worthwhile investigating in case they become similarly popular to the still dominant LIKES reaction (96% for Salzburg; 99% for the three remaining cities)
- The typical limitations of purely quantitative forecasting in times of external shocks / structural breaks (i.e., the COVID-19 pandemic) also apply here

Publications from this Research Project

- This paper: Gunter, U., Önder, I., Gindl, S. (2019): Exploring the Predictive Ability of LIKES of Posts on the Facebook Pages of Four Major City DMOs in Austria. *Tourism Economics*, 25, 375 – 401.
- Önder, I., Gunter, U., Gindl, S. (2020): Utilizing Facebook Statistics in Tourism Demand Modeling and Destination Marketing. *Journal of Travel Research*, 59, 195 – 208.
- Gunter, U., Önder, I., Gindl, S. (2018): Using Facebook Likes and Google Trends Data to Forecast Tourism. *EViews Econometric Analysis Insight Blog*, URL: http://blog.eviews.com/2018/08/using-facebook-likes-and-google-trends.html.

Thank you for your attention!

Ulrich Gunter (ulrich.gunter@modul.ac.at)

Appendix

In-Sample Goodness-of-Fit Measures

Table 2. In-sample goodness-of-fit measures (adjusted R^2, BIC, and AIC) of ADL and MIDAS models per city.

City	Model	Adjusted R^2	BIC	AIC
Graz	FCAST_GR_A_LI	*0.821168*	*18.44225*	18.26230
	FCAST_GR_A_TR	0.811343	18.45403	18.30407
	FCAST_GR_A_LI_TR	0.818829	18.49676	18.28681
	FCAST_GR_M_LI	0.803491	18.49305	*18.23608*
	FCAST_GR_M_LI_TR	0.801453	18.54880	18.25971
Innsbruck	FCAST_IN_A_LI	0.775755	18.92707	18.77711
	FCAST_IN_A_TR	0.773093	18.93887	18.78891
	FCAST_IN_A_LI_TR	0.773199	18.98011	18.80015
	FCAST_IN_M_LI	*0.802152*	*18.87761*	*18.62064*
	FCAST_IN_M_LI_TR	0.799221	18.93775	18.64865
Salzburg	FCAST_SB_A_LI	0.859368	*19.90563*	19.78739
	FCAST_SB_A_TR	0.846444	19.99355	19.87531
	FCAST_SB_A_LI_TR	*0.863267*	19.94218	*19.76353*
	FCAST_SB_M_LI	0.785433	19.98818	19.78579
	FCAST_SB_M_LI_TR	0.789078	20.06822	19.79836
Vienna	FCAST_VI_A_LI	0.945060	22.04524	21.70275
	FCAST_VI_A_TR	0.938854	22.08192	21.83658
	FCAST_VI_A_LI_TR	0.946445	22.01971	21.67721
	FCAST_VI_M_LI	0.955560	21.98171	21.57382
	FCAST_VI_M_LI_TR	*0.958121*	*21.96537*	*21.52611*

Source: TourMIS, Facebook Inc., Google LLC, and own calculations.
Note: BIC: Bayesian information criterion; AIC: Akaike information criterion; ADL: autoregressive distributed lag; MIDAS: mixed data sampling. The highest adjusted R^2 values and lowest BIC and AIC values per city are given in italics.

Graz

Graz	*h=1*			*h=2*			*h=3*			*h=6*			*h=12*			*h=24*		
Forecast model	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
FCAST_GR_NAIVE	2764.19	2285.26	4.58	2622.68	2056.55	4.12	2390.61	1943.33	3.86	2949.27	2517.03	4.96	3156.12	2585.91	5.05	5569.04	4528.02	8.58
FCAST_GR_ETS	**2094.13**	**1739.54**	**3.49**	**2090.27**	**1740.21**	**3.48**	**2117.54**	**1720.78**	**3.43**	**2102.05**	**1715.60**	**3.41**	**2073.45**	**1730.28**	**3.41**	**2919.50**	**2481.63**	**4.80**
FCAST_GR_ARMA	2275.49	1862.76	3.71	2330.20	1917.14	3.81	2417.99	2018.93	4.02	3273.97	2796.88	5.53	4716.39	4266.43	8.36	8450.28	7843.97	15.03
FCAST_GR_A_LI	2402.51	1948.98	3.89	2437.81	2039.55	4.05	2441.47	1901.72	3.75	3331.27	2791.31	5.46	4581.46	4119.59	8.00	7660.71	7185.54	13.76
FCAST_GR_A_TR	2431.16	2010.72	4.00	2558.77	2103.44	4.20	2732.29	2294.08	4.58	3849.98	3293.95	6.52	5317.96	4828.85	9.48	7670.77	7204.14	13.81
FCAST_GR_A_LI_TR	2489.23	2010.70	4.00	2595.95	2175.35	4.32	2689.01	2147.92	4.25	3832.78	3296.40	6.48	5298.70	4977.81	9.73	8050.31	7605.60	14.58
FCAST_GR_M_LI	2363.57	1994.52	3.98	2592.42	2210.57	4.40	2616.68	2286.26	4.55	3406.86	3025.53	5.97	5105.71	4543.06	8.90	7525.91	7124.71	13.66
FCAST_GR_M_LI_TR	2403.17	2024.26	4.04	2684.89	2301.12	4.59	2760.86	2410.61	4.81	3646.49	3239.24	6.42	5376.76	4766.86	9.36	7470.14	7088.02	13.60
Forecast encomp. test	F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value	
	2.31	0.06		1.74	0.14		**2.18**	0.07		**4.35**	0.00		**2.32**	0.08		3.78	0.11	

Innsbruck

Innsbruck	*h=1*			*h=2*			*h=3*			*h=6*			*h=12*			*h=24*		
Forecast model	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
FCAST_IN_NAIVE	2911.27	**2163.63**	**2.87**	3042.16	2494.68	3.32	3320.29	2801.96	3.74	3917.26	**3307.55**	**4.35**	**4834.97**	**3859.50**	**5.01**	5281.43	4864.39	6.33
FCAST_IN_ETS	2813.25	2355.94	3.14	2981.35	2454.43	3.27	**3246.12**	**2628.01**	**3.50**	**3884.37**	3324.59	4.40	4868.51	4440.00	5.81	**2997.37**	**2343.49**	**3.00**
FCAST_IN_ARMA	**2700.90**	2214.88	2.93	**2967.05**	**2396.79**	**3.17**	3334.32	2747.95	3.62	4278.93	3777.40	4.96	5818.82	4601.69	5.96	8373.45	7992.16	10.38
FCAST_IN_A_LI	3186.86	2587.35	3.43	3786.69	3033.59	4.02	4079.49	3356.59	4.43	5309.87	4512.48	5.90	6846.80	6263.89	8.12	10132.50	9804.34	12.74
FCAST_IN_A_TR	3021.48	2411.30	3.20	3479.49	2882.22	3.83	3852.10	3186.14	4.22	5368.59	4743.68	6.25	6883.27	5509.23	7.15	7736.06	7271.80	9.42
FCAST_IN_A_LI_TR	3289.39	2709.69	3.60	3938.32	3196.48	4.24	4198.05	3487.93	4.60	5509.15	4712.34	6.16	7004.95	6403.17	8.30	9382.21	8991.05	11.67
FCAST_IN_M_LI	2870.09	2284.83	3.03	3593.54	2886.79	3.81	3754.06	3046.36	4.00	4960.07	4235.48	5.54	6518.38	5841.50	7.58	9508.79	9138.66	11.89
FCAST_IN_M_LI_TR	2915.22	2338.68	3.10	3687.26	2964.23	3.91	3948.85	3170.19	4.16	5543.11	4682.65	6.12	7298.24	6573.09	8.54	9636.23	9217.60	11.98
Forecast encomp. test	F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value	
	2.88	0.02		**2.38**	0.05		**2.79**	0.03		**5.49**	0.00		**2.24**	0.09		2.21	0.23	

Salzburg

Salzburg	*h=1*			*h=2*			*h=3*			*h=6*			*h=12*			*h=24*		
Forecast model	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
FCAST_SB_NAIVE	4923.29	3553.32	2.75	6046.84	4690.85	3.60	7287.82	5770.48	4.41	8927.62	7116.69	5.40	**9453.95**	**7586.29**	5.70	13980.08	12915.28	9.49
FCAST_SB_ETS	4899.43	3571.33	2.73	6001.03	4513.54	3.43	6848.16	**5175.33**	**3.92**	**7842.46**	**6067.76**	**4.58**	9582.59	7611.23	**5.67**	14008.32	13270.45	9.74
FCAST_SB_ARMA	5039.46	3690.06	2.82	6257.93	4700.53	3.57	7242.75	5449.87	4.13	8822.60	7023.98	5.31	11590.01	9861.32	7.39	18984.79	18409.50	13.57
FCAST_SB_A_LI	5031.23	3574.41	2.78	5975.57	4562.22	3.55	7345.39	5685.92	4.41	9564.89	8091.47	6.29	11246.53	10231.30	7.86	**12447.10**	**11929.72**	**8.80**
FCAST_SB_A_TR	5418.75	4136.50	3.20	7171.79	5651.20	4.32	8506.37	7099.51	5.42	10621.07	9263.39	7.05	12118.73	10733.23	8.11	15555.90	14269.29	10.42
FCAST_SB_A_LI_TR	**4807.45**	**3467.34**	**2.69**	**5662.29**	**4324.28**	**3.35**	**6692.19**	5316.39	4.11	8380.96	7303.86	5.64	10772.03	9564.60	7.27	14391.15	13469.05	9.86
FCAST_SB_M_LI	5346.01	4127.72	3.21	6813.36	5739.27	4.42	8414.74	6989.92	5.36	10454.56	8497.79	6.45	11123.70	9512.50	7.15	15494.28	14218.07	10.43
FCAST_SB_M_LI_TR	5293.97	4215.73	3.27	6678.80	5537.73	4.26	8183.40	6733.08	5.16	10221.26	8363.90	6.36	10794.83	9226.69	6.95	15189.41	14013.76	10.31
Forecast encomp. test	F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value	
	0.35	0.92		**2.32**	0.06		**2.15**	0.07		**3.33**	0.01		**5.54**	0.00		**27.97**	0.00	

Vienna

Vienna	*h=1*			*h=2*			*h=3*			*h=6*			*h=12*			*h=24*		
Forecast model	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
FCAST_VI_NAIVE	18837.96	15573.75	2.88	17122.97	14216.93	2.59	21141.79	17280.46	3.17	21445.42	18775.84	3.40	32892.57	28866.68	5.18	59141.53	57007.83	10.01
FCAST_VI_ETS	12987.36	10404.10	1.91	13192.09	11067.88	2.03	14710.64	12140.39	2.23	14891.37	11246.23	2.04	17046.89	**13241.96**	**2.36**	**16552.05**	**11488.44**	**2.00**
FCAST_VI_ARMA	21083.22	16899.31	3.10	21524.22	17522.09	3.21	23709.61	18743.25	3.42	30660.75	27470.38	4.99	52741.54	50711.55	9.11	91994.41	91324.16	16.06
FCAST_VI_A_LI	14157.73	11902.31	2.20	13995.52	11741.19	2.17	14496.41	12126.80	2.23	14462.43	11825.21	2.16	21403.37	18638.04	3.37	34779.54	30587.33	5.42
FCAST_VI_A_TR	14499.79	12456.23	2.29	14671.72	12849.38	2.36	15087.23	13072.70	2.41	13516.57	10706.12	1.95	19529.28	15428.93	2.79	28780.03	22717.06	3.98
FCAST_VI_A_LI_TR	13497.36	11489.74	2.12	13336.21	11310.99	2.09	13559.38	11670.69	2.15	**12719.92**	**10531.06**	**1.92**	**16767.19**	13790.08	2.50	30623.90	26645.56	4.70
FCAST_VI_M_LI	13130.46	10430.64	1.94	13218.84	10453.16	1.93	13986.43	11731.06	2.17	14527.85	12008.87	2.20	24052.38	20613.50	3.72	40717.98	35590.09	6.30
FCAST_VI_M_LI_TR	**12618.69**	**10290.92**	**1.91**	**12630.74**	**10220.88**	**1.88**	**13228.39**	**11142.11**	**2.06**	13296.65	10783.91	1.97	20691.11	17440.72	3.15	39597.42	32996.03	5.82
Forecast encomp. test	F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value		F-statistic	p-value	
	0.64	0.72		**2.34**	0.05		**7.18**	0.00		**5.14**	0.00		**2.70**	0.05		2.26	0.23	